

# Signal Estimation with Mixtures

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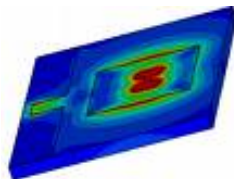
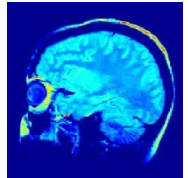
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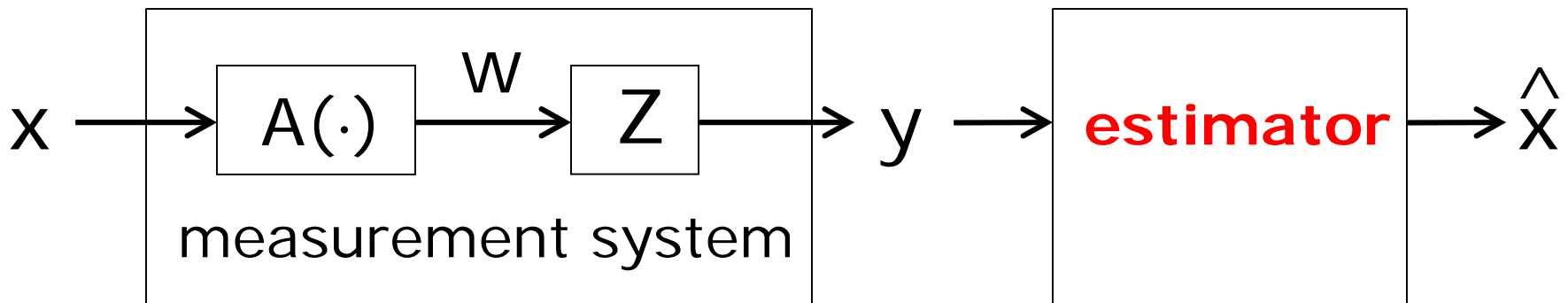
# Signal Estimation

- Medical imaging (tomography)
- Source and channel coding
- Financial prediction
- Electromagnetic scattering
- Seismic imaging (oil industry)
- Speech recognition
- *Many more...*



# Problem Setting

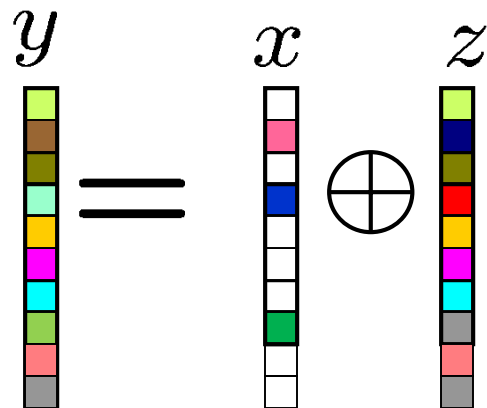
- Real-valued input  $x$  (vector); *unknown* distribution
- *Measurement system*  $A$ 
  - identity operator ( $w=x$ )
  - matrix-vector product ( $w=A^*x$ )
  - nonlinear ( $w=A(x)$ )
- *Noise* (additive,  $f_{Y_i|W_i}$ , non-iid,...)
- *Measurements*  $y$
- *Goal*: estimate  $x$  from  $y, A, f_Z$



# ***Scalar Channel***

# Scalar Channel

- Length-N *input* vector  $x$
- Additive *noise*  $z$
- *Observations*  $y = x + z$
- **Goal**: estimate  $x$  from  $y$
- Will use *mean square error* criteria

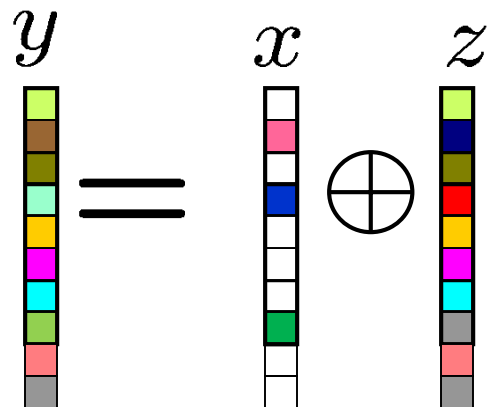


# Bayesian Denoising [Bayes 1763]



- View  $X$  and  $Z$  as random vectors
- Known distributions
- $X \sim f_x(x)$ ,  $Z \sim f_z(z)$
  
