Quantized Variational Bayesian Joint Channel Estimation and Data Detection for Uplink Massive MIMO Systems with Low Resolution ADCs

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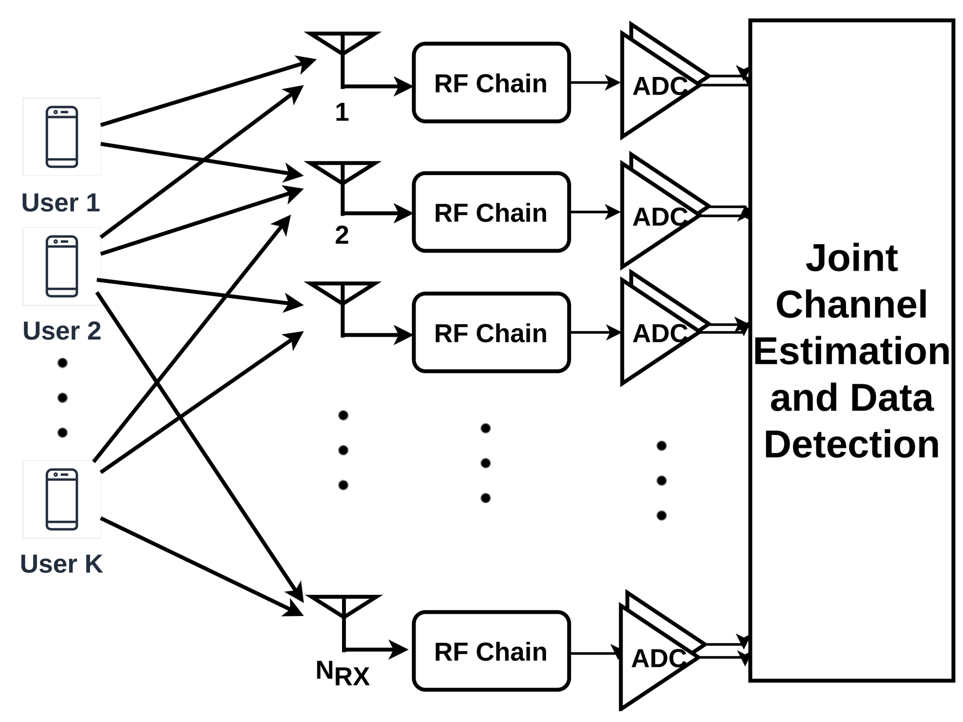
Motivation

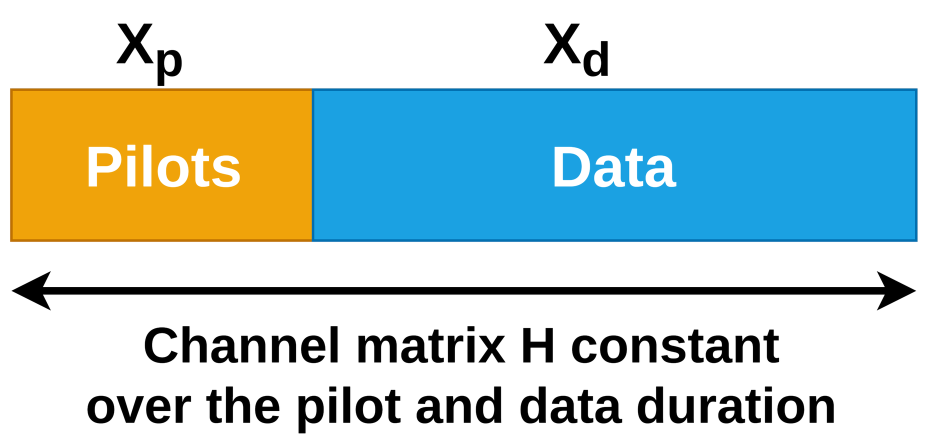
- Massive MIMO: key technology for 5G
- Power consumption of ADC increases exponentially with bit width
  $\implies$ Need for coarse quantization
- Pilots and data are both quantized
- Prefect CSIR: not practical
- Soft symbol estimates necessary in coded communication systems

Contributions

- Joint channel estimation and data detection as a statistical inference problem
- Variational Bayes algorithm to infer the marginal distributions of the transmitted symbols and the channel
- Symbol error probability performance evaluation

System Model





Uplink channel

$$\mathbf{H} = [\mathbf{h}_1, \ldots, \mathbf{h}_K] \in \mathbb{C}^{N_{RX} \times K}$$

