Activity Detection and Channel Estimation for Massive Random Access Systems using Learning-based Sparse Recovery

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DRDO

A. P. Sabulal, S. Bhashyam, "Joint Sparse Recovery using Deep Unfolding With Application to Massive Random Access," ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Barcelona, Spain, 2020, pp. 5050-5054.

U. K. Sreeshma Shiv, S. Bhashyam, C. R. Srivatsa and C. R. Murthy, "Learning-Based Sparse Recovery for Joint Activity Detection and Channel Estimation in Massive Random Access Systems," in IEEE Wireless Communications Letters, vol. 11, no. 11, pp. 2295-2299, Nov. 2022

Recent Research: Overview

Research Interests

- Communication and Information Theory
- Statistical Inference

Recent work

- MIMO
- Sequential hypothesis testing
- Model-based learning for wireless communication
    - Learning-based sparse recovery for massive random access

More details at https://www.ee.iitm.ac.in/skrishna/

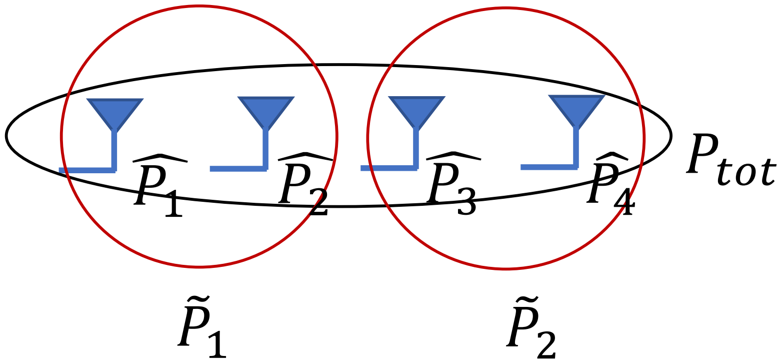
Multiple-Input Multi-Output (MIMO)

Capacity under per-group power constraints

- Distributed antennas
  - Cell-free MIMO, CoMP
- Hardware constraints

Rank-constrained MIMO capacity

- Limited by RF chains
- Iterative algorithm

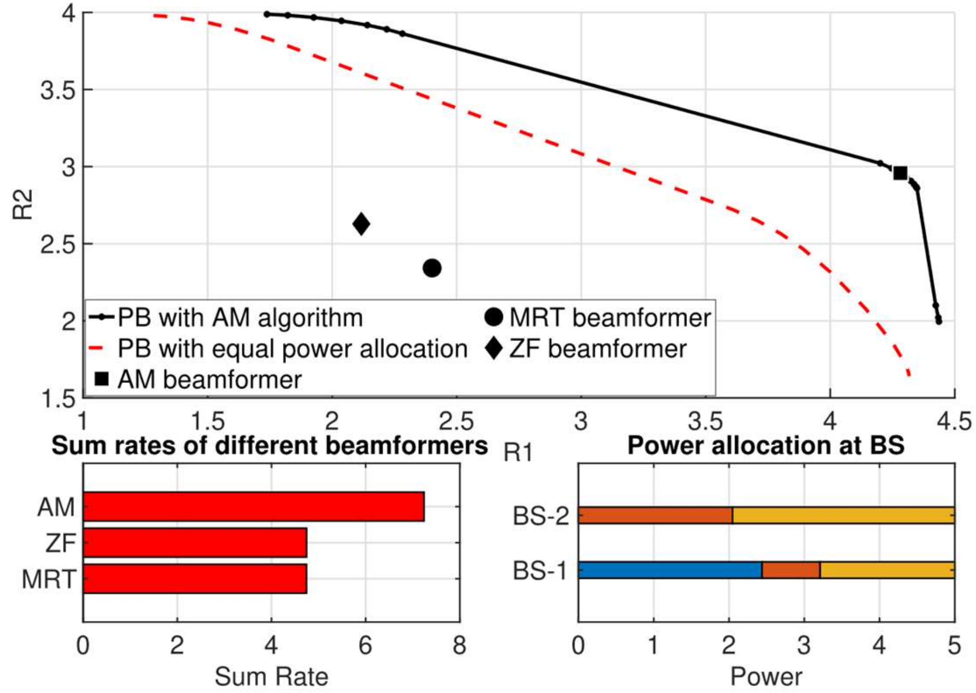


- R. Chaluvadi, S. S. Nair, S. Bhashyam, "Optimal Multi-antenna Transmission with Multiple Power Constraints," IEEE Transactions on Wireless Communications, vol. 18, no. 7, pp. 3382-3394, July 2019.

Distributed MIMO

Distributed beamforming

- Limited coordination
- Alternating optimization

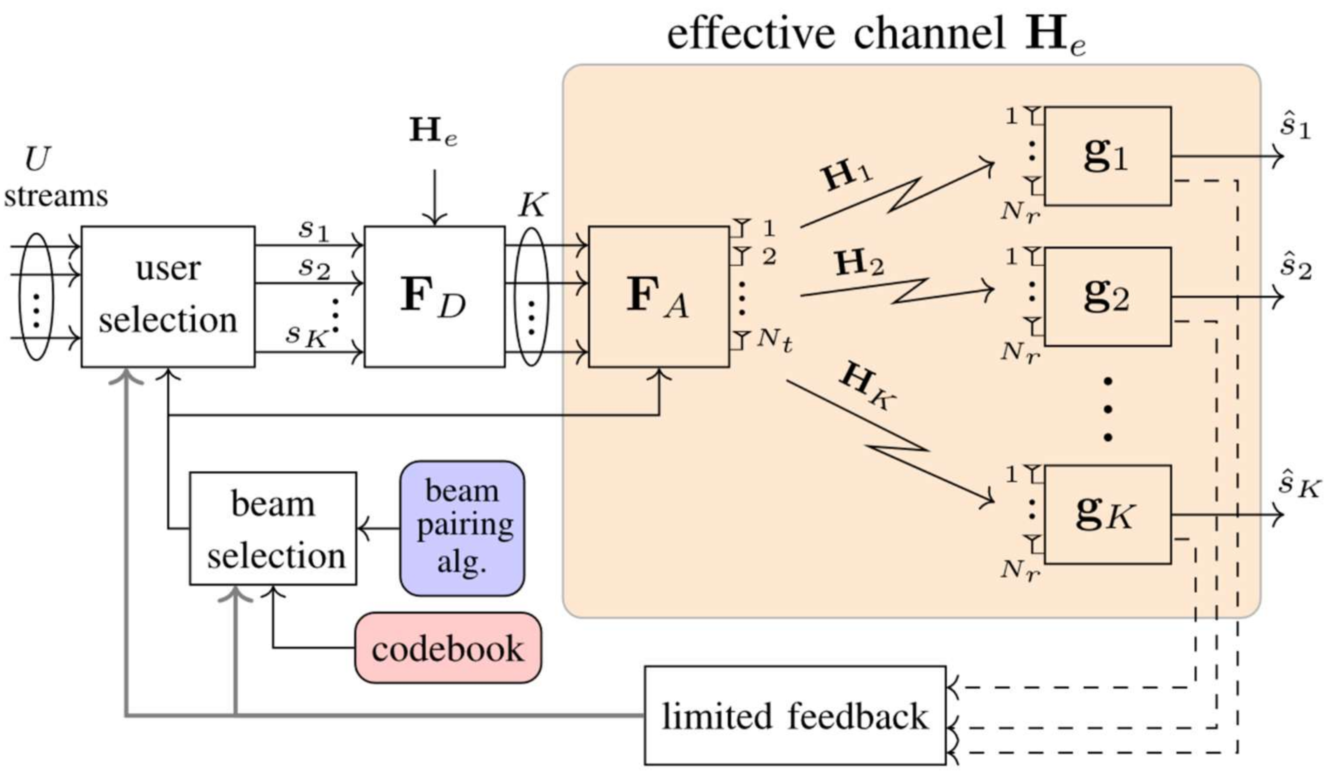


2 cells, 3 bands, 2 antennas per cell

- V. N. Moothedath and S. Bhashyam, "Distributed Pareto Optimal Beamforming for the MISO Multi-band Multi-cell Downlink," in IEEE Transactions on Wireless Communications, vol. 19, no. 11, pp. 7196-7209, Nov. 2020.

Hybrid beamforming with partial channel knowledge

Top-*p* beam information for each user

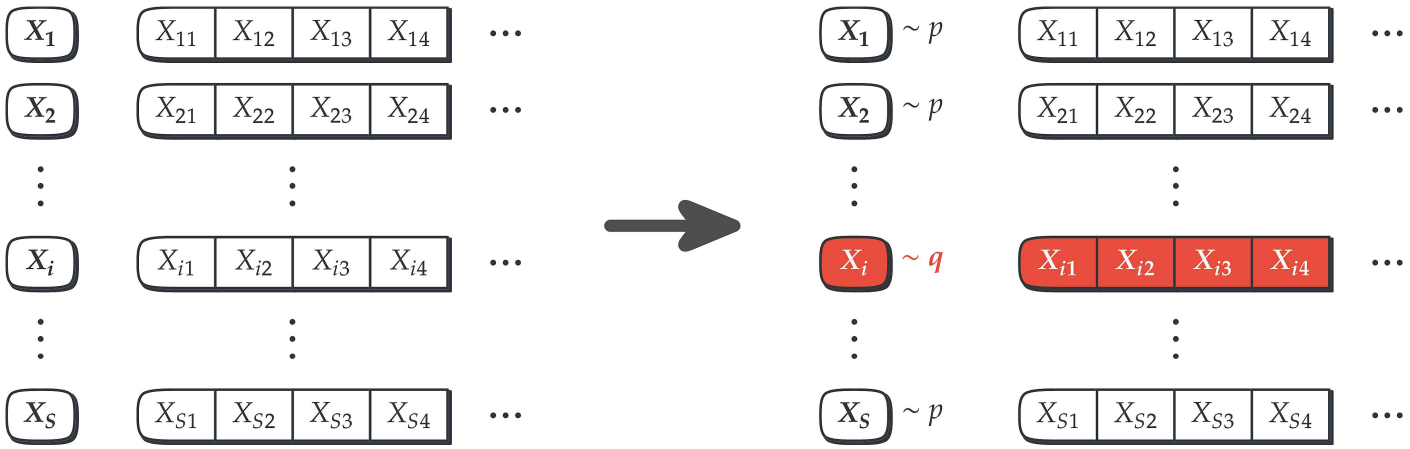


- Digital: Linear and Nonlinear precoding
- Analog: DFT vs Taylor codebook
- Robust precoding

- S. S. Nair and S. Bhashyam, "Hybrid beamforming in MU-MIMO using partial interfering beam feedback," in IEEE Communications Letters, vol. 24, no. 7, pp. 1548-1552, July 2020.
- S. S. Nair and S. Bhashyam, "Robust Nonlinear Precoding in MU-MIMO using Partial Interfering Beam Feedback," *2023 IEEE Wireless Communications and Networking Conference (WCNC)*, Glasgow, United Kingdom, 2023, pp. 1-6.