- Conditional expectation achieves minimum mean square error (MMSE)

$$E[X|Y] = \int x \mathbf{f}_x(\mathbf{x}|y) dx$$



# Parametric Input Distribution

- Prior  $f_x(x)$  often *unknown*
- To keep things simple...
  - suppose prior is parametric distribution  $f(x|\theta)$

- *What's  $\theta$ ???*



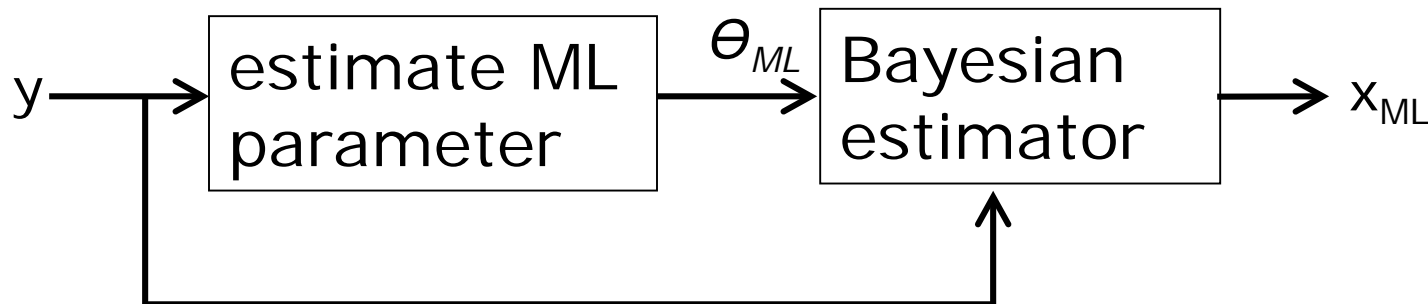
# Plug-in Estimator

- Step 1: compute ML parameter

$$\Theta_{ML} = \operatorname{argmax}_{\theta} f(y | \Theta)$$

- Step 2: plug  $\Theta_{ML}$  into Bayesian estimator

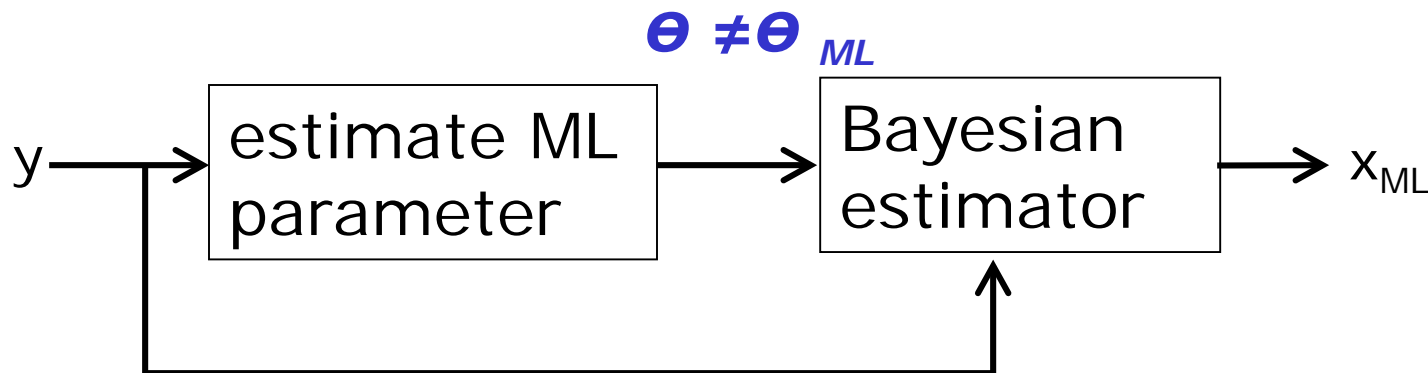
$$x_{ML} = E[X|Y, \Theta_{ML}] = \int x \mathbf{f}_x(x | y, \Theta_{ML}) dx$$





# Limitation

- ML parameter (usually) converges to true  $\Theta$  for large  $N$
- For small  $N$ , *mismatch* between  $\Theta$  and  $\Theta_{ML}$  will increase mean square error (MSE) [Verdú 2010]
- Plug-in discards all other  $\Theta$  that might also be informative



