

# CoSaMP with Redundant Dictionaries

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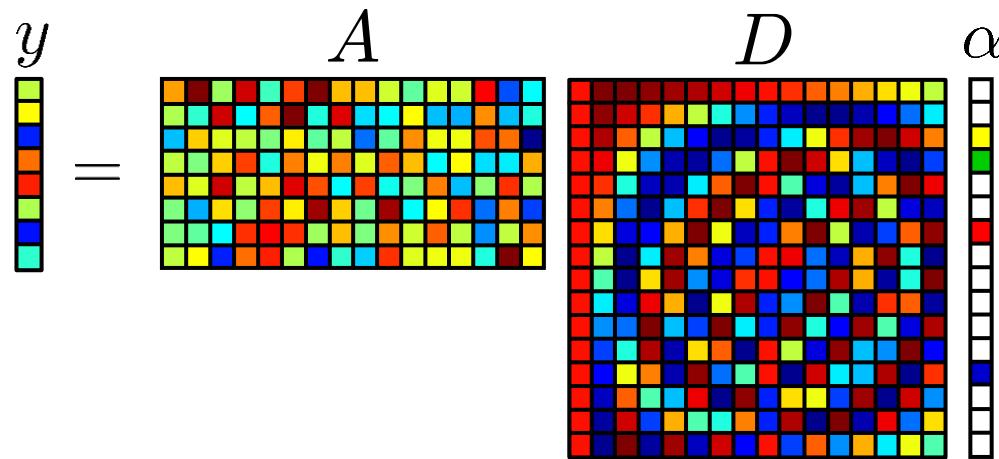
*Michael Wakin*



# Compressive Sensing

$$y = Ax$$

# Compressive Sensing

$$y = A \alpha$$


$$y \rightarrow \hat{\alpha} \rightarrow \hat{x} = D\hat{\alpha}$$

# The Treachery of Images



*Ceci n'est pas une pipe.*

Magritte

# The Treachery of $\alpha$

$$y = A D \alpha$$

A diagram illustrating the equation  $y = A D \alpha$ . On the left, there is a vertical vector  $y$  composed of colored squares (yellow, blue, orange, green, red). In the center, there is a matrix multiplication expression  $= A D$ . To the left of the equals sign is a matrix  $A$ , which is a 5x5 grid of colored squares. To the right of the equals sign is a matrix  $D$ , which is a 5x5 grid of colored squares. To the right of the multiplication expression is a vertical vector  $\alpha$  composed of colored squares (yellow, green, red). The colors in the matrices  $A$  and  $D$  are such that they map the colors in  $y$  to the colors in  $\alpha$ .

# The Treachery of $\alpha$

$$y = A D \alpha$$

- Given  $x$ , choice of  $\alpha$  is no longer unique
- Correlations in  $D$  make it difficult to establish guarantees via standard tools
- If  $D$  is poorly conditioned, we can have  $\|D\hat{\alpha} - D\alpha\|_2 \gg \|\hat{\alpha} - \alpha\|_2$  or  $\|D\hat{\alpha} - D\alpha\|_2 \ll \|\hat{\alpha} - \alpha\|_2$

# *Signal-focused* Recovery Strategy

- Focus on  $x$  instead of  $\alpha$
- Measure error in terms of  $\|\hat{x} - x\|_2$  instead of  $\|\hat{\alpha} - \alpha\|_2$

$$\sqrt{1 - \delta_k} \|\alpha\|_2 + \|AD\alpha\|_2 + \sqrt{1 + \delta_k} \|\alpha\|_2$$



$$\sqrt{1 - \delta_k} \|D\alpha\|_2 + \|AD\alpha\|_2 + \sqrt{1 + \delta_k} \|D\alpha\|_2$$

# CoSaMP

initialize:  $r = y, x^0 = 0, \ell = 0, \Gamma = \emptyset$

until converged:

proxy:  $h = A^*r$

identify:  $\quad = \{2k \text{ largest elements of } |h|\}$

merge:  $T = \quad \cup \Gamma$

update:  $\widetilde{x} = \underset{\text{supp}(z) \subseteq T}{\arg \min} \|y - Az\|_2$

