Joint Active User Detection and Channel Estimation in Massive Access Systems

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Introduction

- **Future 6G systems** will employ a massive number of antennas, far beyond 5G, to achieve ultra-high data rates and reliability.
- **High-resolution ADCs are impractical** for such large arrays due to excessive power consumption and cost.
- **One-bit ADCs as alternatives** provide a low-cost and energy-efficient solution but cause extreme information loss from coarse quantization.
- **Sparse user activity** in mMTC further complicates reliable detection, making advanced inference critical.
- **Proposed ADVI-based solution** compensates quantization loss and detects sparse active users, enabling practical one-bit ADCs for 6G.

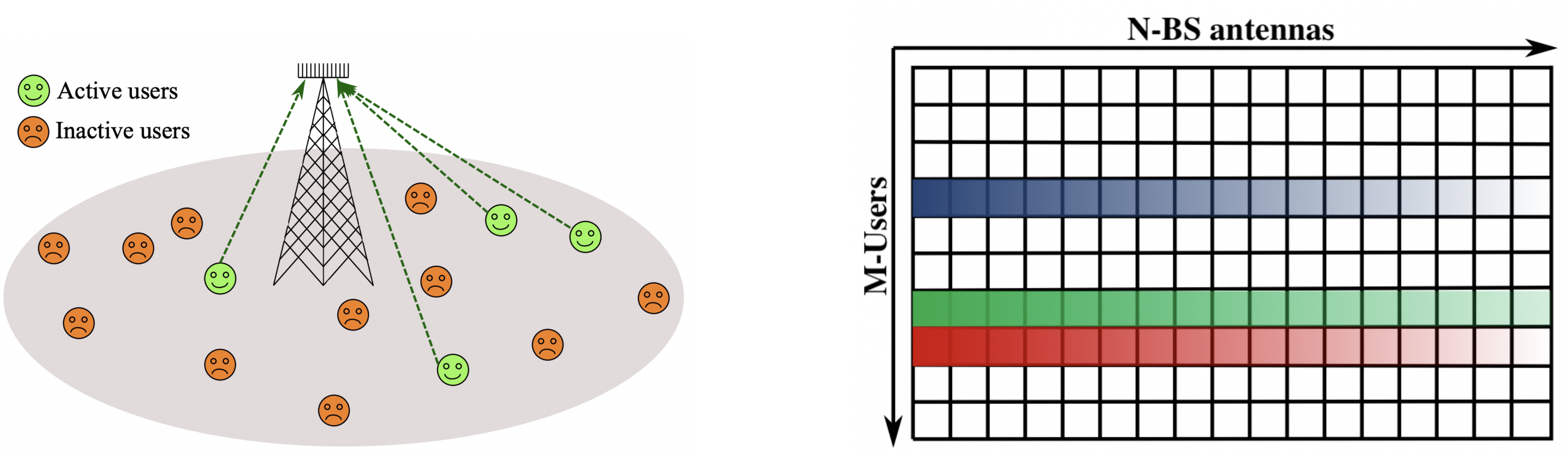

Figure 1. (a) Sporadic traffic of users in mMTC mMIMO system (b) User activity sparsity

System Model

We consider an uplink mMTC system with M single-antenna users and a base station (BS) equipped with N antennas.

The active users simultaneously transmit pilots over T_p time slots, and the BS utilizes these signals for AUD and channel estimation.

- **Dense setting :** $M_a = M$ i.e., all users are active
- **Sparse Setting :** $M_a \ll M$ i.e., very few users are active

The total received signal $\mathbf{Y_p} \in \mathbb{C}^{N \times T_p}$ at the BS during the pilot phase is:

$$\mathbf{Y}_p = \text{sign}(\mathbf{H}\,\text{diag}(\boldsymbol{\alpha})\,\mathbf{X}_p + \mathbf{N}_p)$$

During the data phase, the received signal $\mathbf{Y_d} \in \mathbb{C}^{N \times T_d}$ at the BS is:

$$\mathbf{Y}_d = \text{sign}(\mathbf{H}\,\text{diag}(\boldsymbol{\alpha})\,\mathbf{X}_d + \mathbf{N}_d)$$

where $\mathbf{H} \in \mathbb{C}^{N \times M}$ is the channel matrix, $\boldsymbol{\alpha} \in \{0,1\}^M$ is user activity, $\mathbf{N}$ is the Gaussian noise and $\mathbf{X}$ is the transmitted signal matrix.

Automatic Differentiation Variational Inference (ADVI)

In under-determined CF-mMIMO with one-bit ADCs, where classical inference fails, ADVI approximates the latent posterior via variational inference.