# ***Achieving MMSE with Mixtures***



# ***Achieving MMSE with Mixtures***

Proposed by Neri Merhav

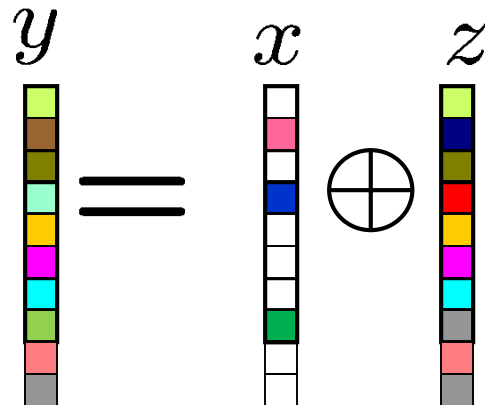
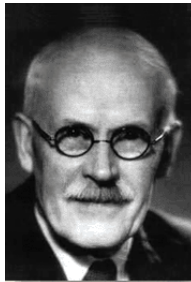


# Mixture Universal Signal Estimator (MUSE)

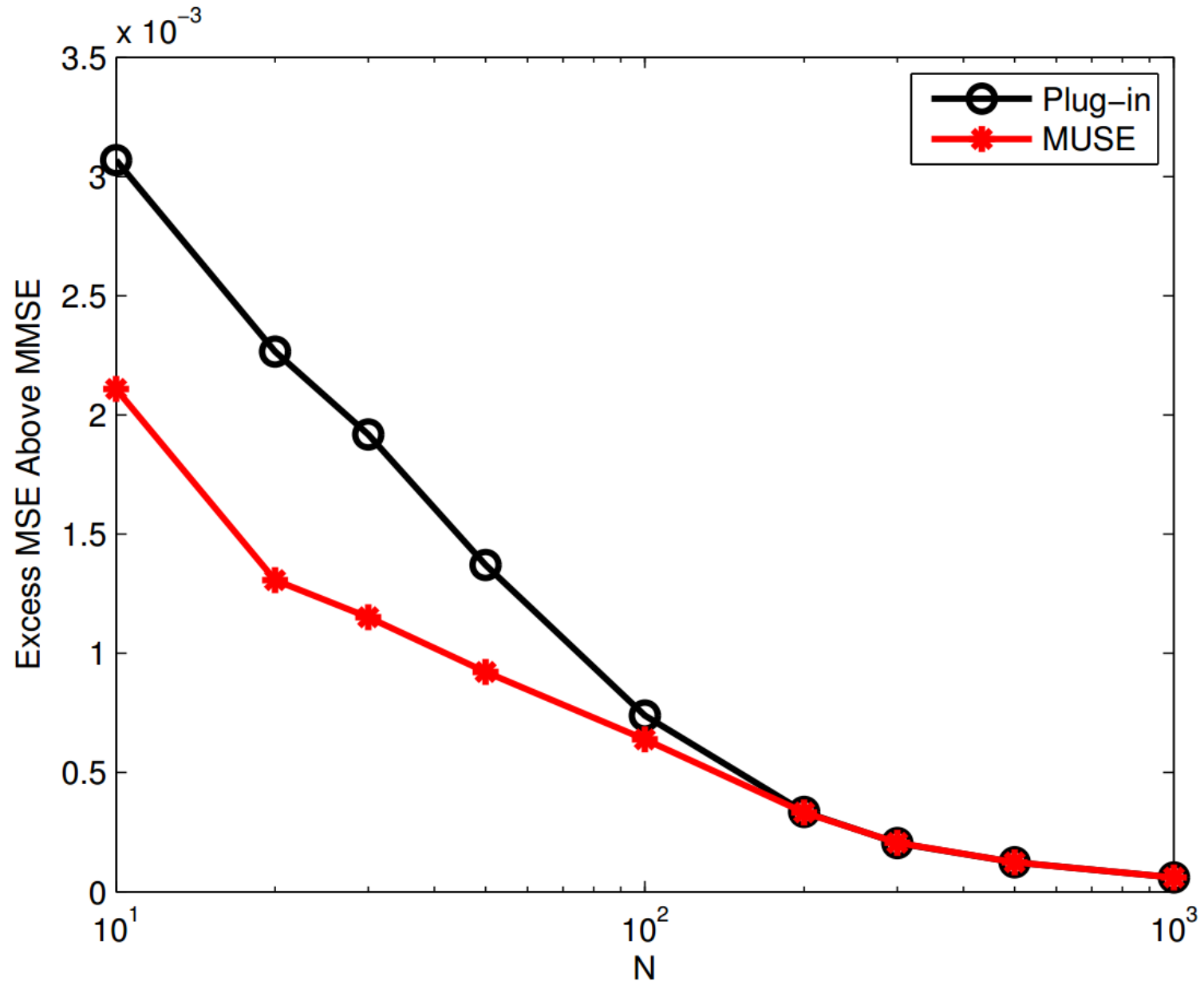
- Scalar channel  $y=x+z$
- Conditional expectation using mixture over  $\Theta$