Unquantized Received Signal

$$\mathbf{Z}_p = [\mathbf{z}_{p,1}, \ldots, \mathbf{z}_{p,\tau_p}] = \mathbf{H}\mathbf{X}_p + \mathbf{W}_p$$
$$\mathbf{Z}_d = [\mathbf{z}_{d,1}, \ldots, \mathbf{z}_{d,\tau_d}] = \mathbf{H}\mathbf{X}_d + \mathbf{W}_d$$

Quantized Received Signal

$$\mathbf{Y}_p = \mathcal{Q}(\mathbf{Z}_p), \quad \mathbf{Y}_d = \mathcal{Q}(\mathbf{Z}_d)$$

Existing Receivers

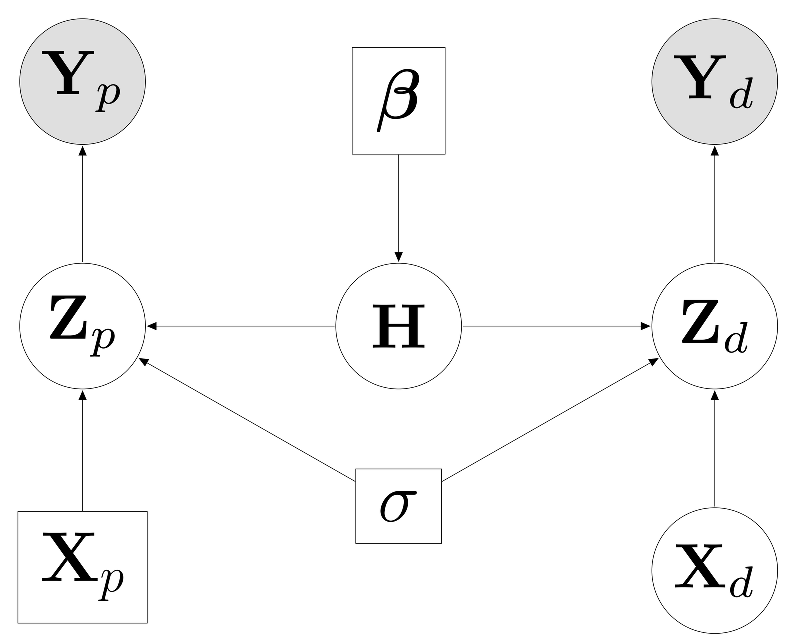
MMSE

- Suboptimal for quantized systems

MAP

- Computationally intractable
- Evidence function hard to compute
- Necessitates approximate inference

Bayesian Network Model



Variational Bayesian Inference

- Mean field theory framework
- Fully factorized approximate posterior
- Marginals of $\mathbf{X}_d$ and $\mathbf{H}$ inferred

Approximate Posterior

$$p(\mathbf{Z}_p, \mathbf{Z}_d, \mathbf{X}_d, \mathbf{H} | \mathbf{Y}_p, \mathbf{Y}_d) \approx q(\mathbf{Z}_p)q(\mathbf{Z}_d)q(\mathbf{X}_d)q(\mathbf{H})$$

Variational Bayes Joint Channel Estimator and Detector

Evidence Lower Bound

$$\mathcal{L}(q) = \ln p(\mathbf{Y}_p, \mathbf{Y}_d, \mathbf{Z}_p, \mathbf{Z}_d, \mathbf{X}_d, \mathbf{H} | \mathbf{X}_p, \boldsymbol{\beta}, \sigma) - \mathrm{KL}(q \| p)$$

Find $q(\mathbf{Z}_p, \mathbf{Z}_d, \mathbf{X}_d, \mathbf{H})$ to **minimize** $\mathrm{KL}(q\|p)$

