

A Guide For Successful Low Rank Matrix Recovery In Seismic Applications

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Motivation

- ▶ acquisition challenges
 - missing data (subsampling or coverage holes)
 - need efficient acquisition design
- ▶ exploit *low-rank* structure of seismic data
 - matrix completion for trace interpolation
 - industrial-scale implementations available
- ▶ need analytical tools
 - how should we subsample?
 - results in literature are not applicable

Contributions

- ▶ Quantification of subsampling
 - “generalized spectral gap” (GSP)
 - computationally cheap

- ▶ Applications to seismic data acquisition
 - multi-use tool for acquisition design

$$\text{GSP} = \frac{\sqrt{nm}}{|\Omega|} \sigma_1 \left(A - \frac{|\Omega|}{nm} \mathbf{1}_{n \times m} \right)$$

Outline

- ▶ Matrix Completion
 - literature
 - seismic trace interpolation

- ▶ Universal Matrix Completion
 - generalized spectral gap
 - uses in seismic data acquisition

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Matrix Completion Literature

Goal is to approximate $\mathbf{X} \in \mathbb{R}^{n \times m}$, given

noisy observed entries $\Omega \subset \{1, 2, \dots, n\} \times \{1, 2, \dots, m\}$

via

$$\mathbf{b}_{i,j} = P_{\Omega}(\mathbf{X})_{i,j} = \begin{cases} \mathbf{X}_{i,j} & \text{if } (i,j) \in \Omega \\ 0 & \text{otherwise} \end{cases}$$

Matrix Completion Literature

If $\text{rank} \approx r \ll \min(n, m)$, we attempt to recover unobserved or noisy entries via

$$\underset{\mathbf{Y}}{\text{minimize}} \|\mathbf{Y}\|_* \text{ subject to } \|P_{\Omega}(\mathbf{Y}) - \mathbf{b}\|_F \leq \epsilon, \quad \left. \vphantom{\underset{\mathbf{Y}}{\text{minimize}}} \right\} \mathbf{NN}(b, \epsilon)$$

where $\|\mathbf{Y}\|_* = \sum_k \sigma_k(\mathbf{Y})$.

Matrix Completion Literature

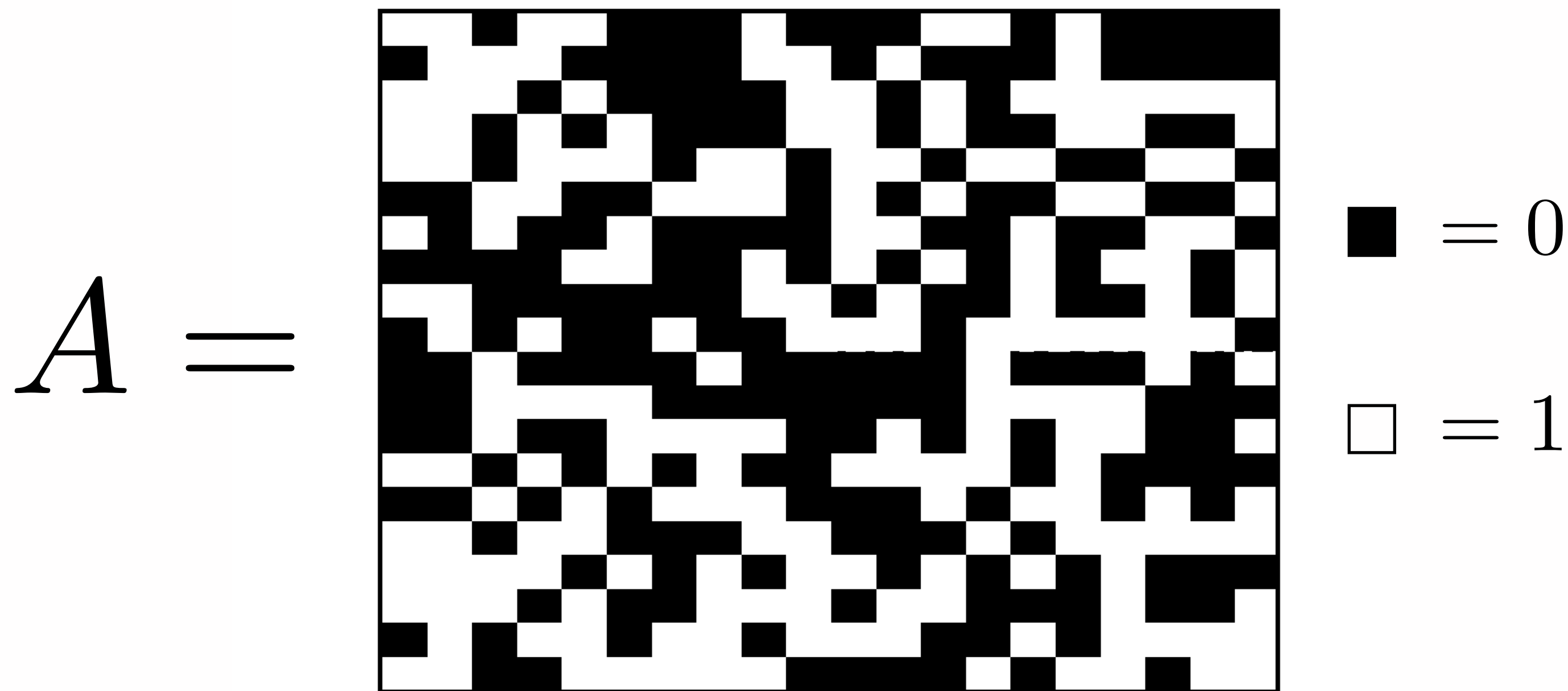
Typical Assumptions:

1. Construct Ω by observing entries uniformly at random.
2. $\mathbf{X} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^*$ is μ -“incoherent”.

$$\|\mathbf{U}(k, :)\|_2^2 \leq \frac{\mu r}{n} \quad \|\mathbf{V}(\ell, :)\|_2^2 \leq \frac{\mu r}{m}$$

Assumption 1: Uniform Random Sampling

$$\text{Sampling Mask: } A_{i,j} = \begin{cases} 1 & \text{if } (i,j) \in \Omega \\ 0 & \text{otherwise} \end{cases}$$

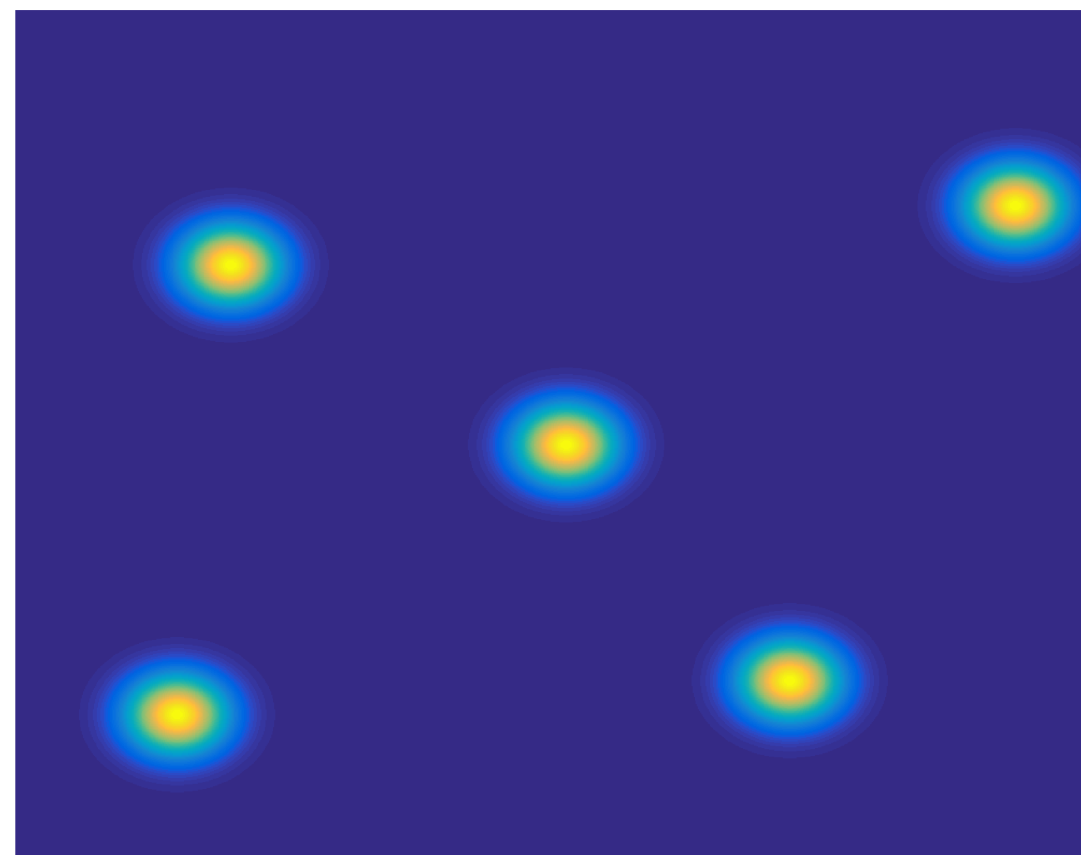


Assumption 2: μ -Incoherence

$$\|\mathbf{U}(k, :)\|_2^2 \leq \frac{\mu r}{n} \quad \|\mathbf{V}(\ell, :)\|_2^2 \leq \frac{\mu r}{m}$$

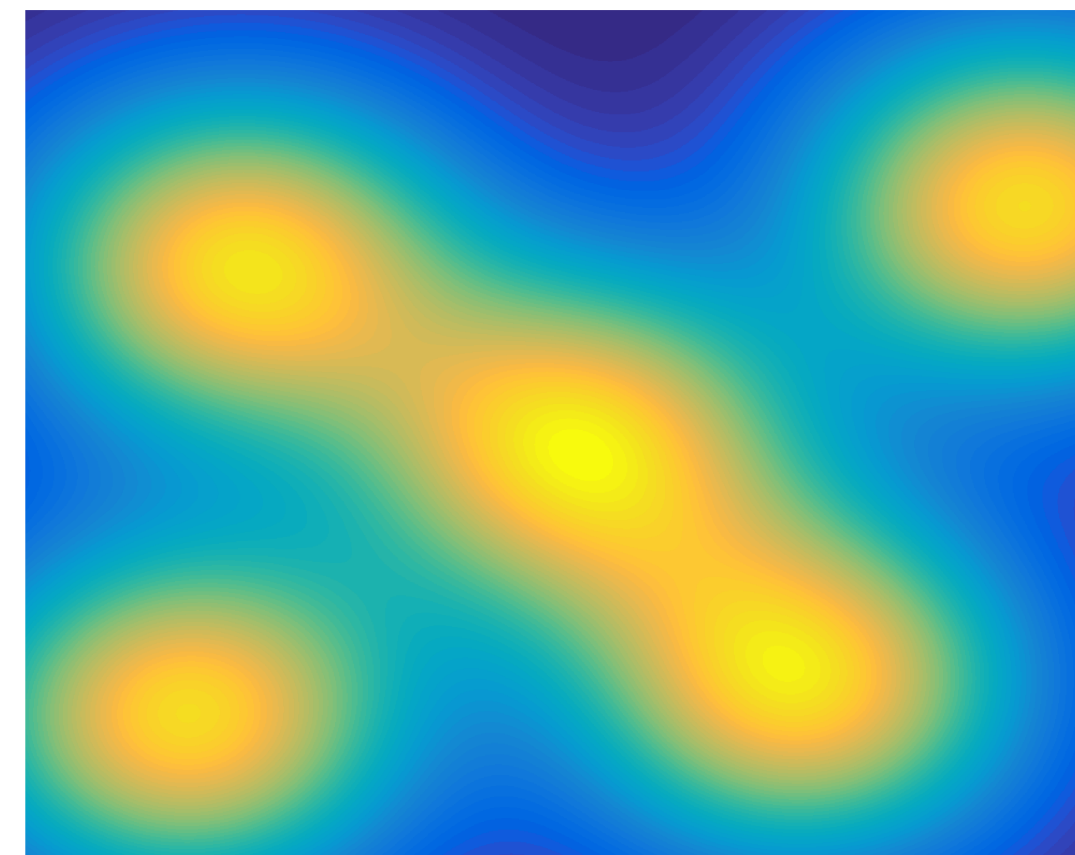
Parameter μ measures how “spread” the energy of data matrix is.

large $\mu \sim \mathcal{O}\left(\frac{n}{r}\right)$



bad for matrix completion

small $\mu \sim \mathcal{O}(1)$



good for matrix completion

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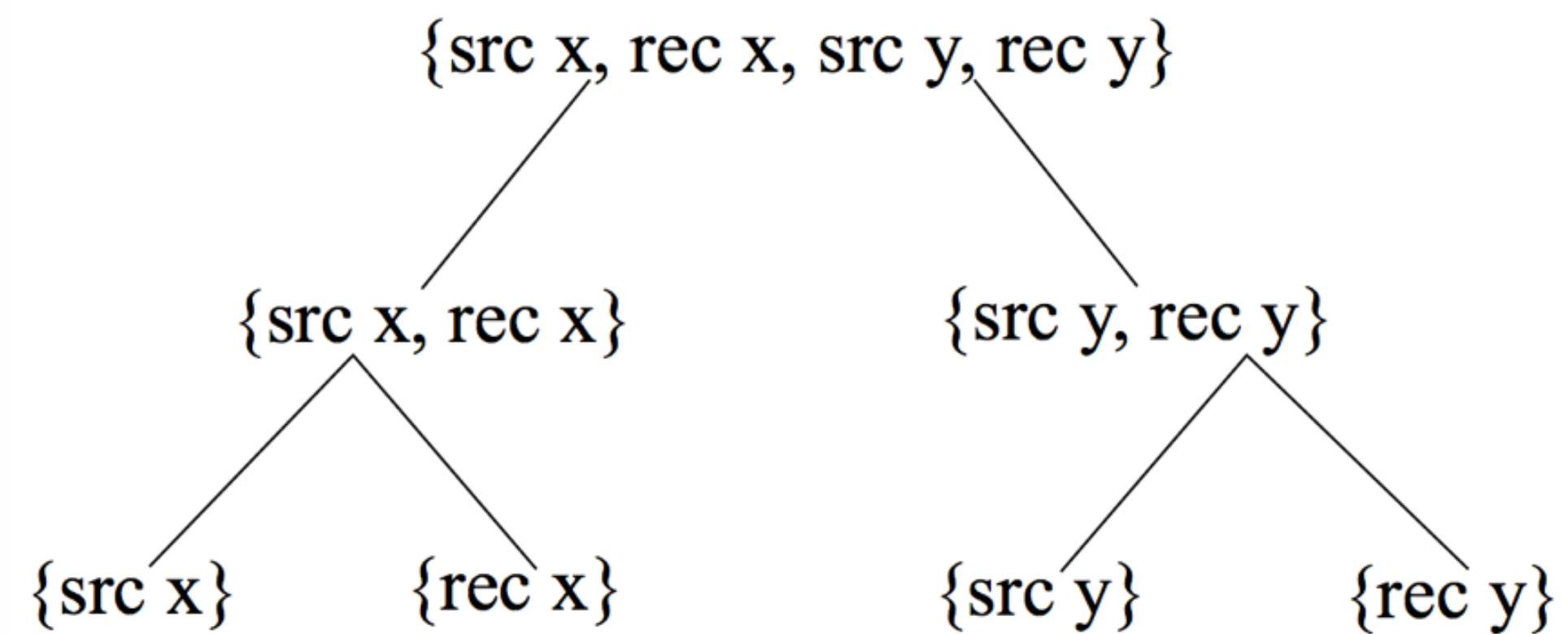
3D Seismic Data Interpolation

- ▶ Consider a 3D seismic survey with coordinates (src x , src y , rec x , rec y , time)
- ▶ Take a Fourier transform in time and restrict ourselves to a single frequency slice.

3D Seismic Data Interpolation

- ▶ Consider a 3D seismic survey with coordinates (src x , src y , rec x , rec y , time)
- ▶ Take a Fourier transform in time and restrict ourselves to a single frequency slice.
- ▶ Unfold into matrix to apply matrix completion (i.e., “matricize”)