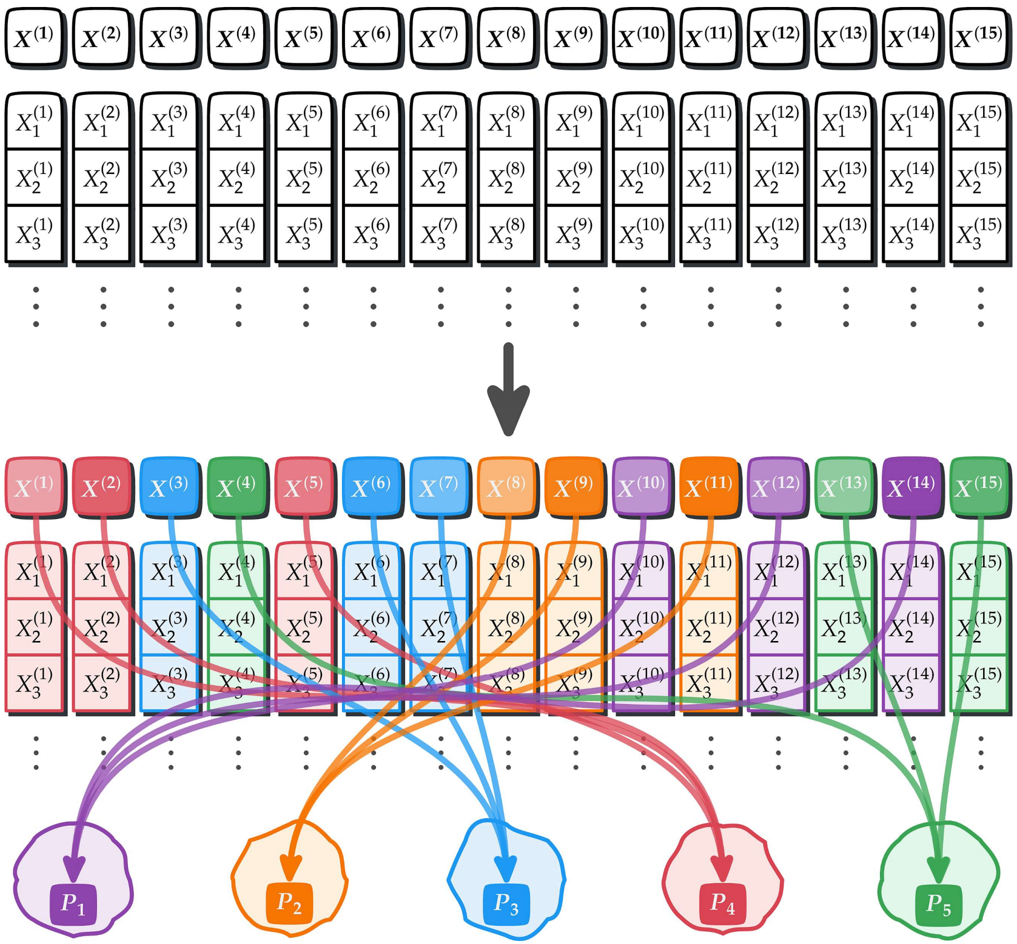
Sequential hypothesis testing in Multi-Armed Bandits

- Anomaly detection –> Generalized hypothesis testing
- Parametric setting: Vector exponential family
- Active sampling under constraints



- G. R. Prabhu, S. Bhashyam, A. Gopalan and R. Sundaresan, "Sequential Multi-Hypothesis Testing in Multi-Armed Bandit Problems: An Approach for Asymptotic Optimality," in IEEE Transactions on Information Theory, vol. 68, no. 7, pp. 4790-4817, July 2022.
- Aditya Deshmukh, Venugopal V. Veeravalli & Srikrishna Bhashyam (2021) Sequential controlled sensing for composite multihypothesis testing, Sequential Analysis, 40:2, 259-289.

Sequential hypothesis testing



- Nonparametric setting
- Anomaly detection & Clustering

- S. C. Sreenivasan and S. Bhashyam, "Sequential Nonparametric Detection of Anomalous Data Streams," in IEEE Signal Processing Letters, vol. 28, pp. 932-936, 2021.
- S. C. Sreenivasan, S. Bhashyam, Nonparametric Sequential Clustering of Data Streams with Composite Distributions, Signal Processing (2022).

Model-based learning for wireless communication:

Learning-based sparse recovery for massive random access

Model-based learning for wireless communication

Model-based signal processing	Deep learning
Domain knowledge	Data-driven, uses large data sets
Analysis and interpretation	Not easy to interpret or analyse

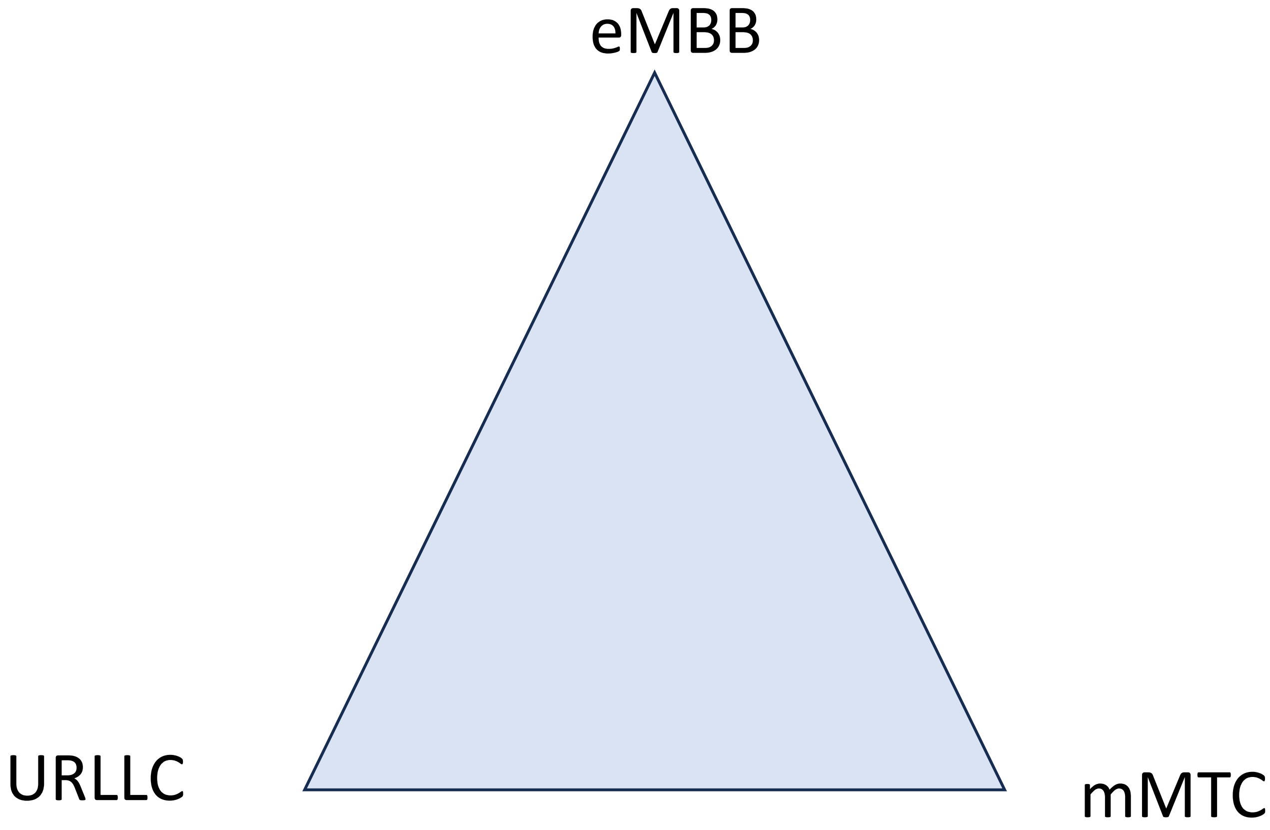
Model-based learning: Hybrid approach

- Deep unfolding
- Model-aided networks

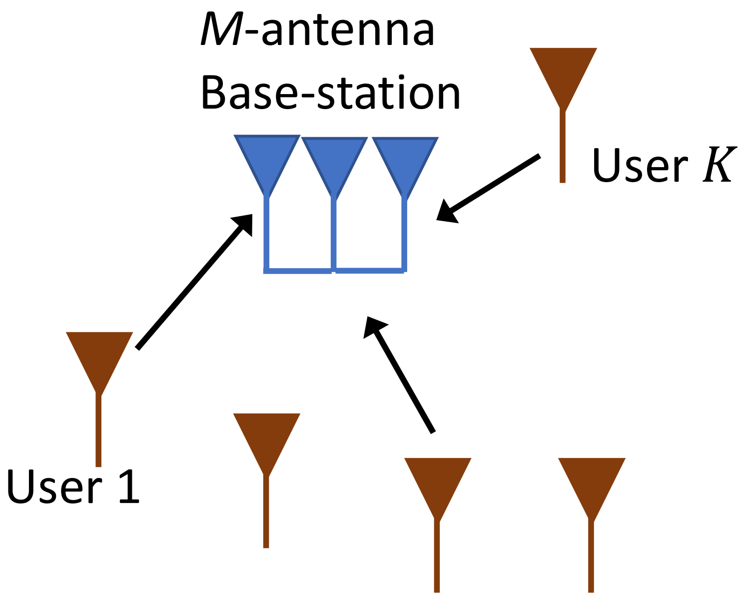
N. Shlezinger, J. Whang, Y. C. Eldar and A. G. Dimakis, "Model-Based Deep Learning: Key Approaches and Design Guidelines," 2021 IEEE Data Science and Learning Workshop (DSLW), 2021, pp. 1-6, doi: 10.1109/DSLW51110.2021.9523403.

5G Cellular Systems

- eMBB: Enhanced Mobile Broadband
- mMTC: Massive Machine Type Communication
- URLLC: Ultra Reliable Low Latency Communication



Massive Random Access for mMTC



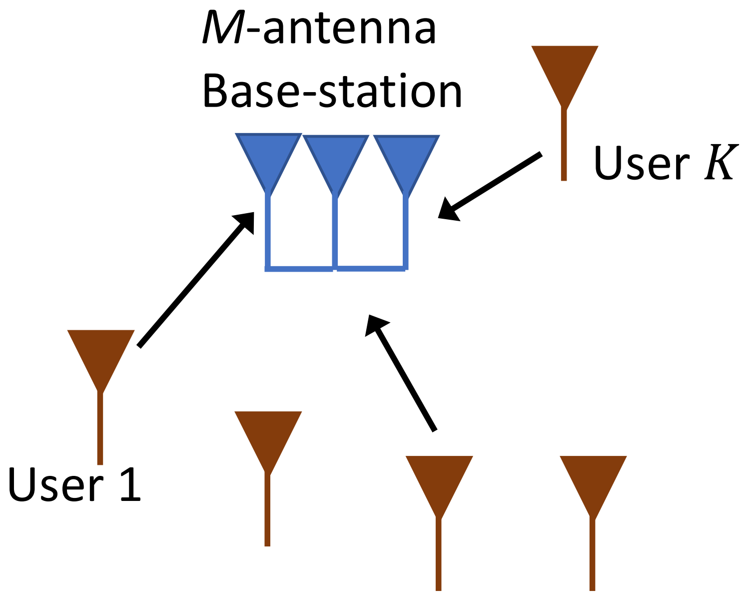
Grant-free random access

Multiple antennas at BS

- Small fraction of users are active at any given time
- Active users have limited data to send
- Overhead to grant resources large

J. Choi, J. Ding, N. -P. Le and Z. Ding, "Grant-Free Random Access in Machine-Type Communication: Approaches and Challenges," in *IEEE Wireless Communications*, vol. 29, no. 1, pp. 151-158, February 2022, doi: 10.1109/MWC.121.2100135.

