Data-driven optimal sparse seismic acquisition design for OBN data

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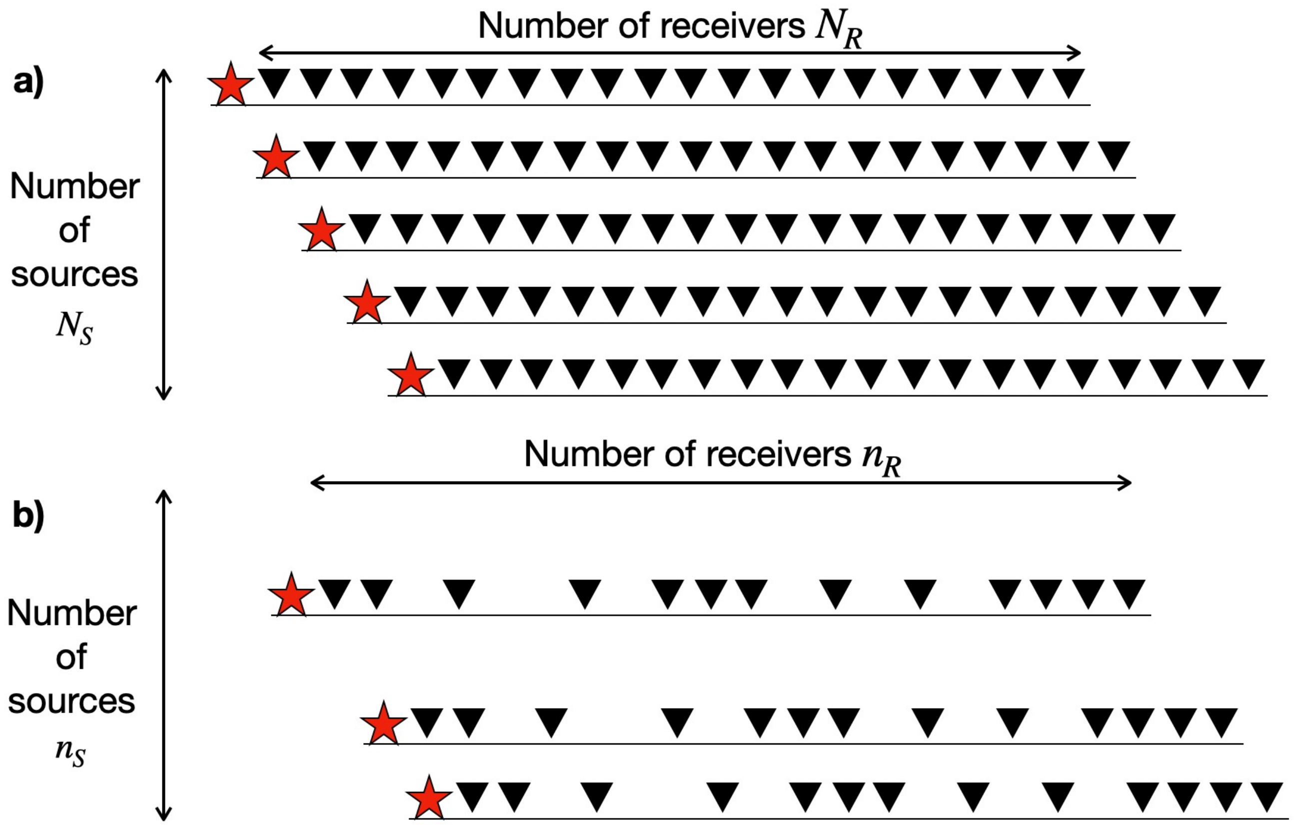
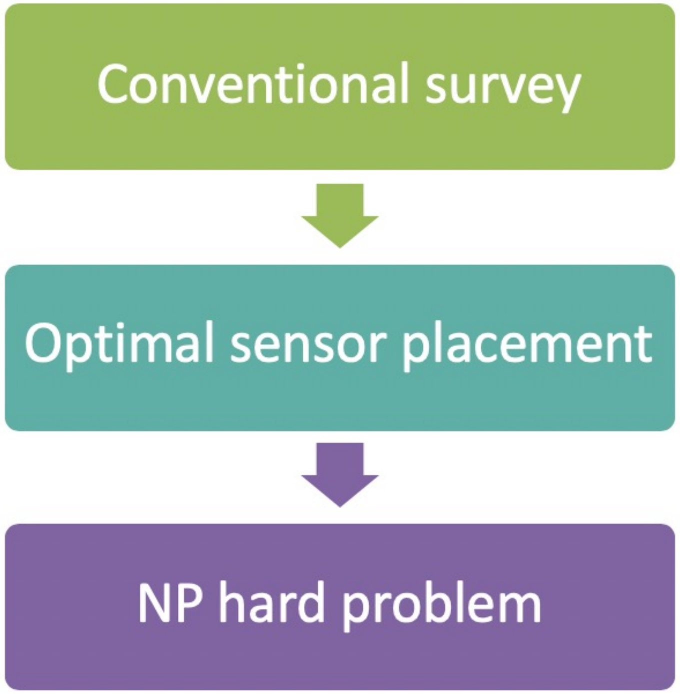
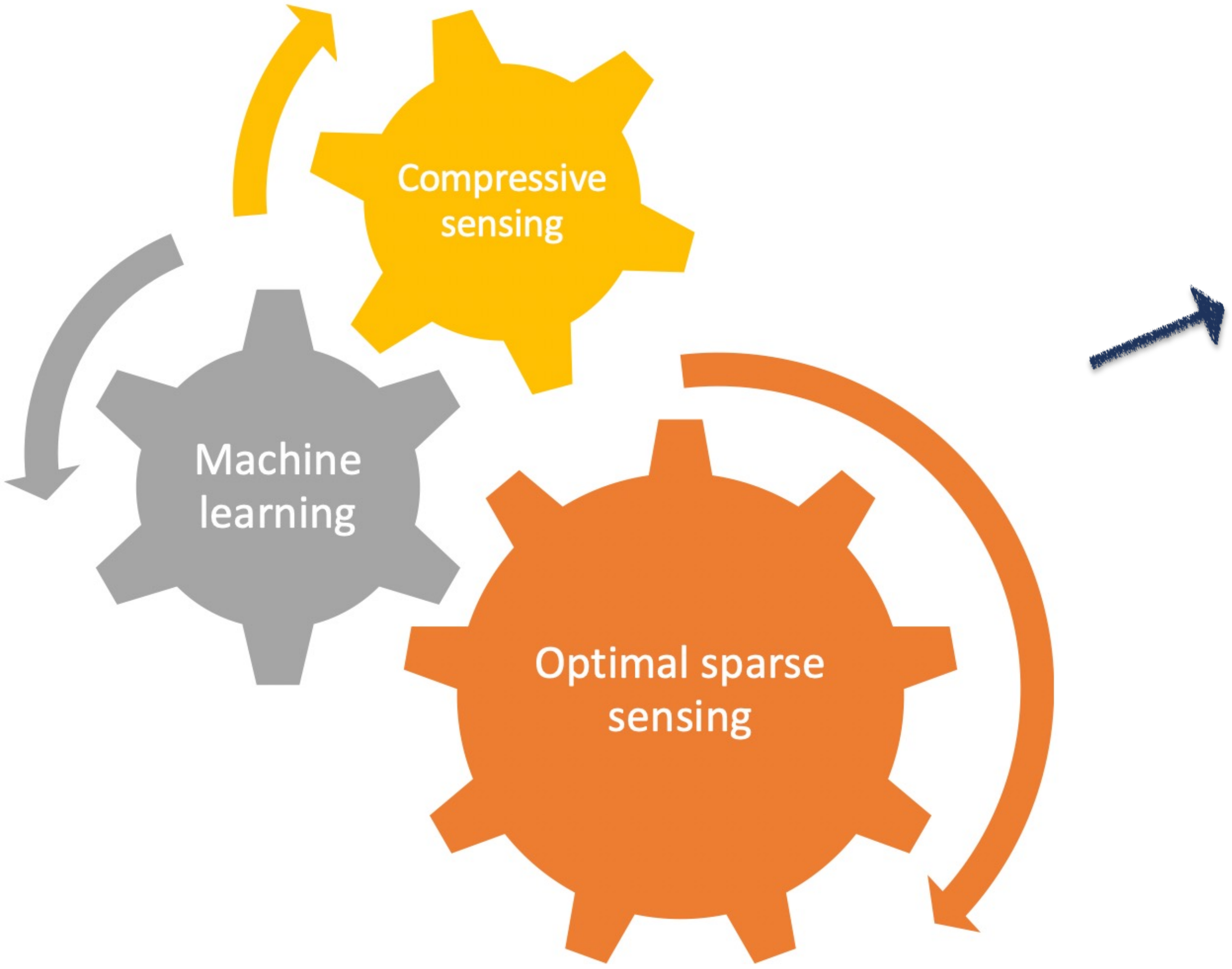
Introduction

