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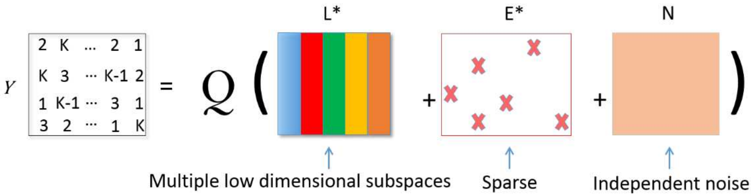
Data Recovery and Subspace Clustering from Quantized and Corrupted Measurements - Ren Wang et al

Goal

- To solve the problem of data recovery and data clustering from quantized and partially corrupted measurements when the data satisfies the union of subspaces (UoS) model

Contributions

- Sparse alternative proximal algorithm (Sparse-APA) to solve the nonconvex constrained maximum log-likelihood problem
- Theoretical analysis of the proposed data recovery method



Problem Statement

- Given observations Y, known boundaries $\omega_0 < \omega_1 < \ldots < \omega_K$ and noise distribution Φ, recover L^* and cluster the data into the corresponding subspaces S_i's simultaneously

- Nonconvex optimization problem

$$\min_{L,E\in\mathbb{R}^{m\times n},C\in\mathbb{R}^{n\times n}} -\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{l=1}^{K}\mathbb{1}_{[Y_{ij}=l]}\log\left(f_l\left(L_{ij}+E_{ij}\right)\right) \quad (1)$$

$$\text{s.t} \quad (L,E,C)\in S_f \quad (2)$$

where $S_f = \{(L,E,C) : L = LC, \text{rank}(L) \leq r, ||L||_\infty \leq \alpha_1, ||E||_\infty \leq \alpha_2, ||E||_0 \leq s, ||c_i||_0 \leq d, C_{ii} = 0, \forall i \in [n]\}$ and $f_l(X_{ij}) = P(Y_{ij} = l|X_{ij}) = \Phi(\omega_l - X_{ij}) - \Phi(\omega_{l-1} - X_{ij})$

- Proximal map associated to κ is defined as

$$prox^{\kappa}(x) = \arg\min_{u}\left\{\kappa(u) + \frac{1}{2}||u-x||_F^2\right\}$$

- Proximal gradient method applied to get the solution
  - Revised objective function is Lipschitz differentiable
  - Sum of the objective function and other functions in the problem (refer the paper for exact details) satisfies the Kurdyka-Lojasiewicz (KL) property
  - Global convergence to a critical point
- Spectral clustering to obtain the final group labels
- Theoretical analyses of the algorithms
  - Probabilistic guarantees

Nonparametric Composite Hypothesis Testing in an Asymptotic Regime - Qunwei Li et al

Goal

- To investigate the nonparametric, composite hypothesis testing (NP-CHT) problem for arbitrary unknown distributions in the asymptotic regime

Contributions

- Asymptotic viewpoint to understand the NP-CHT problem when the number of hypotheses scales exponentially in the sample size
- Maximum mean discrepancy (MMD) and Kolmogorov-Smirnov (KS) distance approaches to solve the NP-CHT problem
  - Derive the error exponents and the discrimination rates (analogous to channel coding rate)
  - Achievability and converse proofs

Problem Statement

- M hypotheses and each hypothesis corresponds to a set $\mathcal{P}_m$ of unknown distributions $\{p_{m,1}, \ldots, p_{m,M_m}\}$ for $m = 1, 2, \ldots, M$
- For each set m, we observe training sequences $\mathbf{X}_m = [\mathbf{x}_{m,1}, \ldots, \mathbf{x}_{m,M_m}] \in \mathbb{R}^{n \times M_m}$
- Determine the hypothesis that the test sequence $\mathbf{y}$ belongs to
- Regime when $M = 2^{nD}$, where D is the discrimination rate

Connection to the Channel Coding Problem

- Total number of hypotheses corresponds to the total number of messages in channel coding
- Discrimination rate D corresponds to the channel coding rate R

Main Results

- MMD-Based Test

$$\delta_{MMD}\left(\{\mathbf{X}_m\}_{m=1}^{M}, \mathbf{y}\right) = \arg\min_{m,i_m} \mathrm{MMD}^2\left(\mathbf{x}_{m,i_m}, \mathbf{y}\right) \quad (3)$$

where

$$\mathrm{MMD}^2(\mathbf{x},\mathbf{y}) = \frac{1}{n(n-1)}\sum_{i=1}^{n}\sum_{j\neq i}^{n} k(x_i,x_j) + \frac{1}{m(m-1)}\sum_{i=1}^{m}\sum_{j\neq i}^{m} k(y_i,y_j) - \frac{2}{nm}\sum_{i=1}^{n}\sum_{j=1}^{m} k(x_i,y_j)$$