Massive Random Access: Our Setting



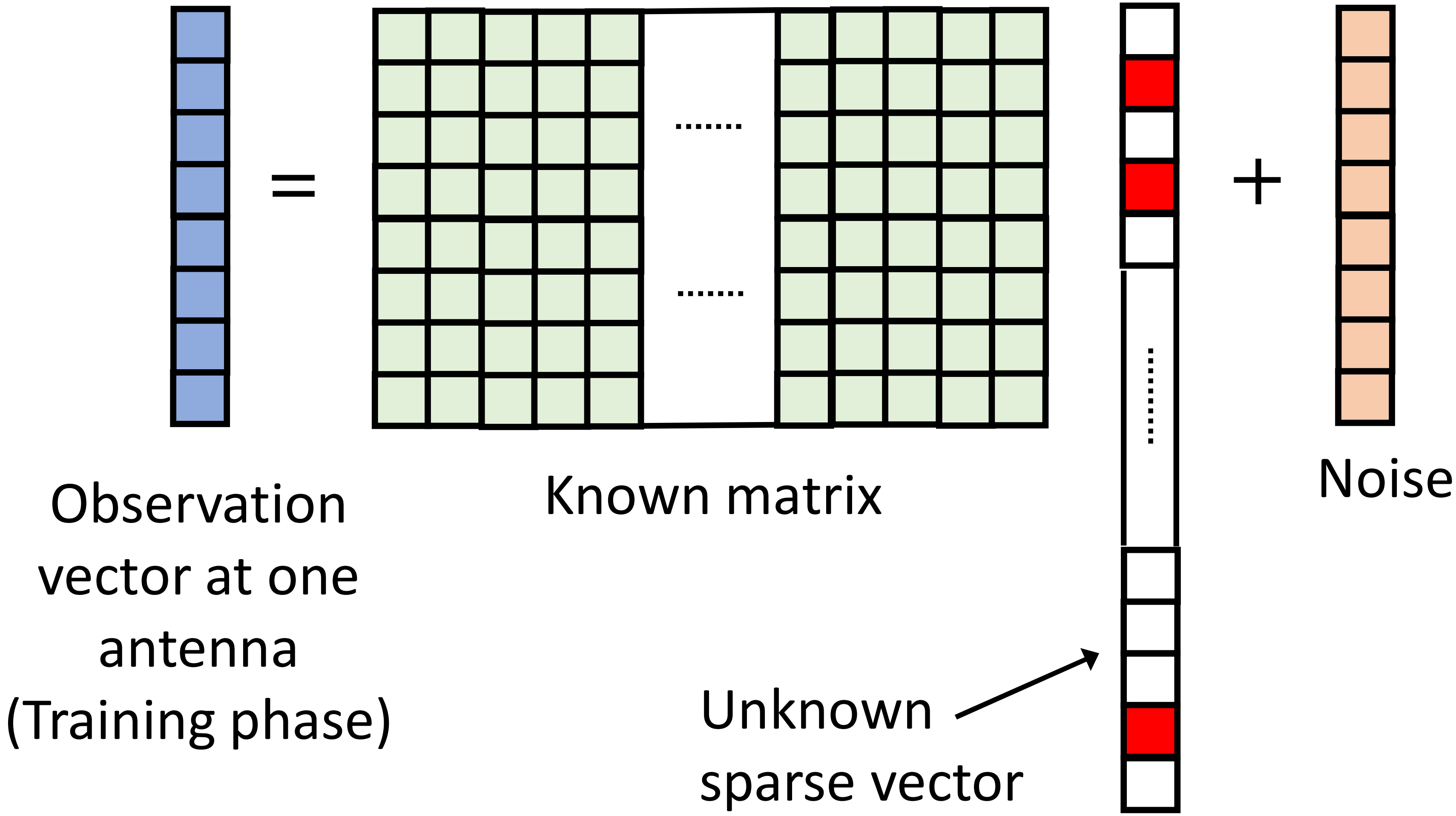
Training phase followed by data

- Small fraction of users are active at any given time
- Identify the active users
- Estimate channel corresponding to the active users

Training	Data

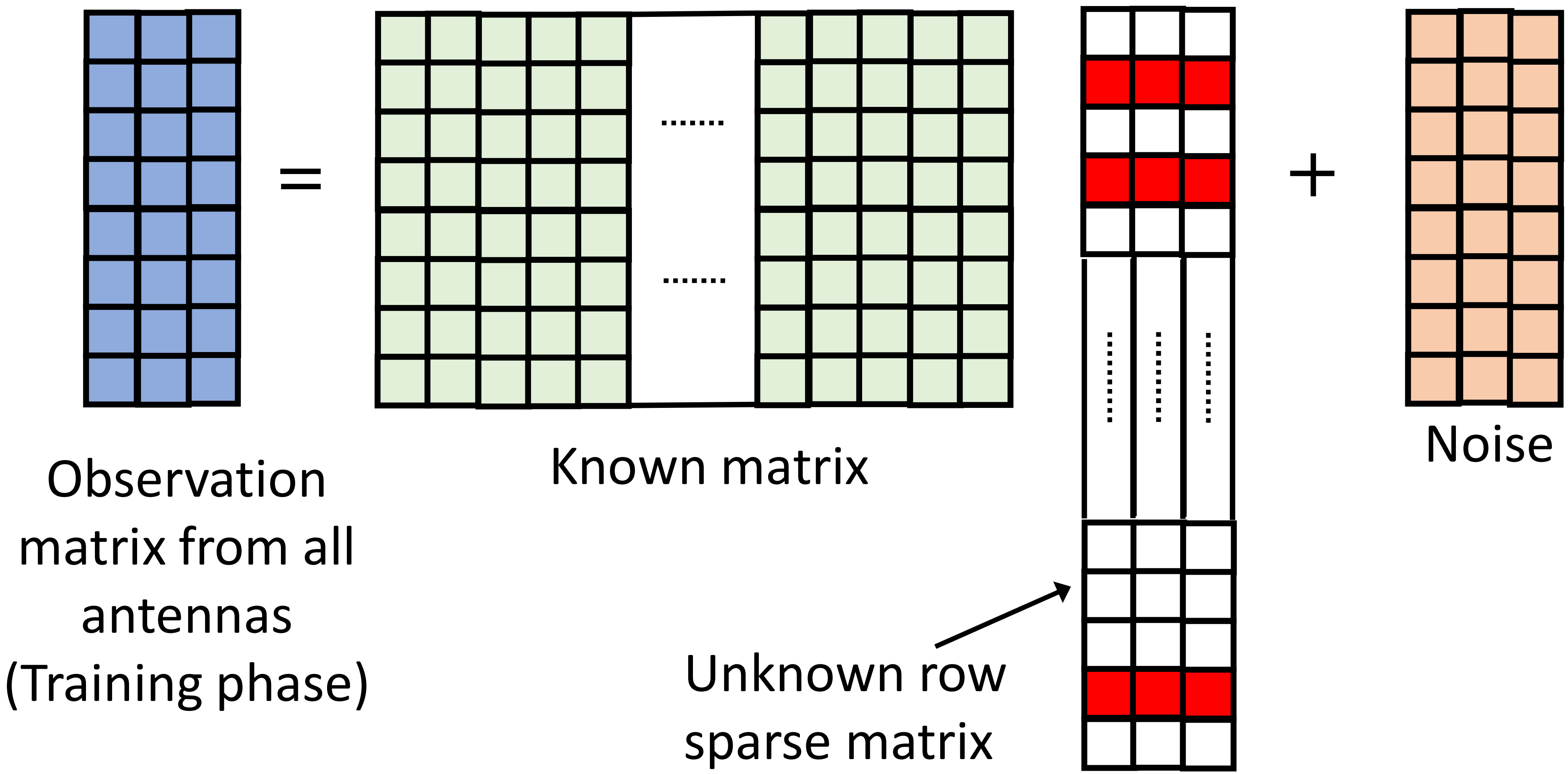
- Active users send training sequences of length L

Sparse recovery:
Activity detection and Channel estimation



Single Measurement Vector (SMV) problem

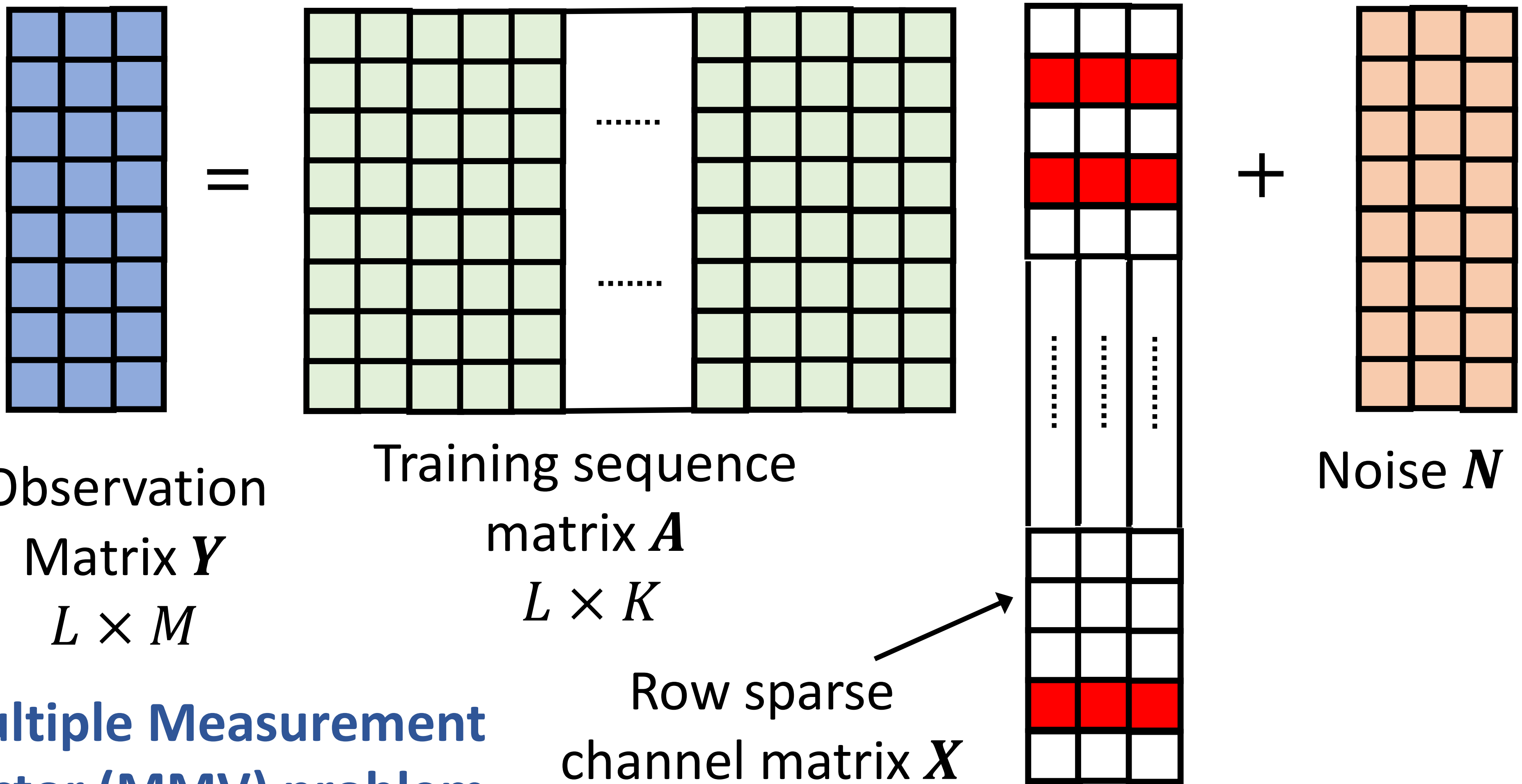
Joint sparse recovery



Multiple Measurement Vector (MMV) problem

Joint Sparse Recovery:
Activity detection and Channel estimation

$$\boldsymbol{Y} = \boldsymbol{A}\,\boldsymbol{X} + \boldsymbol{N}$$



Multiple Measurement Vector (MMV) problem

Plan

- Some sparse recovery methods
- Learning-based sparse recovery
  - Two proposed methods
- Results and discussion

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U. K. Sreeshma Shiv, S. Bhashyam, C. R. Srivatsa and C. R. Murthy, "Learning-Based Sparse Recovery for Joint Activity Detection and Channel Estimation in Massive Random Access Systems," in IEEE Wireless Communications Letters, vol. 11, no. 11, pp. 2295-2299, Nov. 2022

Sparse recovery

Iterative soft thresholding

ISTA

Approximate message passing

AMP
OAMP
Vector AMP

Matching Pursuit

OMP
CoSaMP

Alternating direction method of multipliers

MMV-ADM

Sparse Bayesian learning

SBL
M-SBL

Learning-based sparse recovery

Iterative soft thresholding

- ISTA
- LISTA
- TISTA, MMV-TISTA
- L-MMSE-MMV-TISTA

Approximate message passing

- AMP
- OAMP
- Vector AMP
- L-AMP
- VAMP-net

Matching Pursuit

- OMP
- CoSaMP

Alternating direction method of multipliers

- MMV-ADM
- MMV-MADM
- L-MMV-MADM

Sparse Bayesian learning

- SBL
- M-SBL
- L-SBL

Our Work

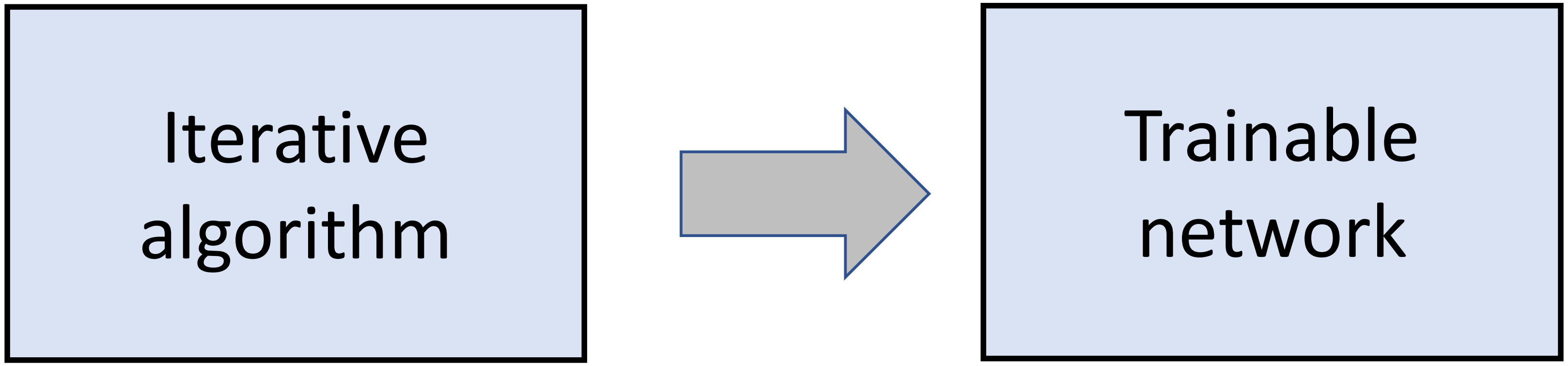
- Proposed methods
  - MMV-MADM and LMMV-MADM
    - Uses deep unfolding, modified cost
  - MMV-TISTA and learnt version
    - Replaces denoiser with a model-based neural network
- New comparisons
  - Performance-complexity trade-offs

A. P. Sabulal, S. Bhashyam, "Joint Sparse Recovery using Deep Unfolding With Application to Massive Random Access," ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Barcelona, Spain, 2020, pp. 5050-5054.