$$E[X|Y] = \int E[X|Y,\theta] \mathbf{f}(\boldsymbol{\theta} / \mathbf{y}) d\theta$$

- Posterior  $f(\theta|y) = \frac{f(y|\theta)f(\theta)}{\int f(y|\theta')f(\theta')d\theta'}$
- Need objective prior for  $\Theta$ , e.g., Jeffreys' prior



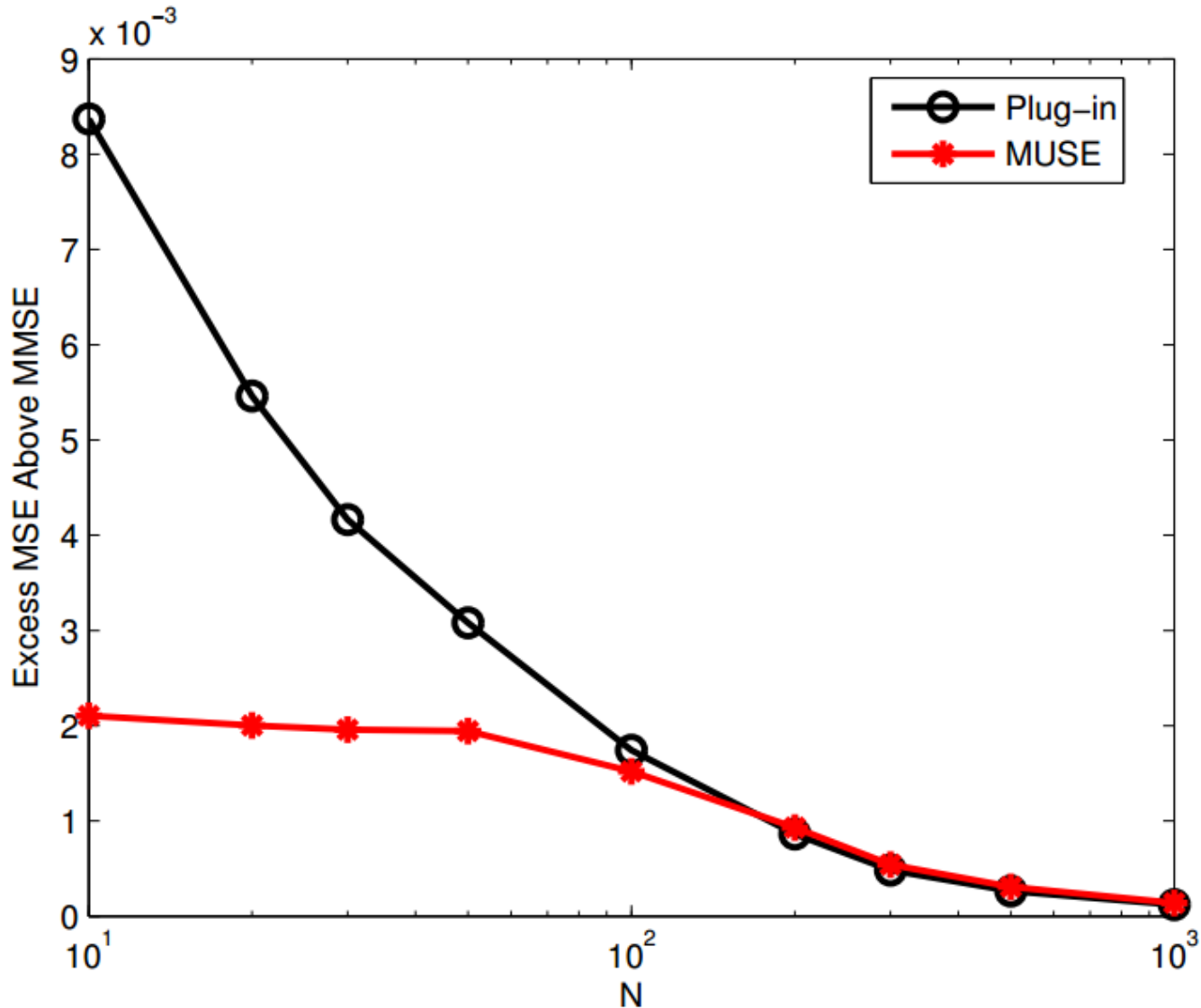
# Bernoulli Input ( $\theta=0.1, \text{Var}(Z)=0.1$ )