Introduction





Introduction



Seismic survey design

Theory - compressive sensing

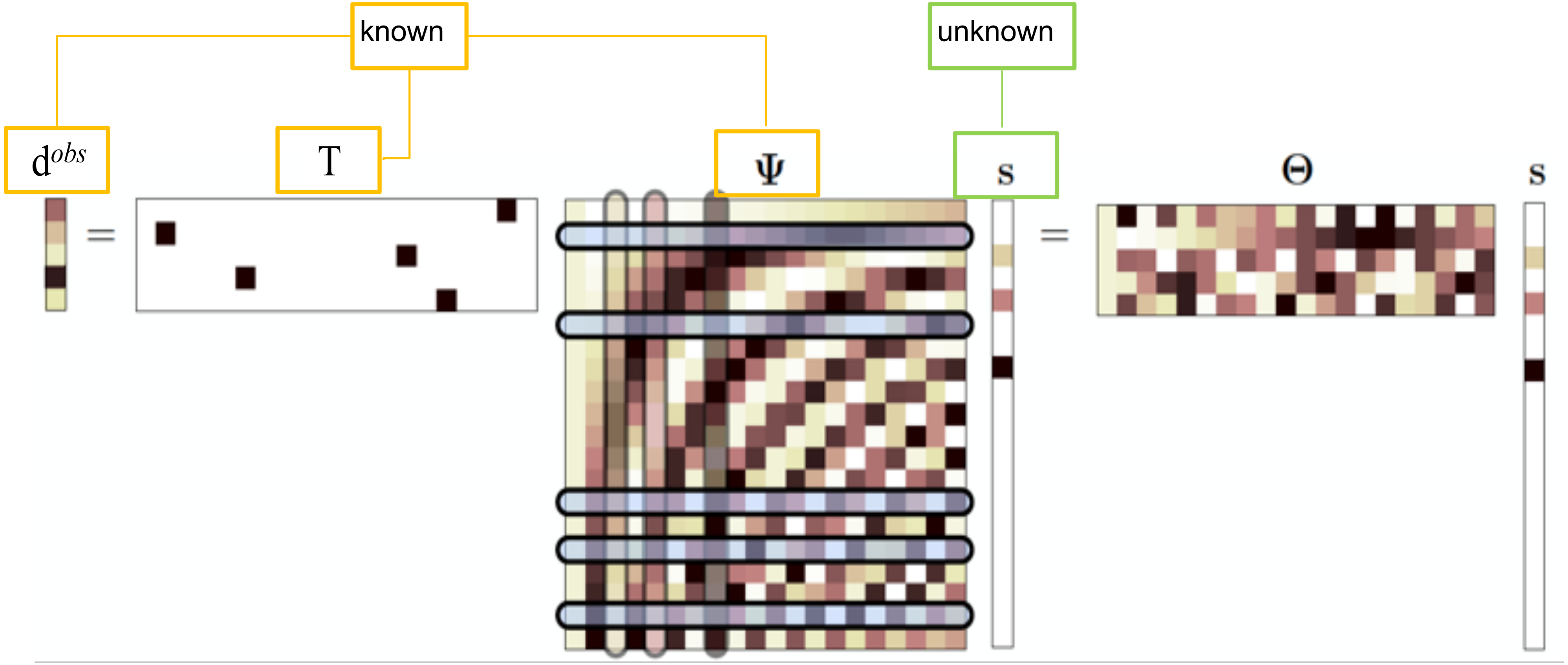
Compressive sensing

$$\mathbf{d}^{obs} = \mathbf{T}\mathbf{d} + \mathbf{n} \tag{1}$$

$$\mathbf{d}^{obs} = \mathbf{T}\boldsymbol{\Psi}\mathbf{s} + \mathbf{n} = \boldsymbol{\Theta}\mathbf{s} + \mathbf{n} \tag{2}$$

$$\mathbf{s}' = \arg\min_{\mathbf{s}} \|\mathbf{s}\|_1 \text{, subject to } \|\mathbf{d}^{obs} - \mathbf{T}\boldsymbol{\Psi}\mathbf{s}\|_2 \leq \sigma \tag{3}$$

Compressive sensing



Compressive sensing

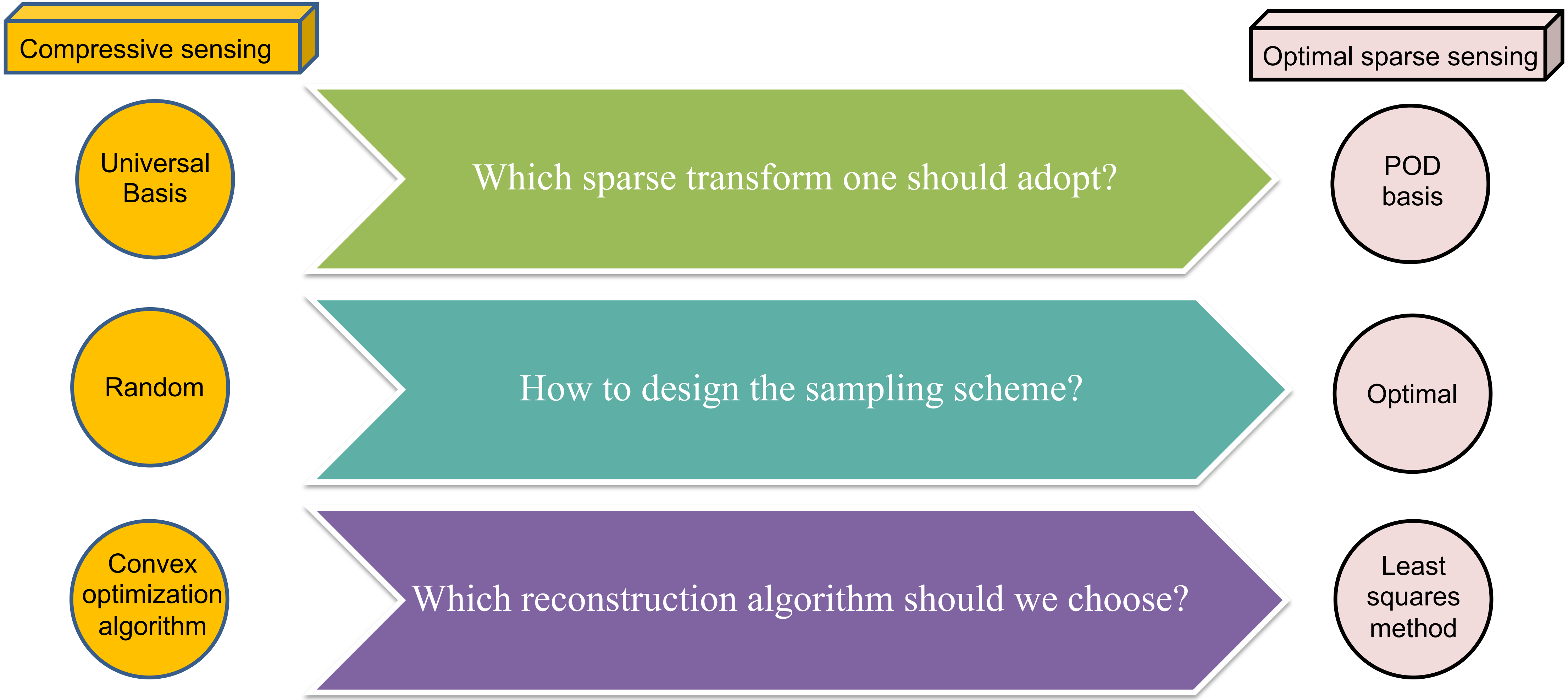
Which sparse transform one should adopt?

How to design the sampling scheme?