3D Data: Matricized

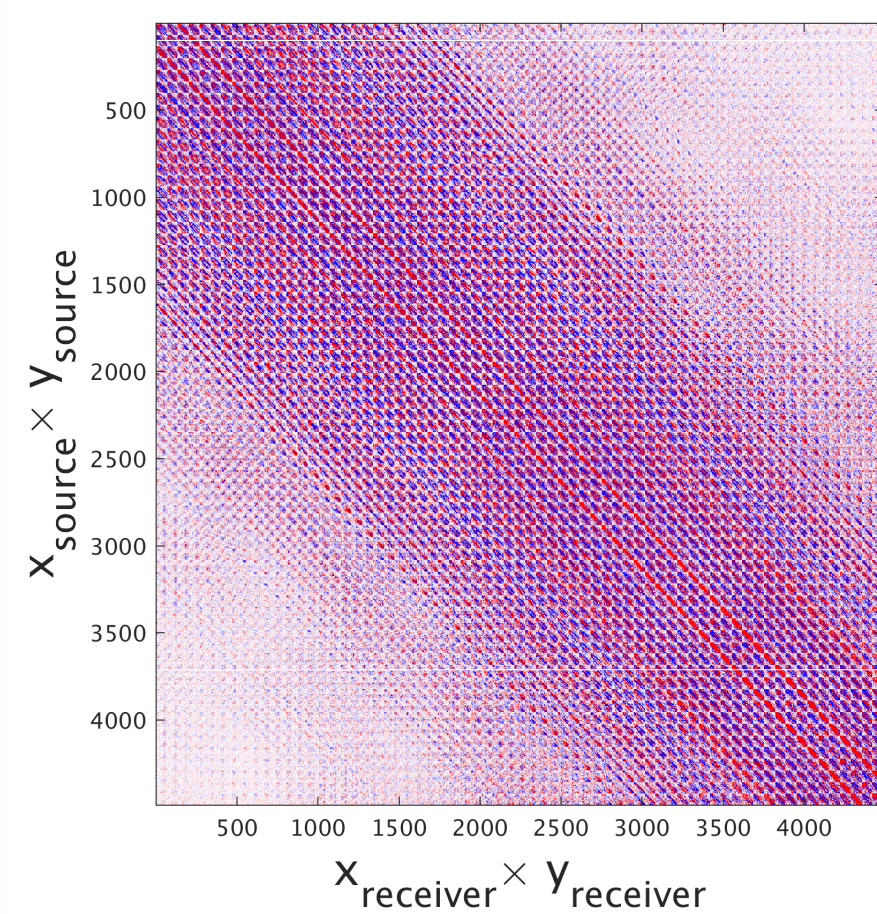


Many options on how to matricize

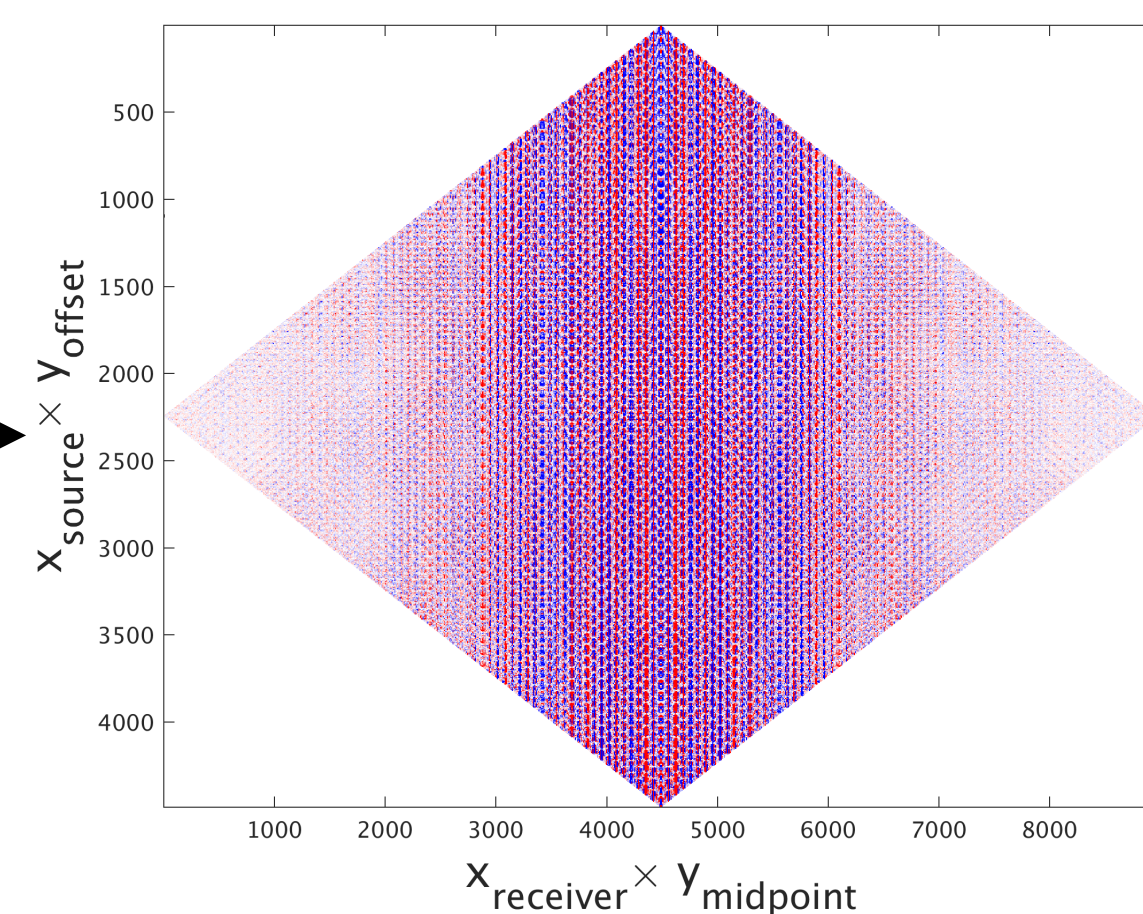
3D Data: Matricized

Canonical

(src,rec)-domain

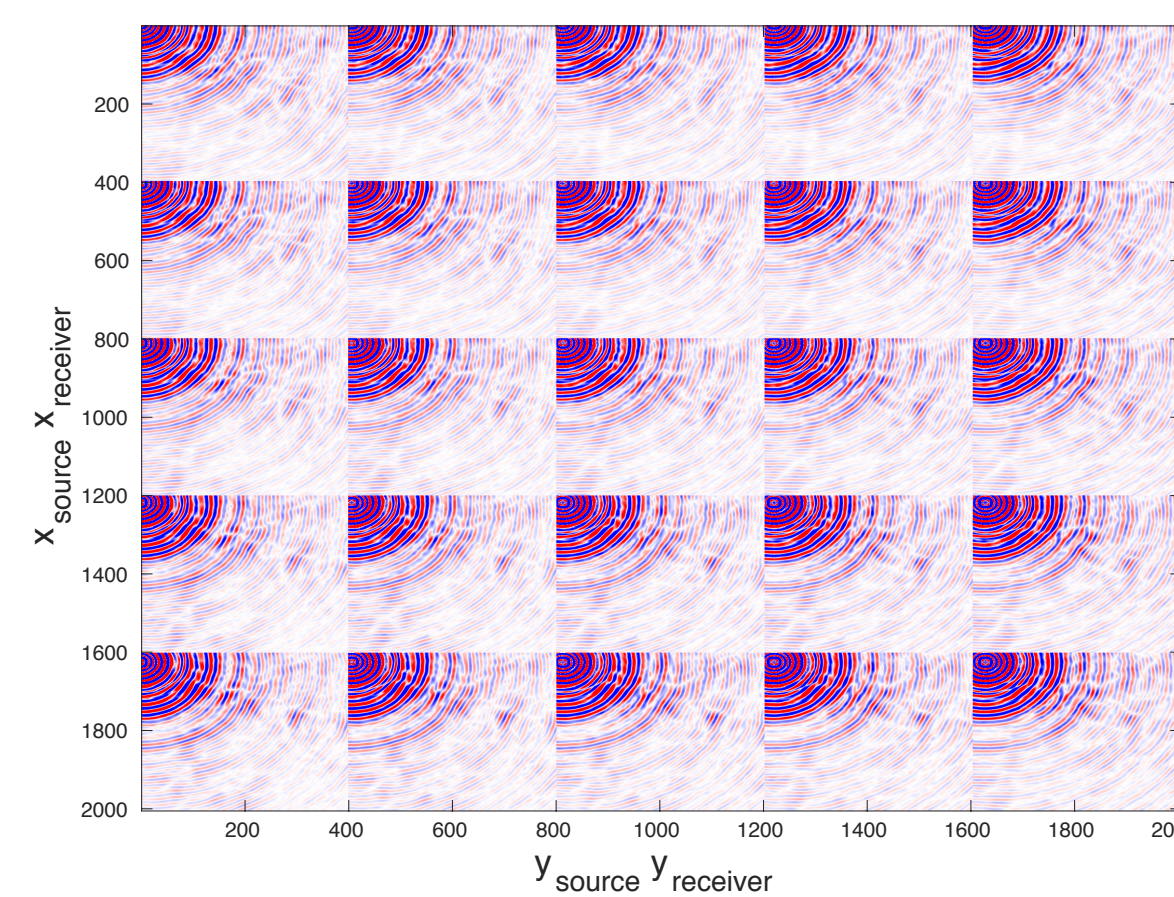


(mid,off)-domain

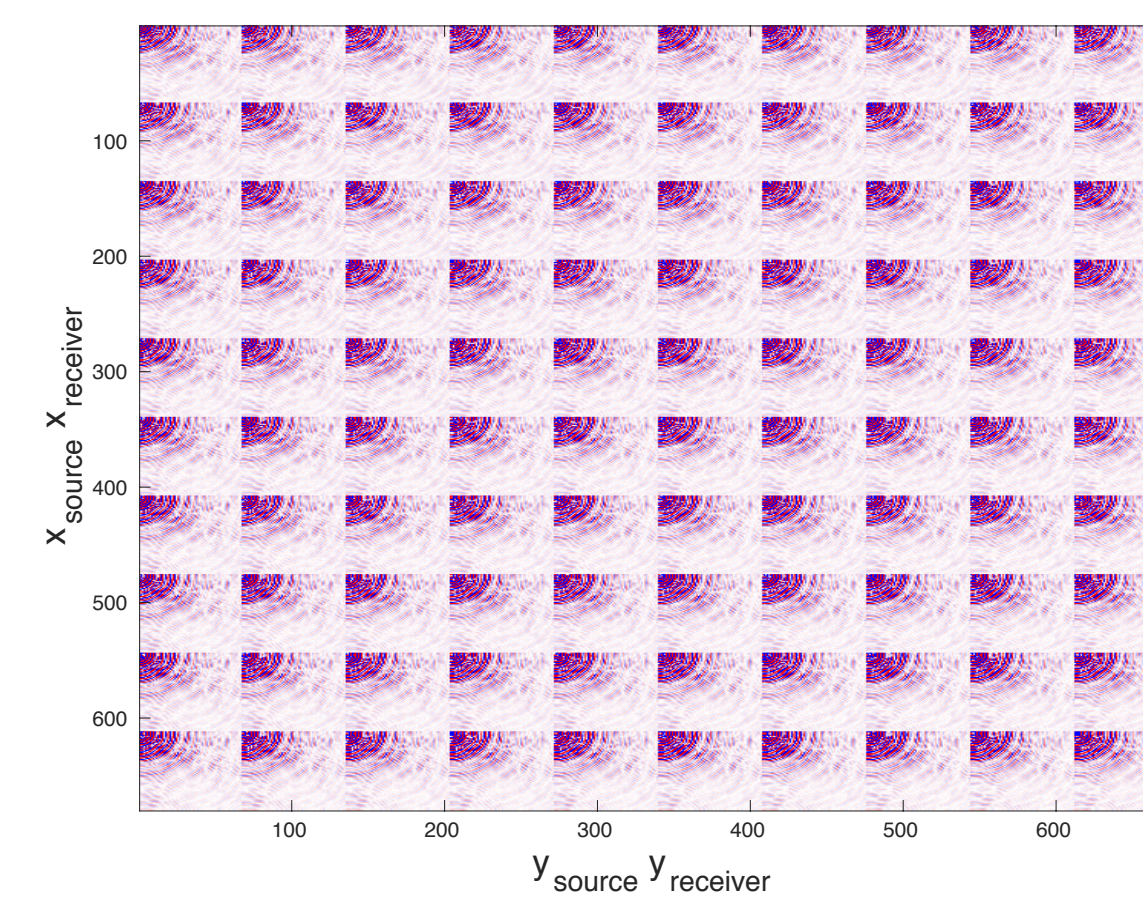


Non-Canonical

(rec,rec)-form

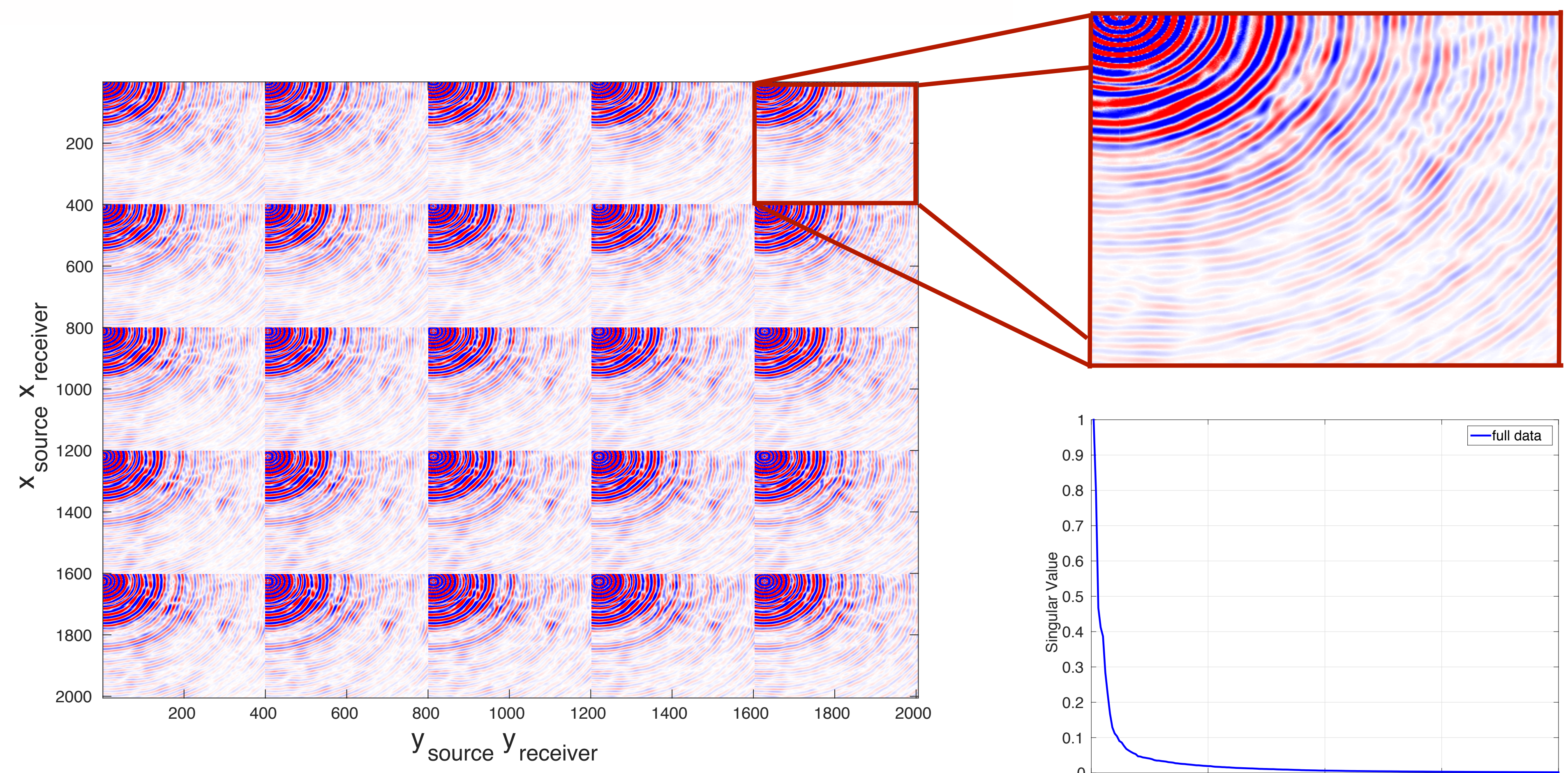


(src,src)-form

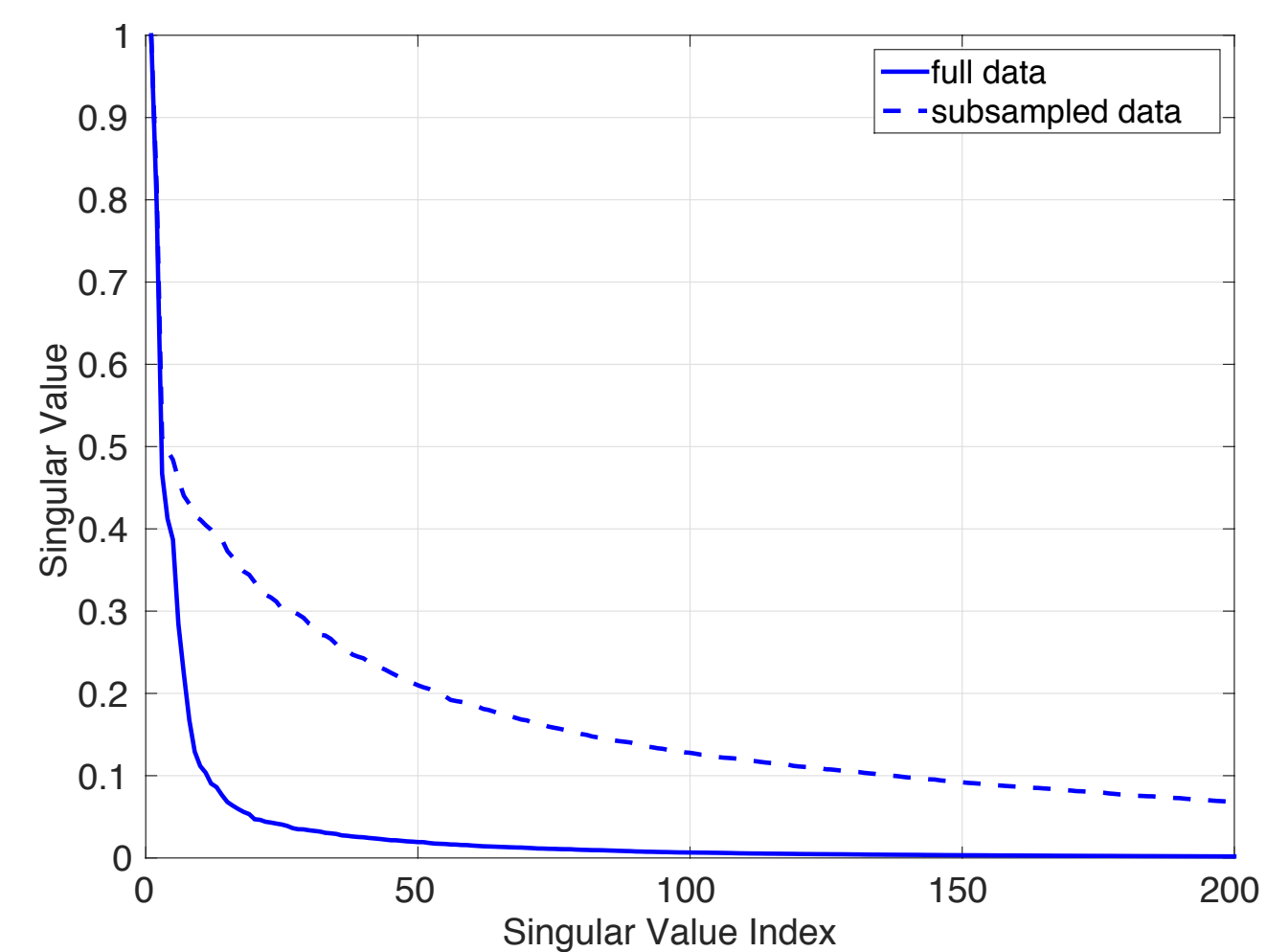
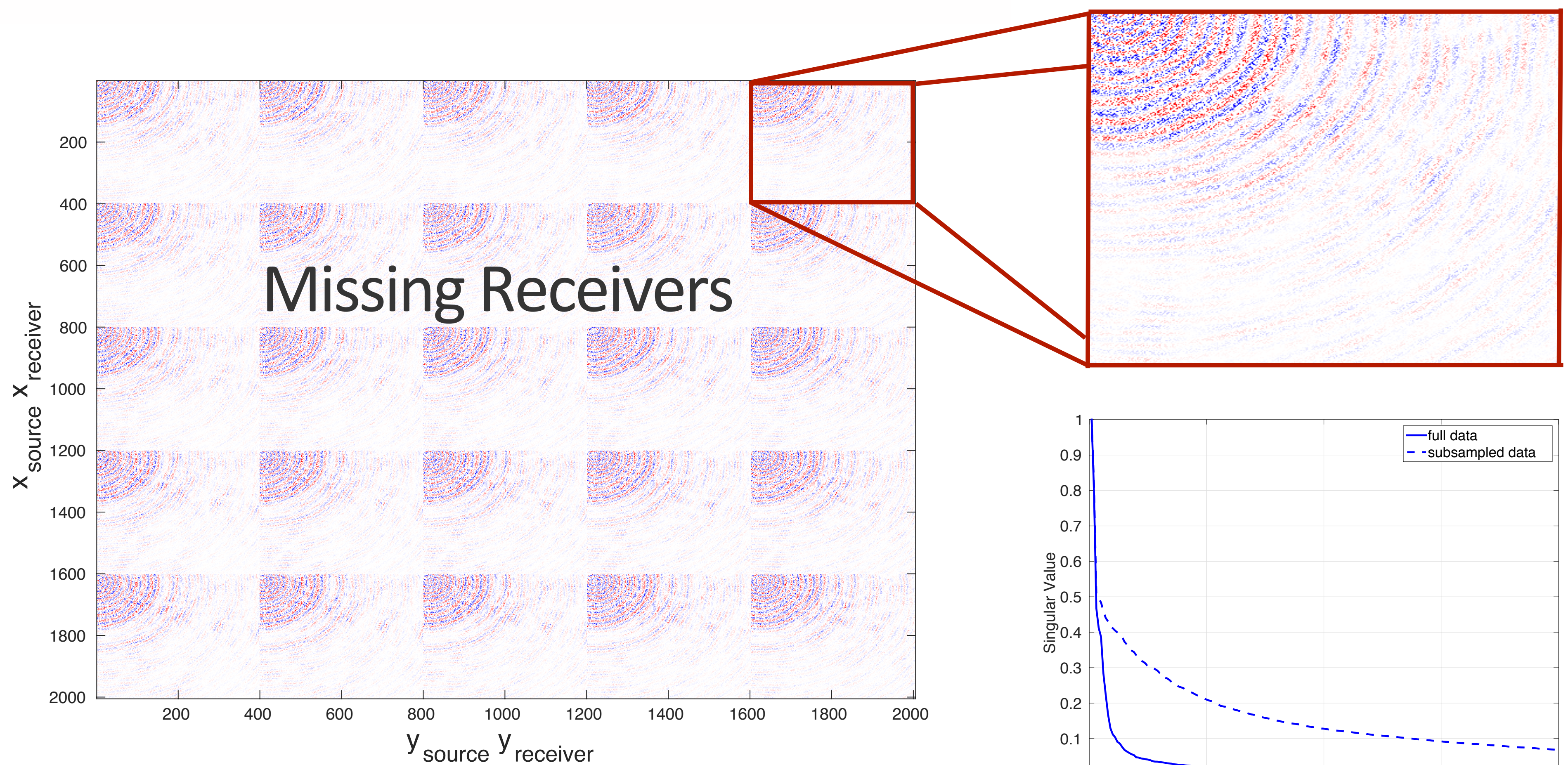