# Bernoulli Gaussian Input

$$f(x|\theta, \mu, \sigma_x) = \theta \cdot N(\mu, \sigma_x^2) + (1 - \theta) \cdot \delta(x)$$

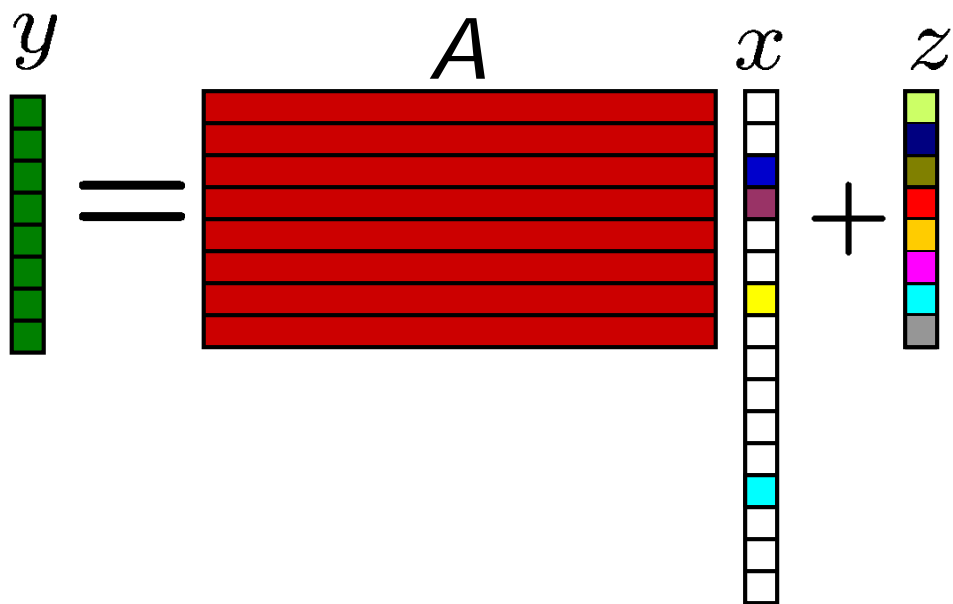
$$\theta = 0.1; \mu = 0; \text{Var}(X) = 0.01, \text{Var}(Z) = 0.1$$



# ***Matrix Channel***

# Example: Compressed Sensing

- Length- $N$  input,  $x \sim f_x(x|\Theta)$  (typically sparse)
- Matrix  $A$
- Additive noise,  $z \sim f_z(z)$  (e.g., i.i.d. Gaussian)
- Modest # measurements  $M$  suffices for robust signal reconstruction





# Approximate Message Passing (AMP)

[Donoho, Maleki, & Montanari 2009]



*AWGN channel*

$$X^{t+1} = \eta_t(X^t + A^T r^t) = \eta_t(X + N(0, \sigma_t^2))$$

$$r^t = y - Ax^t + \frac{r^{t-1}}{M/N} < \underbrace{\eta'_{t-1}(X^{t-1} + A^T r^{t-1})}_{\text{correction term}} >$$