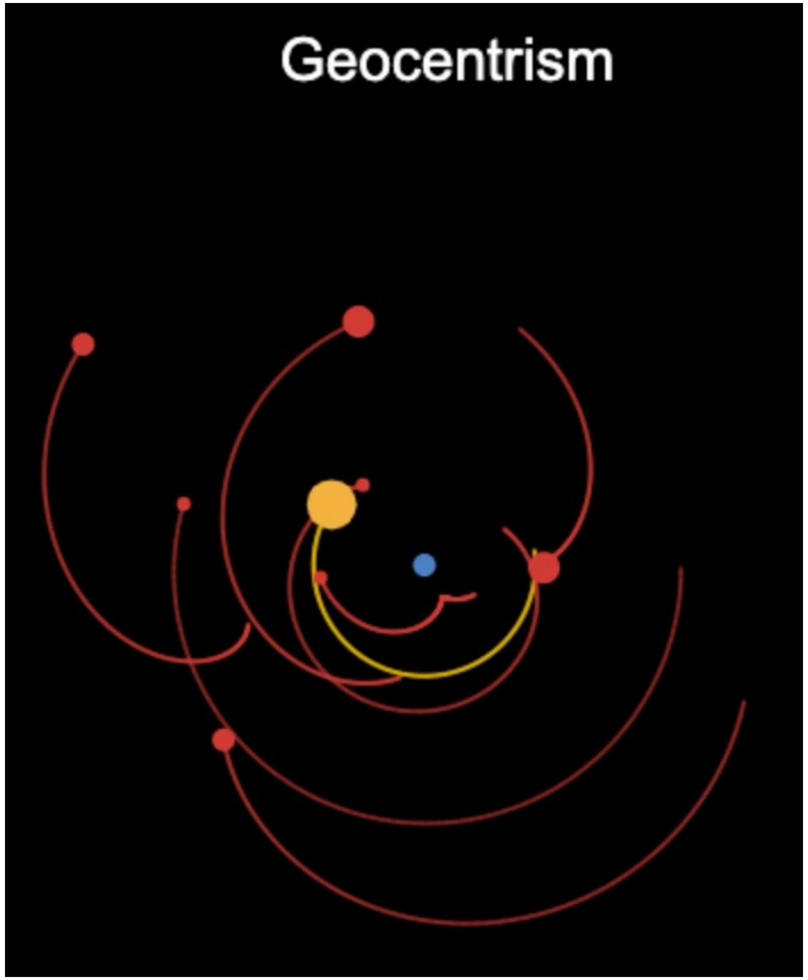
Which reconstruction algorithm should we choose?

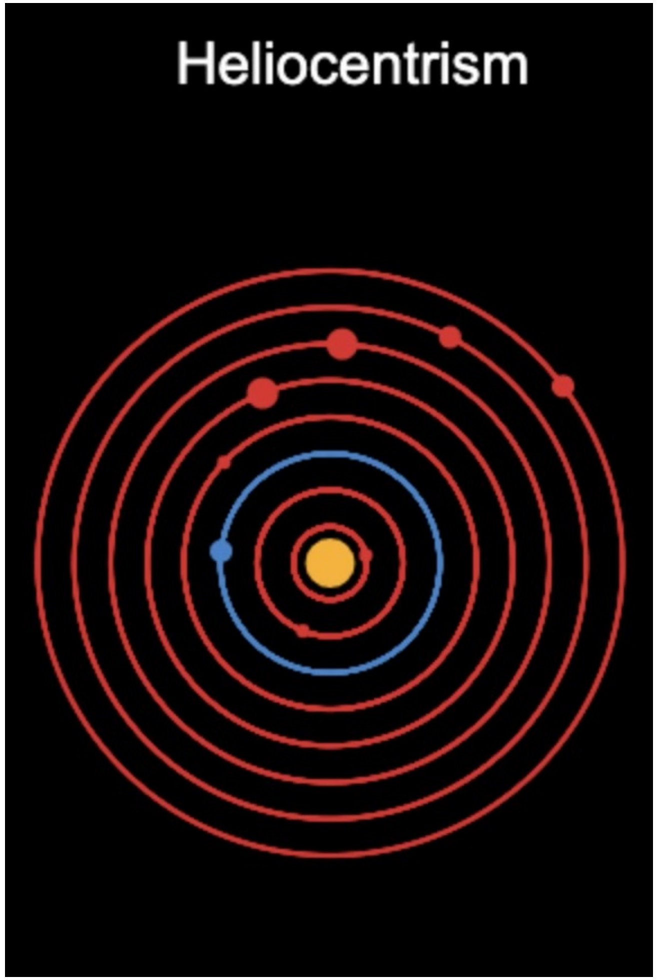
Theory – optimal sparse sensing

Optimal sparse sensing

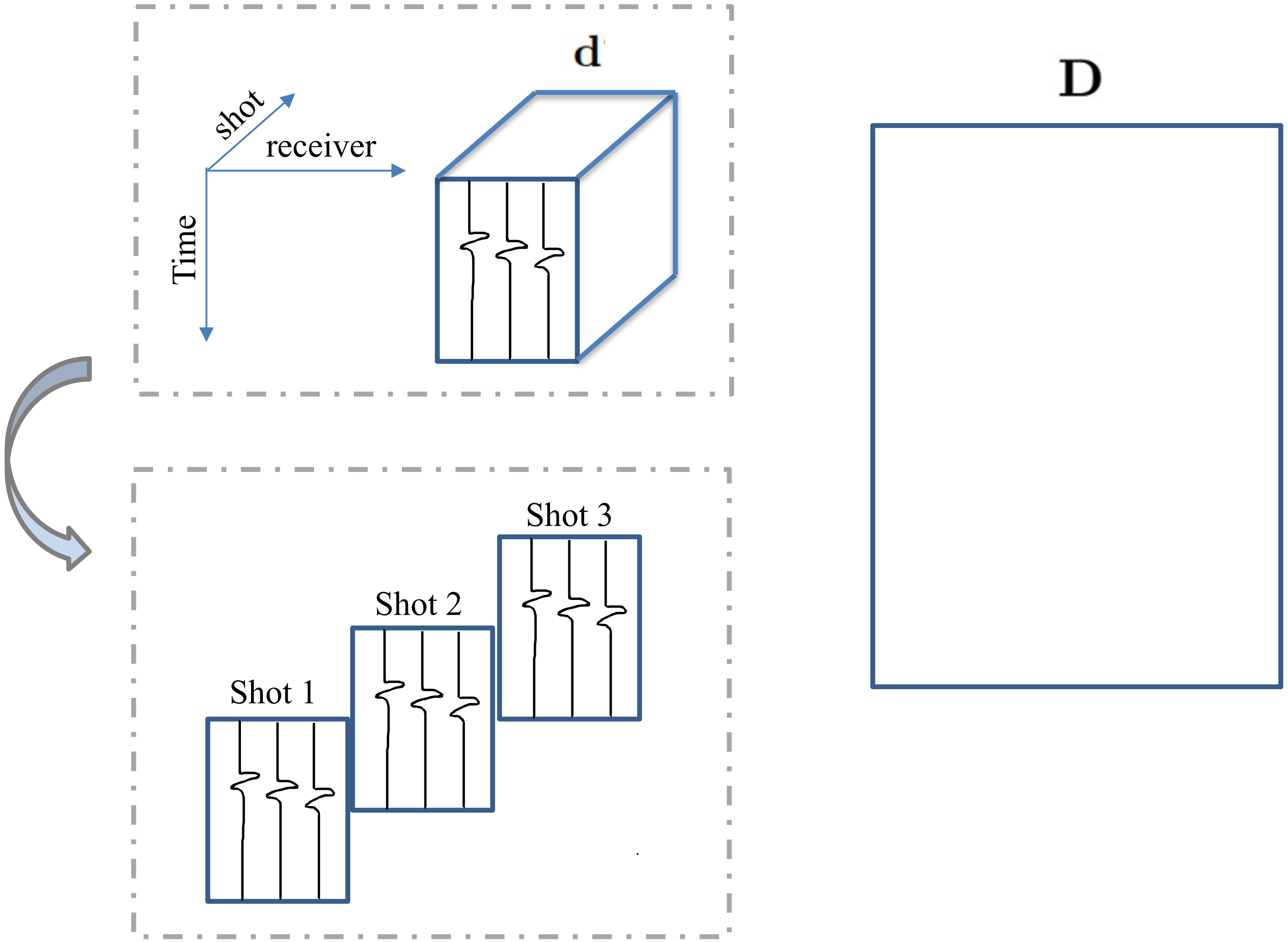


Optimal sparse sensing



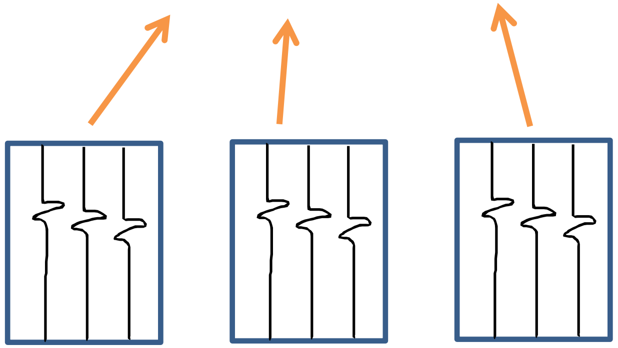


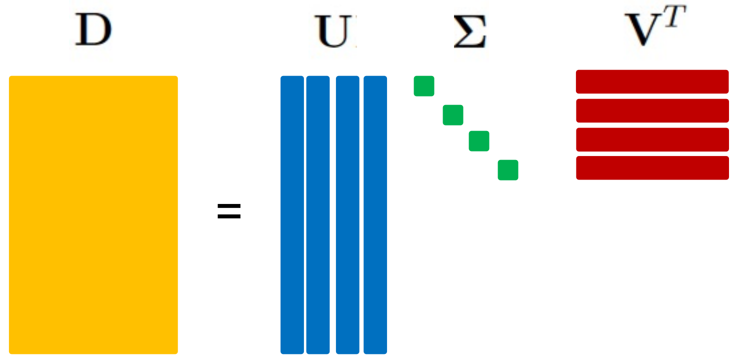
From: Malin Christersson


d
shot
receiver
Time
Shot 3
Shot 2
Shot 1
D

Optimal sparse sensing

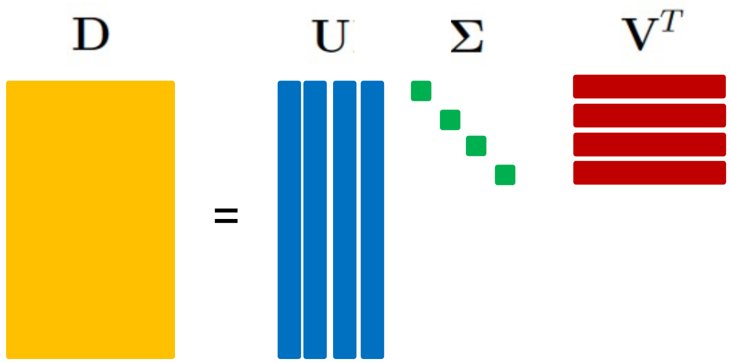
$$\mathbf{D} = \begin{bmatrix} | & | & & | \\ \mathbf{d}_1 & \mathbf{d}_2 & \cdots & \mathbf{d}_n \\ | & | & & | \end{bmatrix} \quad (4)$$