Incoherence: energy of matrices is evenly distributed

3D Data: Matricized - (rec,rec) form



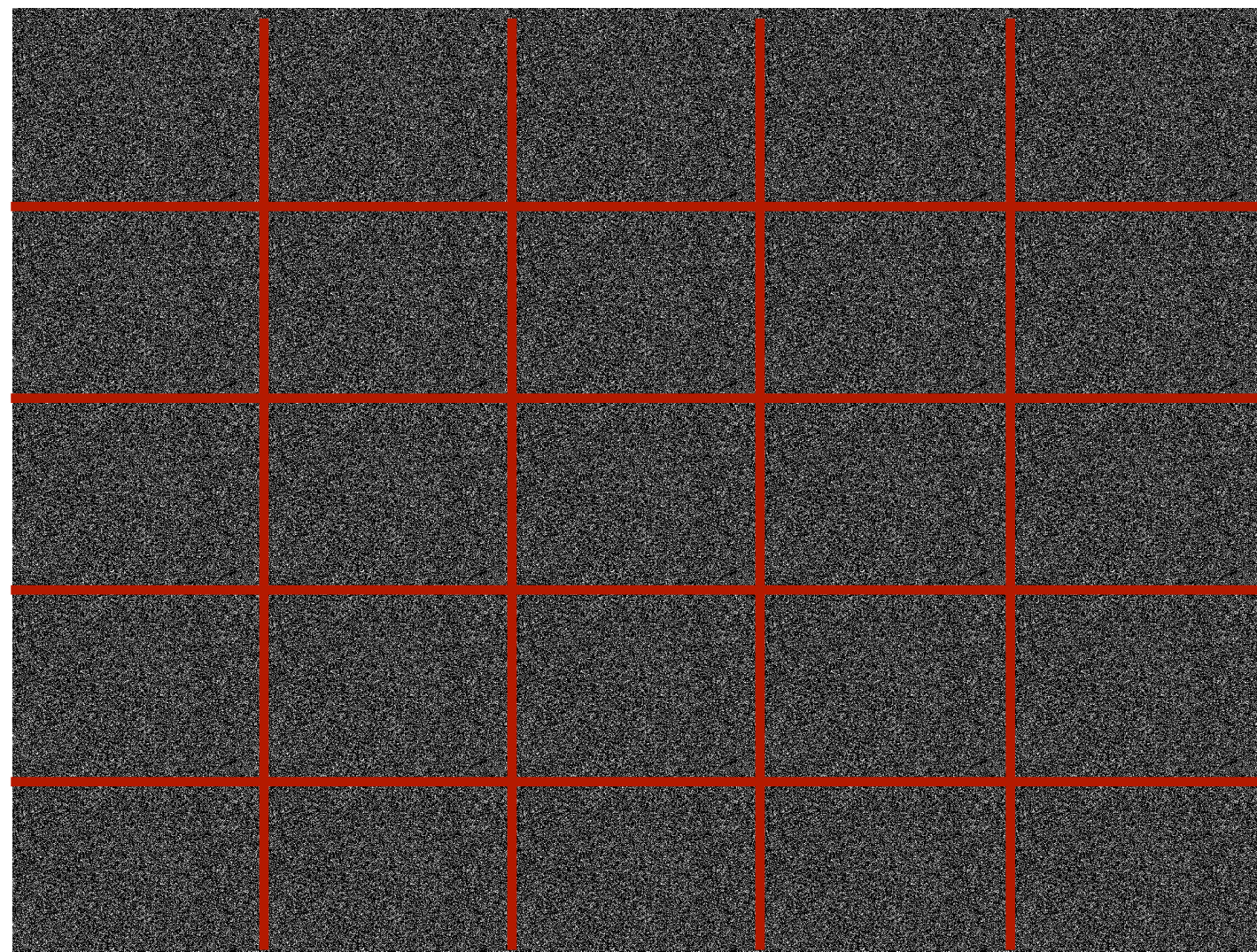
3D Data Matricized - (rec,rec) form



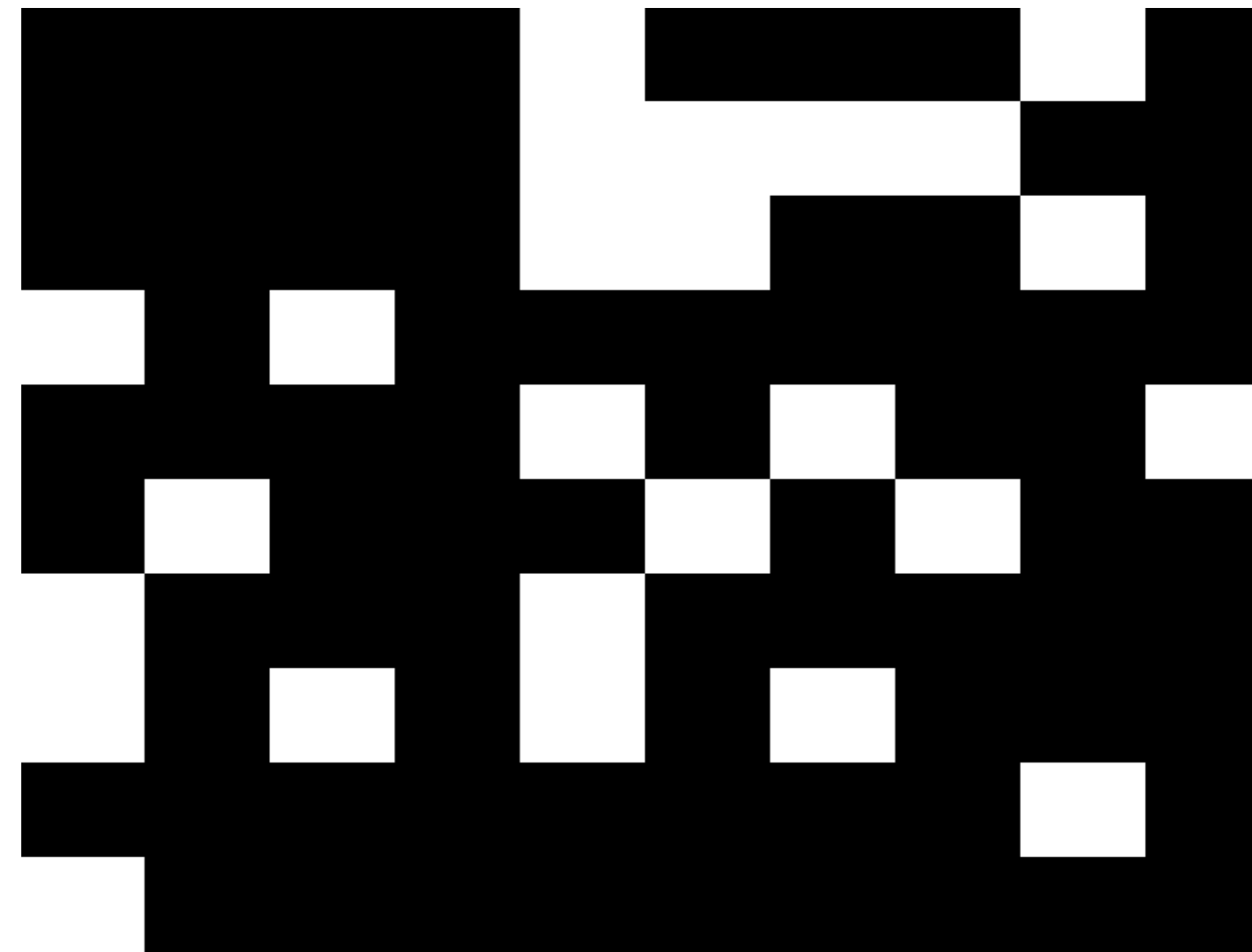
similar low-rank
structure for other
matricizations

3D Seismic Masks: Missing Receivers

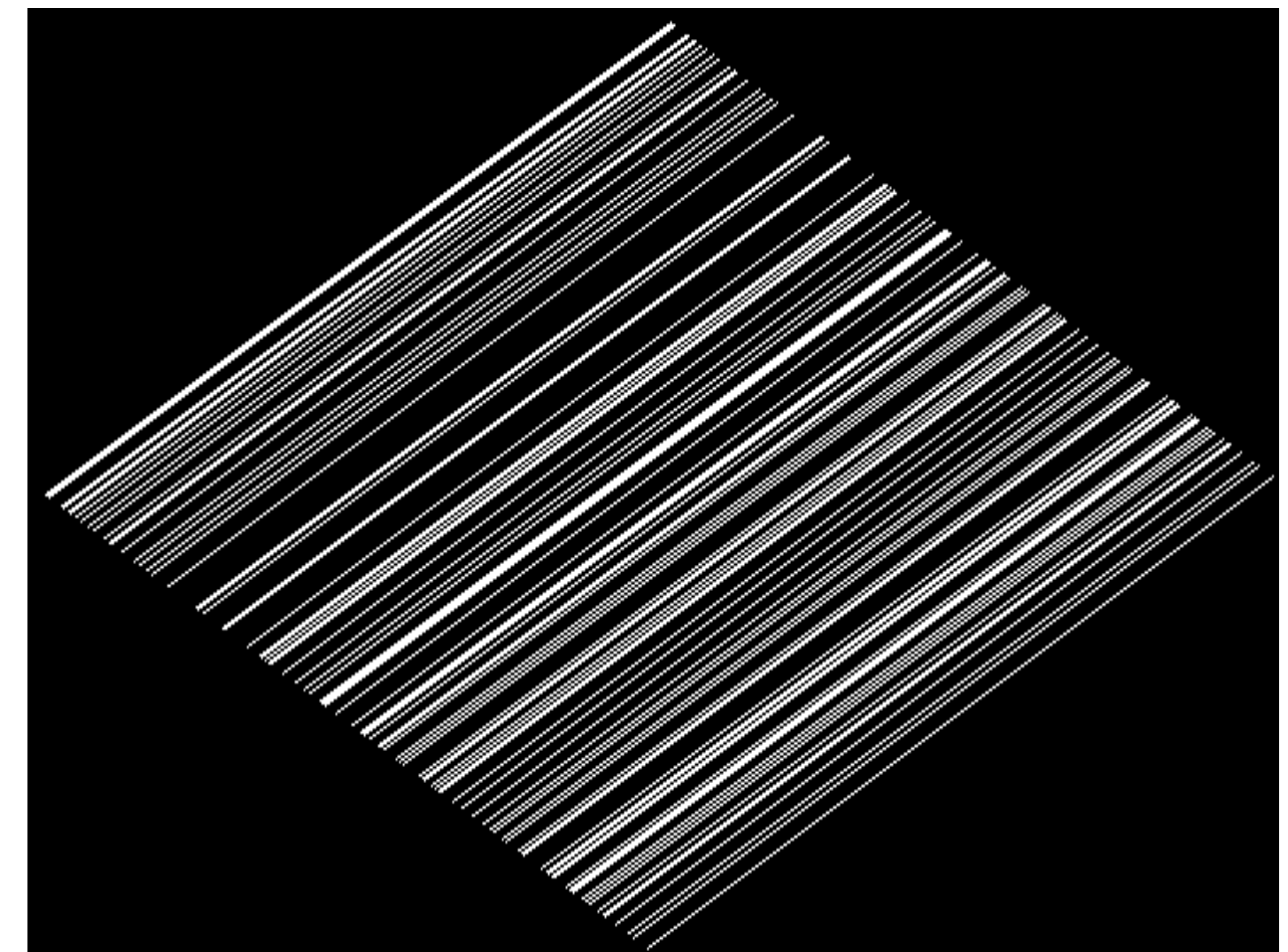
(rec,rec)-form



(src,src)-form






(mid,off)-domain



Sampling mask depends on acquisition: uniform random?

3D Seismic Data Interpolation

- ▶ Low-rank structure 
- ▶ Incoherence (small μ) 
- ▶ Uniform random sampling 

Outline

- ▶ Matrix Completion
 - literature
 - seismic trace interpolation
- ▶ Universal Matrix Completion
 - generalized spectral gap
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How should we subsample?

Consider our sampling mask

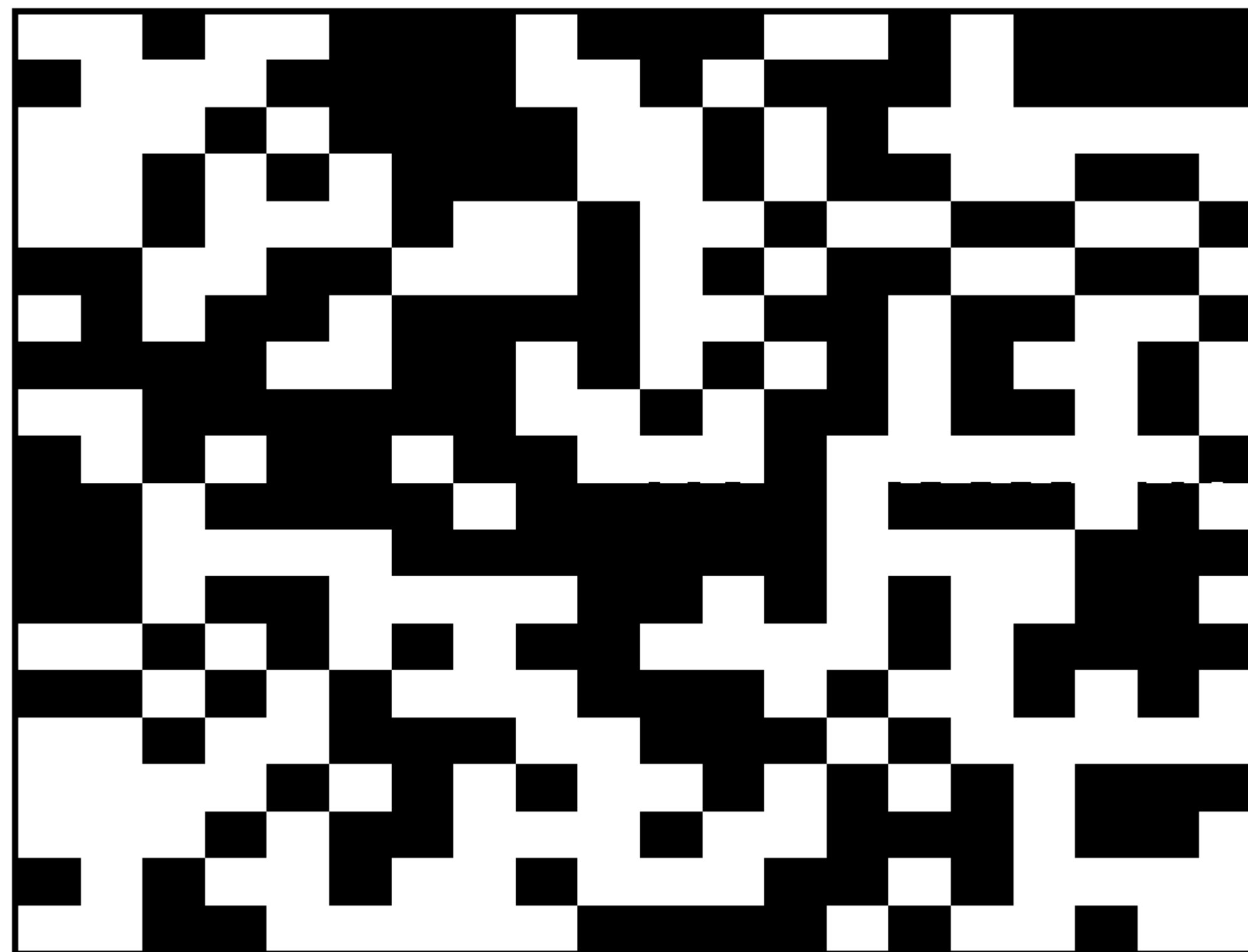
$$A_{i,j} = \begin{cases} 1 & \text{if } (i, j) \in \Omega \\ 0 & \text{otherwise} \end{cases}$$

What determines if A is good for matrix completion?

Example: Ideal Mask

Samples chosen uniformly at random

$A =$



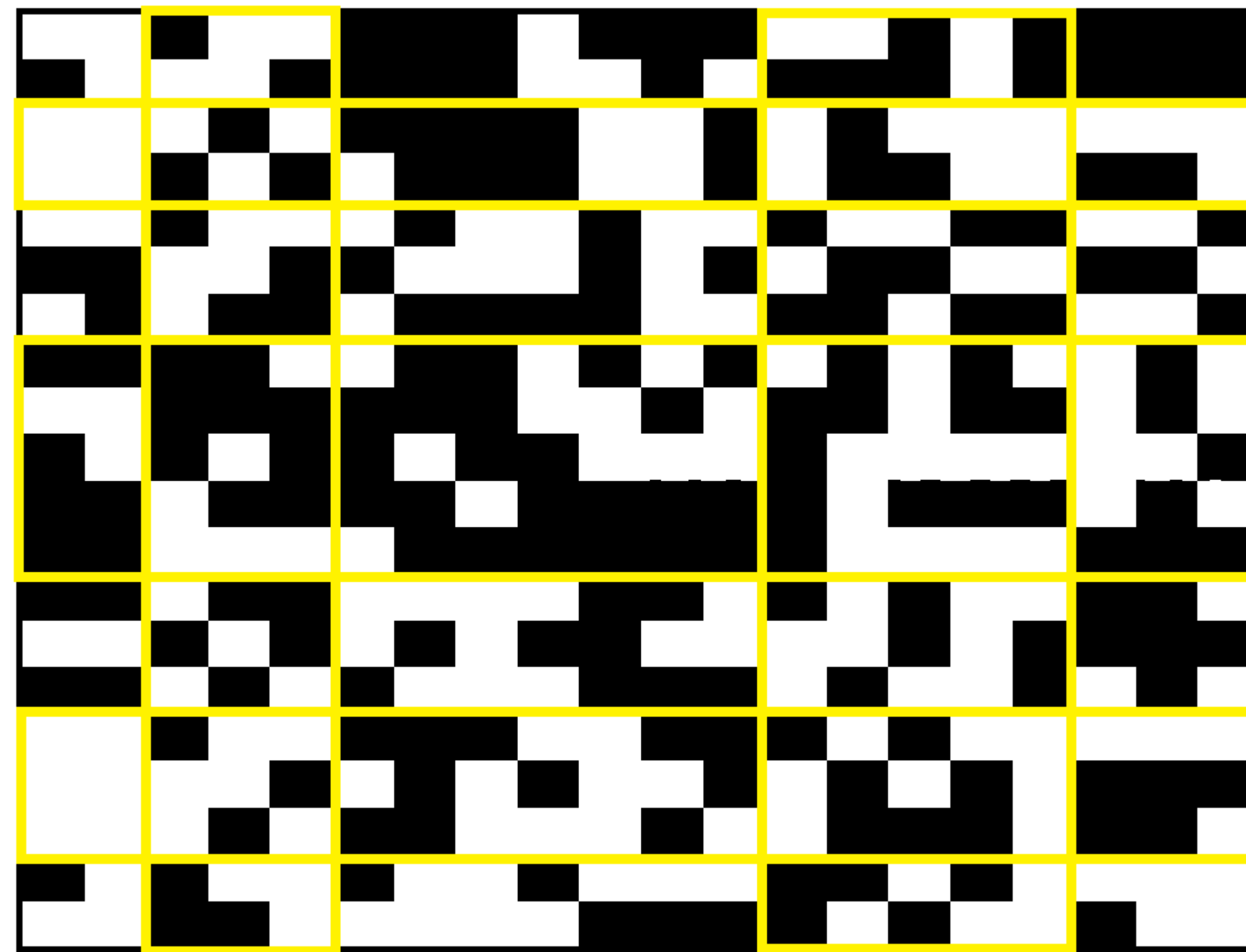
■ = 0

□ = 1

Example: Ideal Mask

Choose any sub matrix

$A =$



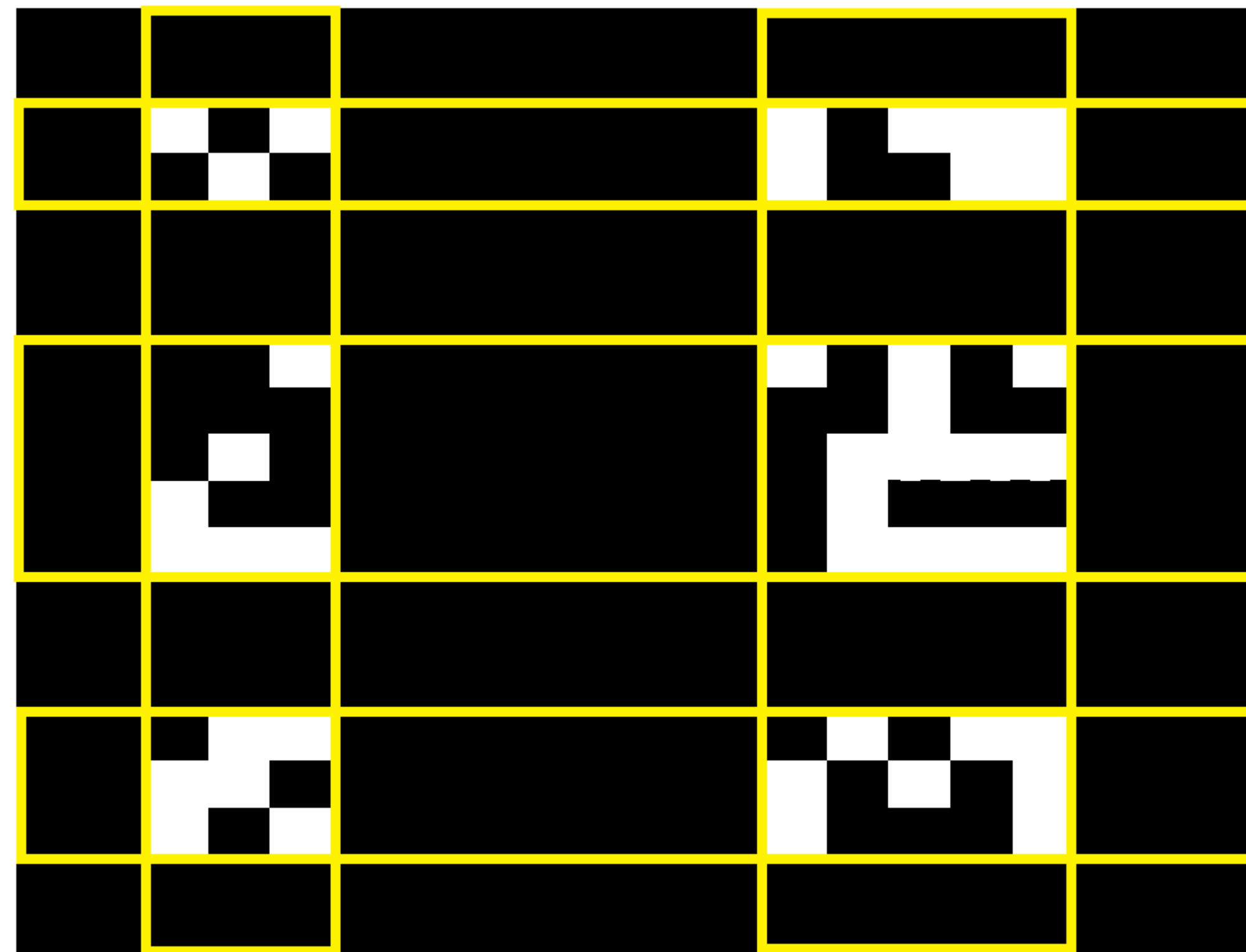
■ = 0

□ = 1

Example: Ideal Mask

All sub matrices are nicely sampled!