Theorem

Suppose the MMD-based test in (3) is applied to the NP-CHT problem under an assumption (refer (2) in the paper), where the kernel satisfies $0 \leq k(x,y) \leq \mathcal{K}$ for all (x,y). Then the average probability of error is upper bounded as

$$P_e \leq 2^{nD}\exp\left(-\frac{n(D_O - D_I)^2}{96\mathcal{K}^2}\right). \quad (4)$$

Thus, the achievable discrimination rate is

$$D = \frac{\log e}{96\mathcal{K}^2}\liminf_{M\to\infty}\min_{1\leq i,j\leq M} MMD^4(p_i,p_j) \quad (5)$$

- Kolmogorov-Smirnov (KS) Test

$$\delta\left(\{\mathbf{X}\}_{m=1}^{M}, \mathbf{y}\right) = \arg\min_{m,i_m} D_{KS}\left(\mathbf{x}_{m,i_m}, \mathbf{y}\right) \tag{6}$$

where $D_{KS}(\mathbf{x},\mathbf{y}) = \sup_{a\in\mathbb{R}} |F_{\mathbf{x}}(a) - F_{\mathbf{y}}(a)|$, and $F_{\mathbf{x}}(a) = \frac{1}{n}\sum_{i=1}^{n} \mathbb{1}_{[-\infty,a]}(x_i)$

Theorem

Suppose the KS-based test in (6) is applied to the NP-CHT problem under an assumption (refer (2) in the paper), where the kernel satisfies $0 \leq k(x,y) \leq \mathcal{K}$ for all (x,y). Then the average probability of error is upper bounded as

$$P_e \leq 6 \times 2^{nD} \exp\left(-\frac{n(D_O - D_I)^2}{8}\right). \tag{7}$$

Thus, the achievable discrimination rate is

$$D = \frac{\log e}{8}\left(D_O - D_I\right)^2 \tag{8}$$

- Converse proof on the discrimination capacity
  - Based on Fano's inequality

Joint Channel Estimation and Multiuser Detection for Uplink Grant-Free NOMA - Yang Du et al

Goal

- Joint channel estimation (CE) and multiuser detection (MUD) in a frame based multiuser transmission scenario

Contributions

- Proposed a novel joint active user detection (AUD), CE, and MUD framework for UL grant free NOMA systems
- Multiple measurement vector-compressive sensing (MMV-CS) problem transferred to a block sparse single measurement vector compressive sensing (BS-SMV-CS) problem
- Block sparsity adaptive subspace pursuit (BSASP) algorithm is proposed to solve the above problem

System Model

- K single antenna UEs out of which sparse set of UEs are active, N antenna BS

$$\mathbf{y}_p = \sum_{k \in \Gamma} h_k \mathbf{a}_k x_{p,k} + \mathbf{n}_p = \mathbf{A}\mathbf{h} + \mathbf{n}_p, \tag{9}$$

$$\mathbf{y}_d^{[j]} = \sum_{k \in \Gamma} h_k \mathbf{a}_k x_{d,k}^{[j]} + \mathbf{n}_d^{[j]} = \mathbf{A}\mathrm{diag}\left(\mathbf{h}\right)\mathbf{x}_d^{[j]} + \mathbf{n}_d^{[j]}. \tag{10}$$

Problem Formulation

- Channel and data share the same support

$$\mathbf{y}_d^{[j]} = \mathbf{A}\mathbf{s}_d^{[j]} + \mathbf{n}_d^{[j]}. \tag{11}$$

- Received pilot and data are combined as

$$\left[\mathbf{y}_p, \mathbf{y}_d^{[j]}\right] = \mathbf{A}\left[\mathbf{h}, \mathbf{s}_d^{[j]}\right] + \left[\mathbf{n}_p, \mathbf{n}_d^{[j]}\right], j = 1, 2, \ldots, J, \tag{12}$$

- The received signal matrix from (12) is vectorized to form a BS-SMV-CS model
- Solved using BSASP algorithm
  - Exploits the block sparsity structure to choose blocks at a time instead of random sparse indices
- Computational complexity analysis

Other Interesting Papers

1. Performance analysis of approximate message passing for distributed compressed sensing
2. On geometric analysis of sparse subspace clustering
3. Optimal detection and error exponents for hidden semi-Markov models
4. Bayesian Nonparametric Causal Inference: Information Rates and Learning Algorithms
5. Near-Optimal Noisy Group Testing via Separate Decoding of Items
6. Maximum entropy low-rank matrix recovery
7. Community Detection with Side Information: Exact Recovery under the Stochastic Block Model