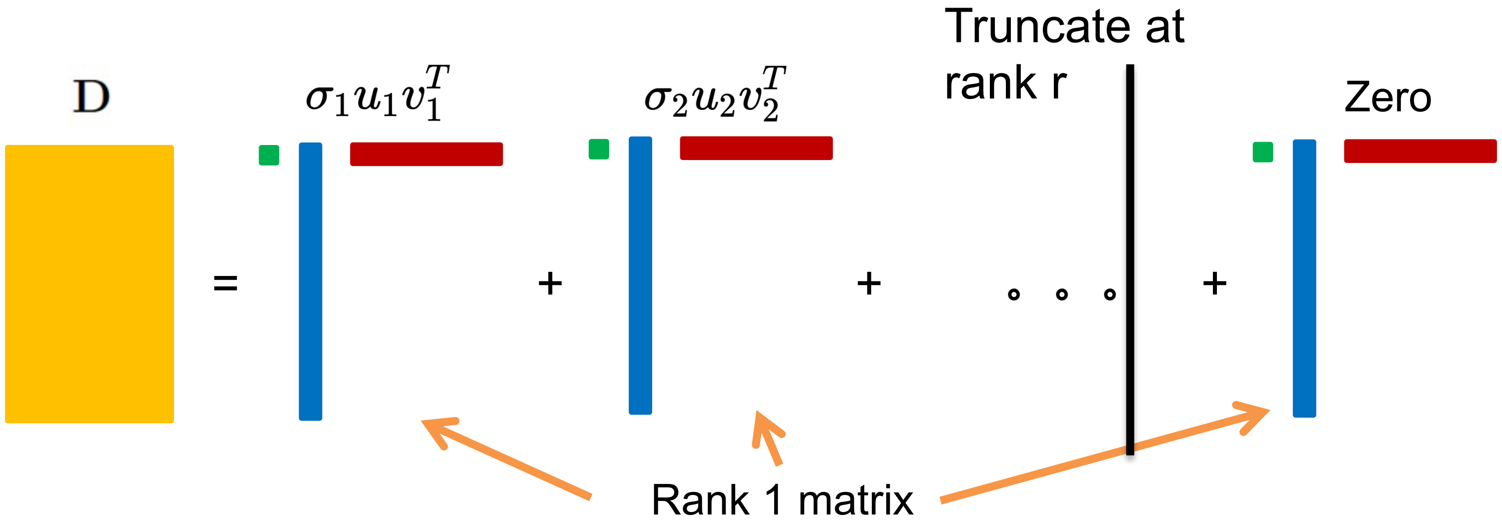




$$\mathbf{D} = \mathbf{U\Sigma V^T} = \begin{bmatrix} | & | & & | \\ \mathbf{u}_1 & \mathbf{u}_2 & \cdots & \mathbf{u}_n \\ | & | & & | \end{bmatrix} \mathbf{\Sigma V^T}$$

Optimal sparse sensing

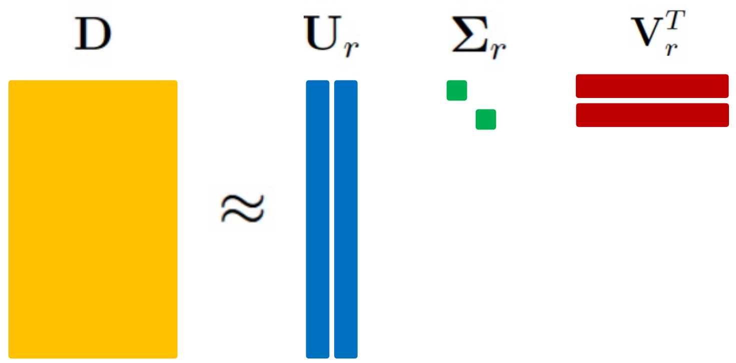




Optimal sparse sensing

According to Eckart-Young theorem:

$$\mathbf{D} = \mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^T \approx \mathbf{U}_r\boldsymbol{\Sigma}_r\mathbf{V}_r^T = \mathbf{U}_r\mathbf{A} \qquad (5)$$

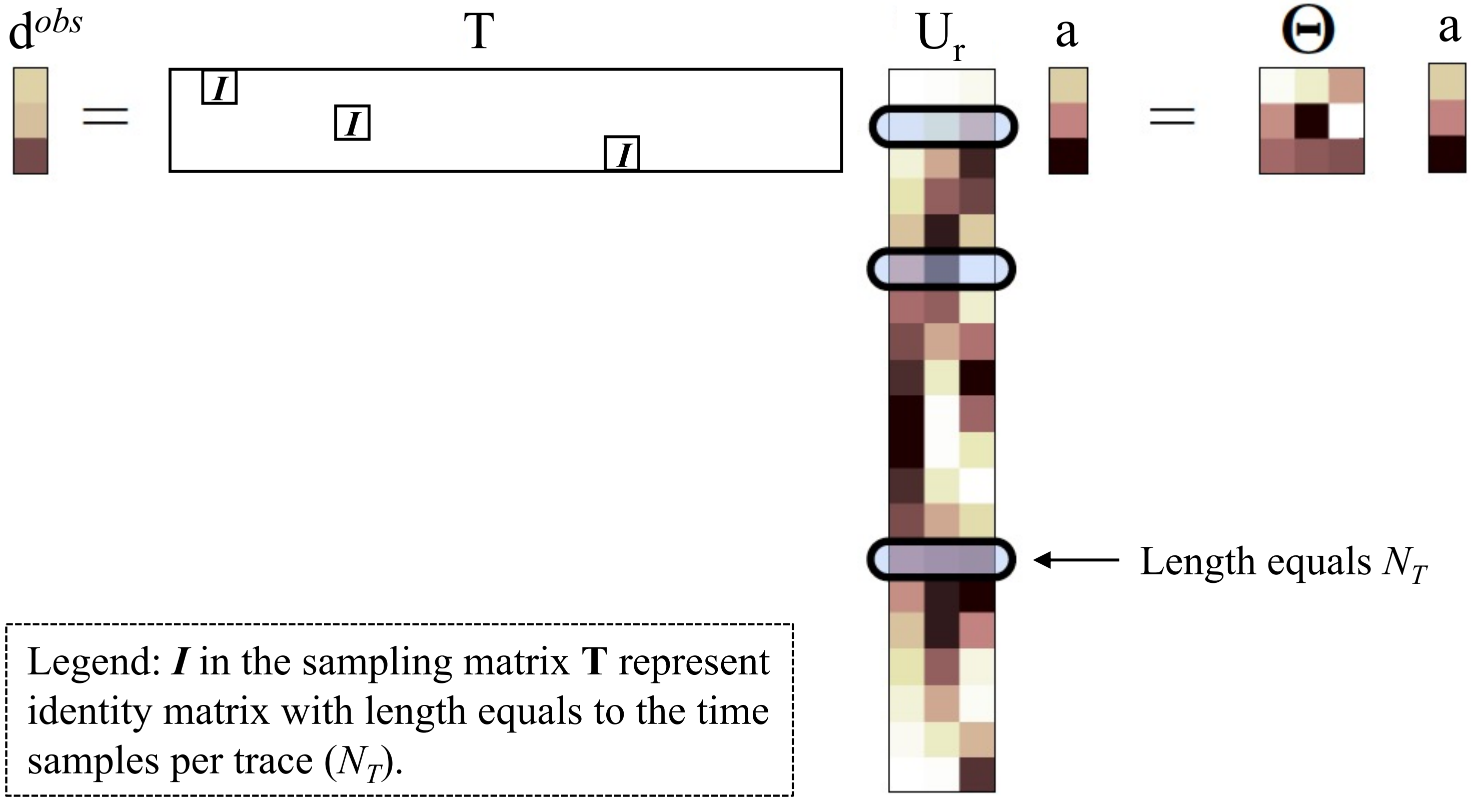


The coefficients are:

$$\mathbf{A} = \begin{bmatrix} | & | & & | \\ \mathbf{a}_1 & \mathbf{a}_2 & \cdots & \mathbf{a}_r \\ | & | & & | \end{bmatrix} \qquad (6)$$