$A =$



■ = 0

□ = 1

Spectral Gap [Bhojanapalli, Jain. “Universal Matrix Completion” ICML 2014.](#)

Consider the gap between the two largest singular values A of

$$\frac{\sigma_2(A)}{\sigma_1(A)} = \begin{cases} \approx 1 & \text{small spectral gap} \\ \ll 1 & \text{large spectral gap} \end{cases}$$

Spectral Gap Bhojanapalli, Jain. "Universal Matrix Completion" ICML 2014.

$$\frac{\sigma_2(A)}{\sigma_1(A)} = \begin{cases} \approx 1 & \text{small spectral gap} \\ \ll 1 & \text{large spectral gap} \end{cases}$$

From graph theory:

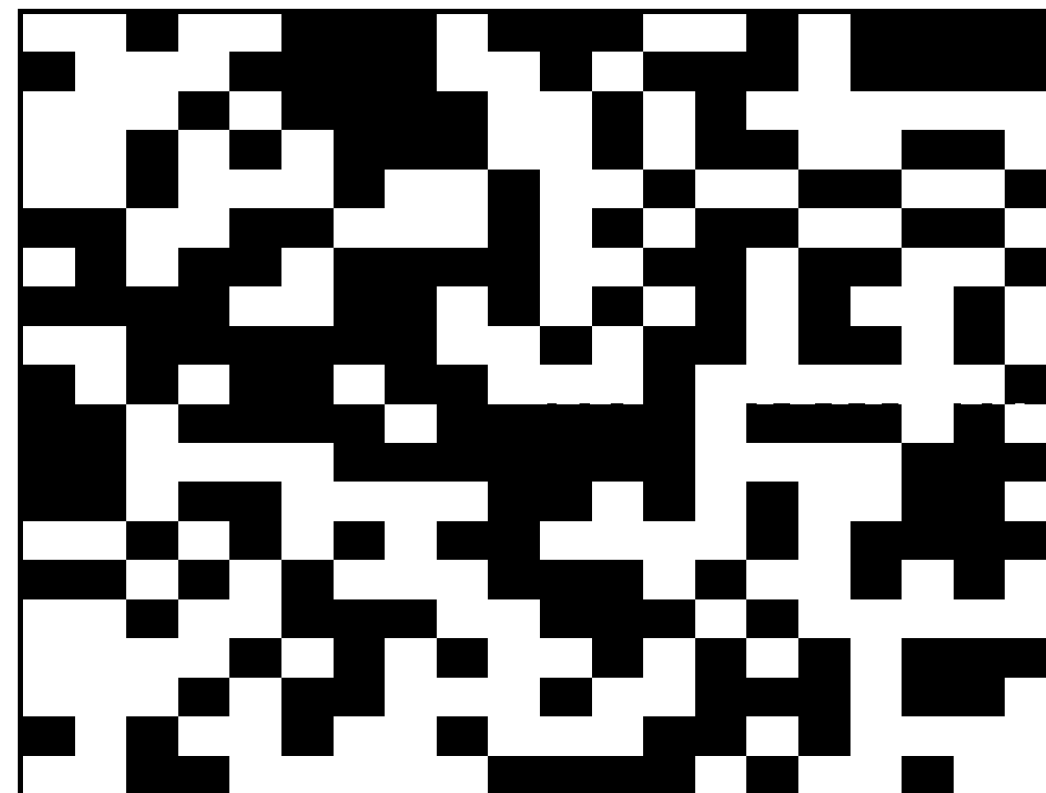
A with Large Spectral Gap \implies all "sub matrices" are nicely sampled

\implies better results for matrix completion

Spectral Gap Bhojanapalli, Jain. "Universal Matrix Completion" ICML 2014.

$$\frac{\sigma_2(A)}{\sigma_1(A)} = \begin{cases} \approx 1 & \text{small spectral gap} \\ \ll 1 & \text{large spectral gap} \end{cases}$$

Restriction: Results only apply to **regular graphs**



equivalent to having same number of samples in each row and column

Generalized Spectral Gap

Extend the results by introducing “generalized spectral gap”:

$$\text{GSP} = \frac{\sqrt{nm}}{|\Omega|} \sigma_1 \left(A - \frac{|\Omega|}{nm} \mathbf{1}_{n \times m} \right) \approx \frac{\sigma_2(A)}{\sigma_1(A)}$$

As before, small GSP is better for matrix completion.

Only assume that each row/column is sampled.

Generalized Spectral Gap

Theorem:

Let $\mathbf{X} \in \mathbb{R}^{n \times m}$ be rank- r , μ -incoherent and “strongly incoherent” matrix.

Let Ω contain at least one entry from each row and column.

Then \mathbf{X} is the unique solution of $\mathbf{NN}(P_{\Omega}(\mathbf{X}), 0)$ given that

$$\text{GSP} \leq \frac{1}{6\mu r}$$

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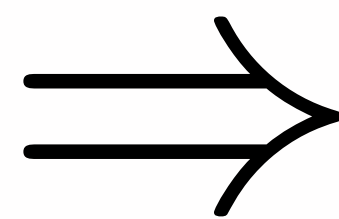
Then \mathbf{X} is the unique solution of $\mathbf{NN}(P_{\Omega}(\mathbf{X}), 0)$ given that

$$\text{GSP} \leq \frac{1}{6\mu r} \iff |\Omega| \geq 6\mu r \sqrt{nm} \sigma_1 \left(A - \frac{|\Omega|}{nm} \mathbf{1}_{n \times m} \right)$$

Generalized Spectral Gap

Bad Case (e.g., periodic sampling):

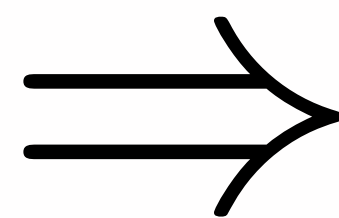
$$\text{GSP} \approx 1$$



exact recovery not possible

Good Case (e.g., random sampling):

$$\text{GSP} \approx \sqrt{\sqrt{nm}/|\Omega|}$$



$$|\Omega| \geq 36\mu^2 r^2 \sqrt{nm}$$

Generalized Spectral Gap

Bad Case (e.g., periodic sampling):

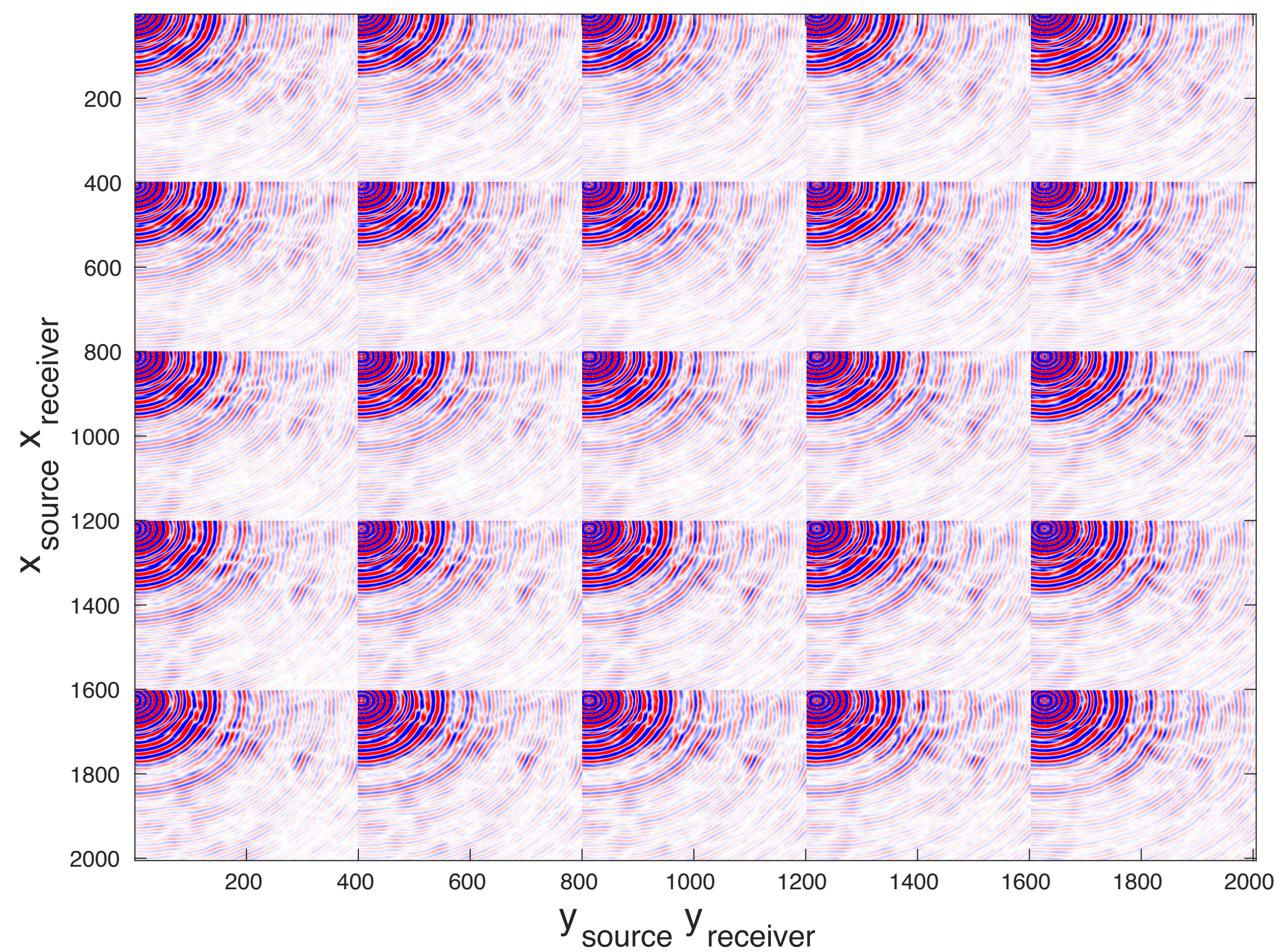
$\text{GSP} \approx 1 \quad \Rightarrow \quad \text{exact recovery not possible}$

Good Case (e.g., random sampling):

$\text{GSP} \approx \sqrt{\sqrt{nm}/|\Omega|} \quad \Rightarrow \quad |\Omega| \geq 36\mu^2 r^2 \sqrt{nm}$

compare to $|\Omega| \geq C\mu^2 r n \log^2(n)$ from literature (non-deterministic)