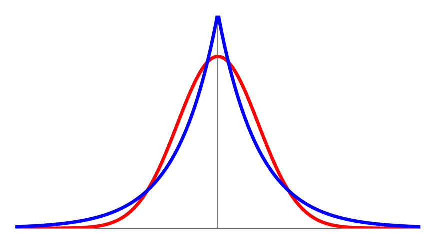

Figure 2. Sparsity promoting Laplace prior on $\boldsymbol{\alpha}$ (blue), Gaussian prior on $\mathbf{H}$ (red)

1. **Prior and Likelihood Distribution**, we assume Laplace prior on $\boldsymbol{\alpha}$ and a gaussian prior on $\mathbf{H}$.

$$p(\boldsymbol{\alpha}) = \frac{1}{2}\exp(-|\boldsymbol{\alpha}|) \;\; ; \;\; p(\mathbf{h}_n) = \mathcal{N}(0, \mathbf{I}_M),$$

The likelihood distribution $p(y_{nt}|\boldsymbol{\alpha}, \mathbf{h}_n)$ is a Gaussian CDF approximated using the sigmoid function, where $y_{nt} = (\mathbf{Y}_p)_{n,t}$

2. **Posterior Inference via Variational Approximation**, from Bayes theorem, the joint posterior is

$$\boxed{p(\boldsymbol{\alpha}, \mathbf{H} \mid \mathbf{Y}) \;\propto\; p(\boldsymbol{\alpha})\, p(\mathbf{H})\, p(\mathbf{Y} \mid \boldsymbol{\alpha}, \mathbf{H})}$$

Because the sigmoid likelihood is non-conjugate to the priors, exact Bayesian inference is intractable; hence we resort to ELBO maximization.

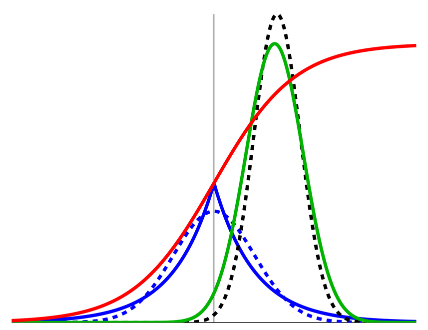

Figure 3. Posterior (black) approximated using Gaussian (green)

3. **ELBO Maximization using Gradient Ascent and Monte-Carlo Integration**, approximate the true posteriors of $\boldsymbol{\alpha}$ & $\mathbf{H}$ with gaussian $q(\boldsymbol{\alpha})$ & $q(\mathbf{H})$. To obtain the optimum posterior estimate, we maximize the ELBO (L).

$$\mathcal{L} = \mathbb{E}_{q(\boldsymbol{\alpha},\mathbf{H})}[\log p(\boldsymbol{\alpha}, \mathbf{H}, \mathbf{Y}_p)] + \mathbb{H}(q(\boldsymbol{\alpha})) + \mathbb{H}(q(\mathbf{H}))$$

with $\boldsymbol{\phi}$ as the set of parameters, the general update rule for parameter $\boldsymbol{\phi}$ at iteration 'i' is given by -

$$\boldsymbol{\phi}^{(i+1)} \leftarrow \boldsymbol{\phi}^{(i)} + \lambda \nabla_{\boldsymbol{\phi}} \mathcal{L}(\boldsymbol{\phi}^{(i)})$$

where λ is the learning rate. We then use K-sample averaging to approximate expectation of the gradient and update the parameters.

4. **User Activity**, we finally map the estimated activity as -

$$\hat{\alpha}_i = \begin{cases} 1, & \text{if} \quad \text{abs(detected activity)} \geq 0.5 \\ 0, & \text{if} \quad \text{abs(detected activity)} < 0.5 \end{cases}$$

After successfully getting posterior estimates $\hat{\boldsymbol{\alpha}}$ and $\hat{\mathbf{H}}$, we use the same method for data detection of the active user rows of $\mathbf{X}_d$.

Note: For the case of dense setting, we can let go of $\boldsymbol{\alpha}$ and only estimate $\mathbf{H}$ using the above method. And later continue with data detection using estimated channel matrix $\hat{\mathbf{H}}$.

Results

We simulate the model using **STAN, a probabilistic programming language** for specifying statistical models. It imperatively defines a log probability function over parameters conditioned on specified data and constants.

All Active Users, for joint CE-DD with QAM signaling, ADVI attains the lowest BER, highlighting its superior detection capability. It consistently outperforms both SVM and PVI in terms of accuracy.

