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Lekshmi Ramesh

Indian Institute of Science
Bangalore

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- The scalar case: Parties observe jointly Gaussian random variables, goal is to estimate correlation coefficient ρ
- Only known previous work is for scalar case and is non constructive

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- Details for the scalar setting
  - Infinitely many samples at A and B, each can estimate its own mean and variance arbitrarily well and normalize
  - Assume $X, Y \sim \mathcal{N}(0,1)$. Equivalent model

$$Y = \rho X + \sqrt{1-\rho^2} Z$$

    where $Z \sim \mathcal{N}(0,1)$ is independent of X

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- Results similar to Gaussian case even when distribution unknown

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- Need subset-wise measurements to capture higher order interactions (e.g. users annotate items with tags: 3-way relation)

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    - Studies two new measurement models

      (i) Homogeneity measurement model: whether or not a subset of points is in the same cluster

      (ii) Parity measurement model: observe sum of labels of data points modulo 2

      Measurements can be noisy (flipped)

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    (i) Homogeneity measurement model: whether or not a subset of points is in the same cluster

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    Measurements can be noisy (flipped)
  - Characterization of number of measurements required to recover communities scales as

$$\frac{2^{d-2}}{d}\frac{n\log n}{(\sqrt{1-\theta}-\sqrt{\theta})^2}$$

    (for the homogeneity model)

X. Li, D. Yin , S. Pawar, R. Pedarsani , and K. Ramchandran

- Support recovery problem: Given

$$y = Ax + w$$

where $A \in \mathbb{R}^{m \times N}$, x k-sparse, recover $\mathrm{supp}(x)$

Sub-Linear Time Support Recovery for Compressed Sensing Using Sparse-Graph Codes

X. Li, D. Yin , S. Pawar, R. Pedarsani , and K. Ramchandran

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- No known algorithms that achieve both $O(k \log N)$ measurement and computational complexity

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    Noisy setting: $O(k \log(N/k))$ time and measurement complexity, under finite alphabet assumption on x

    For general x, additional $\log(N/k)$ factors

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  - Measurement matrix construction based on sparse graph codes

- Setting: Multi agent network engaged in a binary decision task
  Agents only allowed to send one bit messages

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Detection Under One-Bit Messaging Over Adaptive Networks

S. Marano and A. H. Sayed

- Setting: Multi agent network engaged in a binary decision task
  Agents only allowed to send one bit messages
- Contributions
  - Analysis of an adapt then combine (ATC) scheme in the one bit quantized setting
  - Expressions for steady state distribution of messages

- Details: Network has S nodes/agents solving a BHT

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- Each nodes receives iid samples, updates its state based on cooperation with neighbouring nodes

$$v_k(n) = \mu x_k(n) + (1-\mu) y_k(n-1)$$
$$y_k(n) = \sum_{l=1}^{S} a_{kl} v_l(n), \; n \geq 1$$

where $x_k(n)$: data received by node k at time n
$y_k(n)$: local state variable
$v_k(n)$: intermediate value
a_{kl}: weight given to message from node l to k
μ: step size

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- Decision performance characterized in terms of design parameters μ and a_{kl}

Other interesting papers

- On the Error in Phase Transition Computations for Compressed Sensing. *S. Daei, F. Haddadi, A. Amini, and M. Lotz*
- One-Bit Compressive Sensing With Projected Subgradient Method Under Sparsity Constraints. *D. Liu, S. Li, and Y. Shen*
- Vector Approximate Message Passing. *S. Rangan, P. Schniter, and A. K. Fletcher*
- Provable Subspace Clustering: When LRR Meets SSC. *Y.-X. Wang, H. Xu, and C. Leng*