3D Interpolation Example

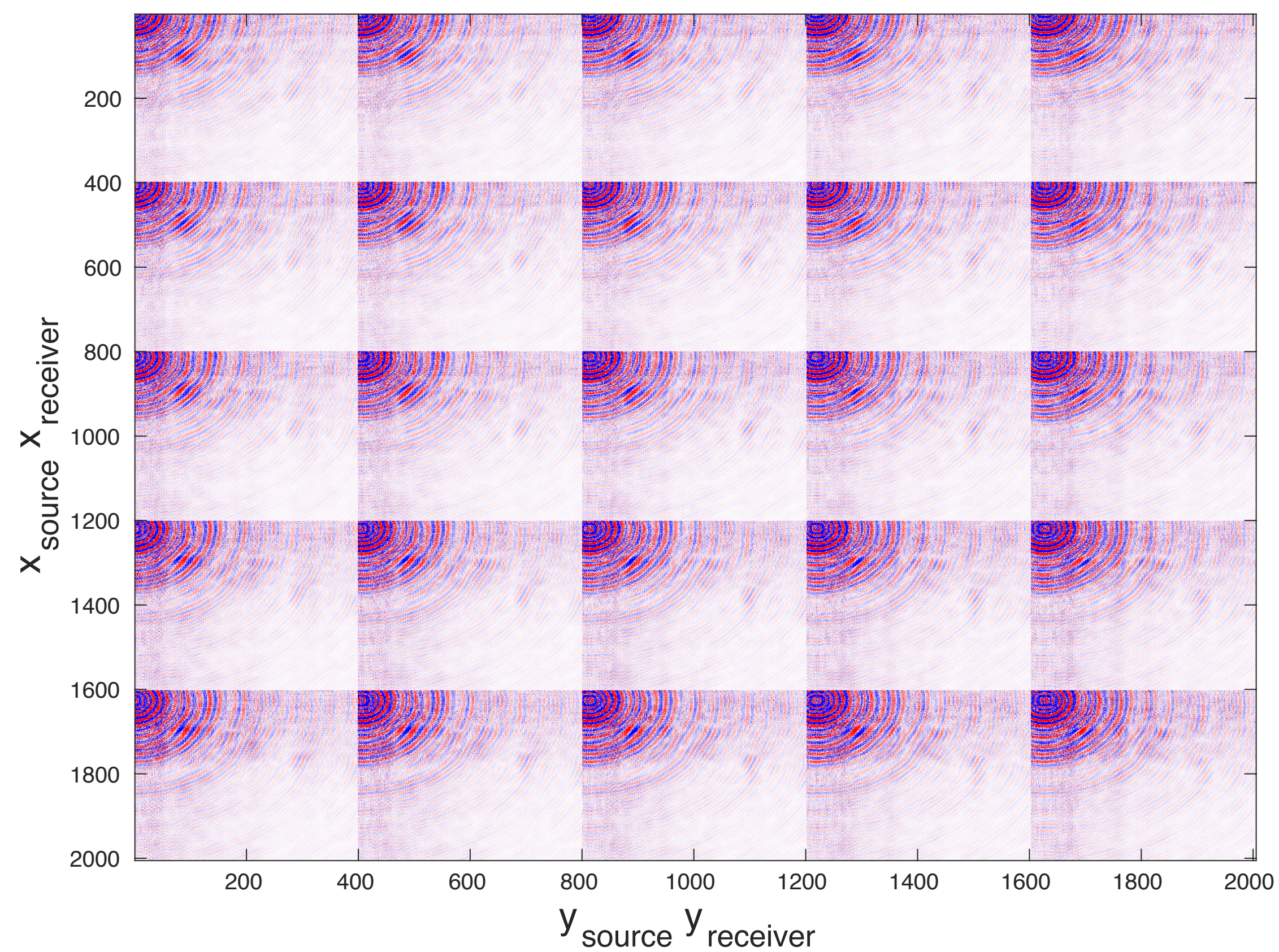


Size: 2005 x 2005

Remove 75 % of
Receivers

Compare small and
large GSP recovery

3D Interpolation Example: **Bad** Recovery

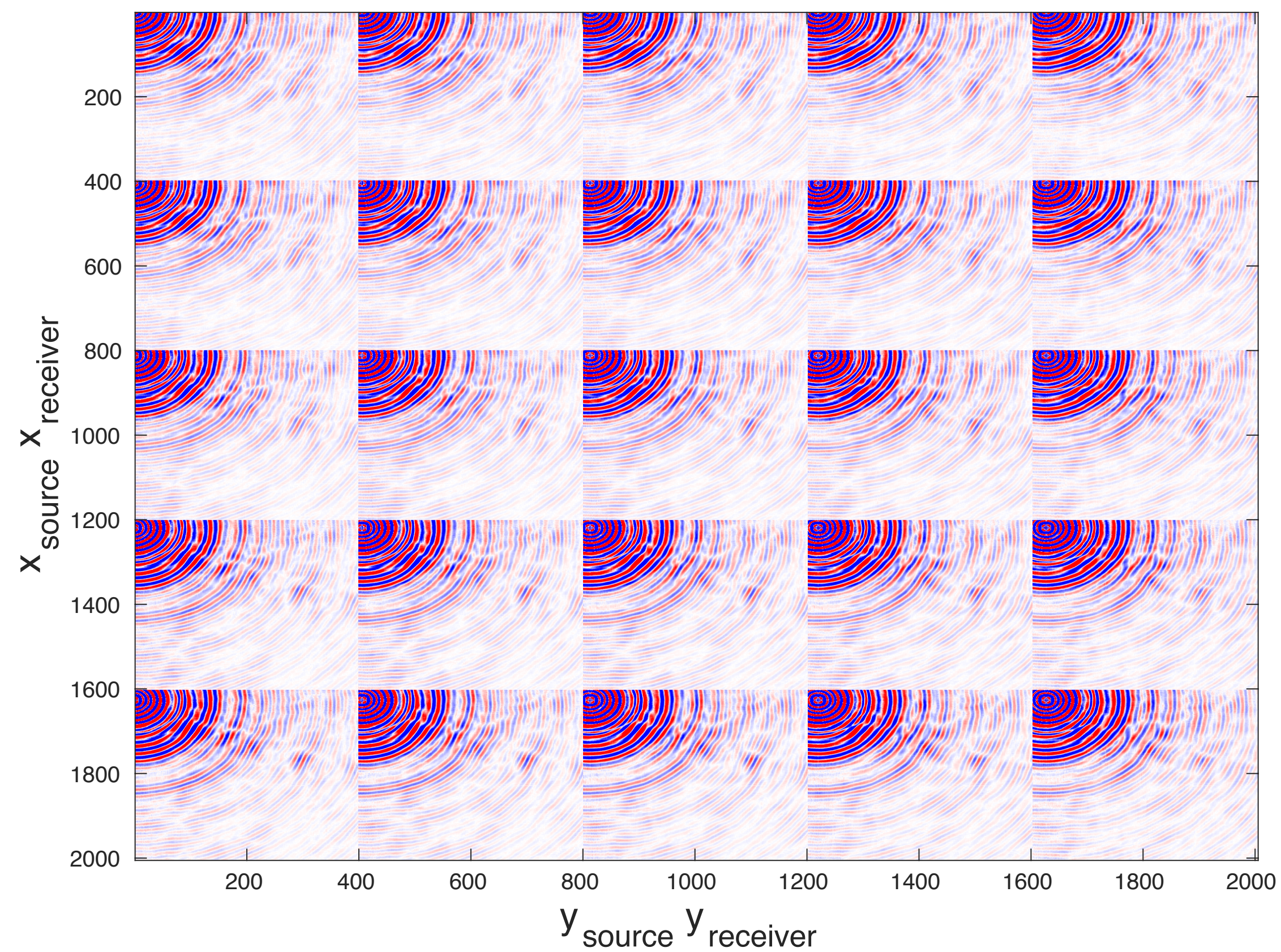


Reconstruction

SNR: 3.5 dB

GSP: .9828

3D Interpolation Example: **Good** Recovery



Reconstruction

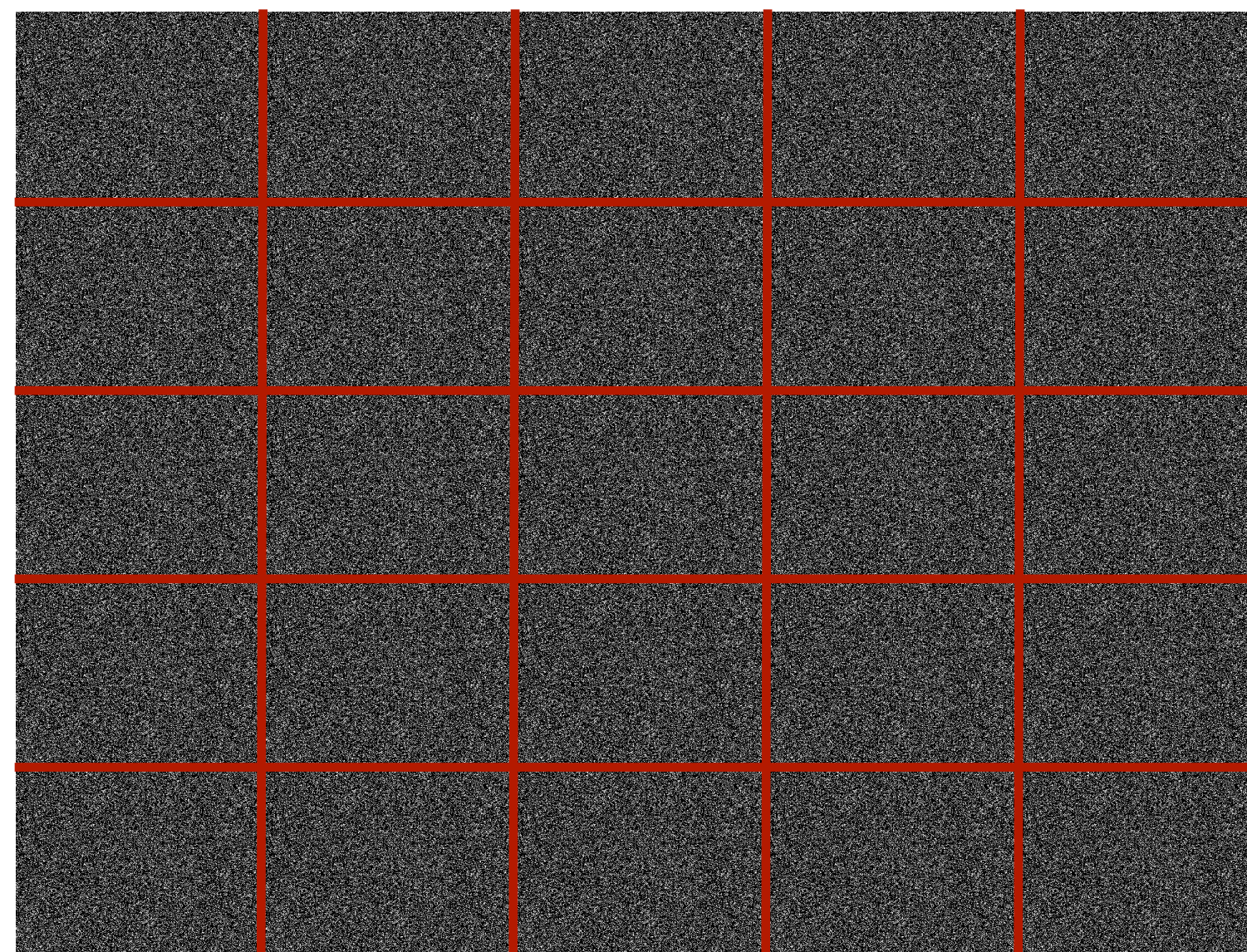
SNR: 20.7 dB

GSP: .1796

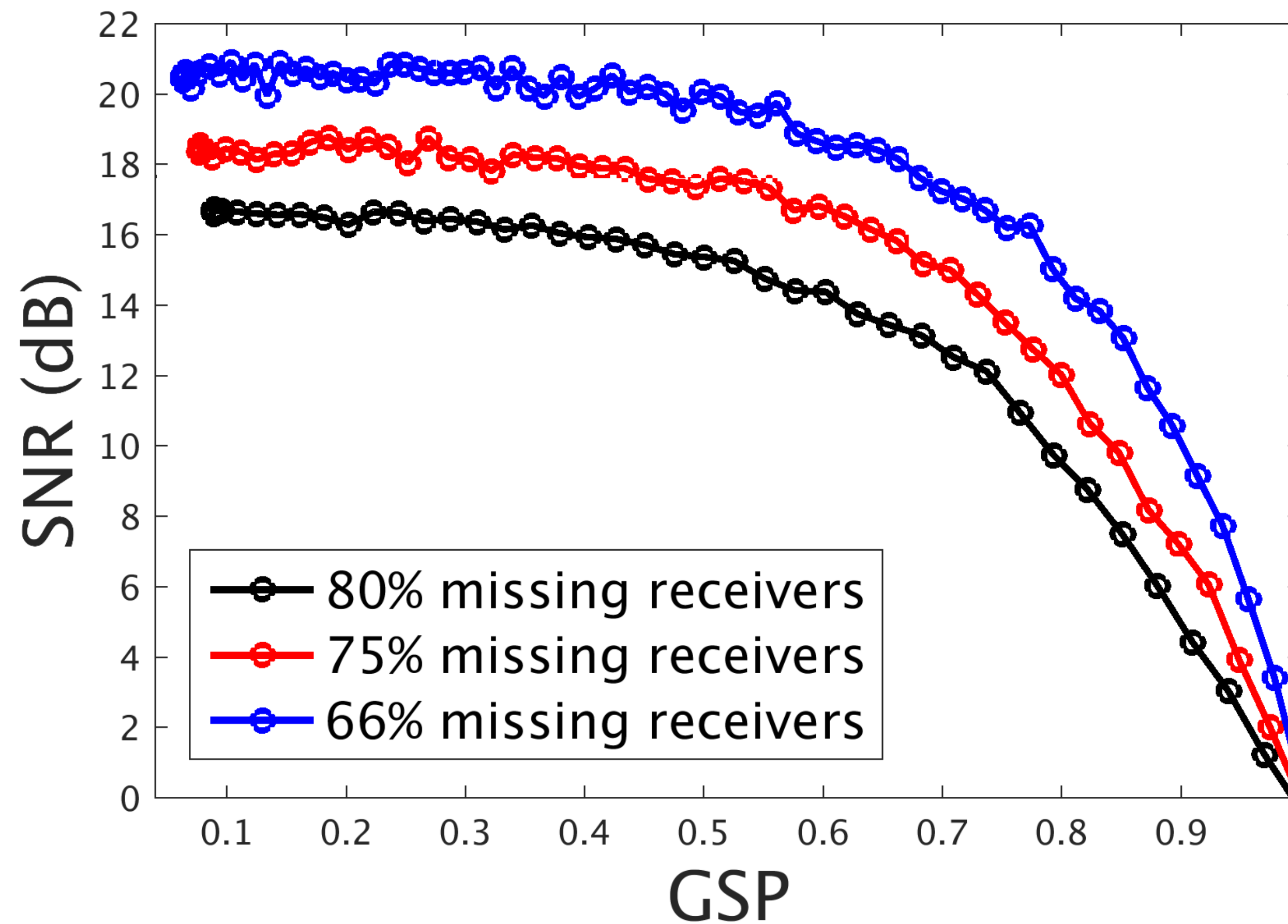
3D Interpolation Experiments

Generate 3D seismic Masks with increasing GSP

Plot correlation with reconstruction SNR



3D Interpolation Experiments



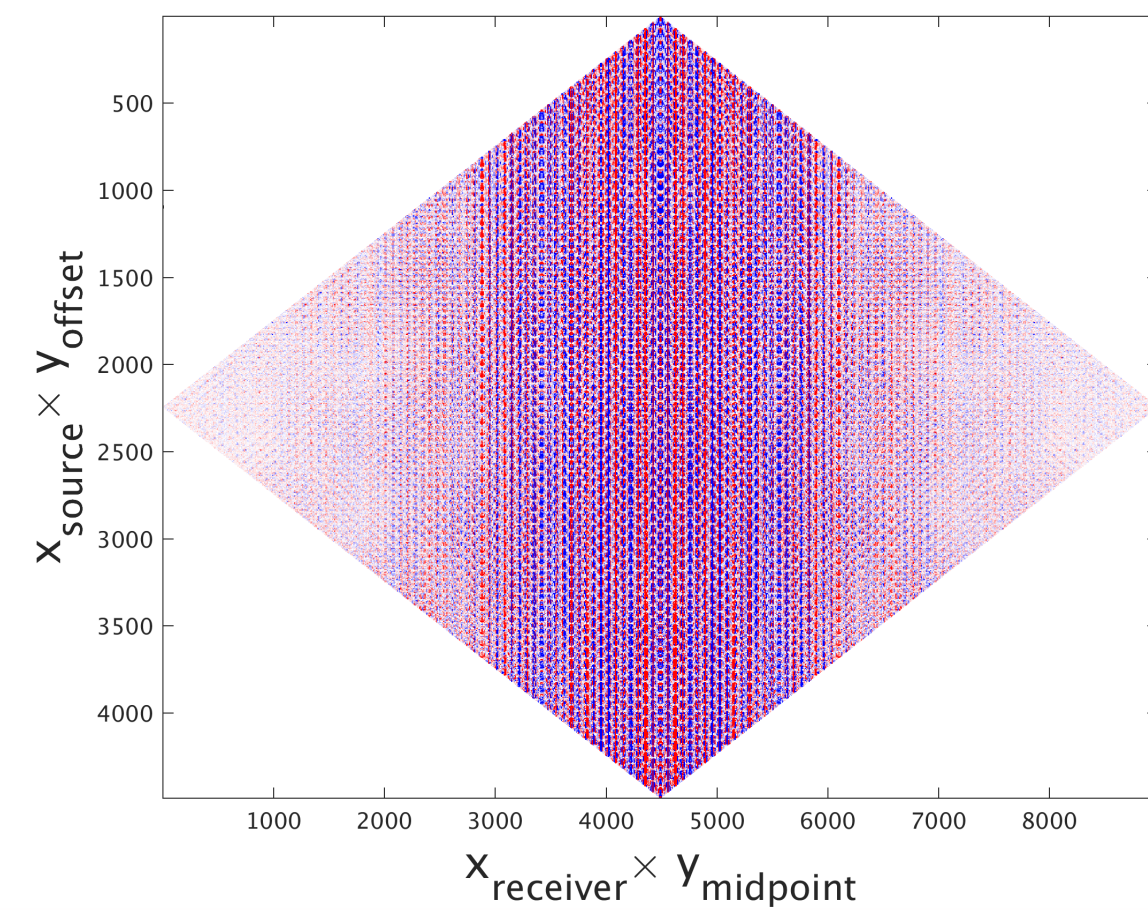
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 - literature
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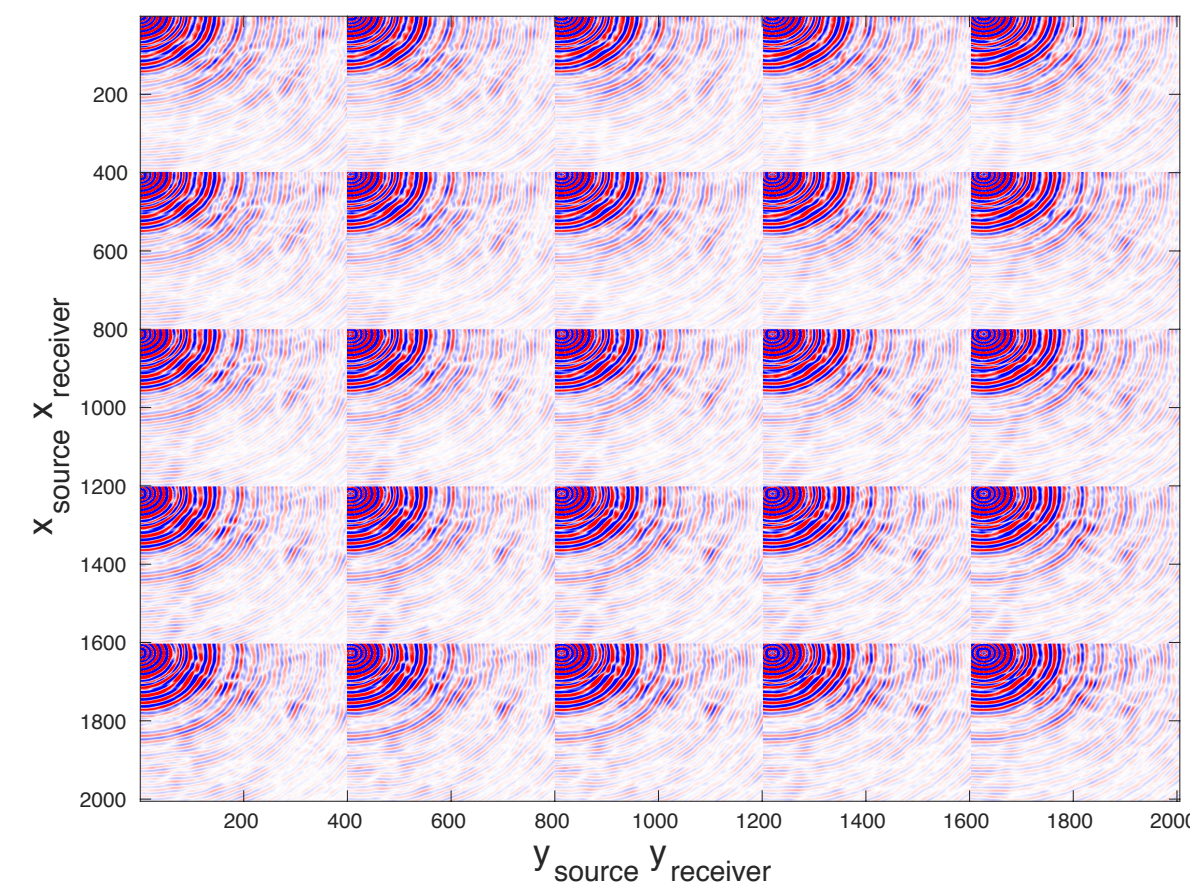
- ▶ Universal Matrix Completion
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Example 1: How to Matricize?

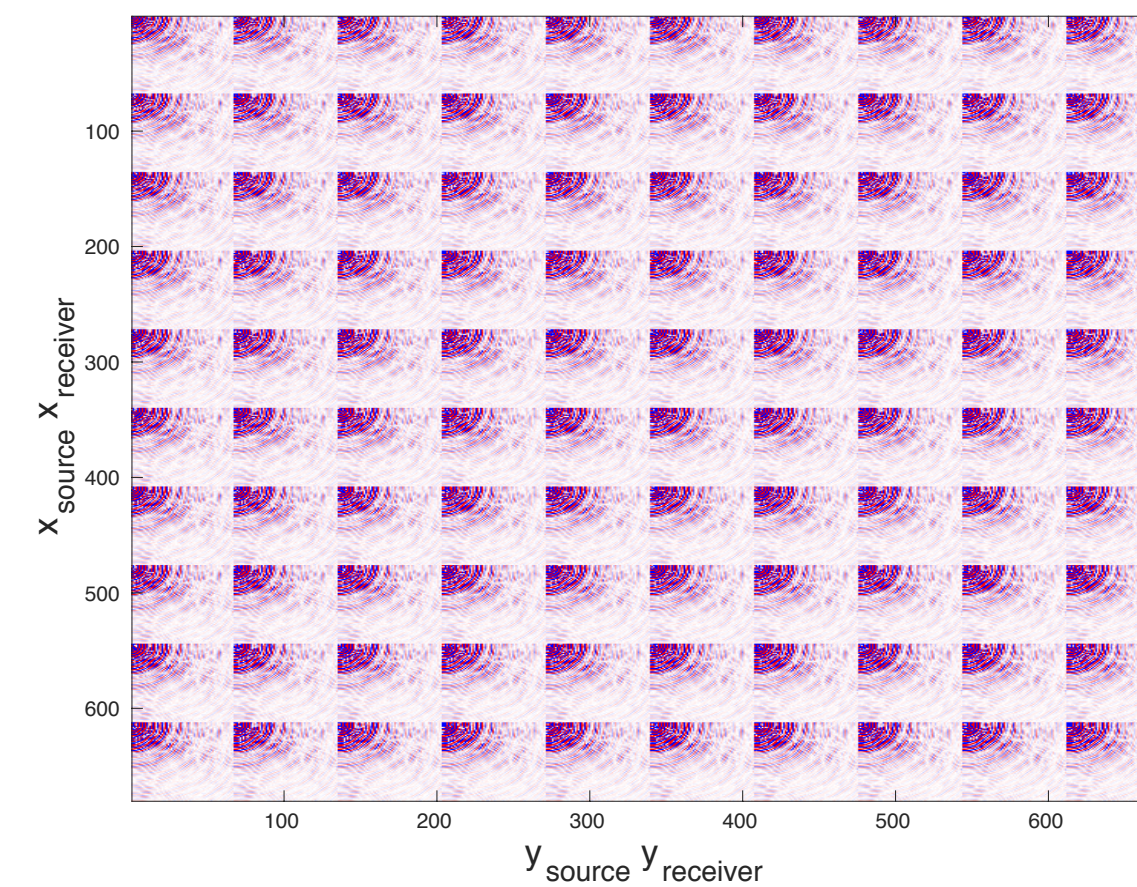
(mid,off)-domain



(rec,rec)-form

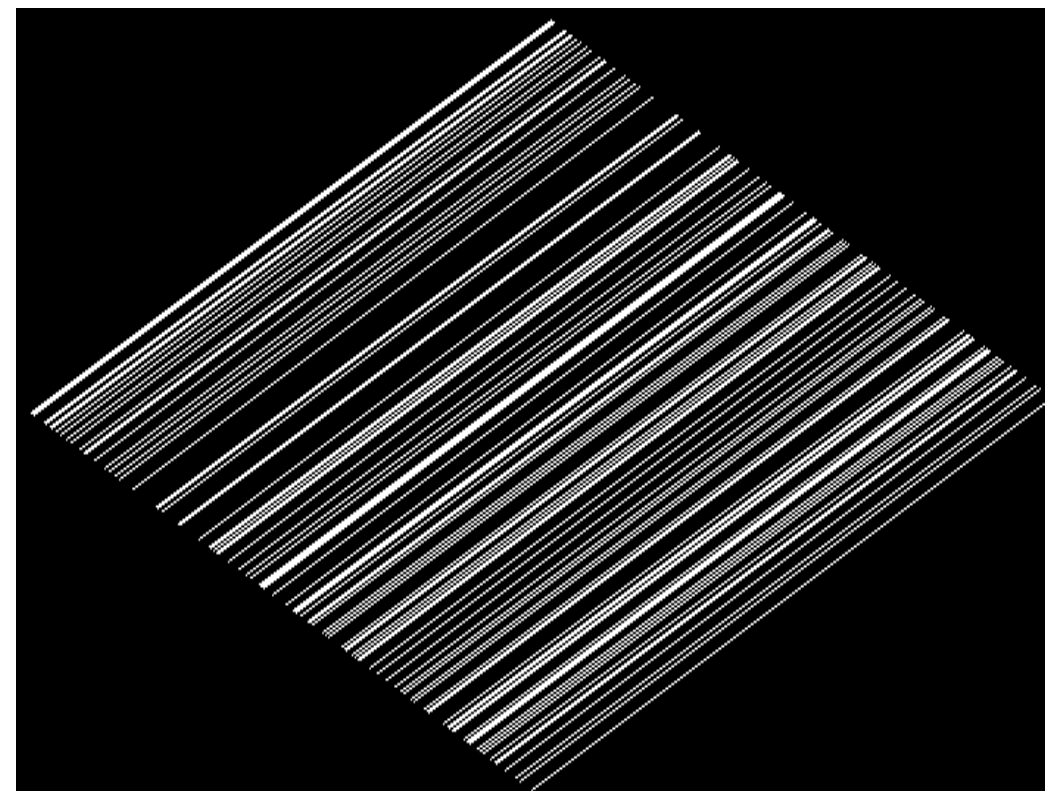


(src,src)-form

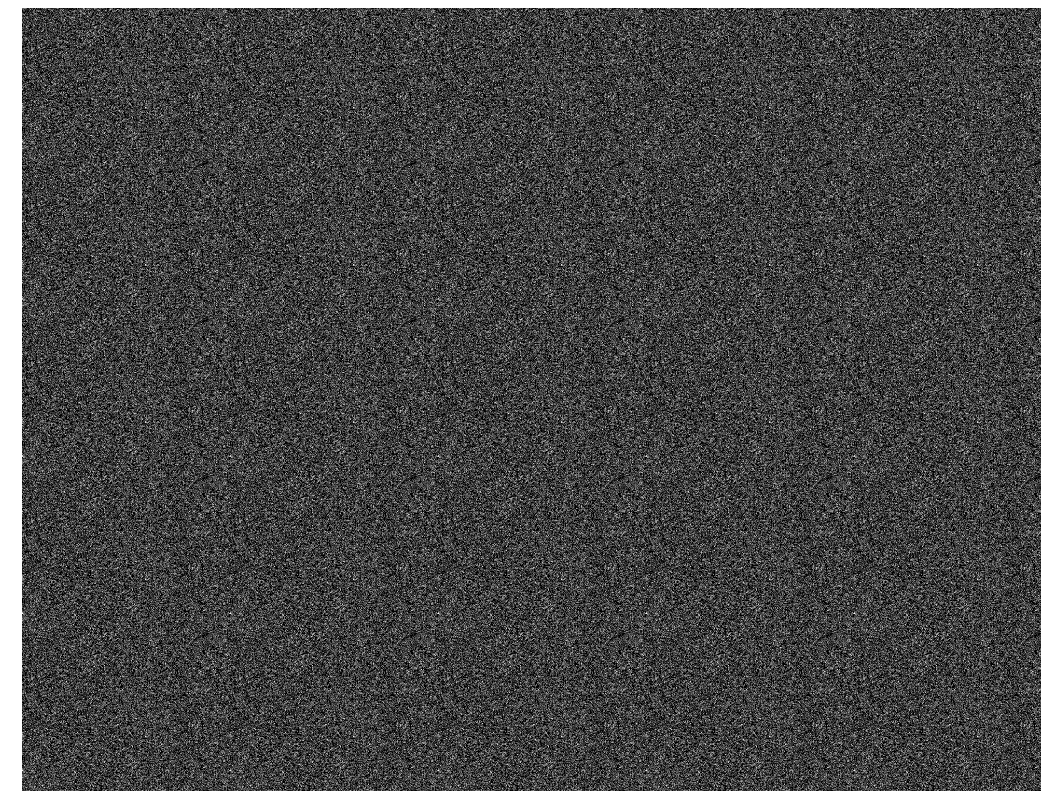


Example 1: How to Matricize?