$\Gamma = \{k \text{ largest elements of } |\widetilde{x}|\}$

$x^{\ell+1} = \widetilde{x}|_{\Gamma}$

$r^{\ell+1} = y - Ax^{\ell+1}$

$\ell = \ell + 1$

output:  $\widehat{x} = x^{\ell}$

# Key Steps

= { $2k$  largest elements of  $|h|$ }

$$\tilde{x} = \underset{\text{supp}(z) \subseteq T}{\arg \min} \|y - Az\|_2$$

$\Gamma = \{k$  largest elements of  $|\tilde{x}|\}$

$$x^{\ell+1} = \tilde{x}|_{\Gamma}$$

# Key Steps

= { $2k$  largest elements of  $|h|$ }

$\Gamma = \{k$  largest elements of  $|\tilde{x}|\}$

$x^{\ell+1} = \tilde{x}|_{\Gamma}$

Given a vector in  $\mathbb{R}^n$ , use hard thresholding to find best sparse approximation

$\mathcal{P}_{\Lambda}$ : orthogonal projector onto  $\mathcal{R}(D_{\Lambda})$

$$\Lambda_{\text{opt}}(z, k) = \arg \min_{|\Lambda|=k} \|z - \mathcal{P}_{\Lambda} z\|_2$$

# Approximate Projection

$\mathcal{P}_\Lambda$ : orthogonal projector onto  $\mathcal{R}(D_\Lambda)$

$$\Lambda_{\text{opt}}(z, k) = \arg \min_{|\Lambda|=k} \|z - \mathcal{P}_\Lambda z\|_2$$

$\mathcal{S}(z, k)$ : estimate of  $\Lambda_{\text{opt}}(z, k)$

$$\|\mathcal{P}_{\Lambda_{\text{opt}}} z - \mathcal{P}_{\mathcal{S}} z\|_2 \cdot \min(\epsilon_1 \|\mathcal{P}_{\Lambda_{\text{opt}}} z\|_2, \epsilon_2 \|z - \mathcal{P}_{\Lambda_{\text{opt}}} z\|_2)$$

measure quality of approximation in  
“signal space”, not “coefficient space”

# Signal Space CoSaMP

initialize:  $r = y, x^0 = 0, \ell = 0, \Gamma = \emptyset$

until converged:

proxy:  $h = A^*r$

identify:  $= \mathcal{S}(h, 2k)$

merge:  $T = \cup \Gamma$

update:  $\tilde{x} = \arg \min_{z \in \mathcal{R}(D_T)} \|y - Az\|_2$

$\Gamma = \mathcal{S}(\tilde{x}, k)$

$x^{\ell+1} = \mathcal{P}_\Gamma(\tilde{x})$

$r^{\ell+1} = y - Ax^{\ell+1}$

$\ell = \ell + 1$

output:  $\hat{x} = x^\ell$

# Recovery Guarantees

Suppose there exists a  $k$ -sparse  $\alpha$  such that  $x = D\alpha$  and that  $A$  satisfies the  $D$ -RIP of order  $4k$ .