# AMP-MUSE

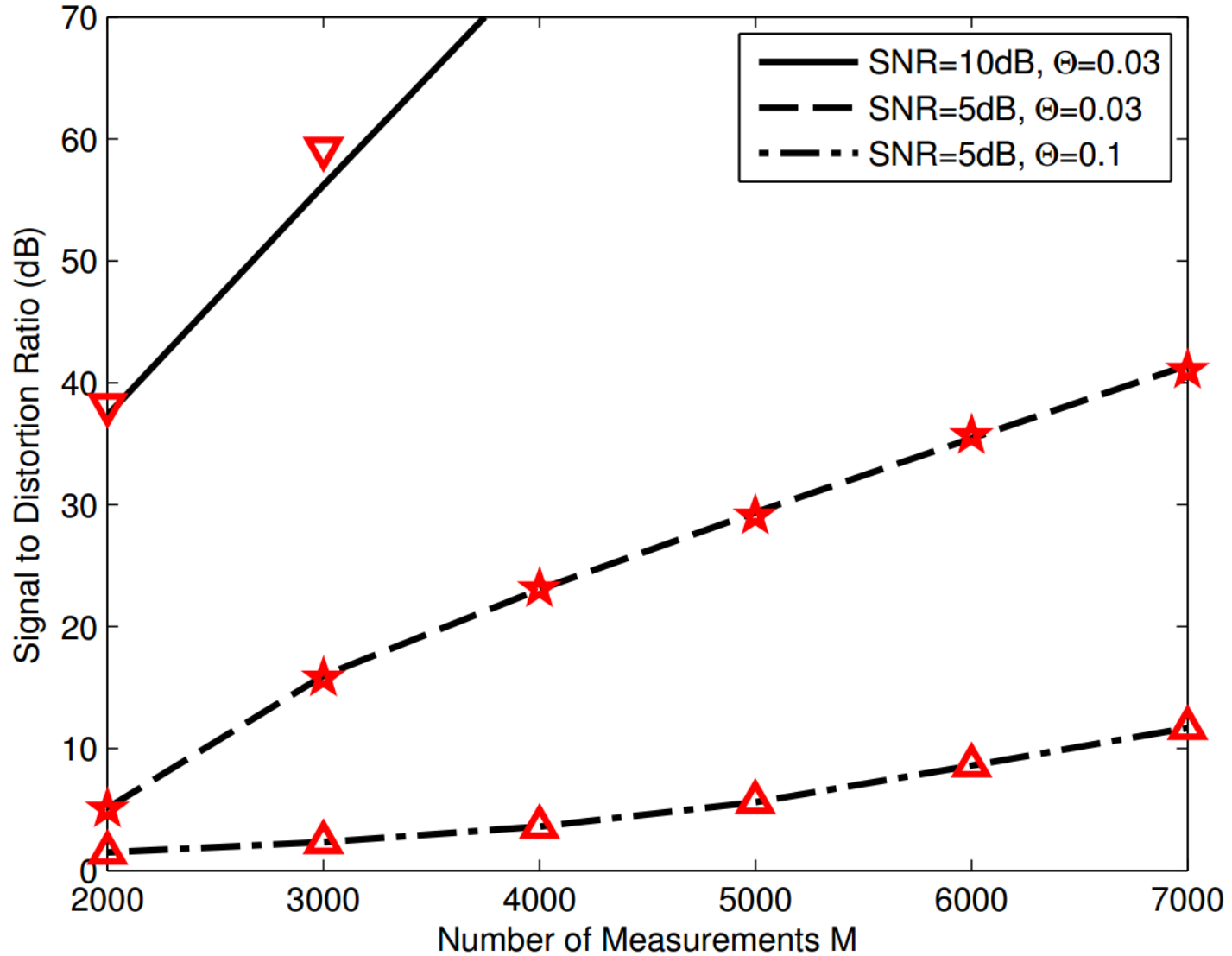
- Following [Donoho et al. 2013] use non-separable MUSE denoiser within AMP

$$X^{t+1} = \eta_t(X^t + A^T r^t) = \eta_{\text{MUSE},t}(X + N(0, \sigma_t^2))$$

*MUSE denoiser*  
↓

$$r^t = y - Ax^t + \frac{r^{t-1}}{M/N} < \eta'_{\text{MUSE},t-1}(X^{t-1} + A^T r^{t-1}) >$$

