Journal Watch
IEEE Transactions on Signal Processing

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Geethu Joseph
SPC Lab, IISc

Iteratively Linearized Reweighted Alternating Direction Method of Multipliers for a Class of Nonconvex Problem

Tao Sun , Hao Jiang, Lizhi Cheng, and Wei Zhu National University of Defense Technology, Changsha, China

Iteratively Linearized Reweighted ADMM

- **Problem:** $\min_{x \in \mathbb{R}^m, y \in \mathbb{R}^n, y} f(x) + \sum_{i=1}^{n} g(h(y_i))$ s.t. $Ax + By = c$
- **ADMM approach:** Iteratively update one variable at a time using augmented Lagrangian problem:

$$\mathcal{L} = f(x) + \sum_{i=1}^{N} g(h(y_i)) + < p, Ax + By - C > + \alpha \left\| Ax + By - c \right\|^2$$

- **Proposed approach:**
  - Iteratively reweighted: first order approximation of $g(h(\cdot))$.
  - Linearlized ADMM: linearize quadratic term
- **Analysis:** Convergence using Łojaseiwicz property
- **Application:** Recovery of blurred and noisy images

Learning to Optimize: Training Deep Neural Networks for Interference Management

Haoran Sun , Xiangyi Chen, Qingjiang Shi, Mingyi Hong , Xiao Fu and Nicholas D. Sidiropoulos
Aalborg University, Denmark

DNN for Interference Management

- **Problem:** Weighted system throughput maximization

$$\max_{p} \sum_{k=1}^{K} \alpha_k \log \left(1 + \frac{|h_{kk}|^2 p_k}{\sum_{j \neq k} |h_{jk}|^2 p_j + \sigma_k^2}\right) \text{s.t.} 0 \leq p_k \leq P_{\max}$$

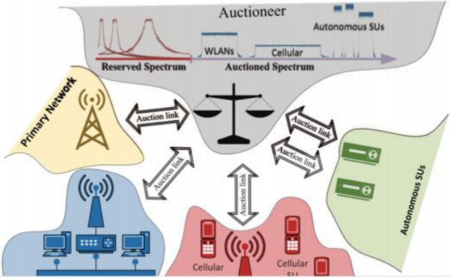
Analysis: Weighted minimum mean squared error

- Construct simple neural networks that consist of ReLUs ($\max\{0, x\}$) and binary units (0-1 decision)
- Compose these small neural networks to approximate a rational function representing one iteration of the algorithm
- Concatenate these rational functions to approximate the entire algorithm
- Bounding the error propagated from the first iteration to the last one

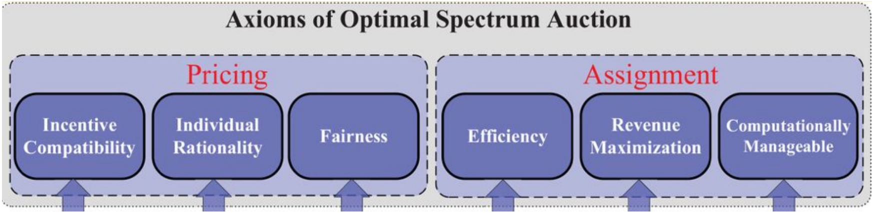
Radio Resource Allocation and Pricing: Auction-Based Design and Applications

Navid Tadayon and Sonia Aissa
University of Quebec, Canada

Resource Allocation



- Nash Equilibrium is revelation of the true valuations
- Use revelation principle to design the optimal mechanism among all auction classes
- Scalable solution



Simultaneously Sparse and Low-Rank Matrix Reconstruction via Nonconvex and Nonseparable Regularization

Wei Chen
Beijing Jiaotong University, China

Sparse and Low-Rank Matrix Reconstruction

- **Problem:**

$$\min_{\boldsymbol{X}} \alpha \left\|\boldsymbol{X}\right\|_0 + (1-\alpha)\left\|\boldsymbol{X}\right\|_{\text{rank}} \text{ s.t.} \mathcal{A}[\boldsymbol{X}] = \boldsymbol{y}$$

  - $\boldsymbol{X} \in \mathbb{R}^{n \times m}$ is sparse and low rank
  - $\alpha \in [0, 1]$

- **Bayesian Approach:** Prior on vectorized $\boldsymbol{X}$: $\boldsymbol{x} \sim \mathcal{N}(0, \boldsymbol{\Phi})$

$$\boldsymbol{\Phi}^{-1} = \boldsymbol{\Gamma}^{-1} + (\boldsymbol{I}_m \otimes \boldsymbol{\Psi})^{-1}$$

  - $\boldsymbol{\Gamma}$: diagonal
  - $\boldsymbol{\Psi}$: positive semidefinite

- **Implementation:** EM algorithm to estimate $\boldsymbol{x}$
- **Analysis:** Convergence under restricted setting
- **Application:** Compressive hyperspectral image reconstruction

Other Papers

- **An Iterative Receiver for OFDM With Sparsity-Based Parametric Channel Estimation**
  - T. L. Hansen, P. B. Jorgensen, M. A. Badiu and B. H. Fleury
- **Large-Scale Spectrum Allocation for Cellular Networks via Sparse Optimization**
  - B. Zhuang, D. Guo, E. Wei and M. L. Honig
- **A Sequential Framework for Composite Hypothesis Testing**
  - S. Bar and J. Tabrikian
- **Cell Detection by Functional Inverse Diffusion and Non-negative Group Sparsity (2 parts)**
  - P. delAguilaPla and J. Jalden