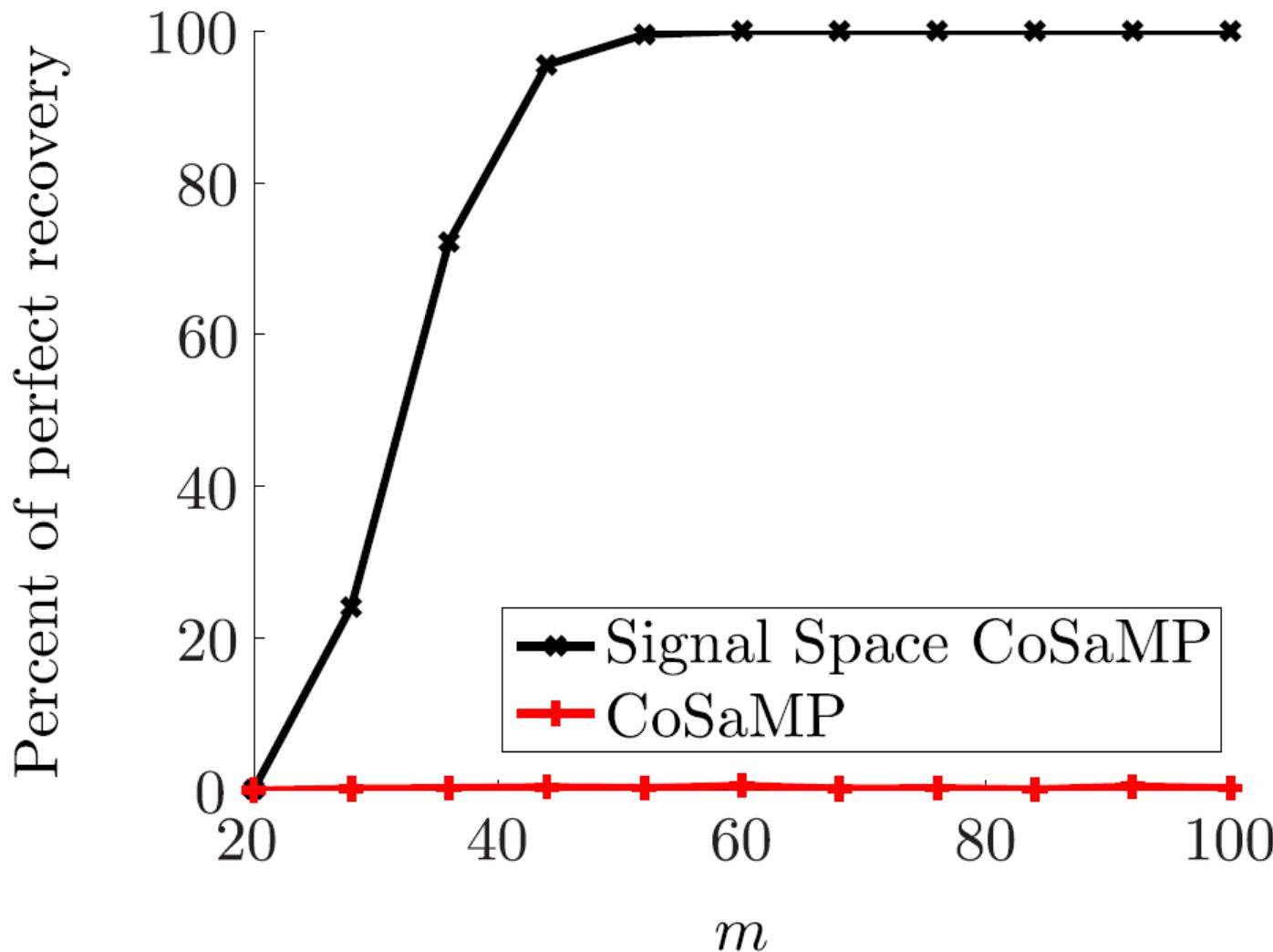
If we observe  $y = Ax + e$ , then

$$\|x - x^{\ell+1}\|_2 \leq C_1 \|x - x^\ell\|_2 + C_2 \|e\|_2$$

For  $\delta_{4k} = 0.029$ ,  $\epsilon_1 = 0.1$ ,  $\epsilon_2 = 1$ ,

$$\|x - x^\ell\|_2 \leq 2^{-\ell} \|x\|_2 + 25.4 \|e\|_2$$