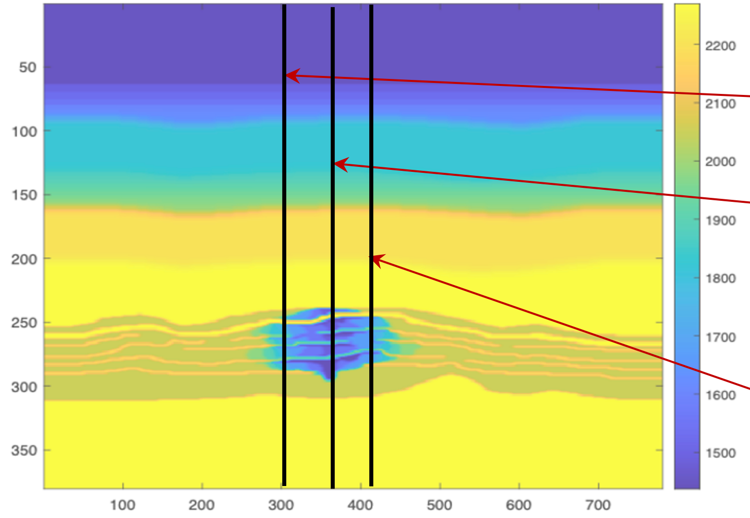
Optimal sparse sensing

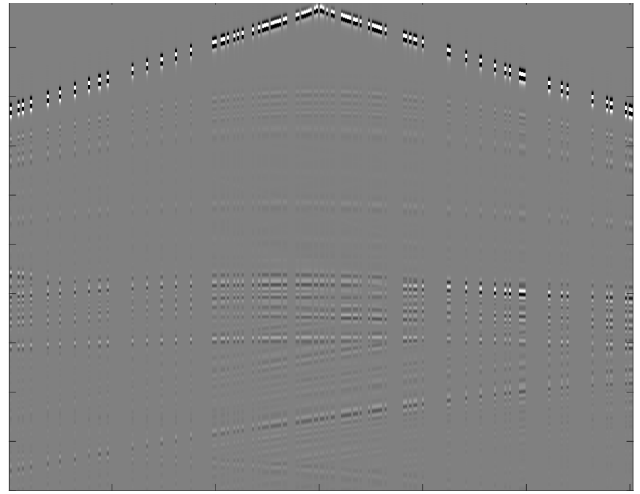
$$\mathbf{d}^{obs} = \mathbf{T}\mathbf{U}_r\mathbf{a} + \mathbf{n} = \mathbf{\Theta}\mathbf{a} + \mathbf{n} \qquad (7)$$

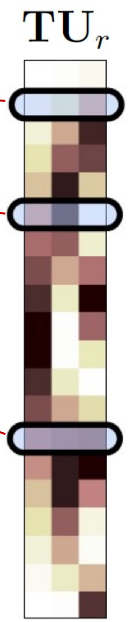


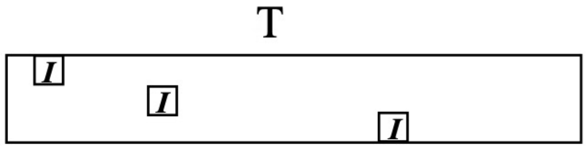
Legend: ***I*** in the sampling matrix **T** represent identity matrix with length equals to the time samples per trace (N_T).

Optimal sparse sensing









Identity matrixes in T align with selected rows in the basis.

$$\mathbf{U}_r^T \mathbf{T}^T = \mathbf{QR} \tag{8}$$

Optimal sparse sensing

$$\hat{\mathbf{a}} = \arg\min_{\mathbf{a}} \|\mathbf{a}\|_2 \,, \text{subject to} \; \|\mathbf{d}^{obs} - \mathbf{T\Psi a}\|_2 \leq \sigma \tag{9}$$

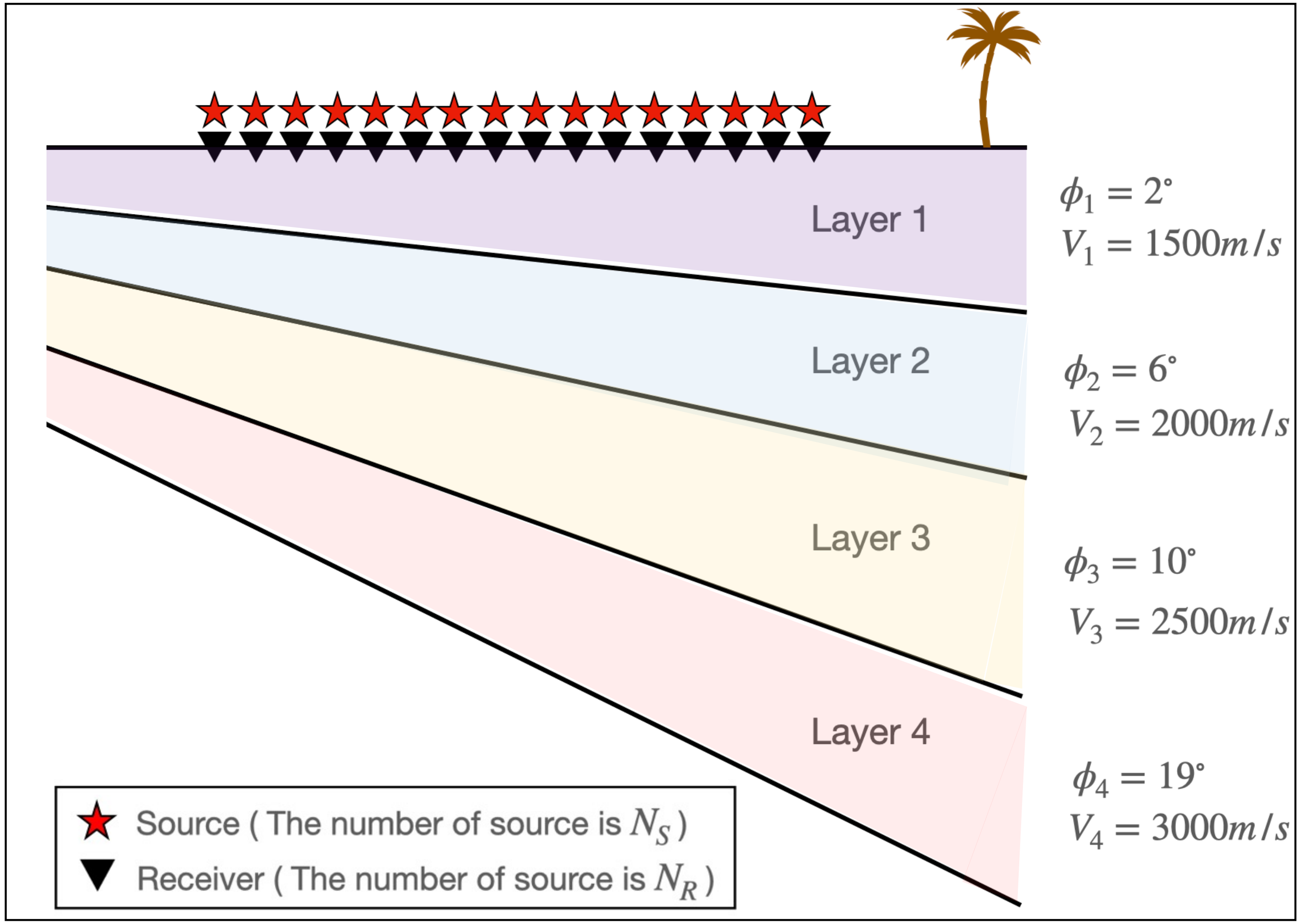
$$\mathbf{d}^{rec} = \mathbf{U}_r \hat{\mathbf{a}} \tag{10}$$

$$\text{SNR} = 10\log_{10} \frac{\|\mathbf{d}^{true}\|_F^2}{\|\mathbf{d}^{rec} - \mathbf{d}^{obs}\|_F^2} \tag{11}$$