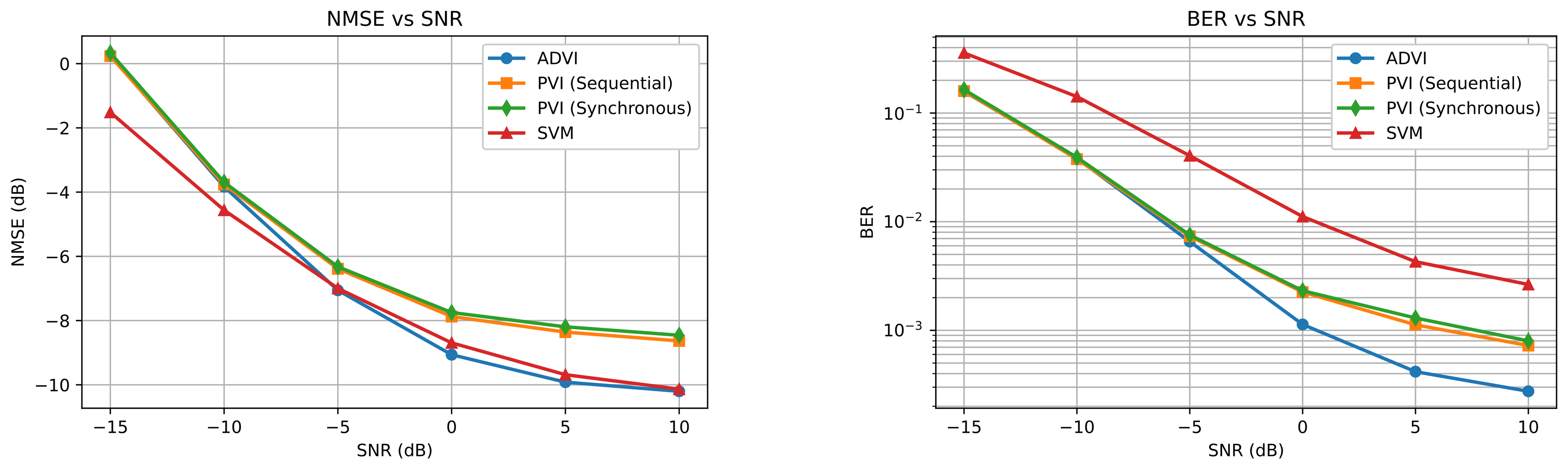

Figure 4. Number of receiver antennas $N = 128$, number of users $M = 20$ (all assumed active in this scenario), pilot sequence length $T_p = 80$, and data sequence length $T_d = 200$

Sparse Active Users, ADVI exhibits superior performance in active user detection (AUD) and channel estimation (CE). Using highly reliable AUD and accurate CE, the algorithm achieves enhanced data detection accuracy, thereby ensuring robust overall system performance under sparse user activity conditions.

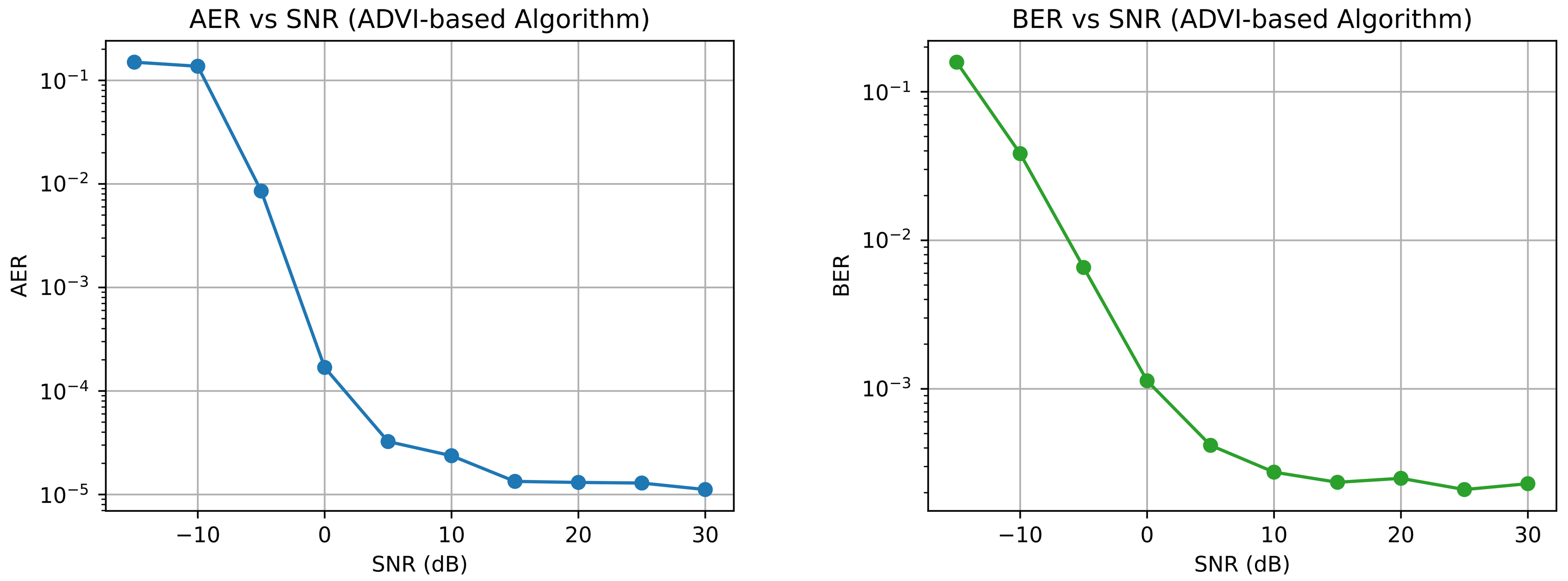

Figure 5. Number of receiver antennas $N = 64$, number of users $M = 100$ operating at 15% sparsity, pilot sequence length $T_p = 40$, and data sequence length $T_d = 100$

The findings demonstrate ADVI's potential to significantly enhance user activity and data detection and channel estimation, ensuring robust performance in complex wireless communication systems.

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