U. K. Sreeshma Shiv, S. Bhashyam, C. R. Srivatsa and C. R. Murthy, "Learning-Based Sparse Recovery for Joint Activity Detection and Channel Estimation in Massive Random Access Systems," in IEEE Wireless Communications Letters, vol. 11, no. 11, pp. 2295-2299, Nov. 2022

Deep Unfolding

Technique 1: Deep unfolding



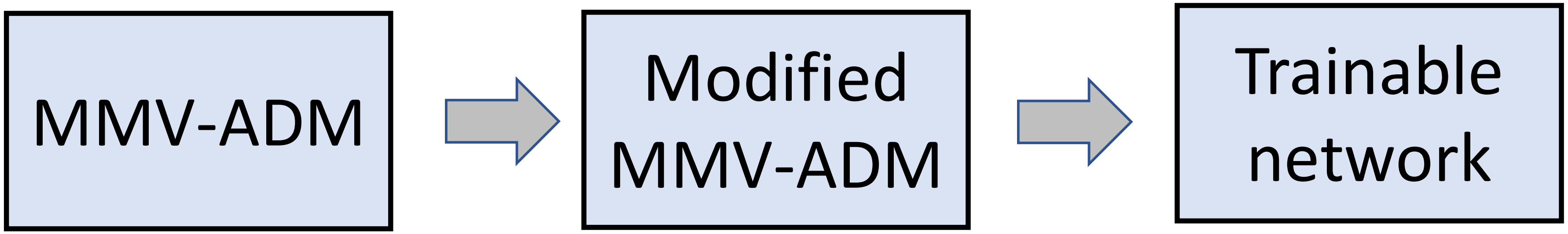
- Each iteration is a layer
- Parameters in each layer untied and trained

John R. Hershey, Jonathan Le Roux, and Felix Weninger, “Deep unfolding: Model-based inspiration of novel deep architectures,” CoRR, vol. abs/1409.2574, 2014.

Alexios Balatsoukas-Stimming and Christoph Studer, “Deep unfolding for communications systems: A survey and some new directions,” arXiv preprint arXiv:1906.05774, 2019.

V. Monga, Y. Li, and Y. C. Eldar, “Algorithm unrolling: Interpretable, efficient deep learning for signal and image processing,” IEEE Signal Processing Magazine, vol. 38, no. 2, pp. 18–44, 2021.

Proposed method: LMMV-MADM



- MMV-ADM
  - Based on alternating direction method of multipliers
- Modification of existing algorithm to help learning
  - Back-projected error
- Unfolding: Significant reduction in training overhead
- Two learning approaches: Supervised, Unsupervised

MMV-ADM

$$\min_{\boldsymbol{X}} \|\boldsymbol{X}\|_{2,1} + \frac{1}{2\mu}\|\boldsymbol{Y} - \boldsymbol{A}\boldsymbol{X}\|_2^2$$

- Alternating direction method
- No matrix inversions ⇨ fast, scalable
- Convergence analysis feasible

H. Lu, X. Long, and J. Lv, "A fast algorithm for recovery of jointly sparse vectors based on the alternating direction methods," in Proceedings of the Fourteenth International Conference on Artificial Intelligence and Statistics, 2011, pp. 461–469.

MMV-ADM

$$\min_{\boldsymbol{X}} \|\boldsymbol{X}\|_{2,1} + \frac{1}{2\mu}\|\boldsymbol{Y} - \boldsymbol{AX}\|_2^2$$

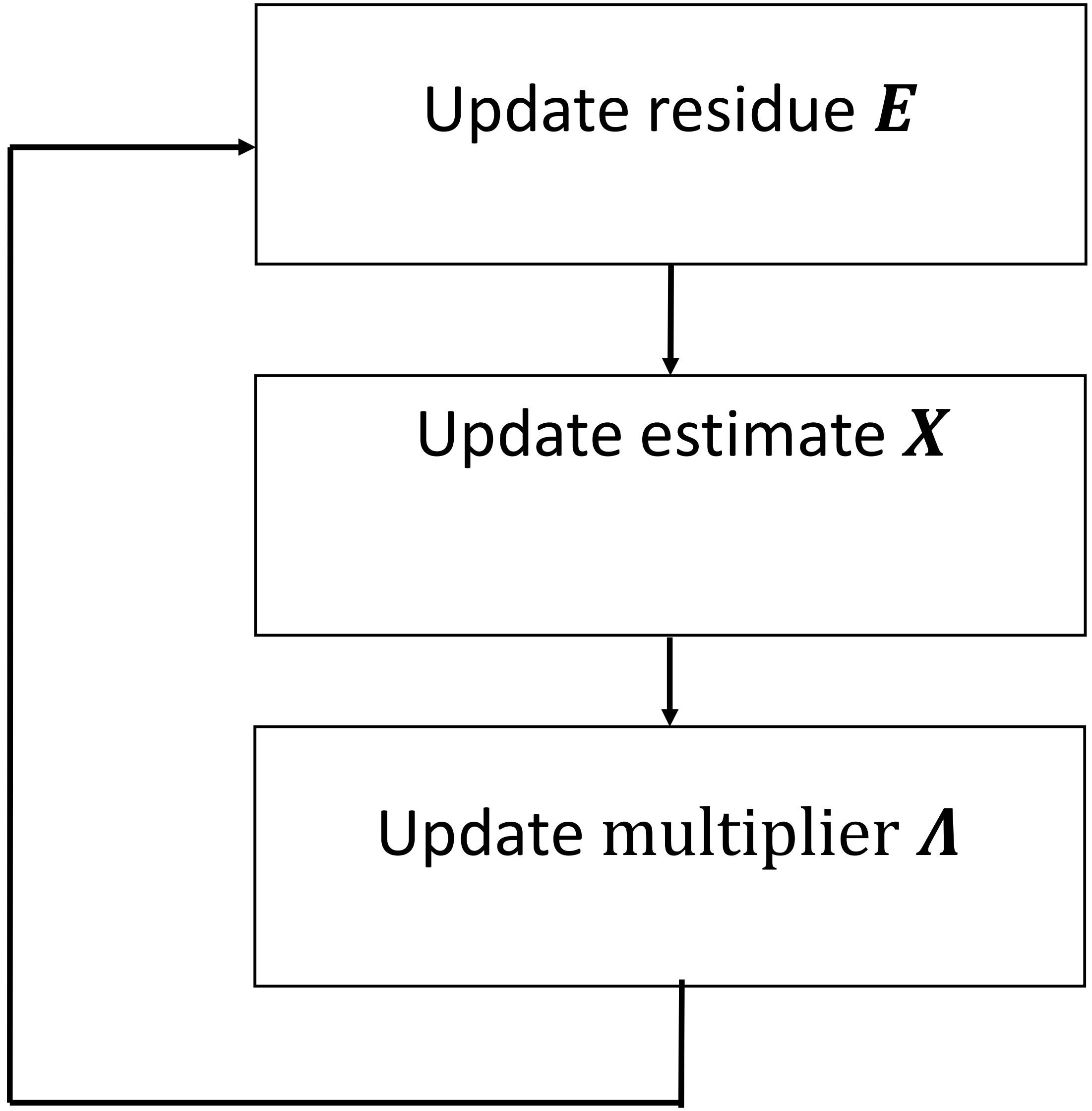
$$\min_{\boldsymbol{X}} \|\boldsymbol{X}\|_{2,1} + \frac{1}{2\mu}\|\boldsymbol{E}\|_2^2 \quad s.t. \;\; \boldsymbol{AX} + \boldsymbol{E} = \boldsymbol{Y}$$

- $\boldsymbol{E} = \boldsymbol{Y} - \boldsymbol{AX}$
- Augmented Lagrangian

$$L(\boldsymbol{X}, \boldsymbol{E}, \boldsymbol{\Lambda})$$
$$= \|\boldsymbol{X}\|_{2,1} + \frac{1}{2\mu}\|\boldsymbol{E}\|_2^2 - < \boldsymbol{\Lambda}, \boldsymbol{AX} + \boldsymbol{E} - \boldsymbol{Y} >$$
$$+ \frac{\beta}{2}\|\boldsymbol{AX} + \boldsymbol{E} - \boldsymbol{Y}\|_F^2$$

MMV-ADM

- Augmented Lagrangian
  $$L(\boldsymbol{X}, \boldsymbol{E}, \boldsymbol{\Lambda})$$
- $\boldsymbol{E} = \boldsymbol{Y} - \boldsymbol{A}\boldsymbol{X}$
- Initialize $\boldsymbol{X}, \boldsymbol{\Lambda}$



MMV-ADM

Initialize $\boldsymbol{\Lambda}, \boldsymbol{X}$

Update residue

$$\boldsymbol{E}^{k+1} = \frac{\mu\beta}{1+\mu\beta}\left[\frac{1}{\beta}\boldsymbol{\Lambda}^{k} - \left(\boldsymbol{A}\boldsymbol{X}^{k} - \boldsymbol{Y}\right)\right]$$

$$\boldsymbol{G}^{k} = \boldsymbol{A}^{T}\left[\boldsymbol{A}\boldsymbol{X}^{k} + \boldsymbol{E}^{k+1} - \boldsymbol{Y} - \frac{1}{\beta}\boldsymbol{\Lambda}^{k}\right]$$

Update estimate

$$\boldsymbol{X}^{k+1} = Row\_shrink\left[\boldsymbol{X}^{k} - \tau\boldsymbol{G}^{k}, \frac{\tau}{\beta}\right]$$

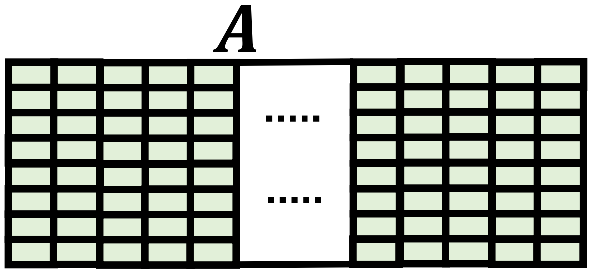
Update multiplier

$$\boldsymbol{\Lambda}^{k+1} = \boldsymbol{\Lambda}^{k} - \gamma\beta\left[\boldsymbol{A}\boldsymbol{X}^{k} + \boldsymbol{E}^{k+1} - \boldsymbol{Y}\right]$$

Parameters to choose: μ, β, γ, τ

Modified MMV-ADM

$$\min_{\boldsymbol{X}} \|\boldsymbol{X}\|_{2,1} + \frac{1}{2\mu}\left\|\boldsymbol{A}^{\dagger}\boldsymbol{Y} - \boldsymbol{A}^{\dagger}\boldsymbol{A}\boldsymbol{X}\right\|_2$$

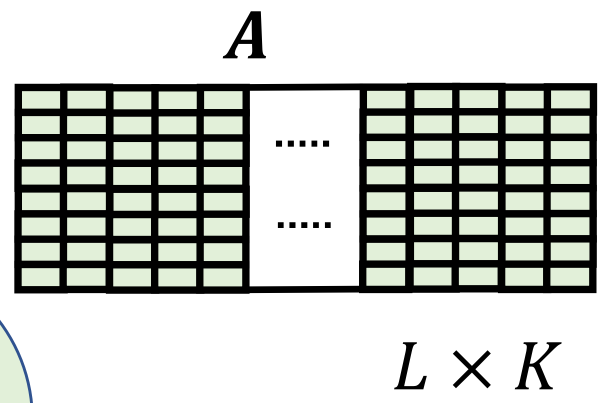


$L \times K$

- Backprojected LS error instead of LS error
  - $\boldsymbol{A}^{\dagger}\boldsymbol{Y} - \boldsymbol{A}^{\dagger}\boldsymbol{A}\boldsymbol{X}$ instead of $\boldsymbol{Y} - \boldsymbol{A}\boldsymbol{X}$
  - $\boldsymbol{A}^{\dagger} = \boldsymbol{A}^{T}[\boldsymbol{A}\boldsymbol{A}^{T}]^{-1}$

- Modified algorithm also fast, scalable
- Unfolding results in a easily trainable network

T. Tirer and R. Giryes, “Back-projection based fidelity term for ill-posed linear inverse problems,” IEEE Transactions on Image Processing, vol. 29, pp. 6164-6179, 2020.