Examples

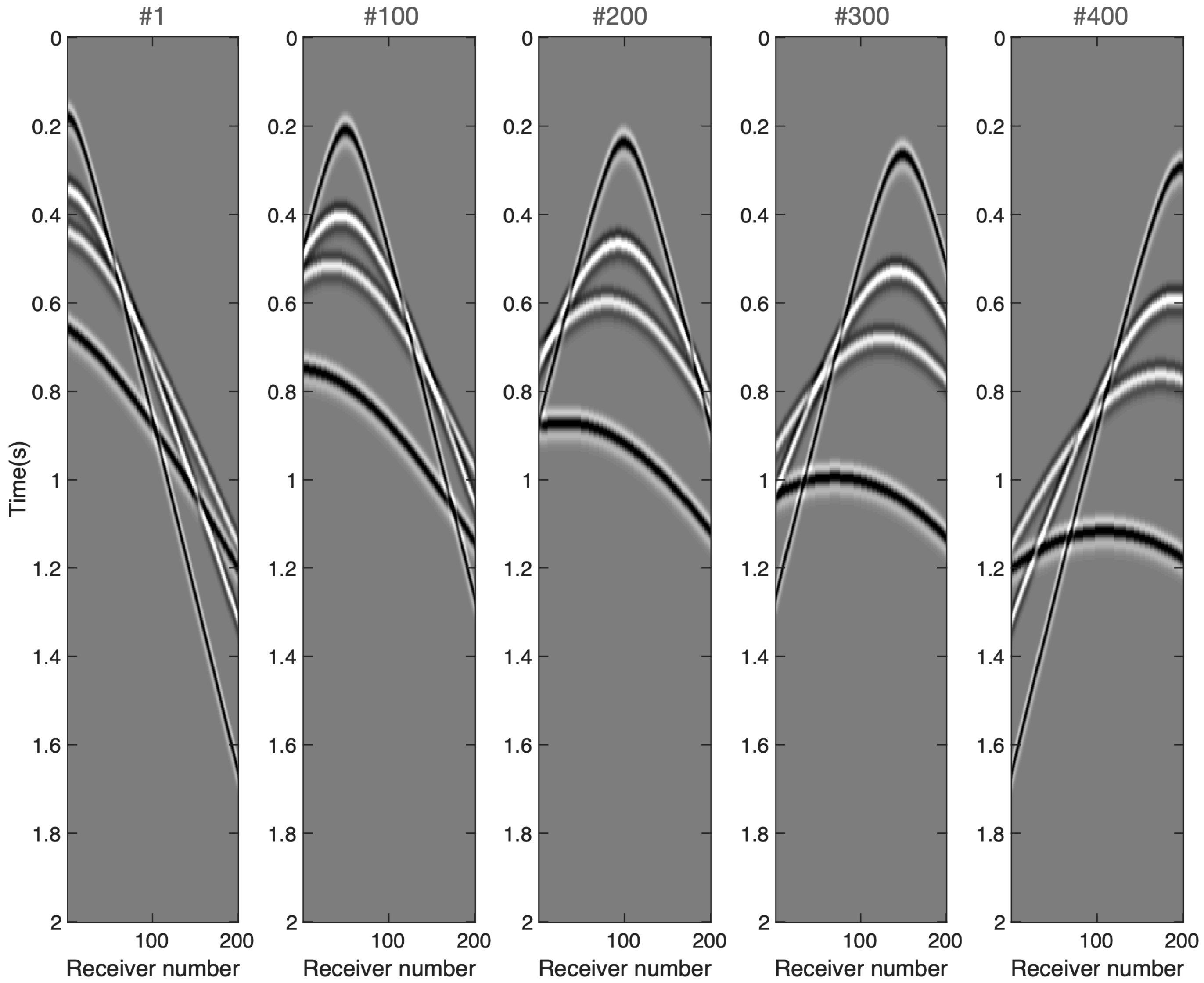
Optimal Receiver Location Selection

Optimal receivers selection

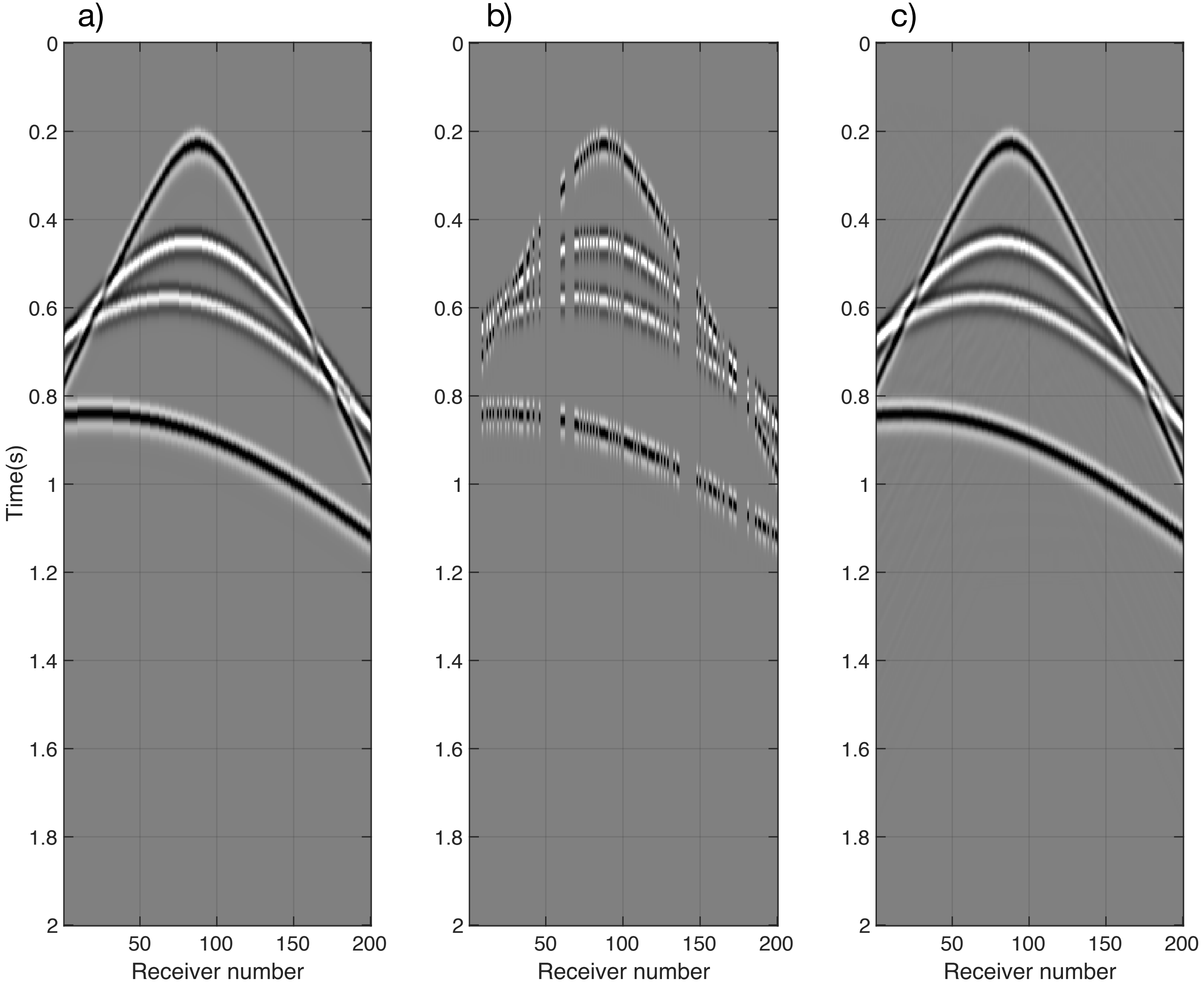


A synthetic 2D velocity model of four dipping reflectors

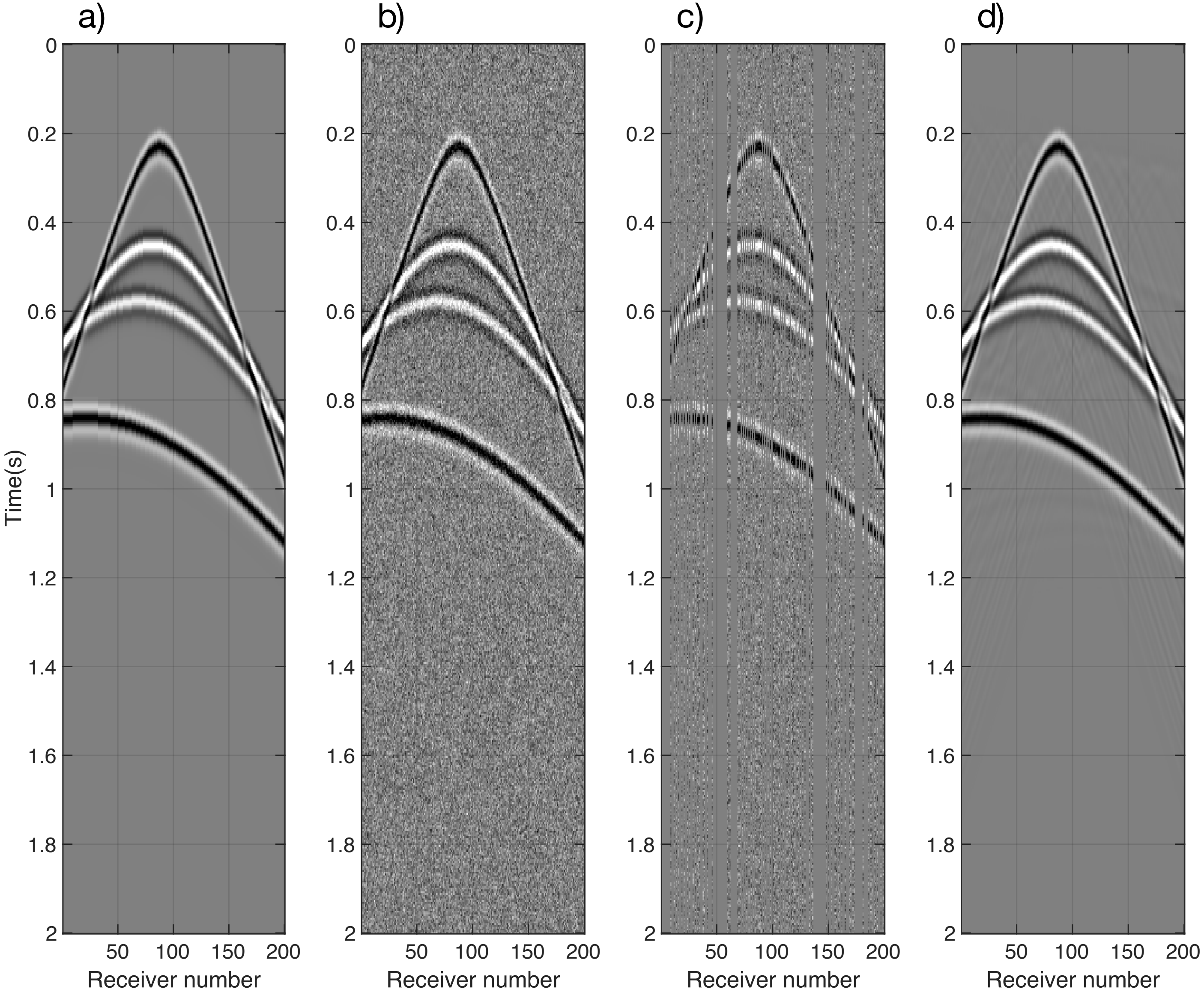