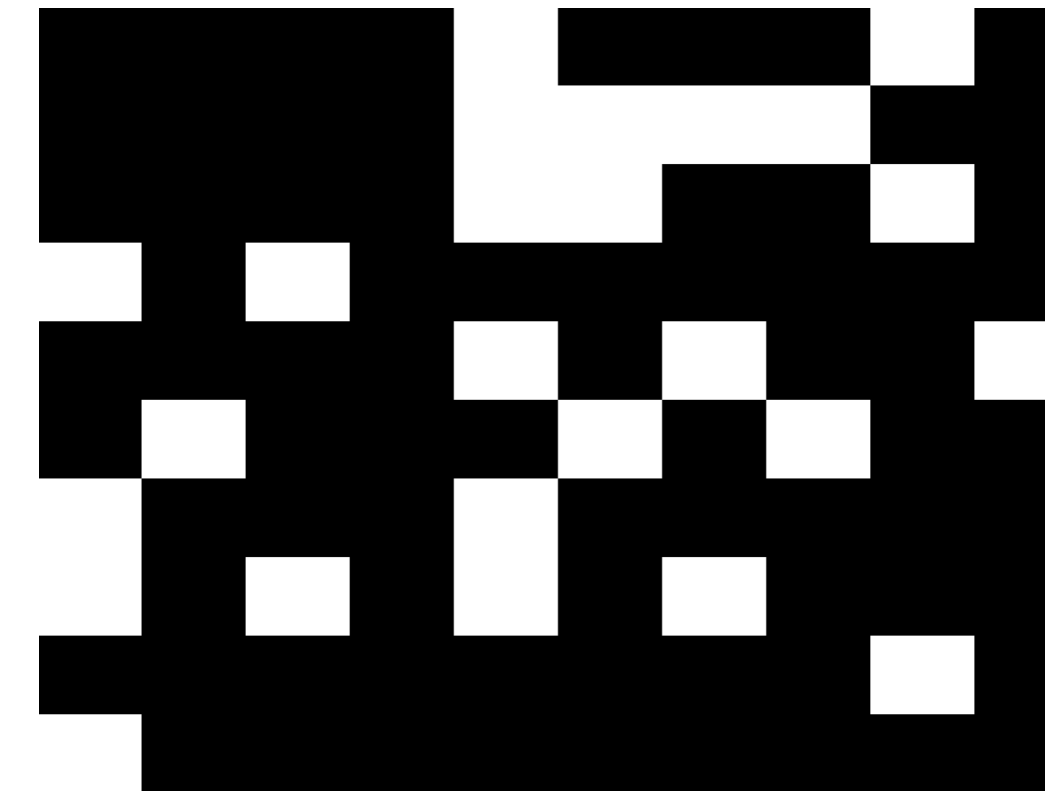
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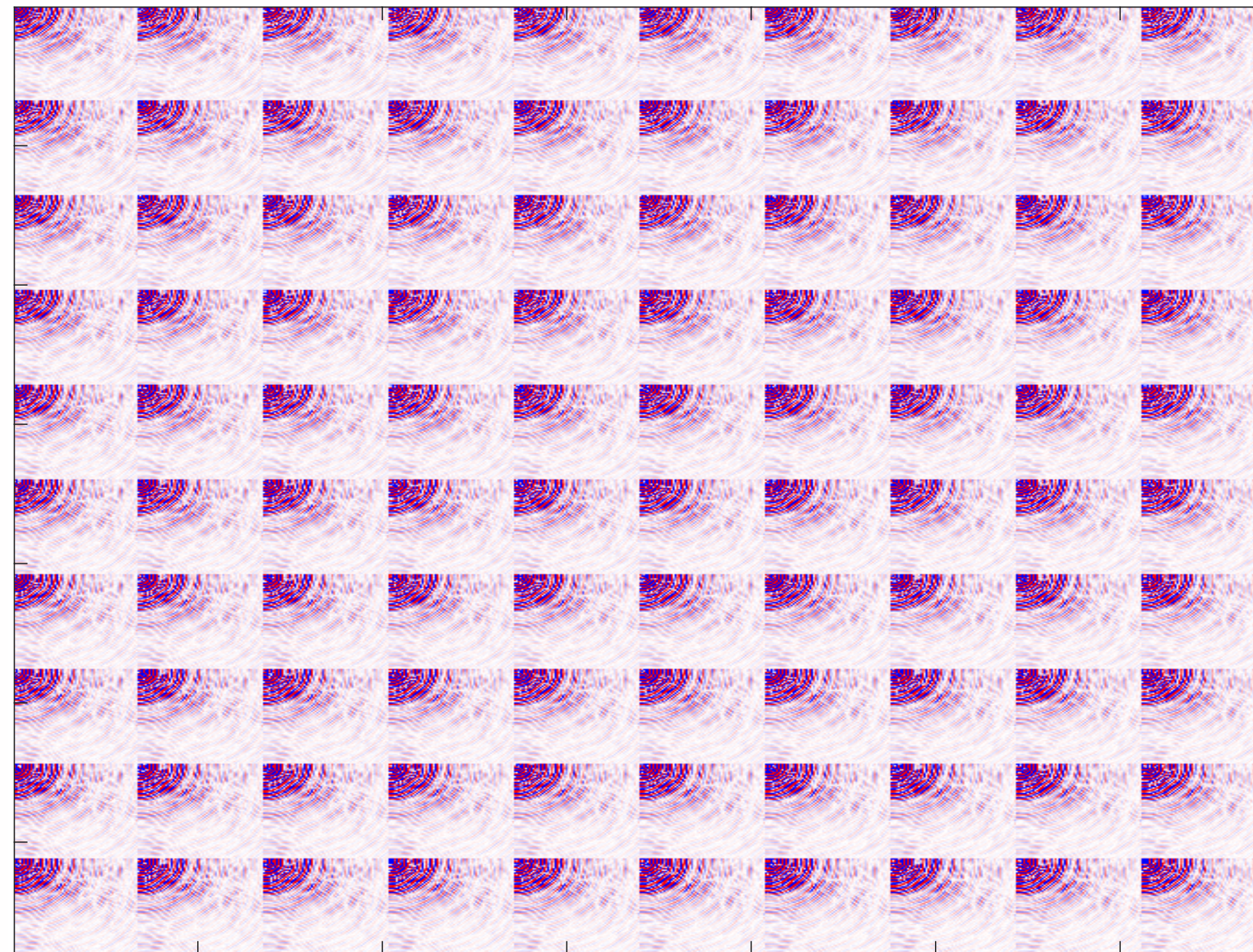


Use GSP to decide which matricization works best for given subsampling

R. Kumar, et al. "Efficient matrix completion for seismic data reconstruction" Geophysics 2014.

Example 2: To window or not to window?

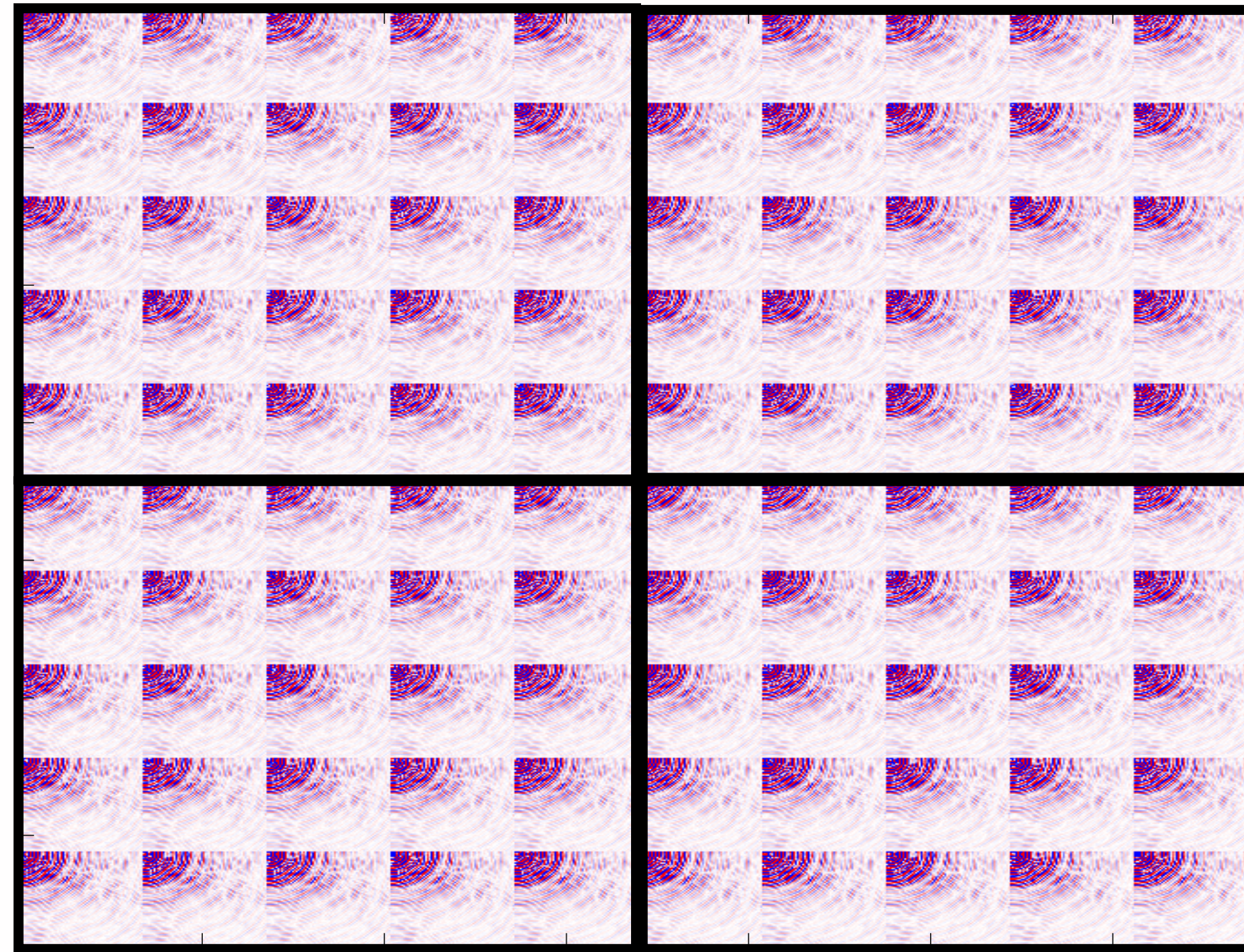
- ▶ Full matrix is too large



R. Kumar, et al. "Efficient matrix completion for seismic data reconstruction" Geophysics 2014.

Example 2: To window or not to window?

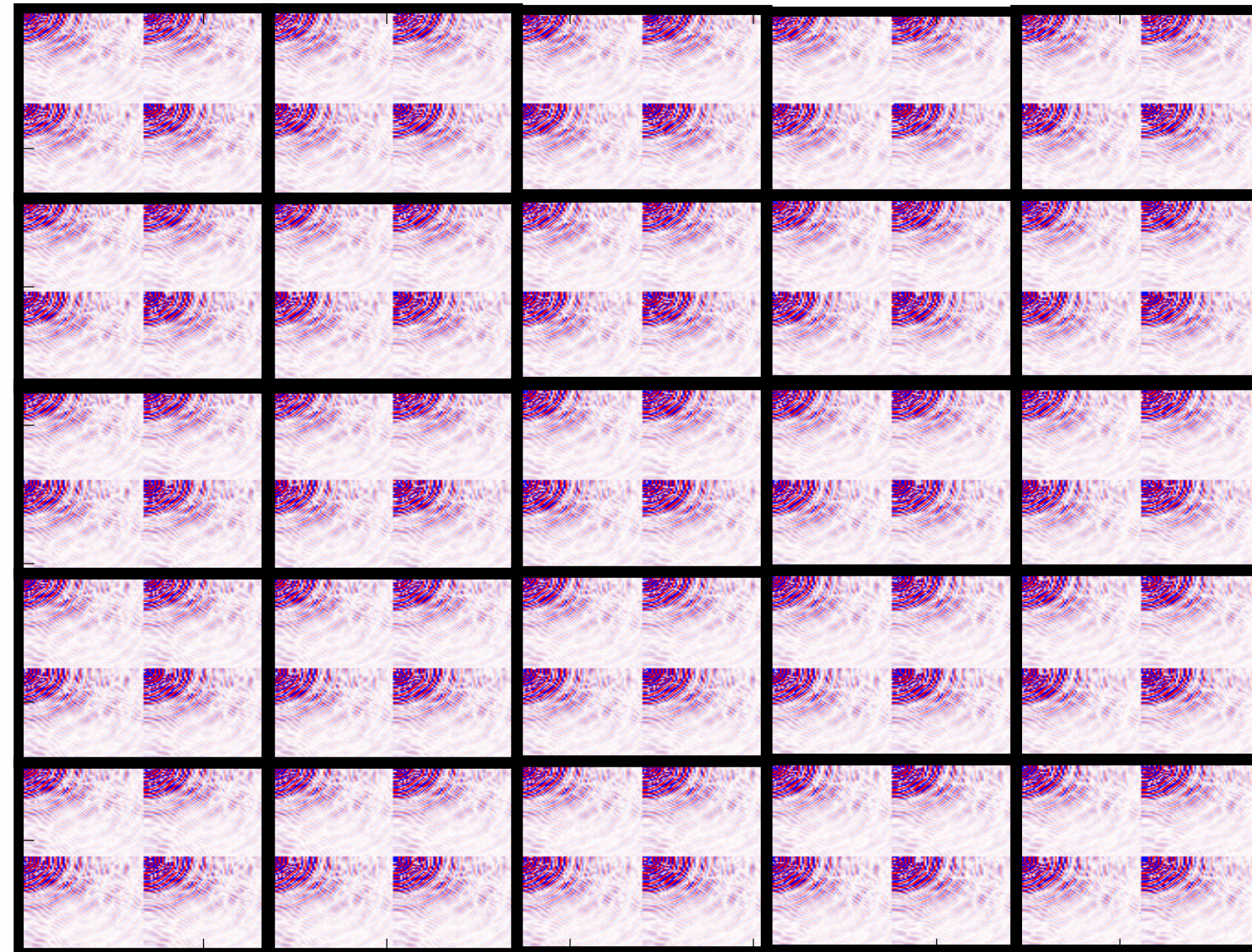
- ▶ Full matrix is too large
- ▶ Split volume into smaller windows
- ▶ Solve in parallel



R. Kumar, et al. "Efficient matrix completion for seismic data reconstruction" Geophysics 2014.

Example 2: To window or not to window?

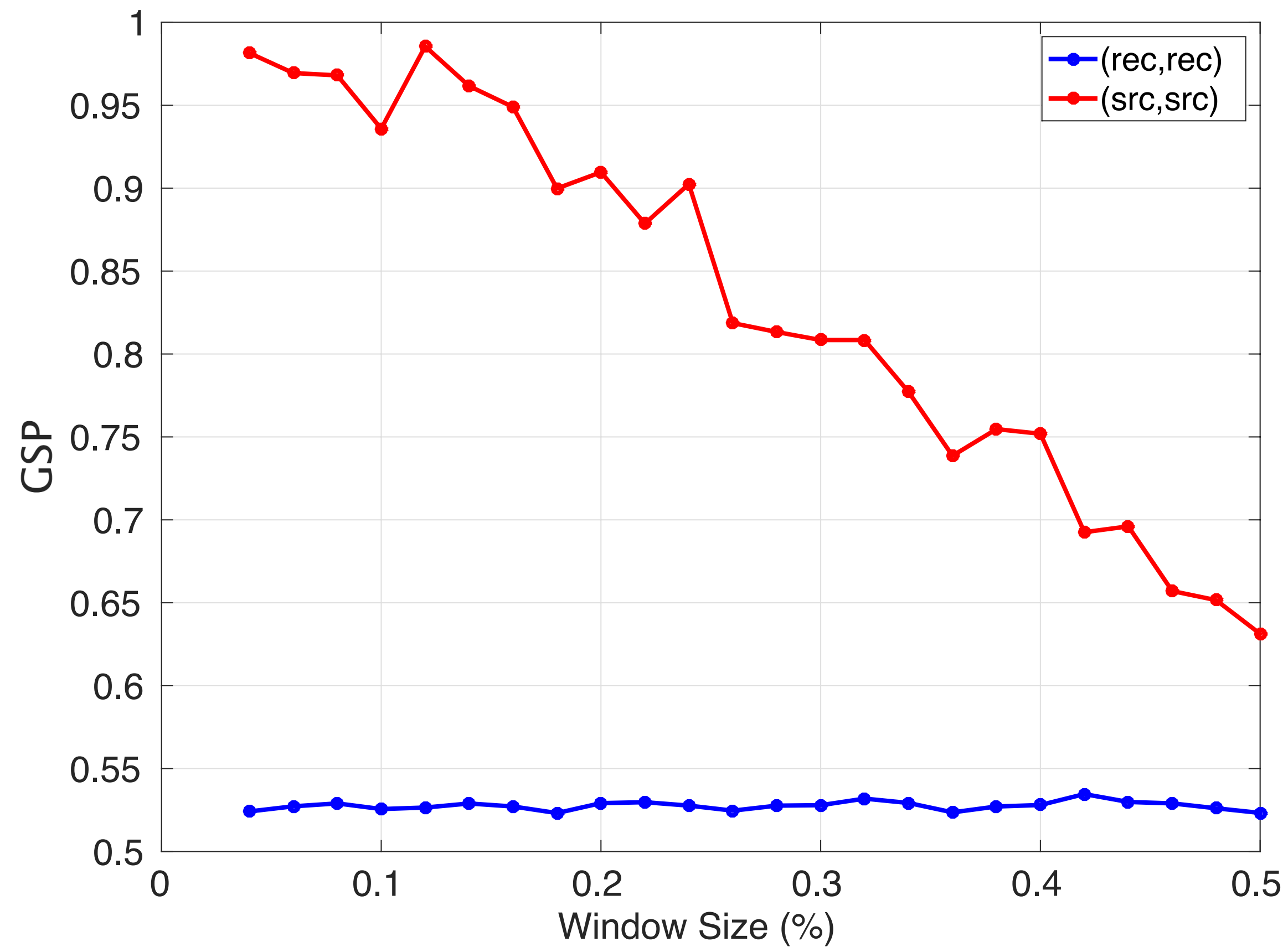
- ▶ Which matricization?
- ▶ What size windows?



R. Kumar, et al. "Efficient matrix completion for seismic data reconstruction" Geophysics 2014.

Example 2: To window or not to window?