# Renormalized Columns



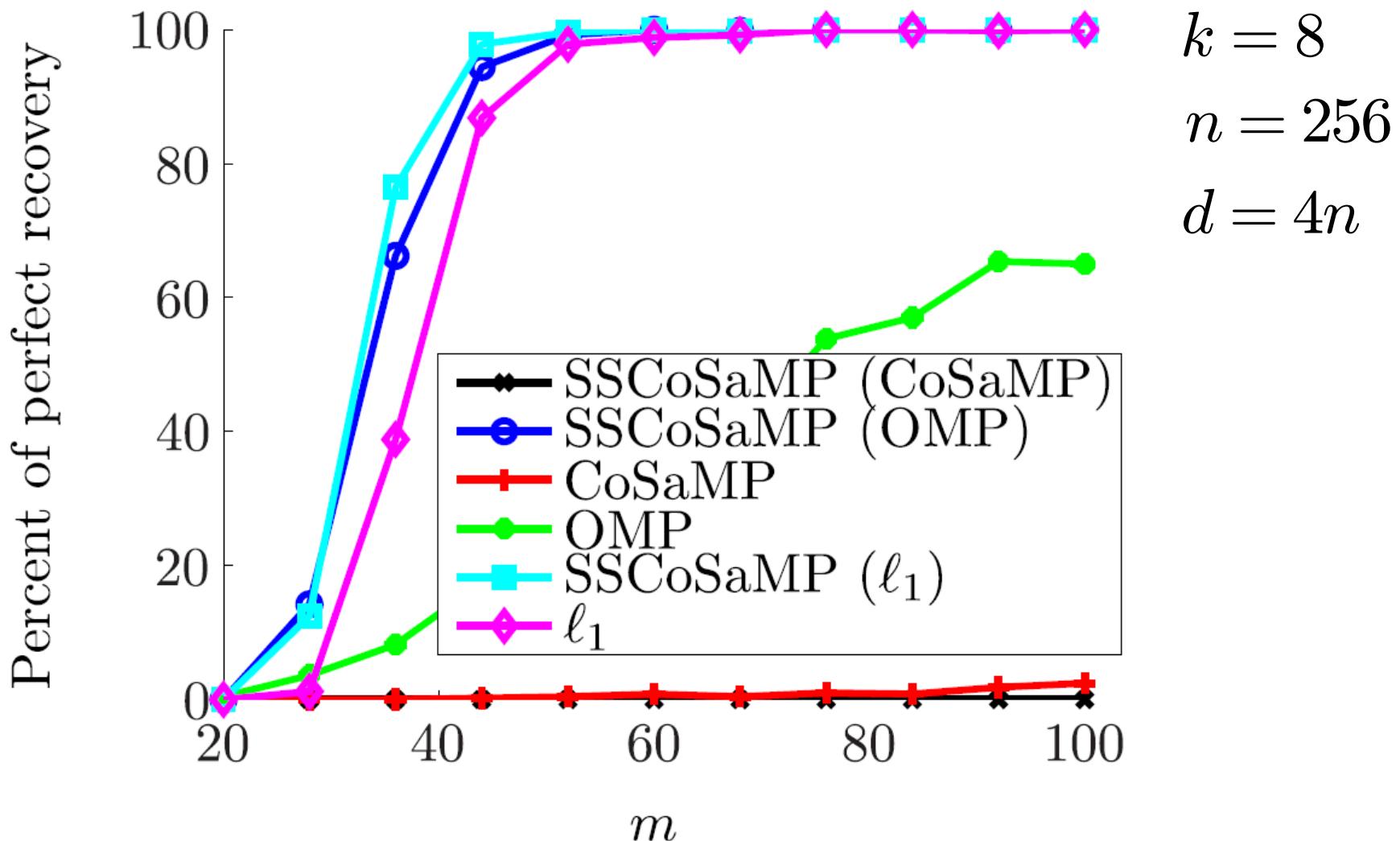
# Practical Choices for $\mathcal{S}(z, k)$

- Given  $z$ , we want to find a  $k$ -sparse  $\alpha$  such that  $z \approx D\alpha$
- Any sparse recovery algorithm!
- CoSaMP
- Orthogonal Matching Pursuit (OMP)
- $\ell_1$ -minimization followed by hard-thresholding