Back-projected error

$$\| \boldsymbol{A}\boldsymbol{x}_0 - \boldsymbol{A}\boldsymbol{x}\|_2^2 = \sum_{i=1}^{L} \lambda_i^2 |\boldsymbol{v}_i^T(\boldsymbol{x}_0 - \boldsymbol{x})|^2$$

$$\left\|\boldsymbol{A}^\dagger(\boldsymbol{A}\boldsymbol{x}_0 - \boldsymbol{A}\boldsymbol{x})\right\|_2^2 = \sum_{i=1}^{L} |\boldsymbol{v}_i^T(\boldsymbol{x}_0 - \boldsymbol{x})|^2$$

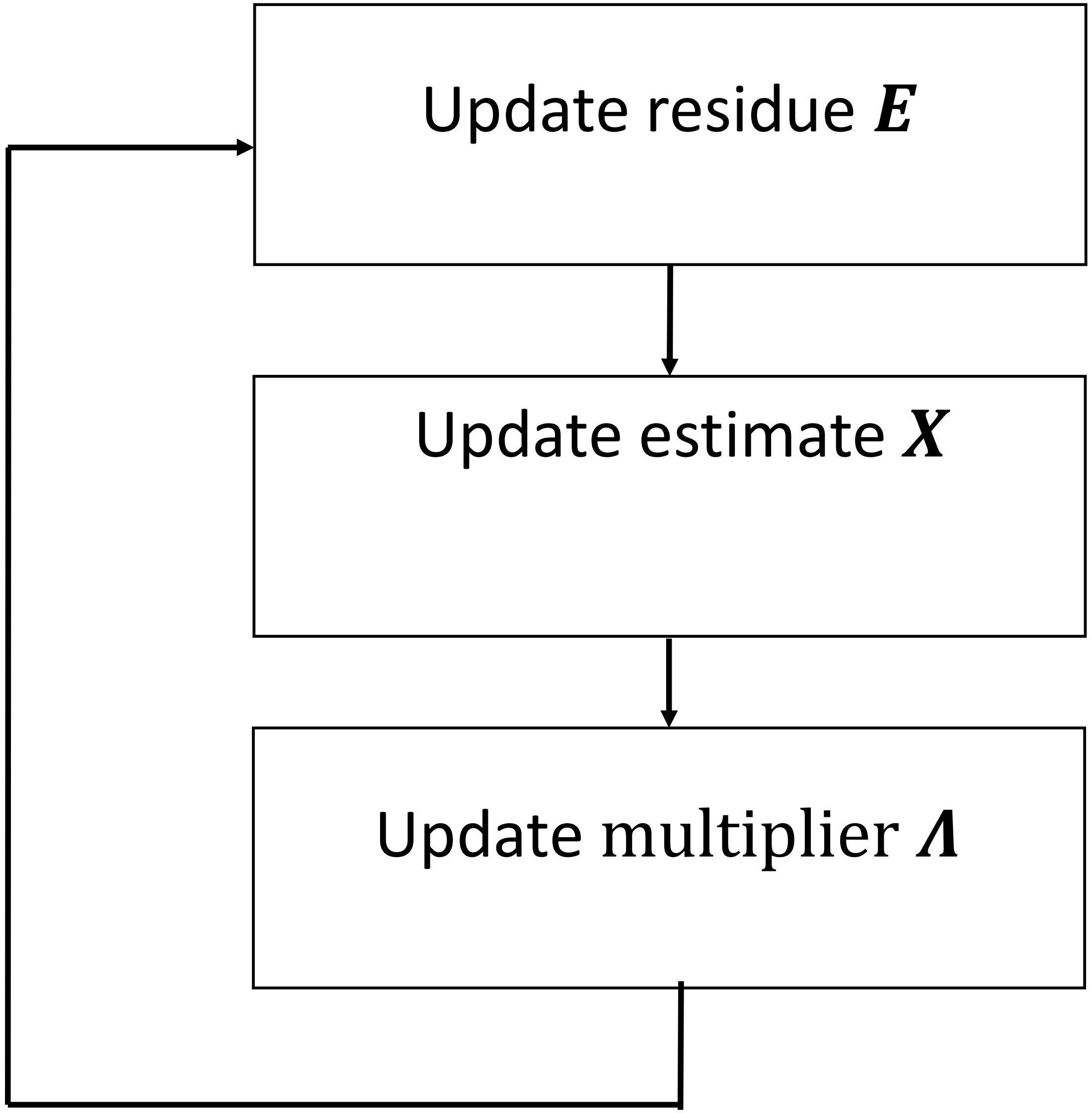
$$\|\boldsymbol{x}_0 - \boldsymbol{x})\|_2^2 = \sum_{i=1}^{K} |\boldsymbol{v}_i^T(\boldsymbol{x}_0 - \boldsymbol{x})|^2$$

- λ_i: i th singular value of $\boldsymbol{A}$
- $\boldsymbol{v}_i$: i th right singular vector of $\boldsymbol{A}$

Modified MMV-ADM

- Augmented Lagrangian
  $$L(\boldsymbol{X}, \boldsymbol{E}, \boldsymbol{\Lambda})$$
- $\boldsymbol{E} = \boldsymbol{A}^{\dagger}\boldsymbol{Y} - \boldsymbol{A}^{\dagger}\boldsymbol{A}\boldsymbol{X}$
- Initialize $\boldsymbol{X}, \boldsymbol{\Lambda}$

4 scalar parameters to choose: μ, β, γ, τ



MMV-MADM

Initialize $\boldsymbol{\Lambda}, \boldsymbol{X}$

Update residue $$\widetilde{\boldsymbol{E}}^{k+1} = \frac{\mu\beta}{1+\mu\beta}\left[\frac{1}{\beta}\widetilde{\boldsymbol{\Lambda}}^{k} - \left(\boldsymbol{A}\boldsymbol{X}^{k} - \boldsymbol{Y}\right)\right]$$

$$\boldsymbol{G}^{k} = \boldsymbol{A}^{\dagger}\left[\boldsymbol{A}\boldsymbol{X}^{k} + \widetilde{\boldsymbol{E}}^{k+1} - \boldsymbol{Y} - \frac{1}{\beta}\widetilde{\boldsymbol{\Lambda}}^{k}\right]$$

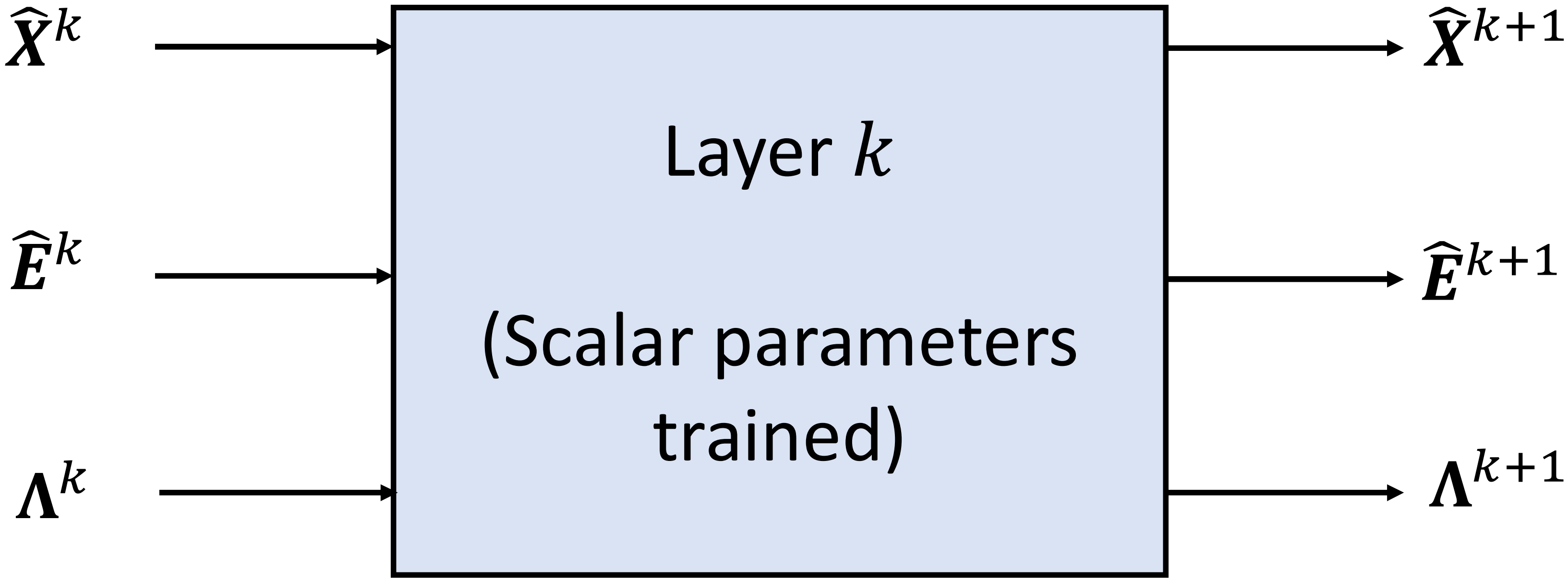
Update estimate $$\boldsymbol{X}^{k+1} = Row\_shrink\left[\boldsymbol{X}^{k} - \tau\boldsymbol{G}^{k}, \frac{\tau}{\beta}\right]$$

Update multiplier $$\widetilde{\boldsymbol{\Lambda}}^{k+1} = \widetilde{\boldsymbol{\Lambda}}^{k} - \gamma\beta\left[\boldsymbol{A}\boldsymbol{X}^{k} + \widetilde{\boldsymbol{E}}^{k+1} - \boldsymbol{Y}\right]$$

$\widetilde{\boldsymbol{\Lambda}} = \boldsymbol{A}\boldsymbol{\Lambda}$, $\widetilde{\boldsymbol{E}} = \boldsymbol{A}\boldsymbol{E}$

Parameters to choose: μ, β, γ, τ

Unfolded network



- One iteration of ADM algorithm is one layer

Training the network: Supervised

- True $\boldsymbol{X}, \boldsymbol{Y}$ pairs available
- Generated using a channel model for training

- Layers trained sequentially
- MSE between layer output $\widehat{\boldsymbol{X}}^{k+1}$ and true $\boldsymbol{X}$ used as loss function for training