Optimal receivers selection



Optimal receivers selection

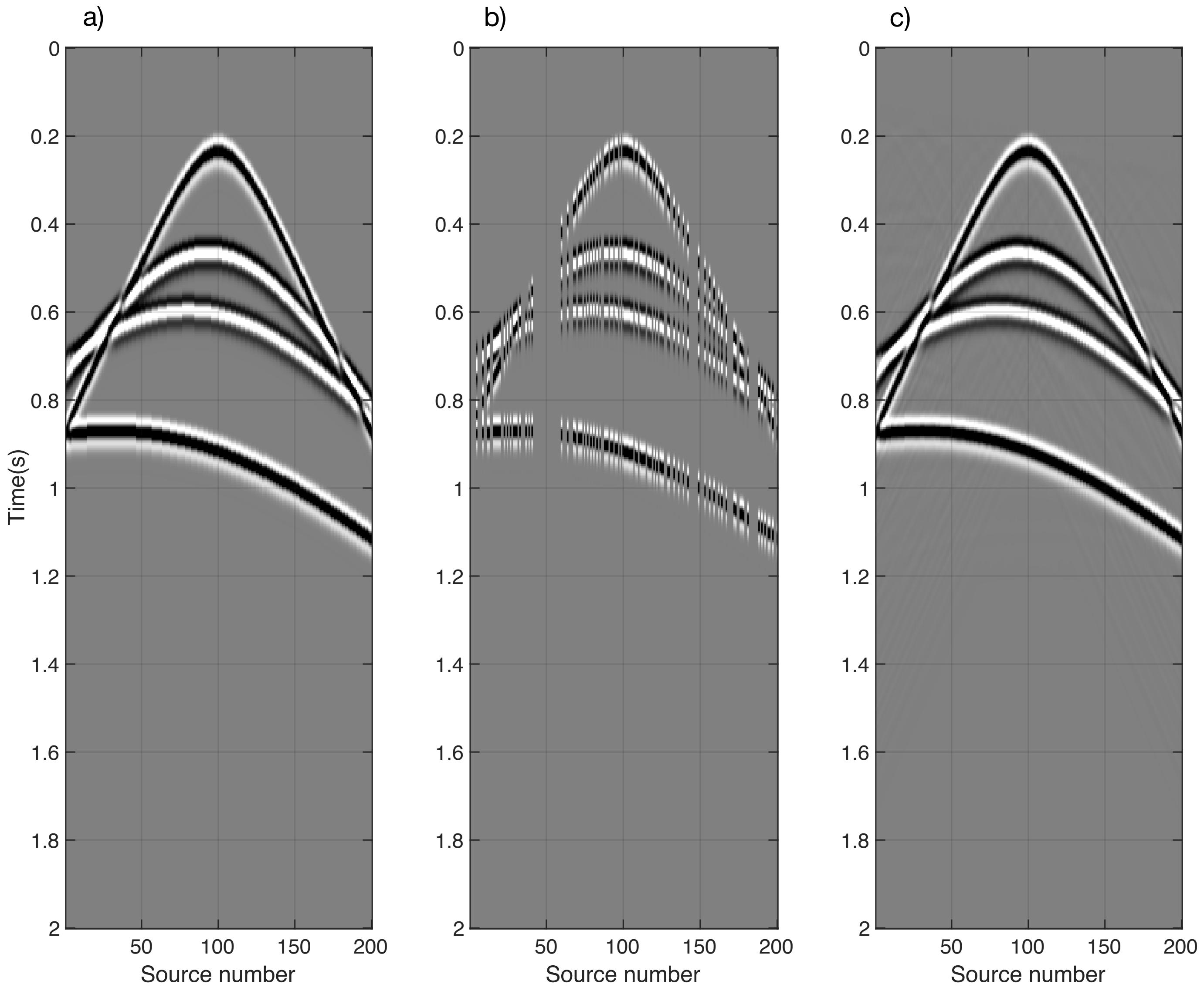


Optimal receivers selection

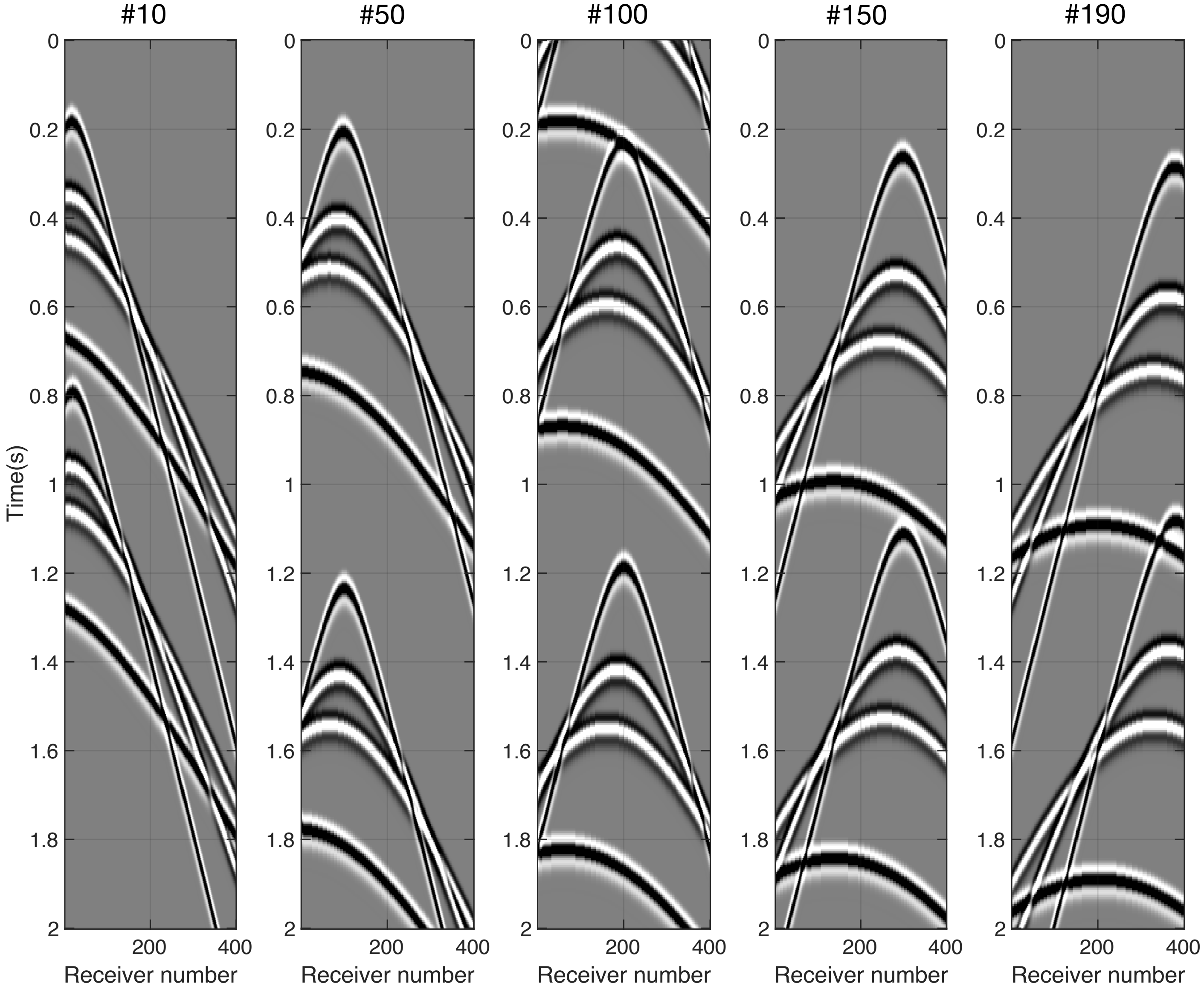


Optimal Source Location Selection

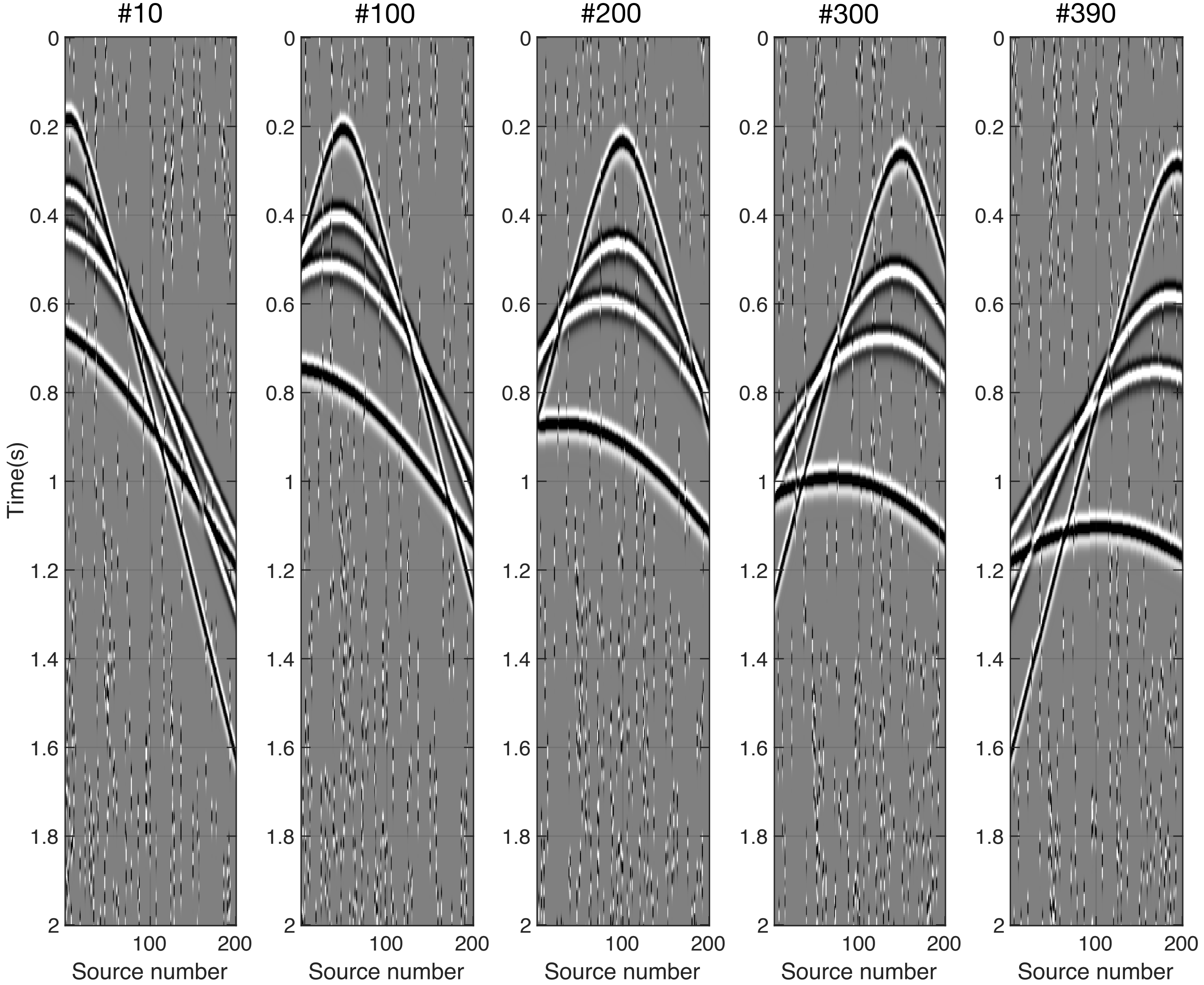