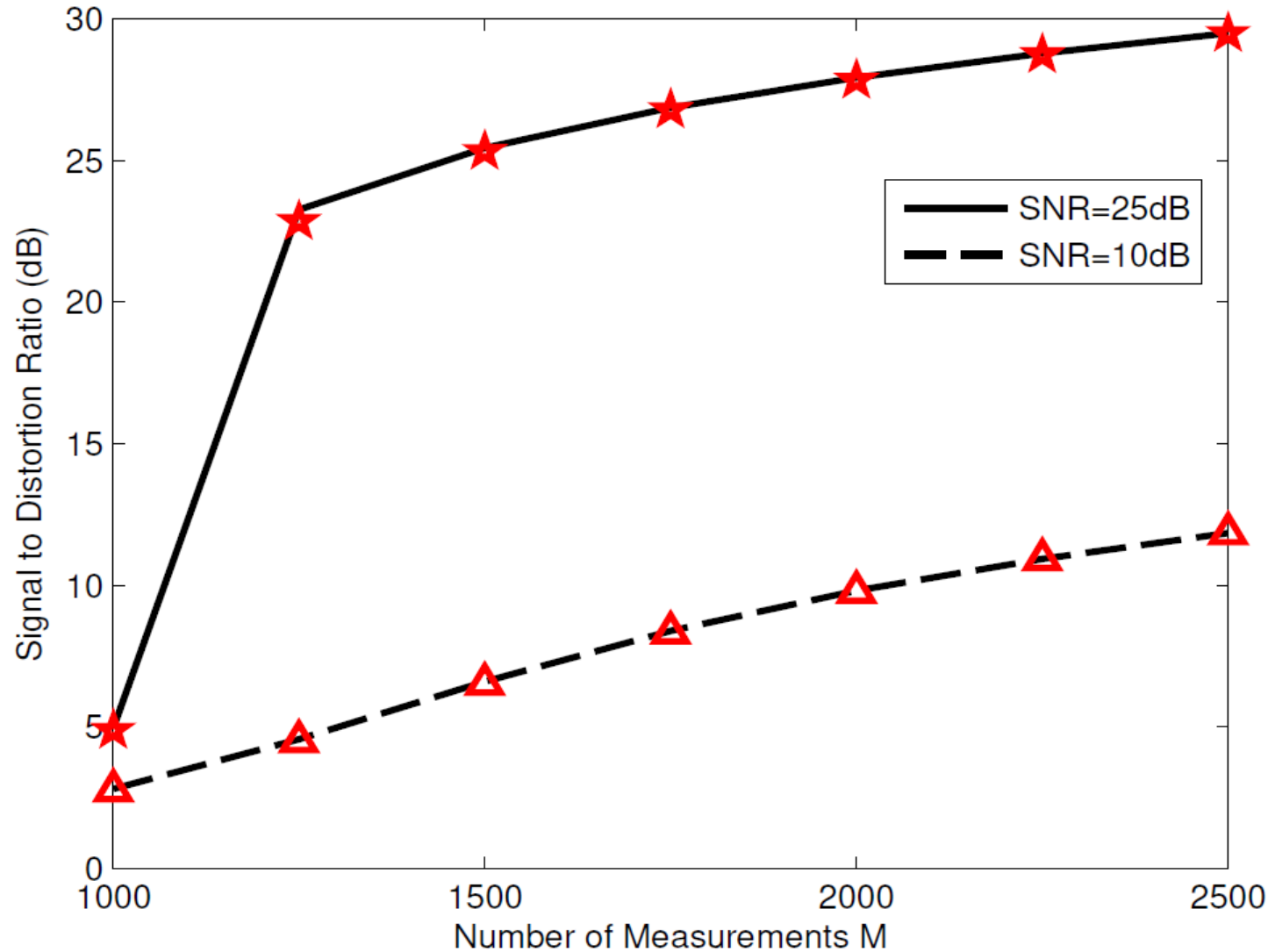
# Bernoulli Input with AWGN (N=10,000; i.i.d. matrix)



# Bernoulli Gaussian Input with AWGN

$$f(x|\theta, \mu, \sigma_x) = \theta \cdot N(\mu, \sigma_x^2) + (1 - \theta) \cdot \delta(x)$$

$$N = 5,000; \theta = 0.1; \mu = 0; \sigma_x = 1$$



# ***Final Words***

# Final Words

- Mixture universal signal estimation (MUSE)
  - demonstrated for two toy models
  - approaches MMSE
  - beats plug-in for small problem sizes
- Easily applied to matrix channels (AMP-MUSE)
- Open problem: *optimal* universal signal estimation
  - how quickly can we approach MMSE? (Rissanen-style bounds)
  - what algorithms achieve these bounds?
- *This is ongoing work – many open problems!*

THE END