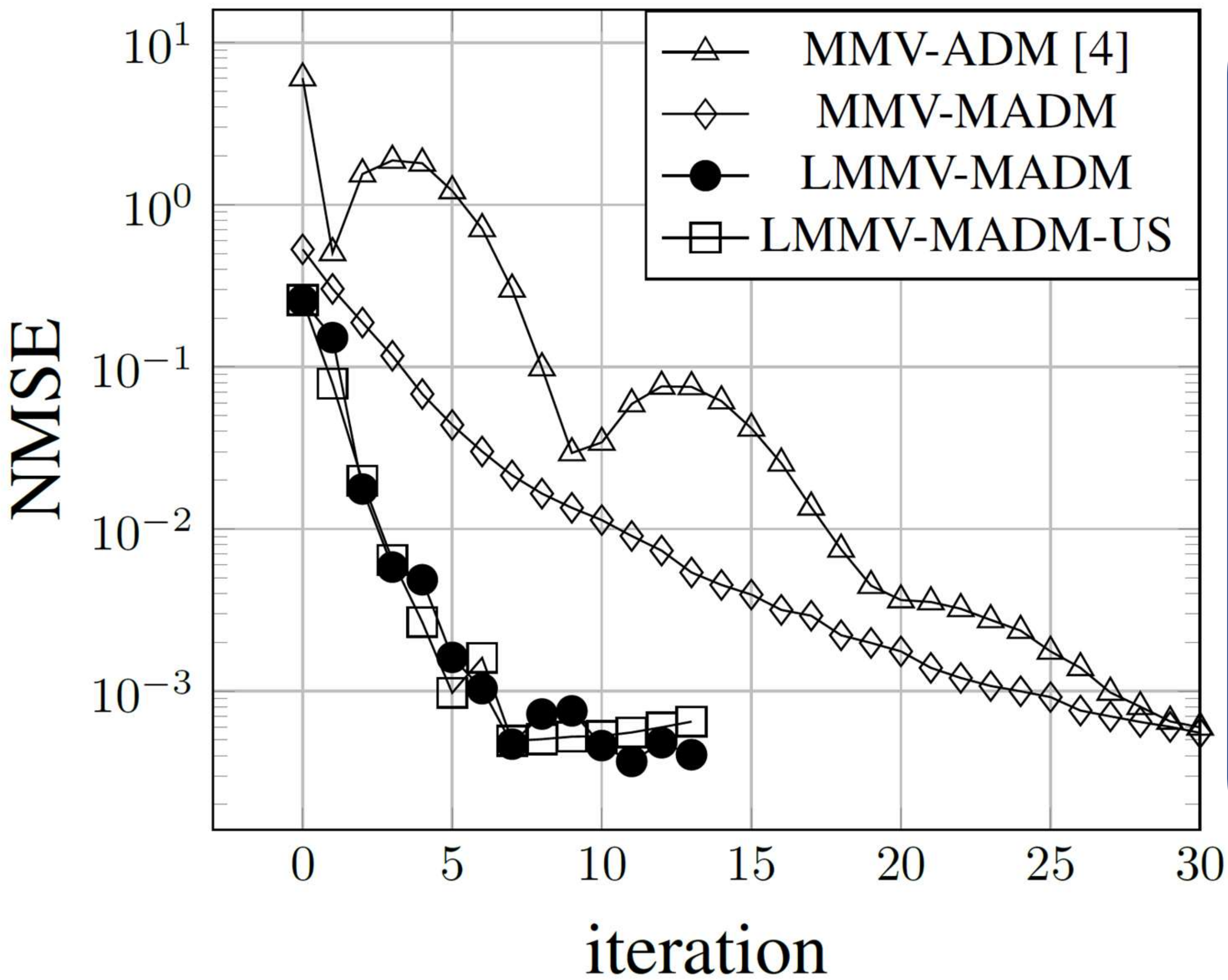
Training the network: Unsupervised

- True $\boldsymbol{X}, \boldsymbol{Y}$ pairs not needed

- Layers trained sequentially
- Loss function for training
  - $\lambda \left\| \widehat{\boldsymbol{X}}^{k+1} \right\|_{2,1/p}^{1/p} + \left\| \boldsymbol{Y} - \boldsymbol{A}\widehat{\boldsymbol{X}}^{k+1} \right\|_F^2$

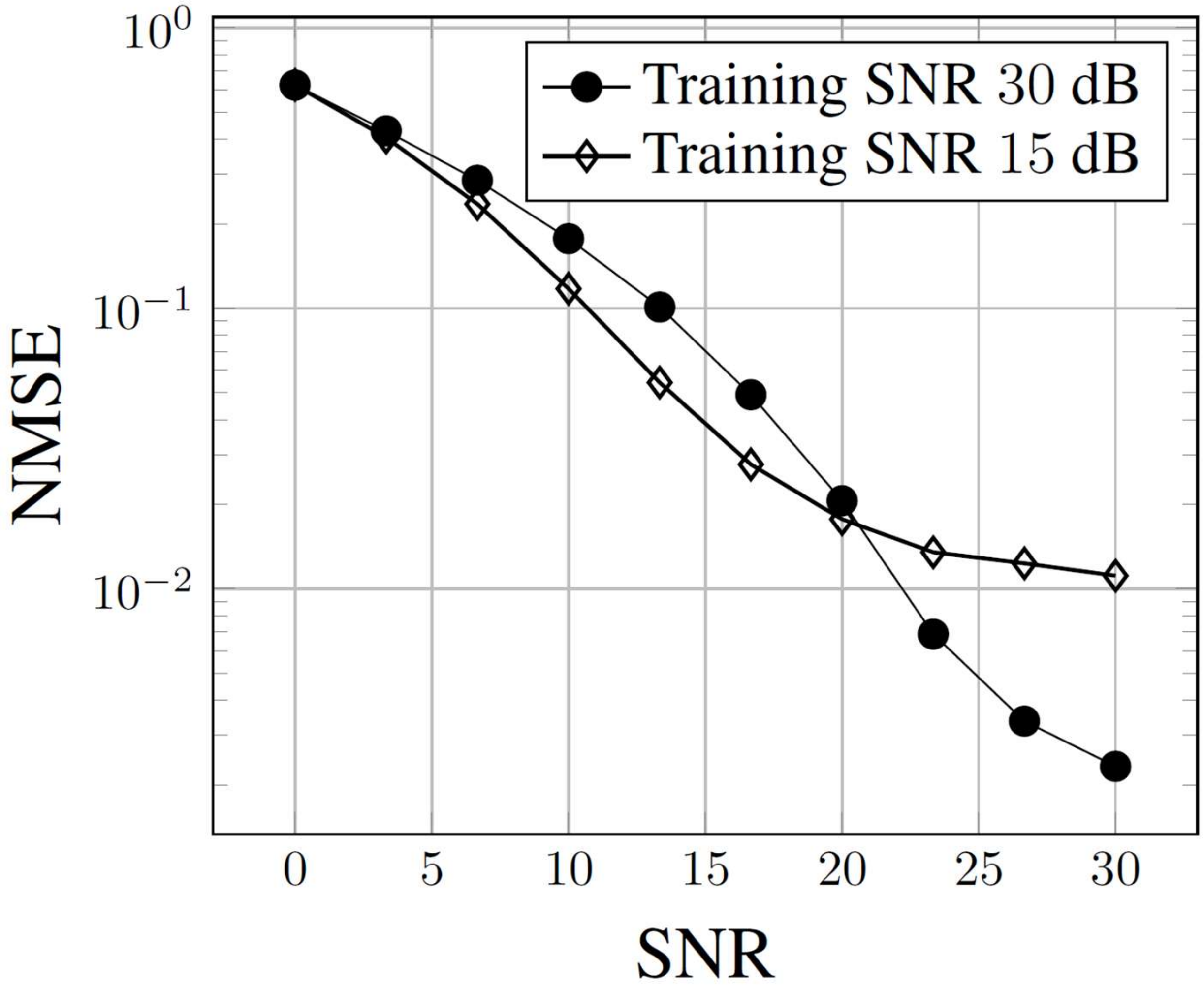
- Unsupervised method can be used after initialization with the supervised method

Performance



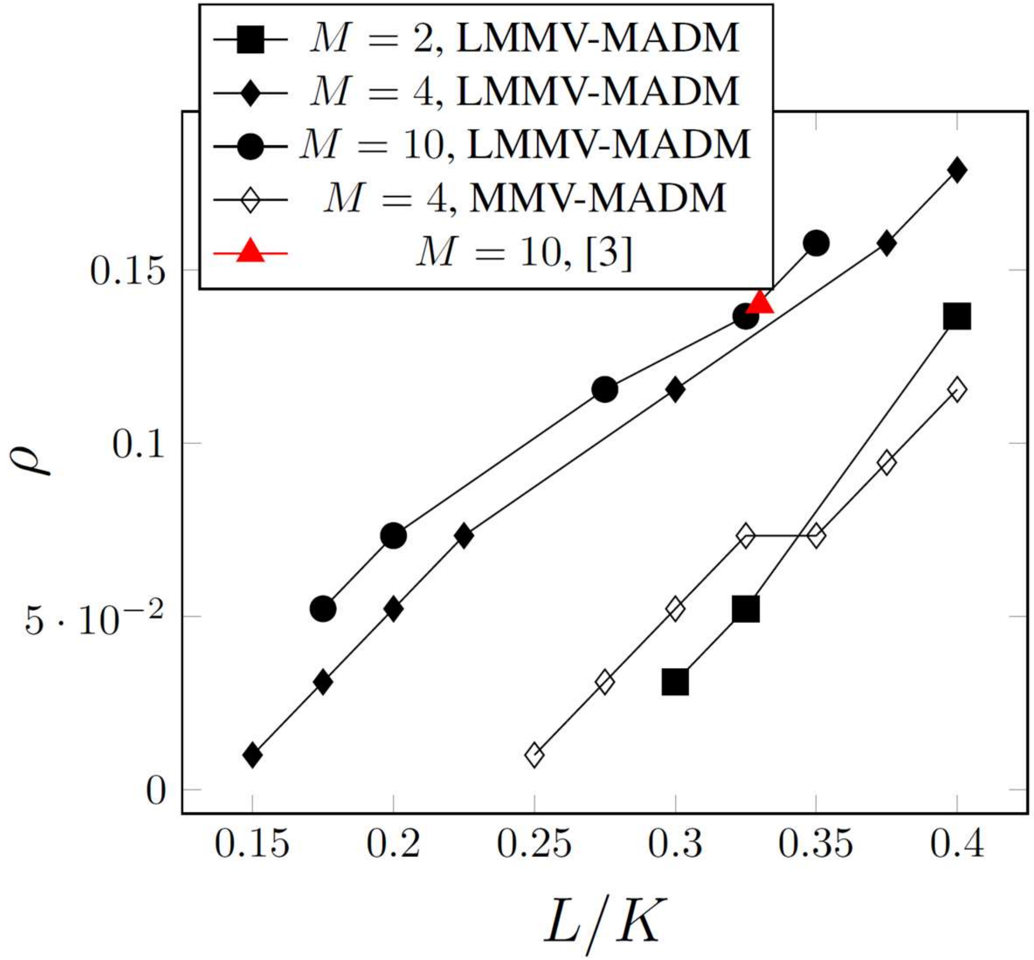
- $K = 2000, L = 500,$ $\rho = 0.05, M = 10$
- Use of back-projected error results in smooth convergence
- Unfolded network converges faster
- Unsupervised training also works well

Training SNR



- $K = 2000, L = 300$, $\rho = 0.05, M = 10$
- Training at $\rho = 0.07$
- Network trained at higher SNR preferable

Performance: Phase transition



- $K = 500$, 20 layer network, MMV-MADM with 40 iterations
- Minimum L/K for a given activity probability ρ
- Training and test SNR at 30 dB
- Training at ρ = 0.2
- Success if NMSE < -20 dB

[3] T. Jiang, Y. Shi, J. Zhang, and K. B. Letaief, "Joint activity detection and channel estimation for IoT networks: Phase transition and computation-estimation tradeoff," IEEE Internet of Things Journal, vol. 6, no. 4, pp. 6212–6225, Aug 2019.