Average GSP for various window sizes

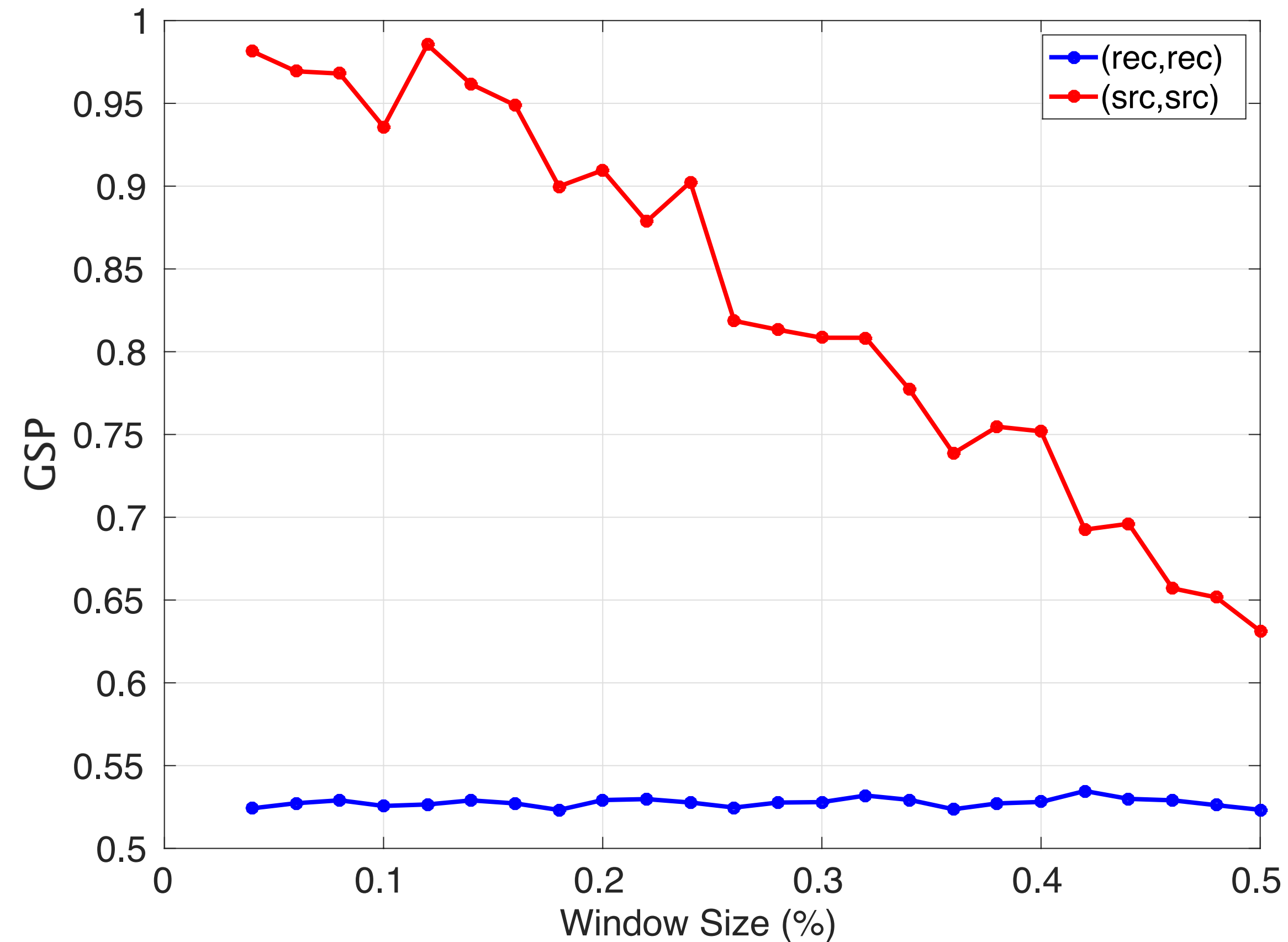


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Example 2: To window or not to window?

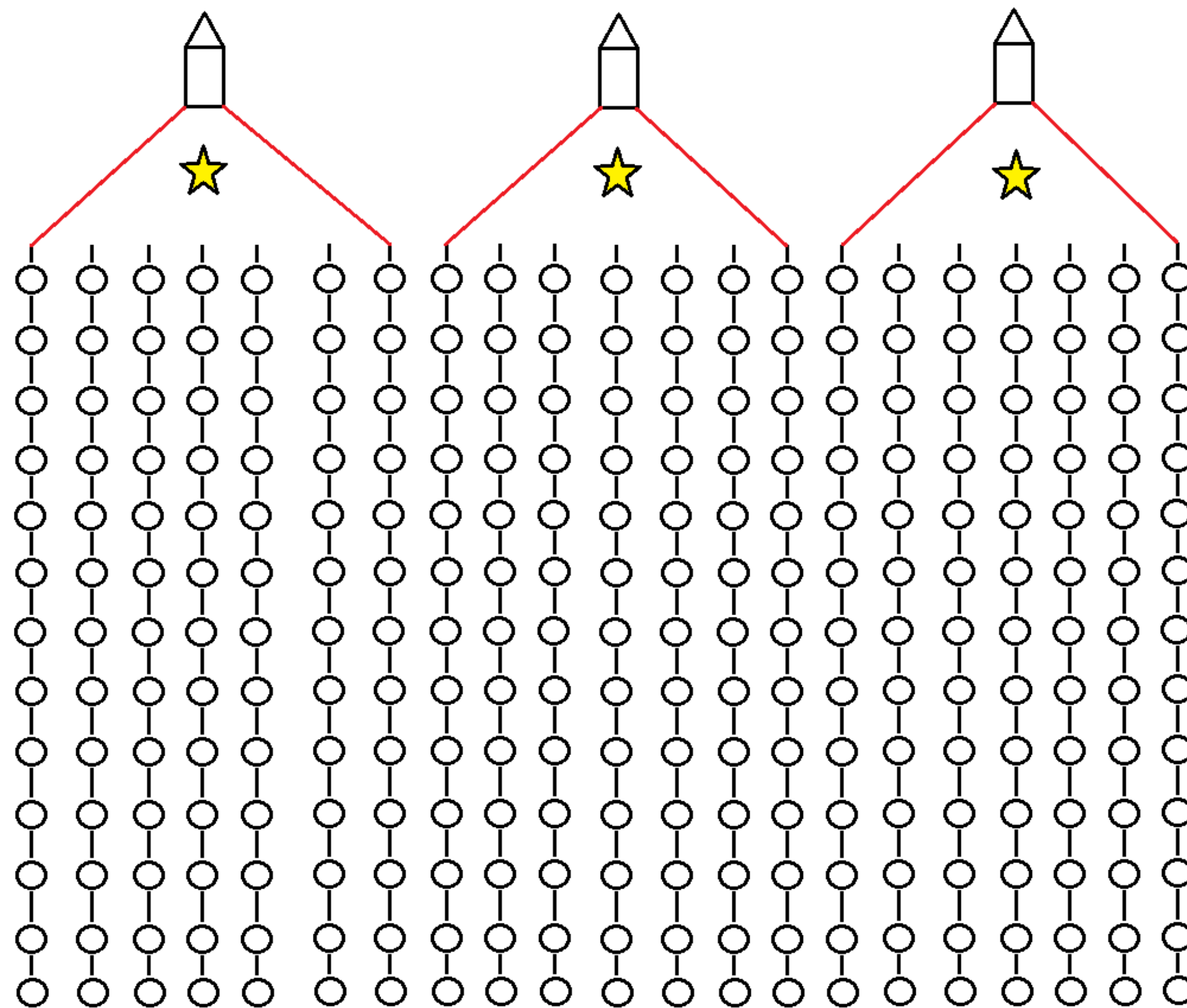
Average GSP for various window sizes

- ▶ (rec,rec) is best in this example
- ▶ GSP is stable as window size decreases



Example 3: Infill Management

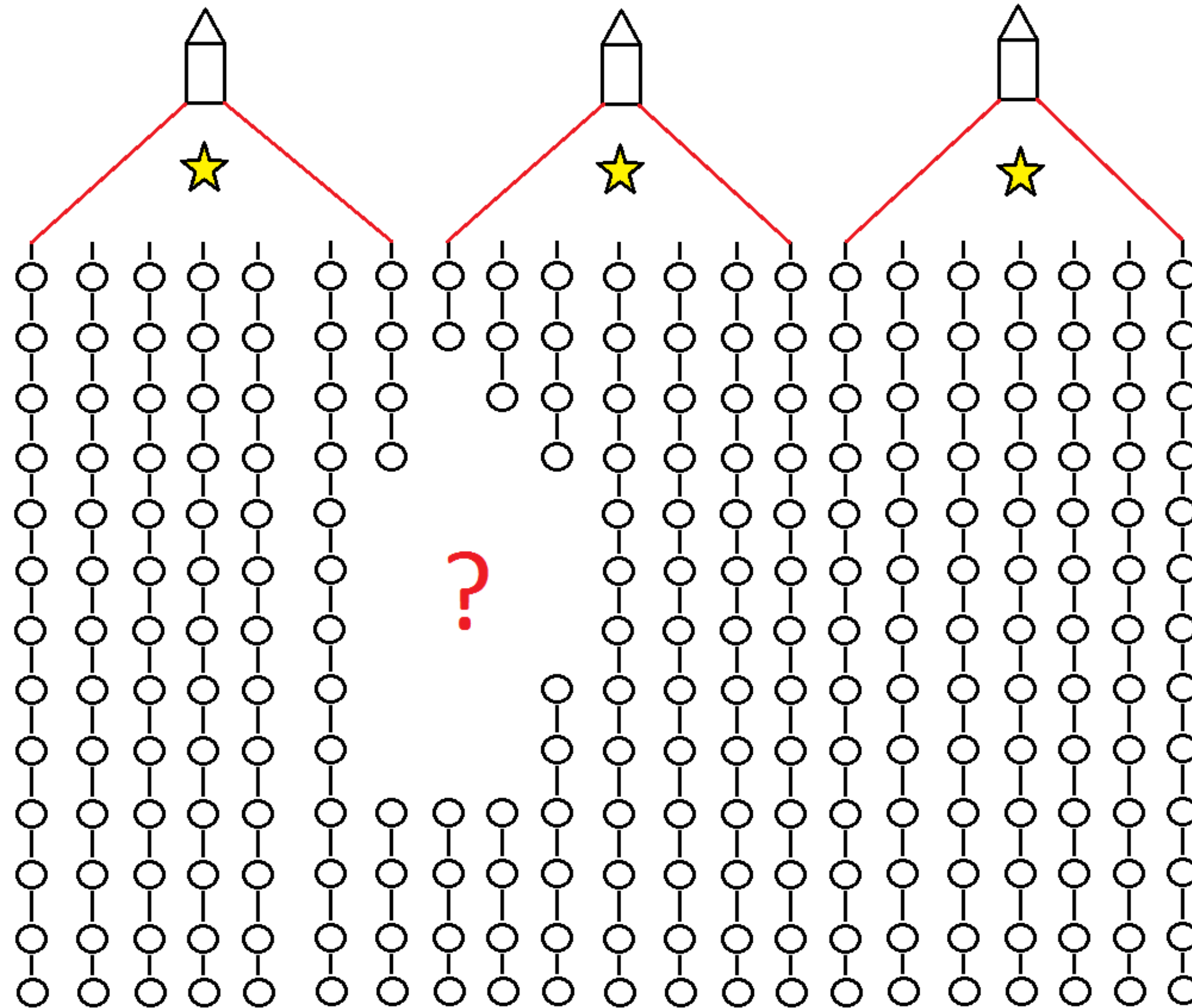
Desired
Sampling



Example 3: Infill Management

Coverage Hole:

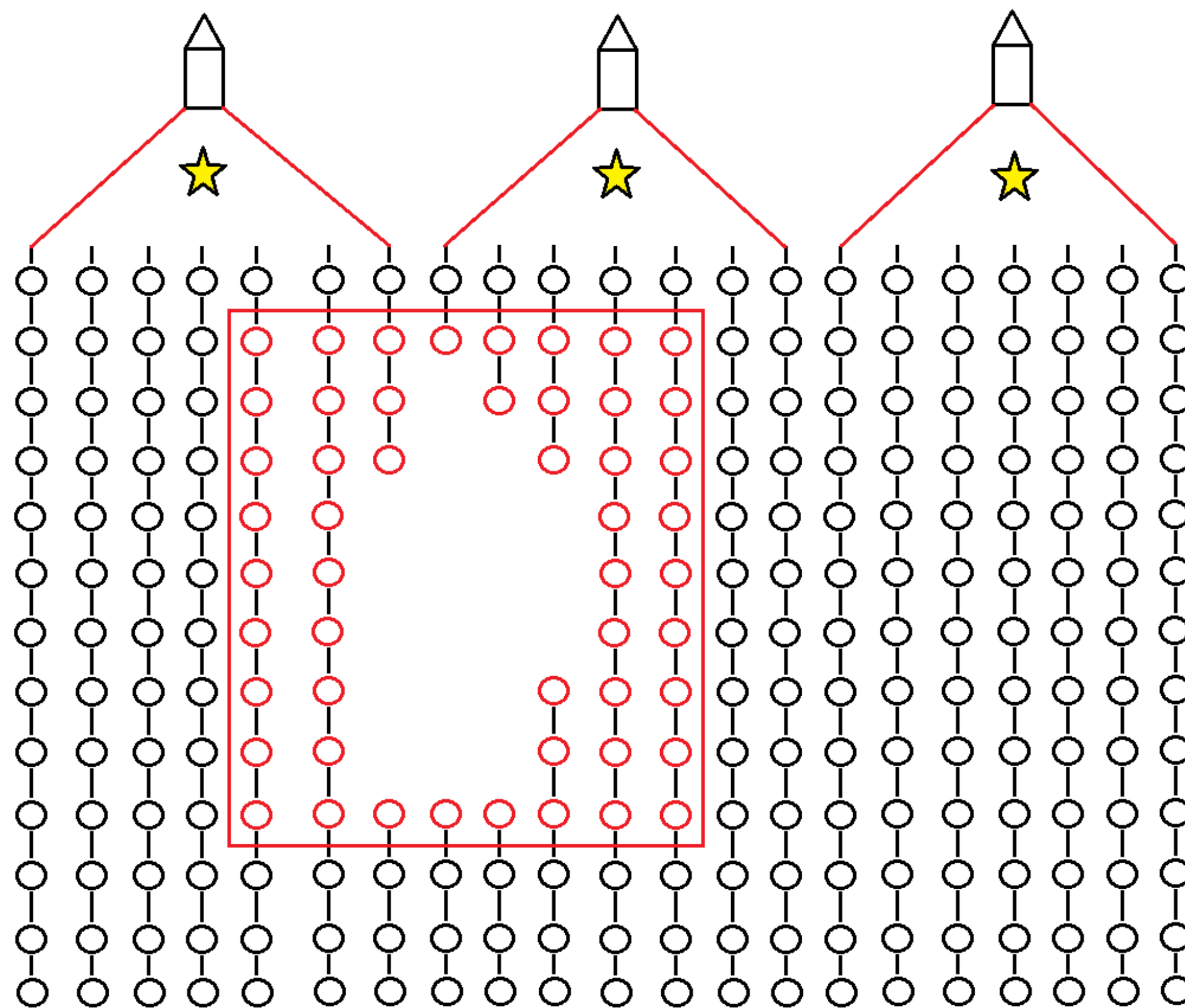
additional infill acquisition?



Example 3: Infill Management

Form local mask:

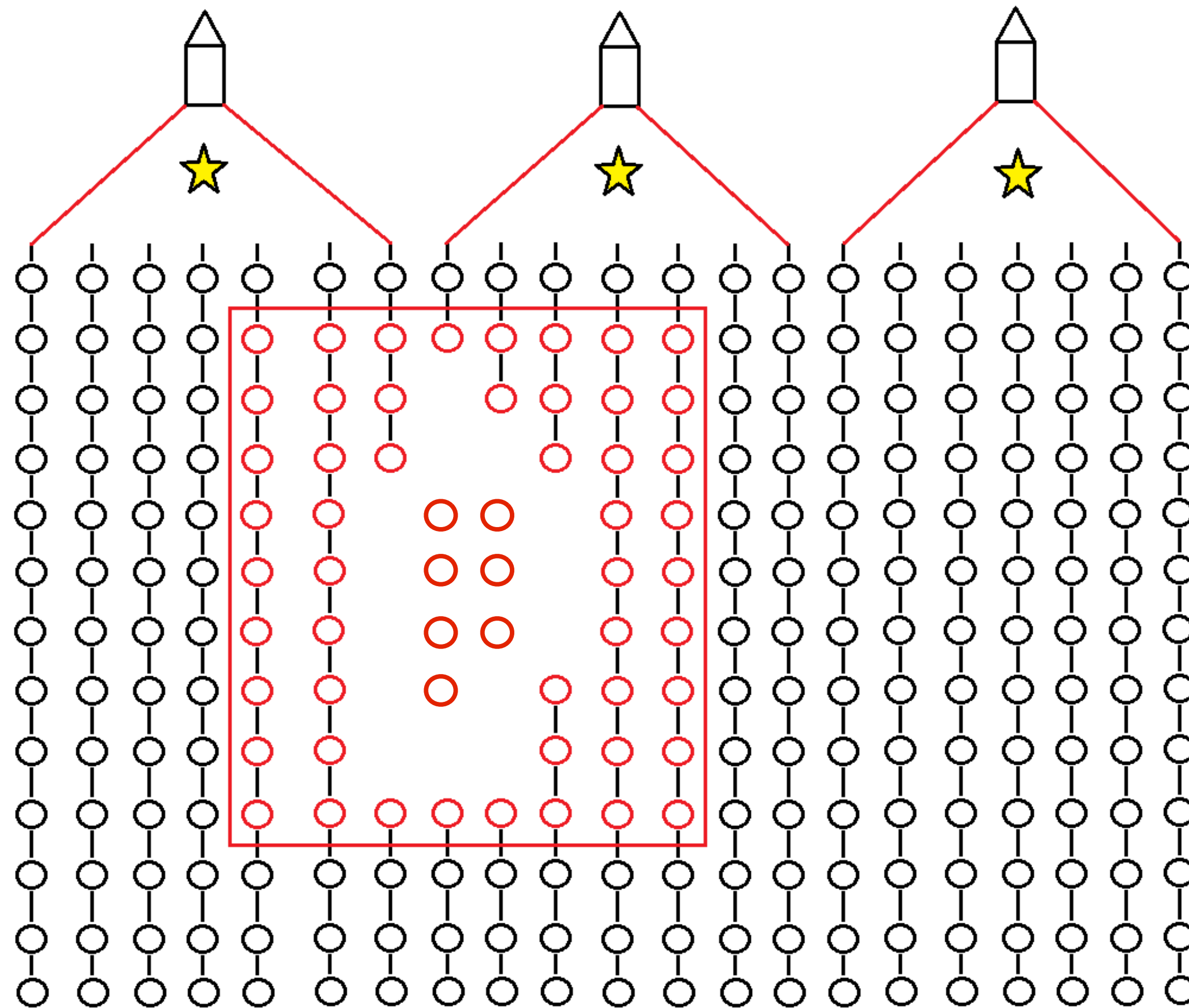
use GSP as
decision tool



Example 3: Infill Management

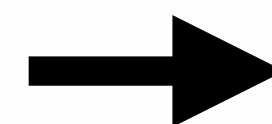
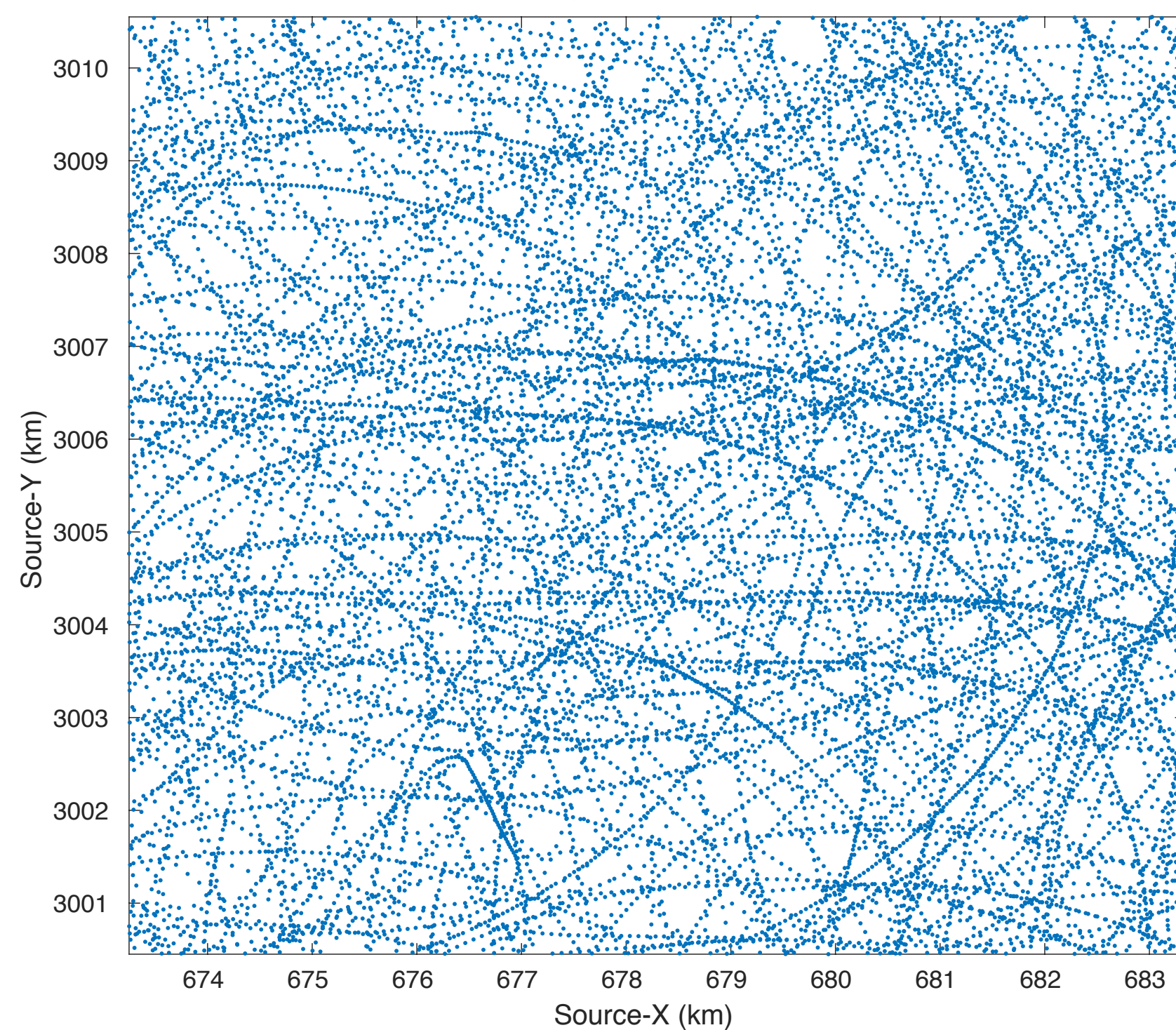
Additional infill acquisition:

use GSP to minimize sampling

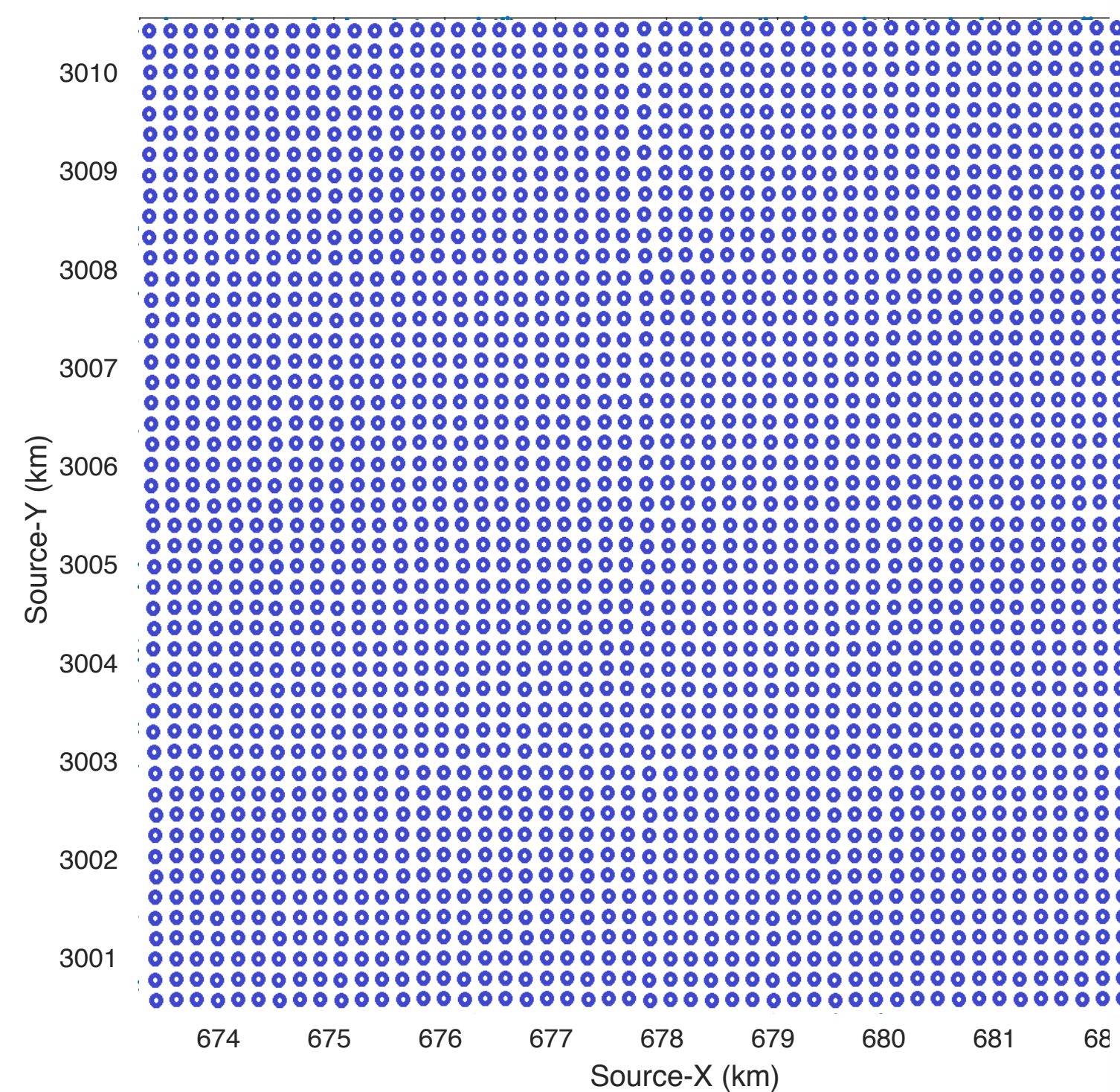


Example 4: Coil Sampling Interpolation

coil sampling source locations



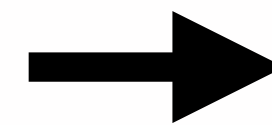
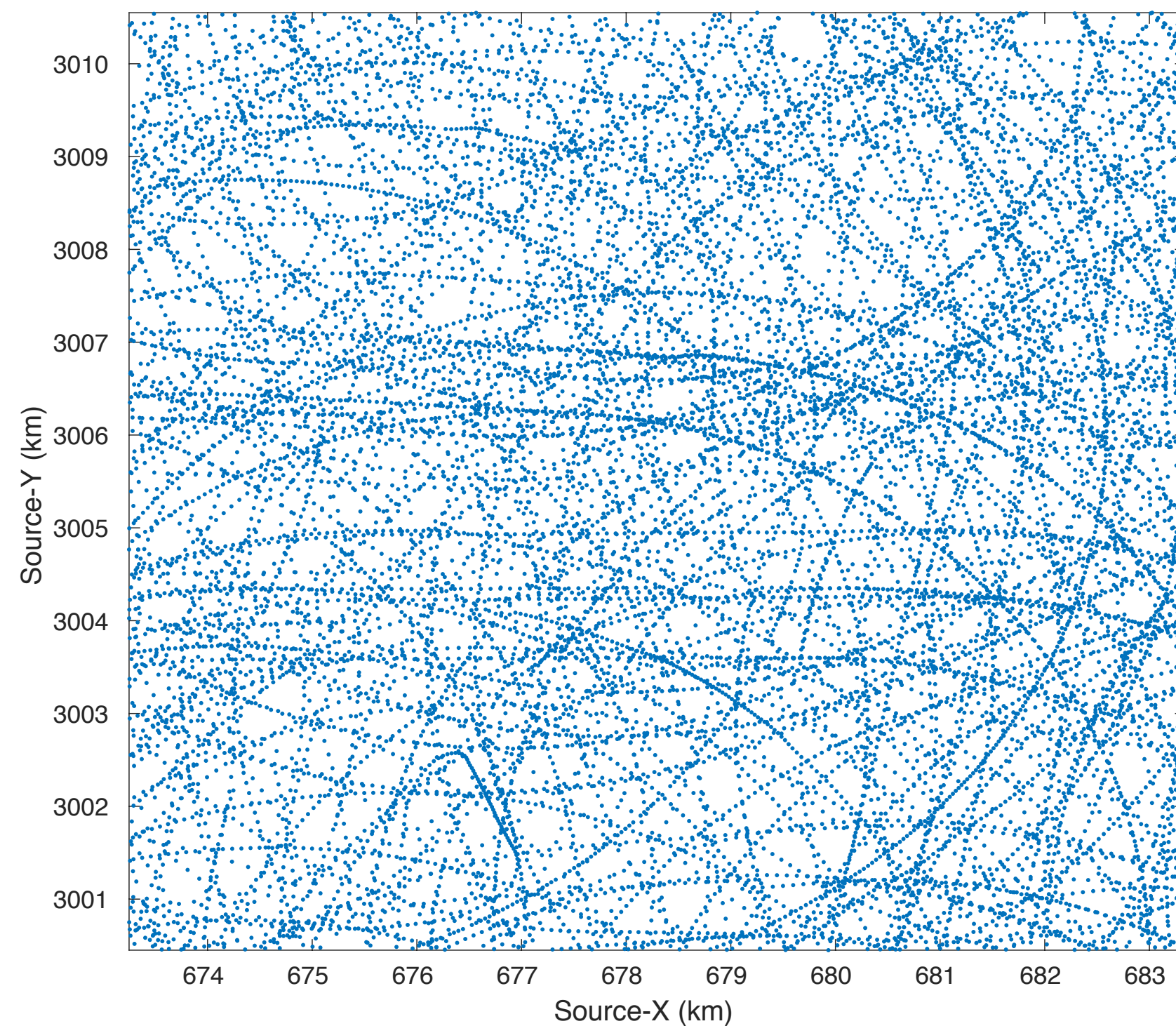
equispaced sources



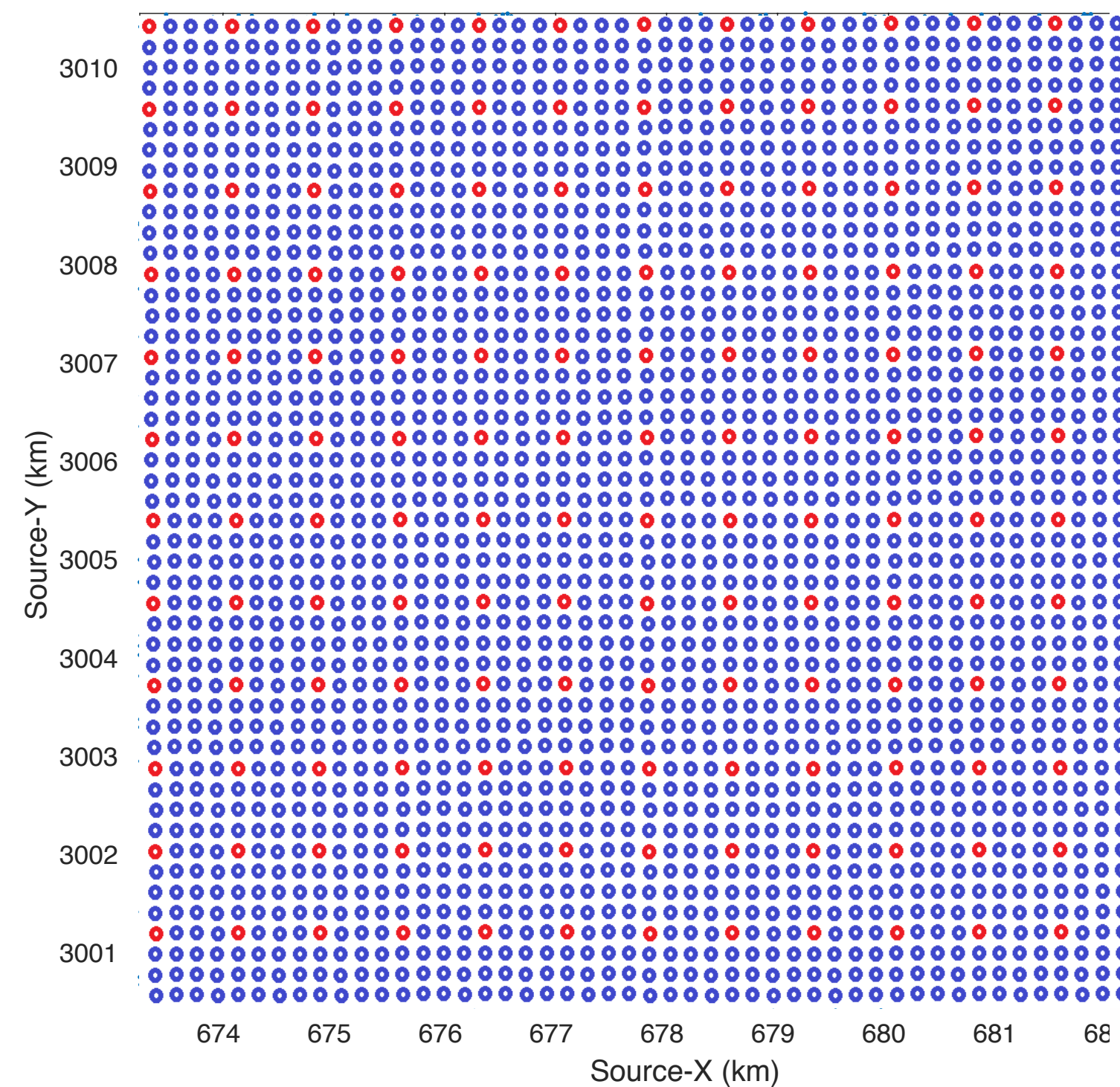
Goal: interpolate coil data onto equispaced grid

Example 4: Coil Sampling Interpolation

coil sampling source locations



equispaced sources



What grid density for sources and receivers?

Example 4: Coil Sampling Interpolation

Receiver Spacing	Source Spacing	Mask GSP
100 m	200 m	0.77
50 m	100 m	0.4
50 m	50 m	0.88

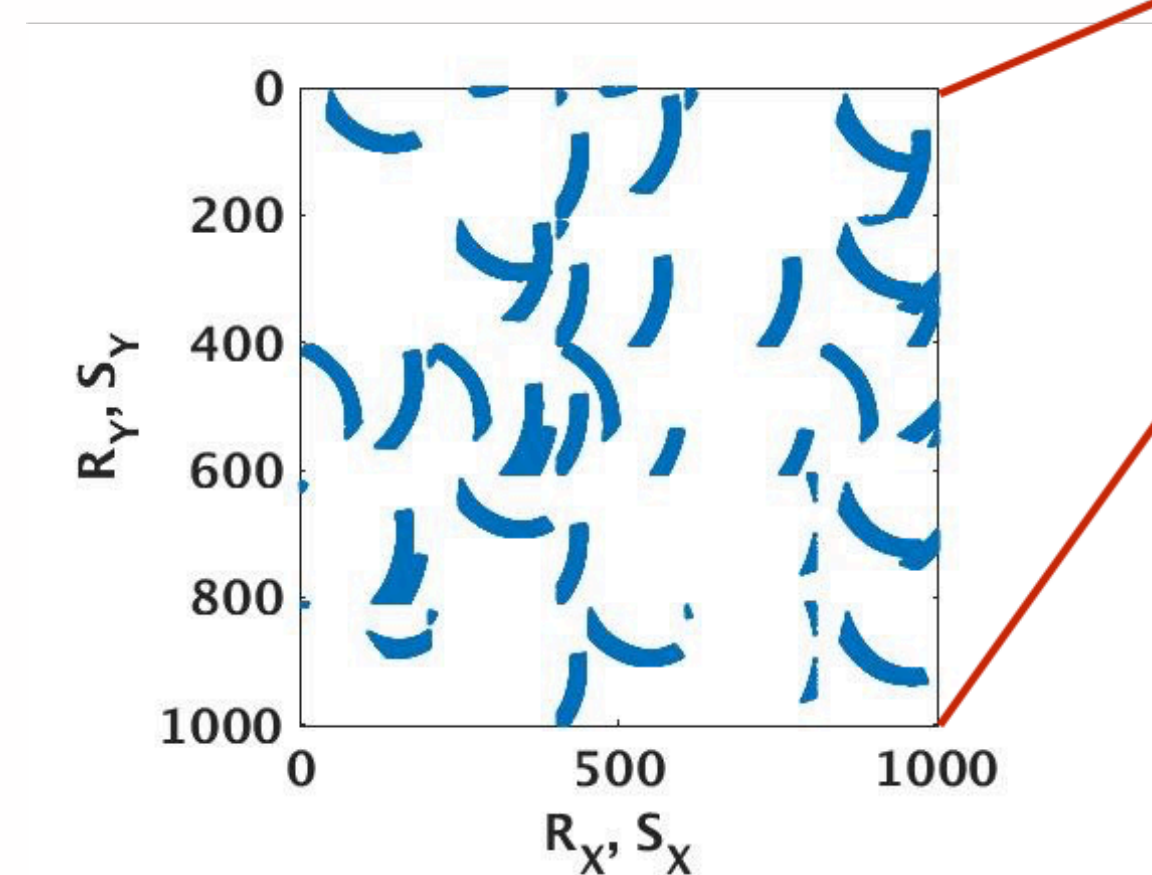
not dense enough: too many sources map to the same grid locations

sweet spot?

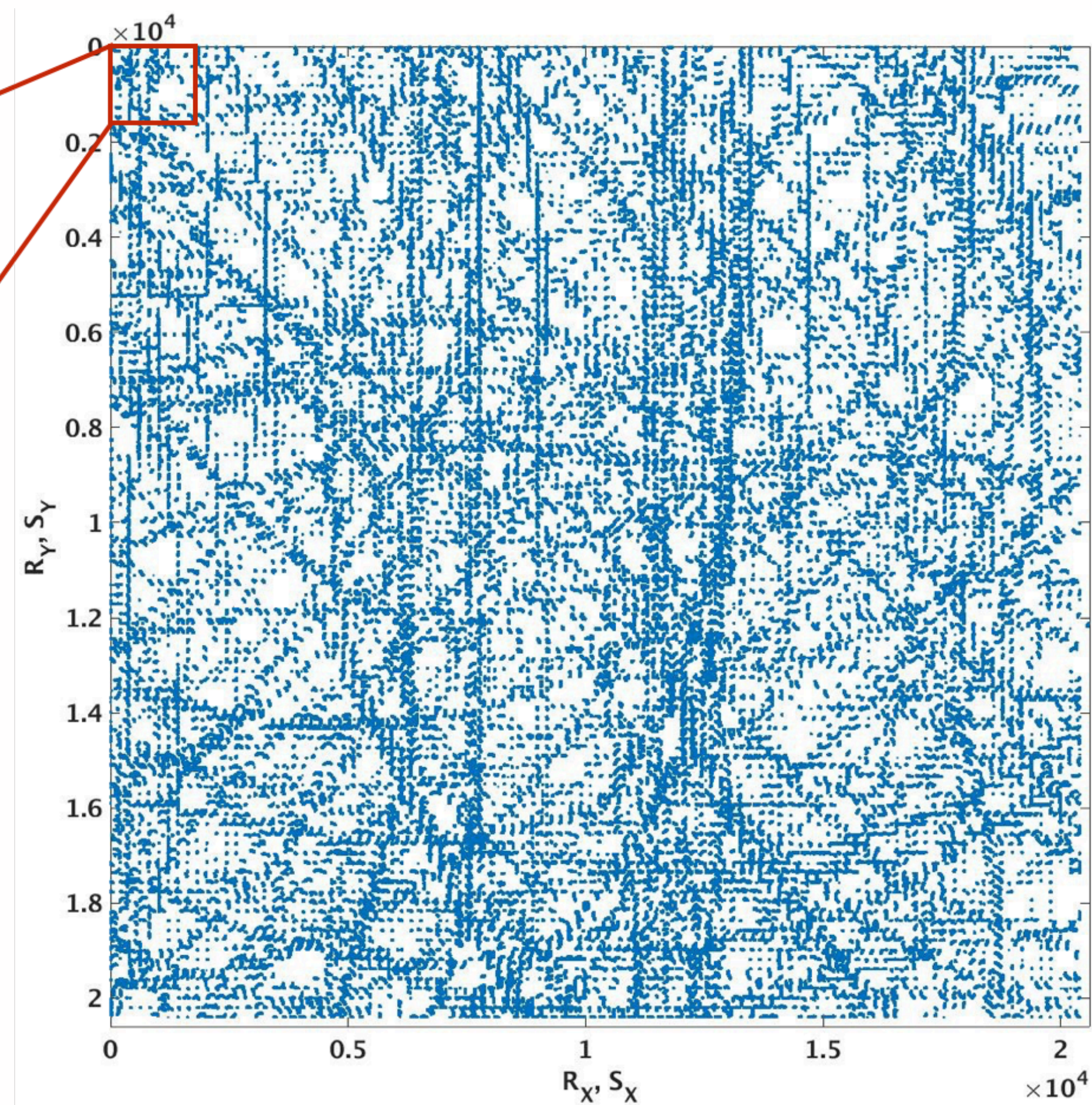
too dense: poor sampling ratio

Example 4: Coil Sampling Design

Sampling Mask: A



GSP: .4



Conclusion

- ▶ Good understanding of how to subsample
- ▶ Simple procedure to quantify acquisition design
 - compute only largest singular value of $A - \frac{|\Omega|}{nm} \mathbf{1}_{n \times m}$
 - useful tool for acquisition design

Future Work

- ▶ Generalize theorem to full rank and noisy case: $\mathbf{NN}(P_{\Omega}(X), \epsilon)$
- ▶ Suggestions? Ideas?

Acknowledgements

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Thank you for your attention!