Computing approximate marginals

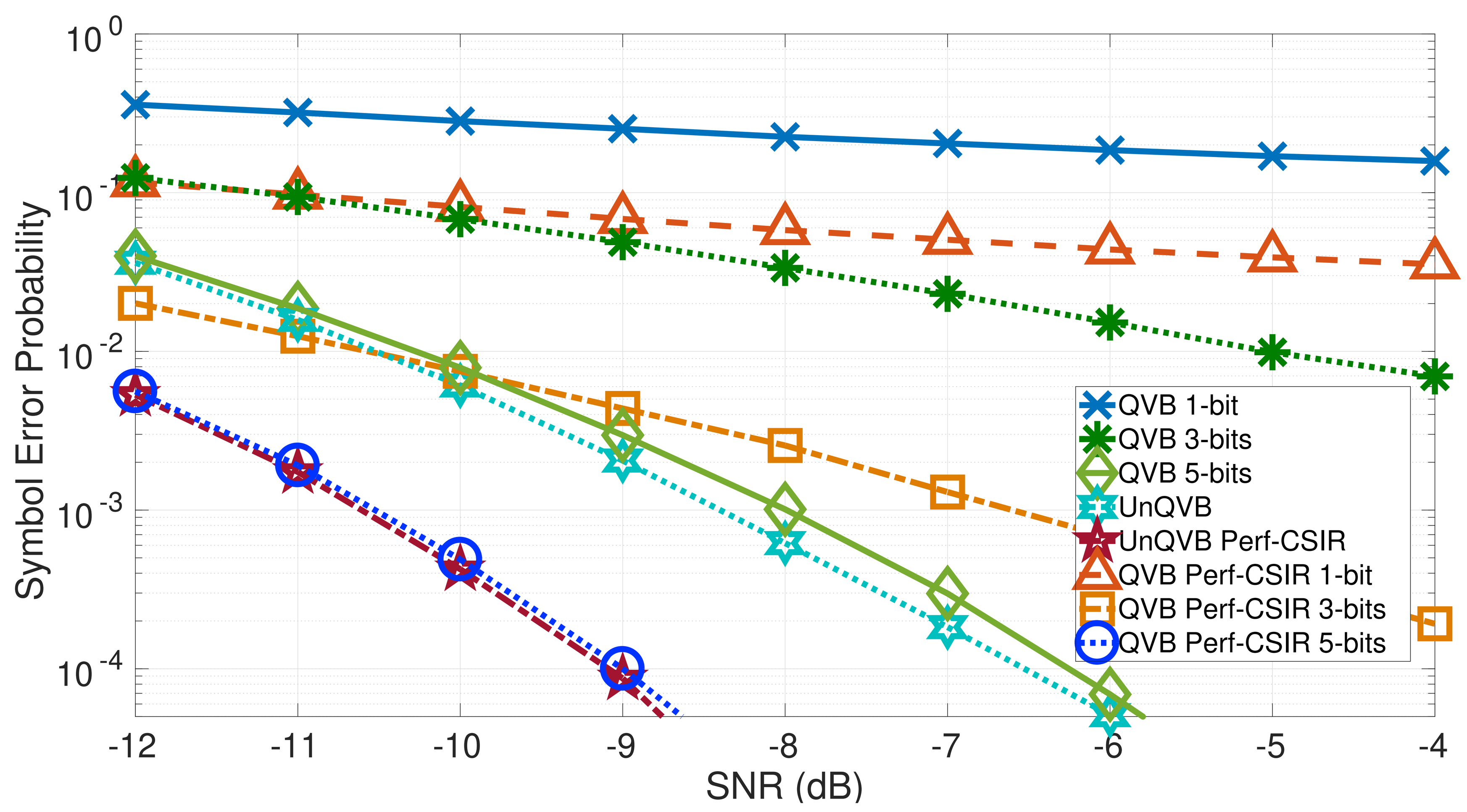
$$\ln q(h_{nk}) \propto \left\langle \ln p\left(\mathbf{Z}_p | \mathbf{X}_p, \mathbf{H}; \sigma^2\right) + \ln p\left(\mathbf{Z}_d | \mathbf{X}_d, \mathbf{H}; \sigma^2\right) + \ln p\left(\mathbf{H} | \boldsymbol{\beta}\right) \right\rangle$$
$$\ln q(x_{d,kt}) \propto \left\langle \ln p\left(\mathbf{Z}_d | \mathbf{X}_d, \mathbf{H}; \sigma^2\right) + \ln p\left(\mathbf{X}_d\right) \right\rangle$$
$$\ln q(\mathbf{z}_{d,t}) \propto \left\langle \ln p\left(\mathbf{Y}_d | \mathbf{Z}_d\right) + \ln p\left(\mathbf{Z}_d | \mathbf{H}, \mathbf{X}_d; \sigma_w^2\right) \right\rangle$$