Model-based Neural Network for Denoising

Trainable ISTA (TISTA)

$\boldsymbol{S}_t$: Estimate of $\boldsymbol{X}$ at iteration t

$$\boldsymbol{R}_t = \boldsymbol{S}_t + \gamma_t \boldsymbol{A}^{\dagger}(\boldsymbol{Y} - \boldsymbol{A}\boldsymbol{S}_t)$$

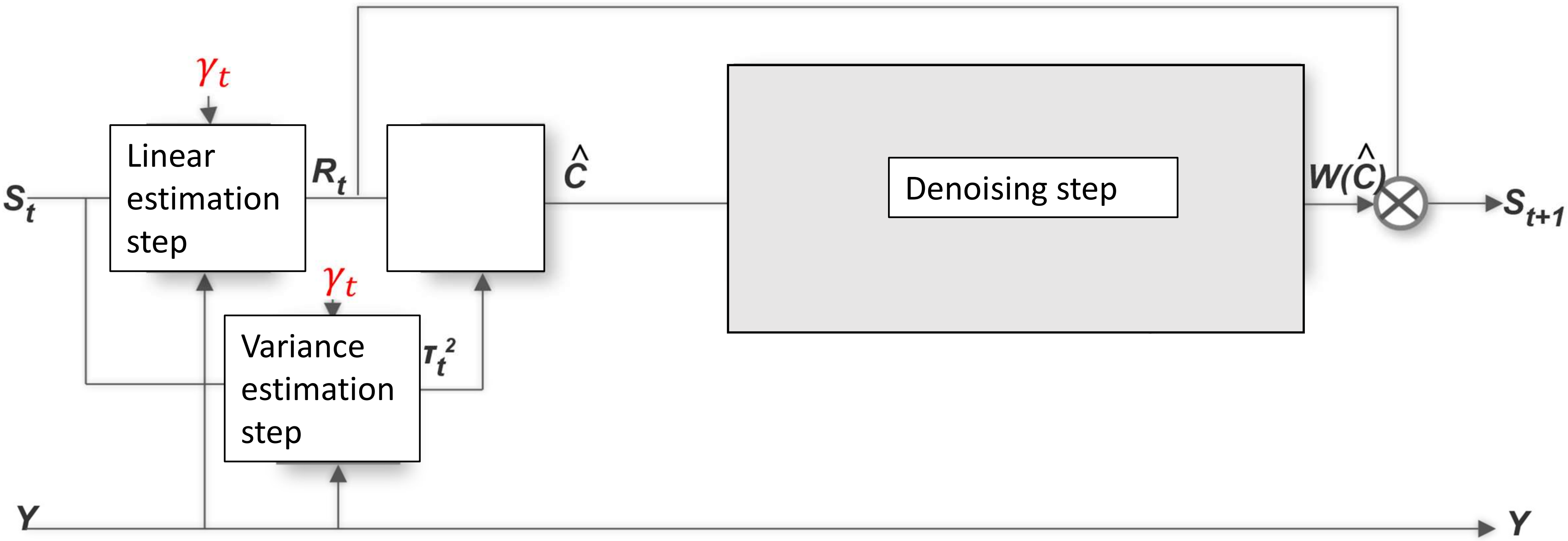
$$\boldsymbol{S}_{t+1} = \eta_{MMSE}\left(\boldsymbol{R}_t, \tau_t^2\right)$$

τ_t^2 : Estimated using $\boldsymbol{Y}$, $\boldsymbol{S}_t$, $\boldsymbol{A}$ and noise variance σ^2

- γ_t : Learnt from data
- Denoising step based on an approximate model

D. Ito, S. Takabe, and T. Wadayama, "Trainable ISTA for sparse signal recovery," IEEE Transactions on Signal Processing, vol. 67, no. 12, pp. 3113–3125, June 2019.

Trainable ISTA (TISTA)



- Already uses deep unfolding
- Denoising step based on an approximate model

D. Ito, S. Takabe, and T. Wadayama, "Trainable ISTA for sparse signal recovery," IEEE Transactions on Signal Processing, vol. 67, no. 12, pp. 3113–3125, June 2019.

Technique 2: Model-based neural network (for row-wise denoising)

$$\boldsymbol{y}_t = \boldsymbol{h}_t + \boldsymbol{z}_t, \qquad \boldsymbol{Y} = [\boldsymbol{y}_1\ \boldsymbol{y}_2 \dots \boldsymbol{y}_T]$$

- $\boldsymbol{h}_t$: Conditionally Gaussian $(\boldsymbol{0}, \boldsymbol{C}_\delta)$ given parameters δ
- $\boldsymbol{z}_t$: Gaussian $(\boldsymbol{0}, \sigma^2\boldsymbol{I})$ noise
- $\delta \sim \boldsymbol{p}(\delta)$
- MMSE estimate of $\boldsymbol{h}_t = \widehat{\boldsymbol{W}}(\widehat{\boldsymbol{C}})\boldsymbol{y}_t$

$$\widehat{\boldsymbol{C}} = \frac{\boldsymbol{1}}{\boldsymbol{\sigma}^2}\sum_{t=1}^{T}\boldsymbol{y}_t\boldsymbol{y}_t{}^{H}$$

$$\widehat{\boldsymbol{W}}(\widehat{\boldsymbol{C}}) = \frac{\int \exp\left(\mathrm{tr}\left(\boldsymbol{W}_\delta\widehat{\boldsymbol{C}}\right) + T\log|\boldsymbol{I} - \boldsymbol{W}_\delta|\right)\boldsymbol{W}_\delta\boldsymbol{p}(\delta)d\delta}{\int \exp\left(\mathrm{tr}\left(\boldsymbol{W}_\delta\widehat{\boldsymbol{C}}\right) + T\log|\boldsymbol{I} - \boldsymbol{W}_\delta|\right)\boldsymbol{p}(\delta)d\delta}$$

$$\boldsymbol{W}_\delta = \boldsymbol{C}_\delta\left(\boldsymbol{C}_\delta + \sigma^2\boldsymbol{I}\right)^{-1}$$

D. Neumann, T. Wiese and W. Utschick, "Learning the MMSE Channel Estimator," in IEEE Transactions on Signal Processing, vol. 66, no. 11, pp. 2905-2917, 1 June1, 2018.

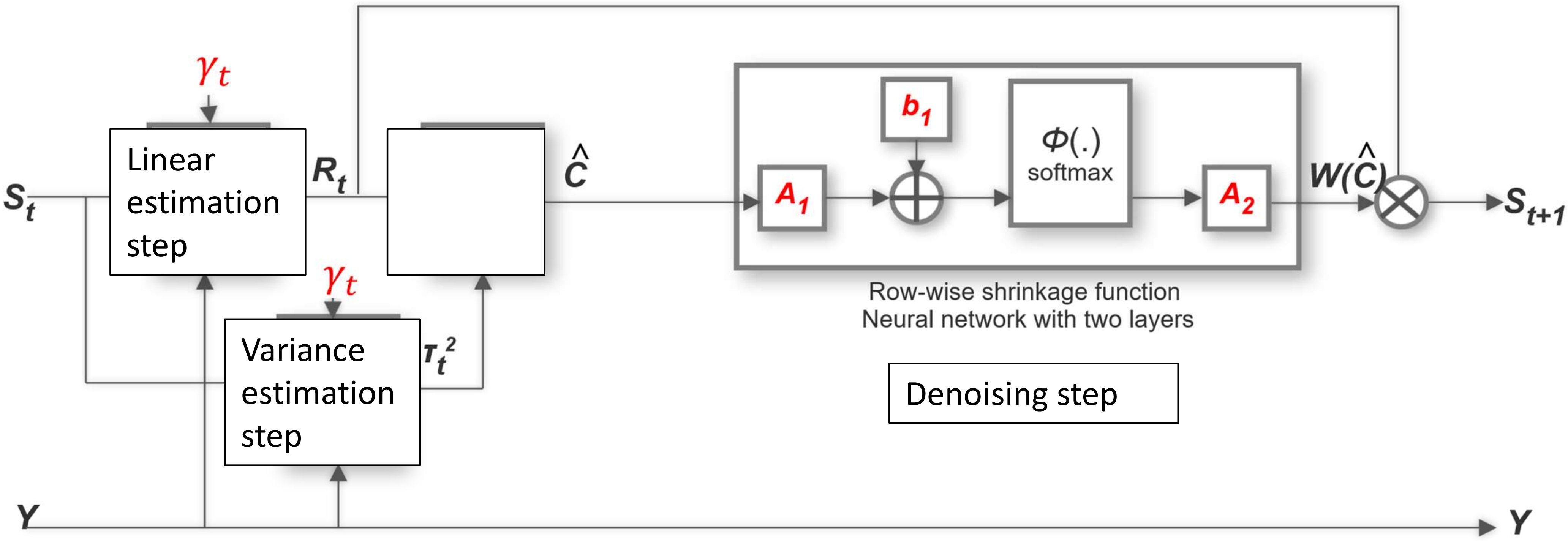
Model-based neural network

$$\widehat{\boldsymbol{W}}(\widehat{\boldsymbol{C}}) = \frac{\sum_{i=1}^{N} \exp\left(\mathrm{tr}\left(\boldsymbol{W}_{\delta_i}\widehat{\boldsymbol{C}}\right) + b_i\right)\boldsymbol{W}_{\delta_i}\, p_i}{\sum_{i=1}^{N} \exp\left(\mathrm{tr}\left(\boldsymbol{W}_{\delta_i}\widehat{\boldsymbol{C}}\right) + b_i\right) p_i}$$

$$\mathrm{vec}\left(\widehat{\boldsymbol{W}}(\widehat{\boldsymbol{C}})\right) = \boldsymbol{A}\,\frac{\exp\left(\mathrm{tr}\left(\boldsymbol{A}^T \mathrm{vec}(\widehat{\boldsymbol{C}})\right) + \boldsymbol{b}\right)}{\boldsymbol{1}^T \exp\left(\mathrm{tr}(\boldsymbol{A}^T \mathrm{vec}(\widehat{\boldsymbol{C}})) + \boldsymbol{b}\right)}$$

- MMSE estimator of $\boldsymbol{h}_t$: a two-stage neural network with linear layers and soft-max activation function
- Use a trained network for the denoising step
  - Parameters learnt from training data
  - Reduces modelling approximation error

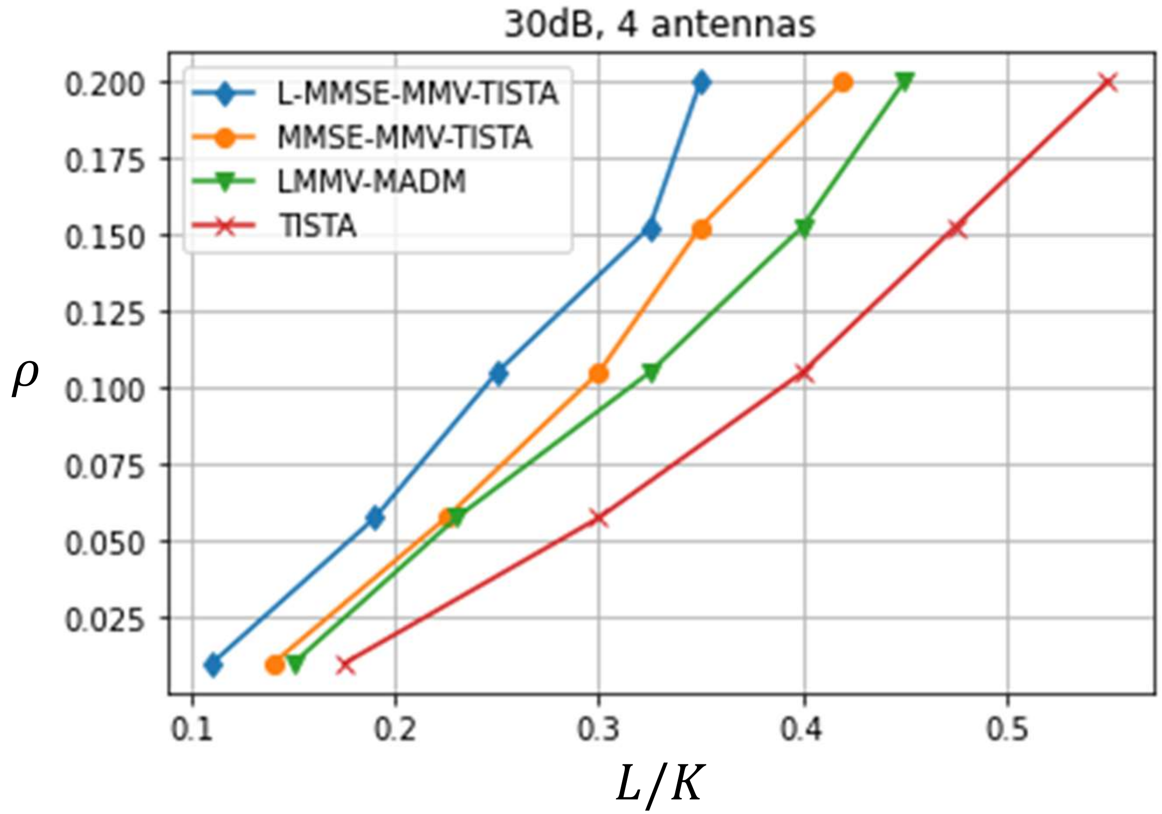
Trainable ISTA (TISTA) and modification



D. Ito, S. Takabe, and T. Wadayama, “Trainable ISTA for sparse signal recovery,” IEEE Transactions on Signal Processing, vol. 67, no. 12, pp. 3113–3125, June 2019.
D. Neumann, T. Wiese and W. Utschick, "Learning the MMSE Channel Estimator," in IEEE Transactions on Signal Processing, vol. 66, no. 11, pp. 2905-2917, 1 June1, 2018.

