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Maximum Likelihood Estimation From Sign Measurements With Sensing Matrix Perturbation

Authors: Jiang Zhu, Xiaohan Wang, Xiaokang Lin, and Yuantao Gu

Problem

- Problem: Estimate $\boldsymbol{w}$ from binary measurement vector

$$\boldsymbol{y} = \text{sign}\left\{(\boldsymbol{H} + \boldsymbol{E})^{\mathsf{T}}\boldsymbol{w} + \boldsymbol{n}\right\},$$

  $\boldsymbol{n} \sim \mathcal{N}(0, \sigma_n^2 \boldsymbol{I})$, $\boldsymbol{e}_{ij} \sim \mathcal{N}(0, \sigma_e^2)$, *iid* and $\boldsymbol{n} \perp\!\!\!\perp \boldsymbol{E}$.
- Application: Estimation of physical quantities based on binary quantized measurements in wireless sensor networks
- ML estimation: $\boldsymbol{y} = \text{sign}\left\{\boldsymbol{H}^{\mathsf{T}}\boldsymbol{w} + \boldsymbol{z}\right\}$

$$\Longrightarrow \boldsymbol{w}_{\text{ML}} = \underset{\boldsymbol{w}}{\text{argmin}} - \sum_{i=1}^{N} \log \Phi \left\{ \boldsymbol{y}_i \frac{\boldsymbol{h}_i \boldsymbol{w}}{\sqrt{\|\boldsymbol{w}\|_2^2 \, \sigma_e^2 + \sigma_n^2}} \right\},$$

Results

- ML estimate is consistent
- The Cramér-Rao Lower Bound on the mean square error is derived
- ML estimation problem is reformulated as a convex optimization problem

$\boldsymbol{w}_{\mathrm{ML}} = \underset{\boldsymbol{w}}{\operatorname{argmin}} - \sum_{i=1}^{N} \log \Phi \left\{ \boldsymbol{y}_i \frac{\boldsymbol{h}_i \boldsymbol{w}}{\sqrt{\|\boldsymbol{w}\|_2^2 \sigma_e^2 + \sigma_n^2}} \right\}$ to

$$\boldsymbol{v}^* = \underset{\boldsymbol{v}}{\operatorname{argmin}} - \sum_{i=1}^{N} \log \Phi \left\{ \boldsymbol{y}_i \boldsymbol{h}_i \boldsymbol{v} \right\},$$

subject to $\|\boldsymbol{v}\|_2^2 \leq \frac{1}{\sigma_e^2}$, and $\boldsymbol{w}_{\mathrm{ML}} = \frac{\sigma_n}{\sqrt{1 - \|\boldsymbol{v}\|_2^2 \sigma_e^2}} \boldsymbol{v}^*$.

Variants of Non-Negative Least-Mean-Square Algorithm and Convergence Analysis

Authors: Jie Chen, Cédric Richard, Jose-Carlos M. Bermudez, and Paul Honeine

NNLMS Algorithm

- The unknown system is characterized by real-valued observations:

$$y(n) = \boldsymbol{\alpha}^{*\top}\boldsymbol{x}(n) + z(n),$$

$\boldsymbol{x}(n) = \left[x(n) \quad x(n-1) \quad \dots \quad x(n-N+1)\right]^\top$, $x(n), z(n)$ are stationary and zero mean

- The optimum non-negative model with mean-square error criterion,

$$\boldsymbol{\alpha}^0 = \underset{\boldsymbol{\alpha}}{\operatorname{argmin}} \mathbb{E}\left\{\left[y(n) - \boldsymbol{\alpha}^\top \boldsymbol{x}(n)\right]^2\right\}) \text{ subject to } \alpha_i^0 \geq 0 \forall i$$

- NNLMS Algorithm: fixed-point iteration scheme

$$\boldsymbol{\alpha}(n+1) = \boldsymbol{\alpha}(n) + \eta e(n)\boldsymbol{D}_x(n)\boldsymbol{\alpha}(n),$$

$$e(n) = y(n) - \boldsymbol{\alpha}^\top(n)\boldsymbol{x}(n), \boldsymbol{D}_x(n) = \operatorname{diag}\{\boldsymbol{x}(n)\}$$

Variants of NNLMS

- Normalized NNLMS: Sensitivity of input power

$$\alpha_{\mathrm{N}}(n+1) = \alpha_{\mathrm{N}}(n) + \frac{\eta}{\|\boldsymbol{x}(n)\|_2^2 + \epsilon} e(n) \boldsymbol{D}_x(n) \alpha_{\mathrm{N}}(n)$$

- Exponential NNLMS: Unbalance of convergence rates for different weights

$$\alpha_{\mathrm{E}}(n+1) = \alpha_{\mathrm{E}}(n) + \eta e(n) \boldsymbol{D}_x(n) \alpha_{\mathrm{E}}^{(\gamma)}(n), 0 < \gamma < 1$$

$\alpha_{\mathrm{E}_i}^{(\gamma)} = \mathrm{sgn}\{\alpha_{\mathrm{E}_i}\} |\alpha_{\mathrm{E}_i}^{(\gamma)}|.$