$$\mathcal{S}(z, k) = H_k \left( \arg \min_{w: Dw=z} \|w\|_1 \right)$$

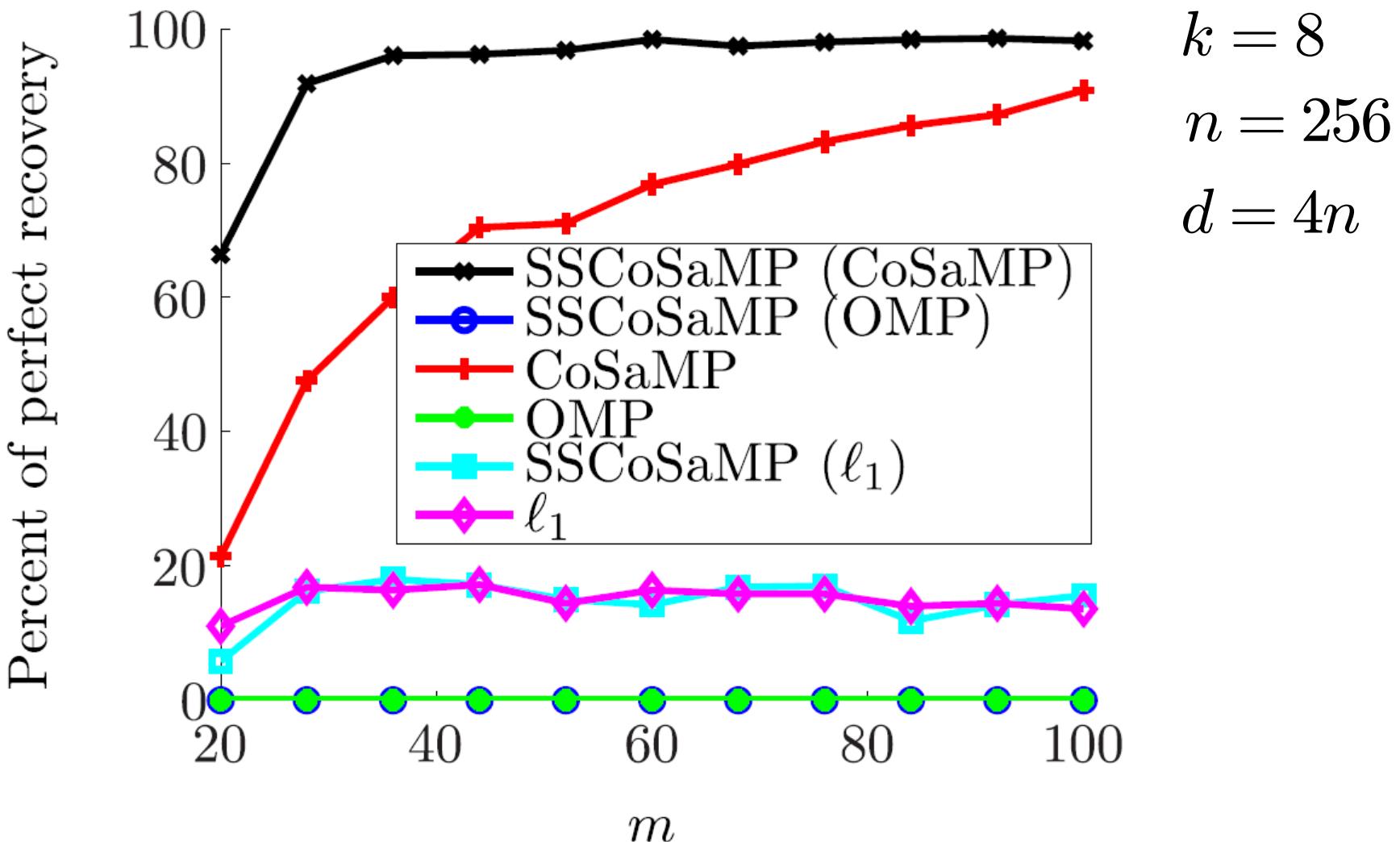
# Overcomplete DFT

Separated coefficients



# Overcomplete DFT

## Clustered coefficients



# Conclusions

- If we care about  $x$ , we should focus on  $x$ , not  $\alpha$
- Signal Space CoSaMP provides a theoretical framework for accommodating general dictionaries  $D$
- Choice of  $\mathcal{S}(z, k)$  is not obvious
  - existing methods appear to work well in practice
  - future work should focus on theoretical guarantees
- Success in this area has implications far beyond Signal Space CoSaMP
  - “signal space IHT”
  - analysis IHT/CoSaMP
  - $\ell_1$ - minimization