Simulation Results

Performance



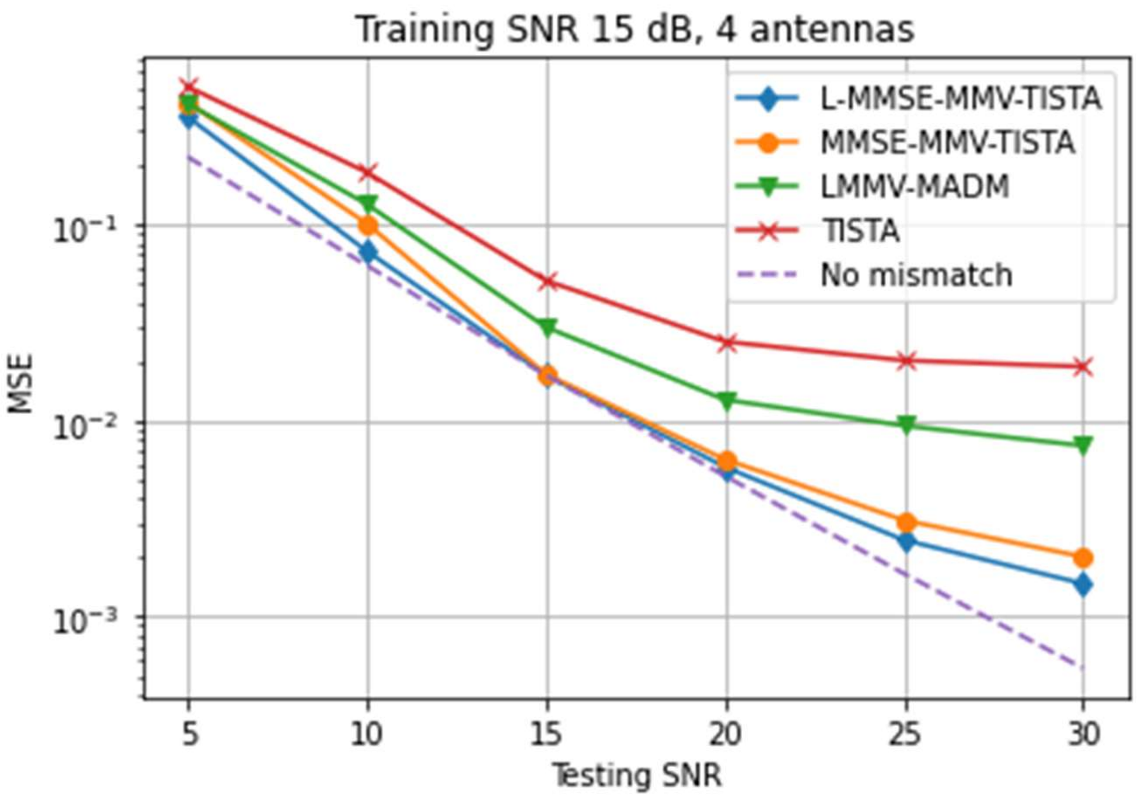
- $K = 500$ users
- 12 layer network
- Minimum L/K for a given activity probability ρ
- Training and test SNR at 30 dB
- Success if NMSE < -20 dB
- Correlated channel

Unfolded network needs fewer iterations

Learnt denoiser gives better performance

U. K. Sreeshma Shiv, S. Bhashyam, C. R. Srivatsa and C. R. Murthy, "Learning-Based Sparse Recovery for Joint Activity Detection and Channel Estimation in Massive Random Access Systems," in IEEE Wireless Communications Letters, vol. 11, no. 11, pp. 2295-2299, Nov. 2022

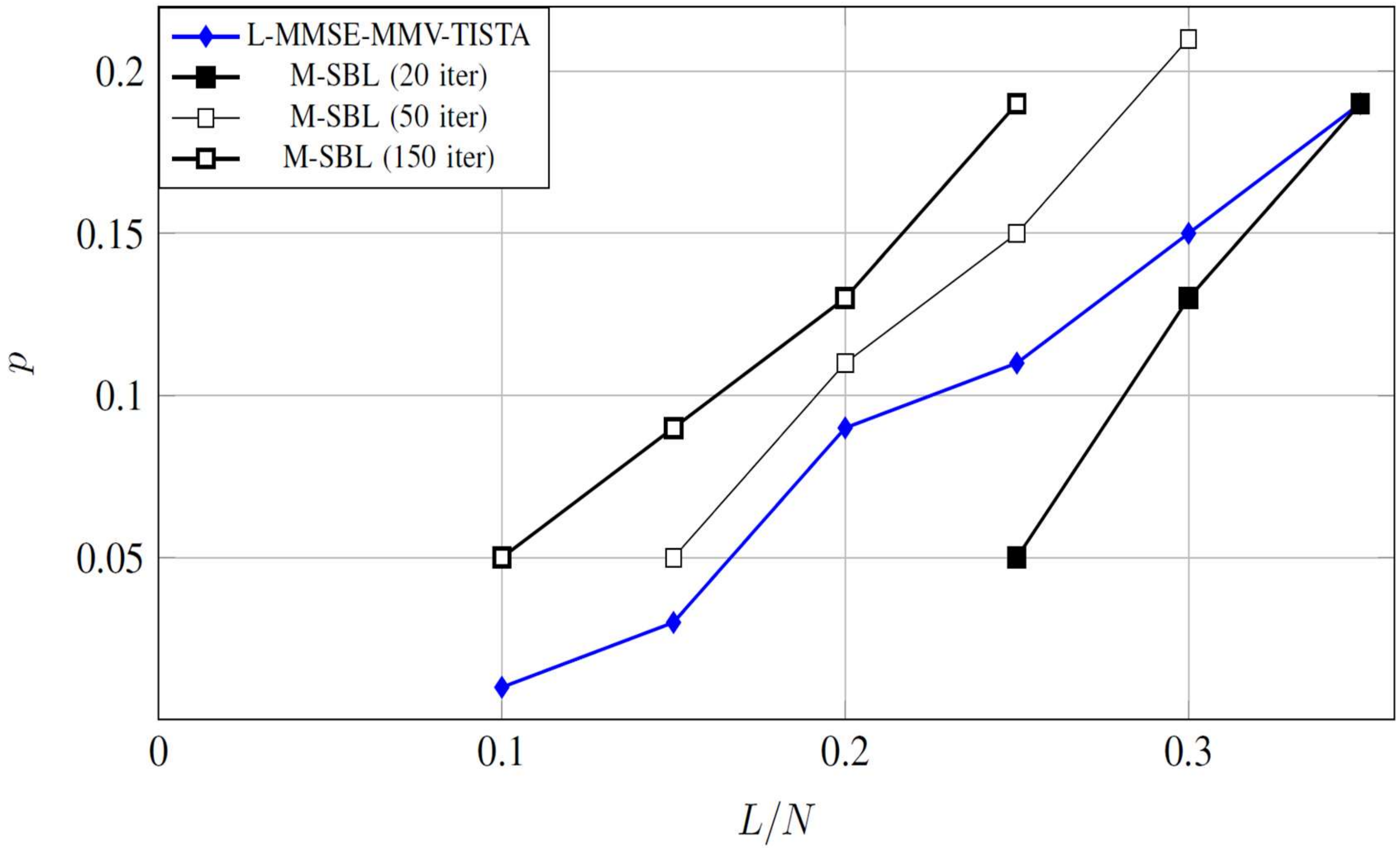
Robustness



Robust to differences in training and testing SNR

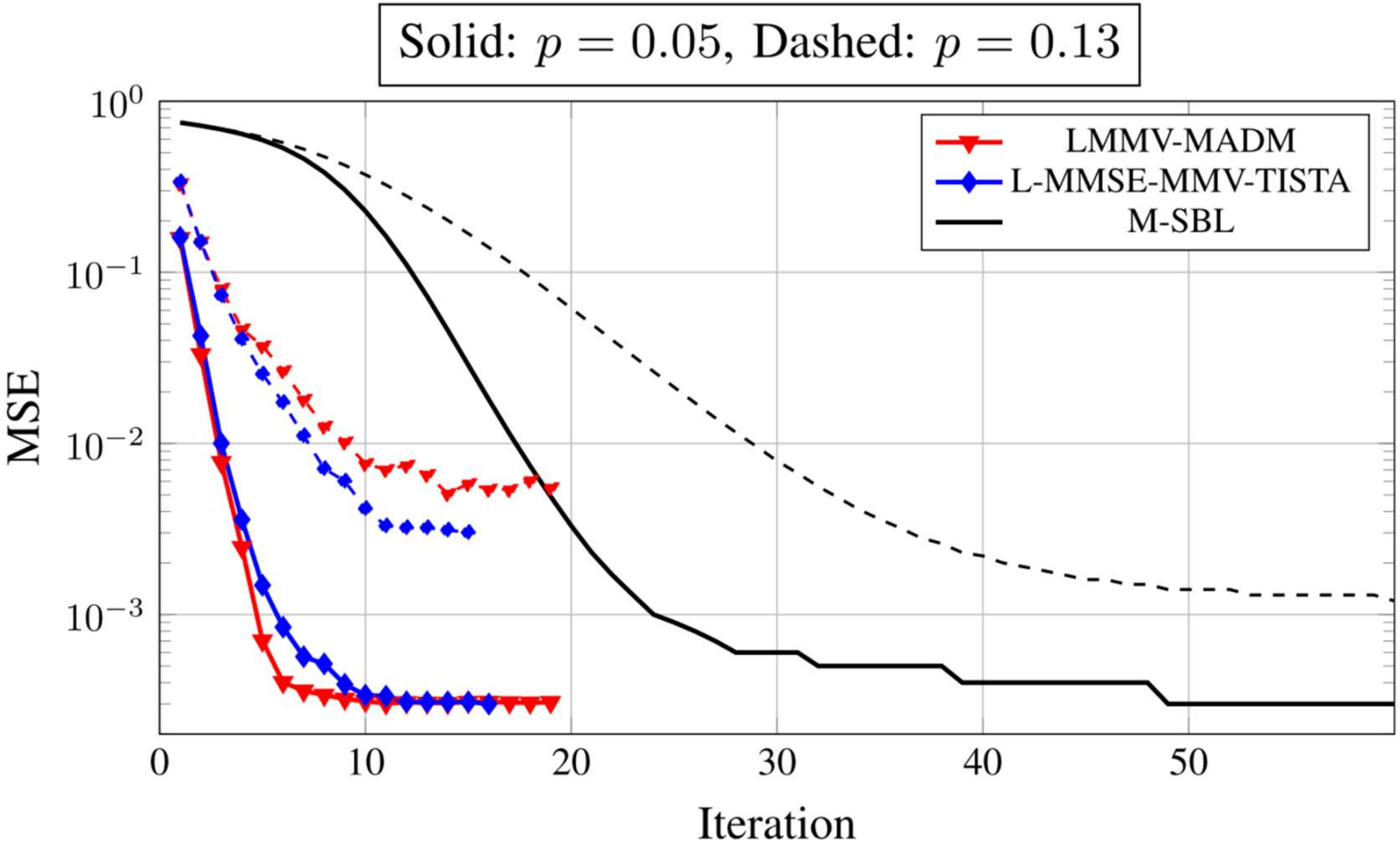
- Robustness study
- $K = 500$, 12 layer network
- $\rho = 0.1$
- Training SNR at 15 dB
- $L = 200$, $M = 4$
- Correlated channel

Comparison with M-SBL



- 500 users, 30 dB, 4 antennas, correlated channel
- M-SBL can perform better with higher complexity

Comparison with M-SBL



- 500 users, 30 dB, 10 antennas, L/N = 0.3
- Complexity advantage for smaller p

Summary

- New learning-based sparse recovery methods
  - Back-projected error
  - Deep unfolding
  - Model-based neural network
  - Both supervised and unsupervised training
- Massive random access
  - Reduction in pilot overhead
- Ongoing work
  - Probability of error threshold
  - Large scale fading effects and estimation for MMV-TISTA
  - Unsourced random access
  - More sparsity structures

Thank you