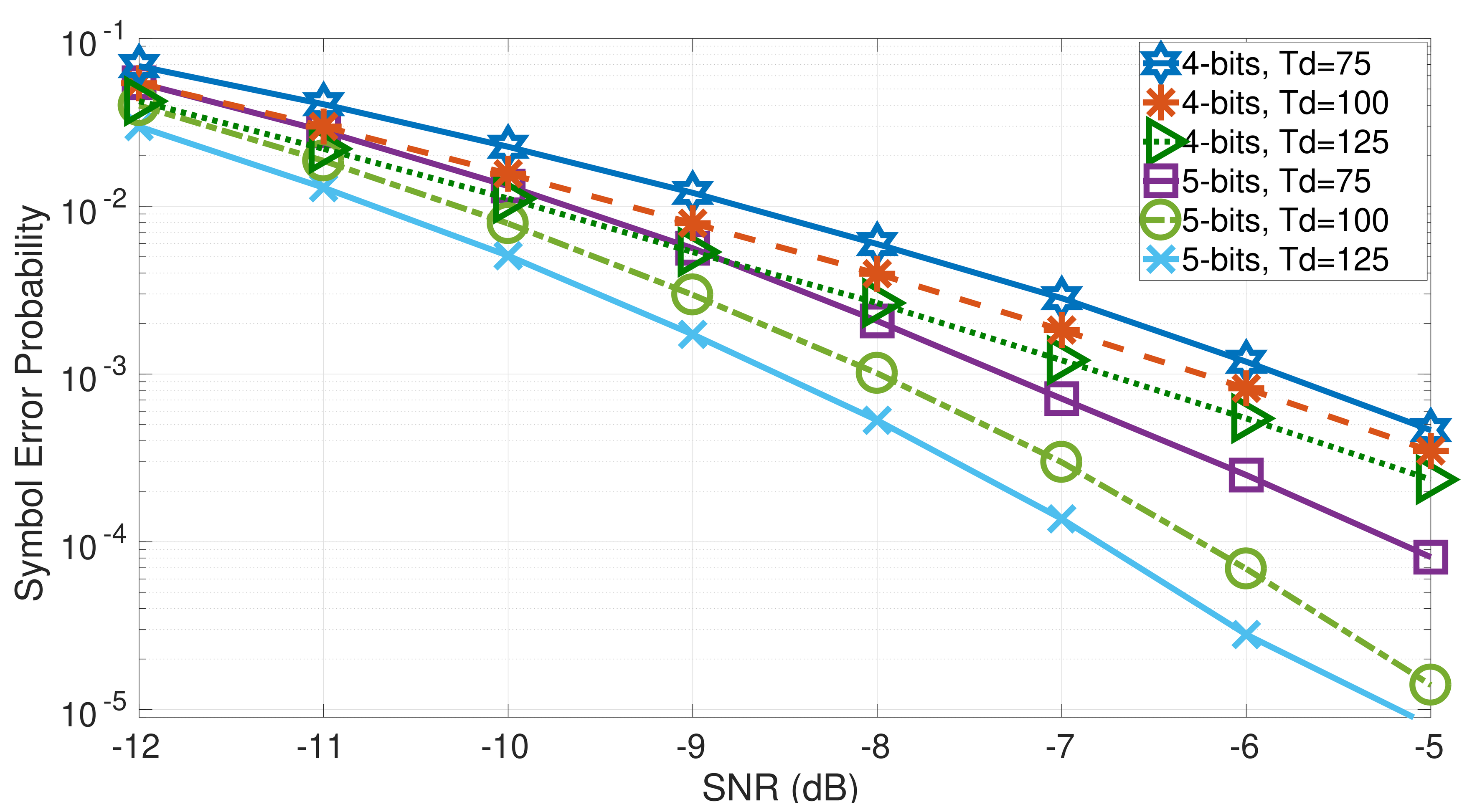
$q(h_{nk}) \implies$ **Complex normal distribution** $q(x_{d,kt}) \implies$ **Boltzmann distribution**

$q(\mathbf{z}_{d,t}) \implies$ **Truncated complex normal distribution**

Simulation Results

Simulation Setup: $N_{\text{RX}} = 128$, $K = 32$, QPSK modulation





Summary

Goal: Joint channel estimation and data detection for massive MIMO systems with low-res-ADCs

Algorithm:
1. Variational Bayes inference based channel estimator and data detector
2. Detector performance proportional to data duration

Advantages

Achieves higher data rate than conventional linear receivers

Low computational complexity

Guaranteed convergence to a local optimum