- Sign-Sign NNLMS: Computational complexity

$$\alpha_{\mathrm{N}}(n+1) = \alpha_{\mathrm{N}}(n) + \eta \mathrm{sgn}\{e(n) \boldsymbol{D}_x(n)\} \alpha_{\mathrm{N}}(n), \eta = 2^{-m}$$

Adaptive Penalty-Based Distributed Stochastic Convex Optimization

Authors: Zaid J. Towfic and Ali H. Sayed

Problem

- A network of N agents, where each node possesses a strongly convex cost function, $J_k(w)$, and a set of affine equality and convex inequality constraints $w \in \mathbb{W}_k$, $w \in \mathbb{R}^M$

$$\underset{w}{\operatorname{argmin}} J^{\text{glob}} = \sum_{k=1}^{N} J_k(w) \text{ s.t. } w \in \mathbb{W} = \bigcap_{k=1}^{N} \mathbb{W}_k$$

- Unconstrained optimization problem that approximates above problem

$$\underset{w}{\operatorname{argmin}} J_\eta^{\text{glob}} = \sum_{k=1}^{N} J'_{k\eta}(w), \; J'_{k\eta}(w) = J_k(w) + \eta p_k(w)$$

$p_k(w)$ is selected so that $\nabla p_k(w) = 0$, when $w \in \mathbb{W}_k$

- The distributed solution relies on local processing with each agent having knowledge of only its own constraint set and cost function

Algorithm

- Gradient descent algorithm at each node and convex combination of estimates of nodes in neighborhood

$$\psi_{k,i} = w_{k,i-1} - \mu \nabla_w J'_{k\eta}(w_{k,i-1})$$
$$= w_{k,i-1} - \mu \nabla_w \{J_k(w_{k,i-1}) + \eta p_k(w_{k,i-1})\}$$
$$w_{k,i} = \sum_{l \in \mathcal{N}_k} a_{l,k} \psi_{l,i}$$

- Adapt-then-Combine:

$$\zeta_{k,i} = w_{k,i-1} - \mu \nabla_w J_k(w_{k,i-1})$$
$$\psi_{k,i} = \zeta_{k,i} - \mu\eta \nabla_w p_k(\zeta_{k,i})$$
$$w_{k,i} = \sum_{l \in \mathcal{N}_k} a_{l,k} \psi_{l,i}$$

- Combine-then-Adapt:

$$\psi_{k,i-1} = \sum_{l \in \mathcal{N}_k} a_{l,k} w_{l,i}$$
$$\zeta_{k,i} = \psi_{k,i-1} - \mu \nabla_w J_k(\psi_{k,i-1})$$
$$w_{k,i} = \zeta_{k,i} - \mu\eta \nabla_w p_k(\zeta_{k,i})$$

Learning Parametric Dictionaries for Signals on Graphs

Authors: Dorina Thanou, David I Shuman, and Pascal Frossard

Problem

- A weighted and undirected graph, $\mathcal{G} = (\mathcal{V}, \mathcal{E}, W)$
- Given a set of training graph signals, $Y = \begin{bmatrix} y_1 & y_2 & \dots & y_M \end{bmatrix} \in \mathbb{R}^{N \times M}$
- Find structured graph dictionary that represent all of the signals in Y as linear combinations of only a few of its atoms
- Structure on dictionary:$\mathcal{D} = \begin{bmatrix} \mathcal{D}_1 & \mathcal{D}_2 & \dots & \mathcal{D}_s \end{bmatrix} \in \mathbb{R}^{N \times NS}$
  - $\mathcal{D}_s = \sum_{k=0}^{K} \alpha_{sk} \mathcal{L}^k \in \mathbb{R}^{N \times N}$, $\mathcal{L}$ is normalized graph Laplacian operator
  - Two additional constraints
    - $0 \preceq \mathcal{D}_s \preceq c\boldsymbol{I}$
    - $(c - \epsilon_1)\boldsymbol{I} \preceq \sum_{s=1}^{S} \mathcal{D}_s \preceq (c + \epsilon_2)\boldsymbol{I}$
- Set of parameters:$\alpha \in \mathbb{R}^{(K+1) \times S}$

Algorithm

- Optimization problem

$$\underset{\alpha, X}{\operatorname{argmin}} \|Y - \mathcal{D}X\|_F^2 - \mu \|\alpha\|_2^2 \,,$$

s.t. sparsity and stucture conditions

Iterative Algorithm:

1. Fix parameters α and solve for X using OMP, under sparsity constraint, $\|x_m\| \leq T_0 \forall m$
2. Using X solve for α using a constrained quadratic optimization

Other Papers

- **Achievable Rates of Full-Duplex MIMO Radios in Fast Fading Channels With Imperfect Channel Estimation**
  - A. C. Cirik, Y. Rong, and Y. Hua
- **Sub-Nyquist Sampling for Power Spectrum Sensing in Cognitive Radios: A Unified Approach**
  - H. Shu, L. Ros, and E. P. Simon
- **State Estimation Over a Lossy Network in Spatially Distributed Cyber-Physical Systems**
  - S. Deshmukh, B. Natarajan, and A. Pahwa
- **One-Shot Blind CFO and Channel Estimation for OFDM With Multi-Antenna Receiver**
  - W. Zhang, Q. Yin, W. Wang, and F. Gao