Optimal sources selection



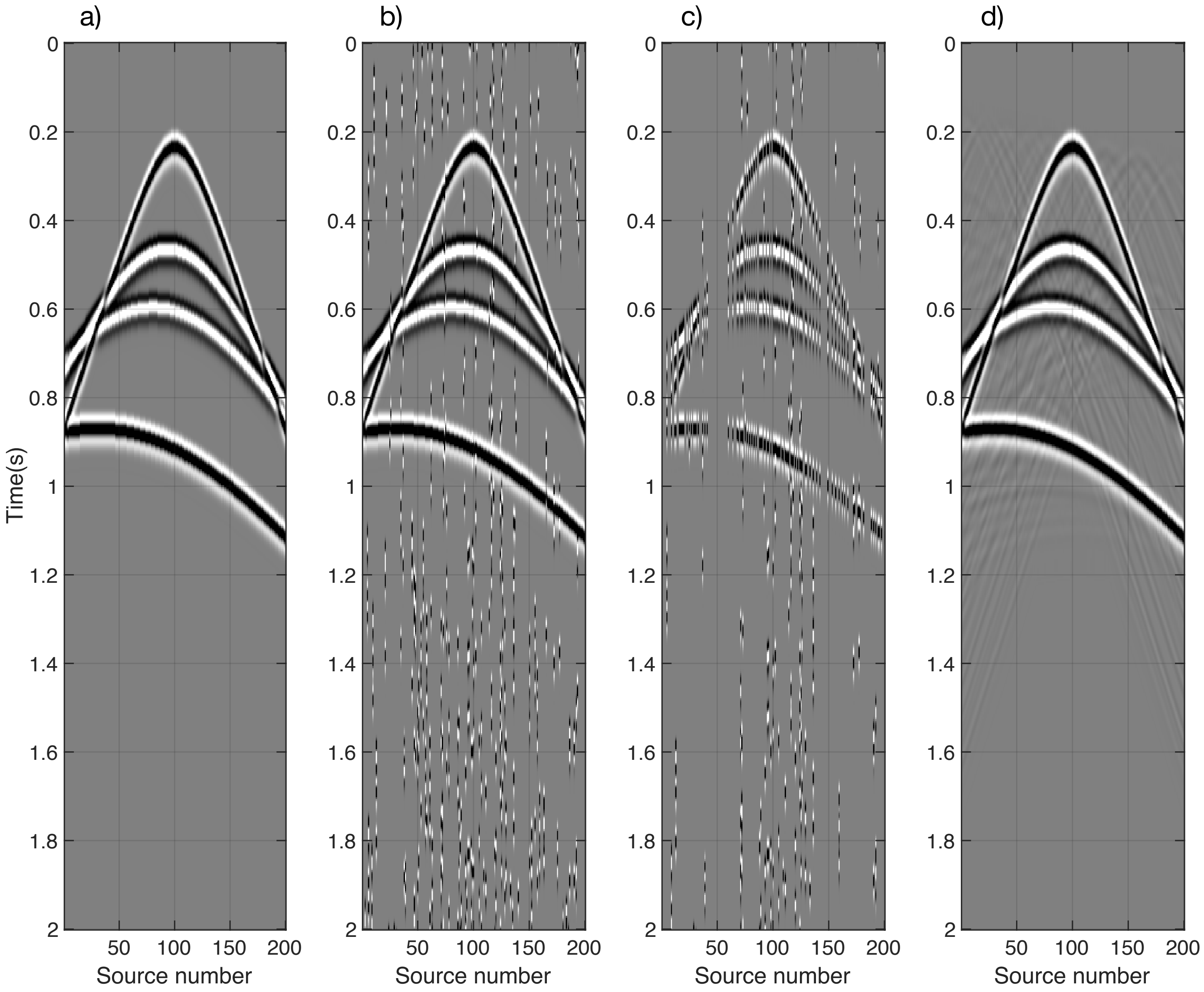
Optimal sources selection



Optimal sources selection



Deblending Noise Elimination



Seismic Acquisition Design Application

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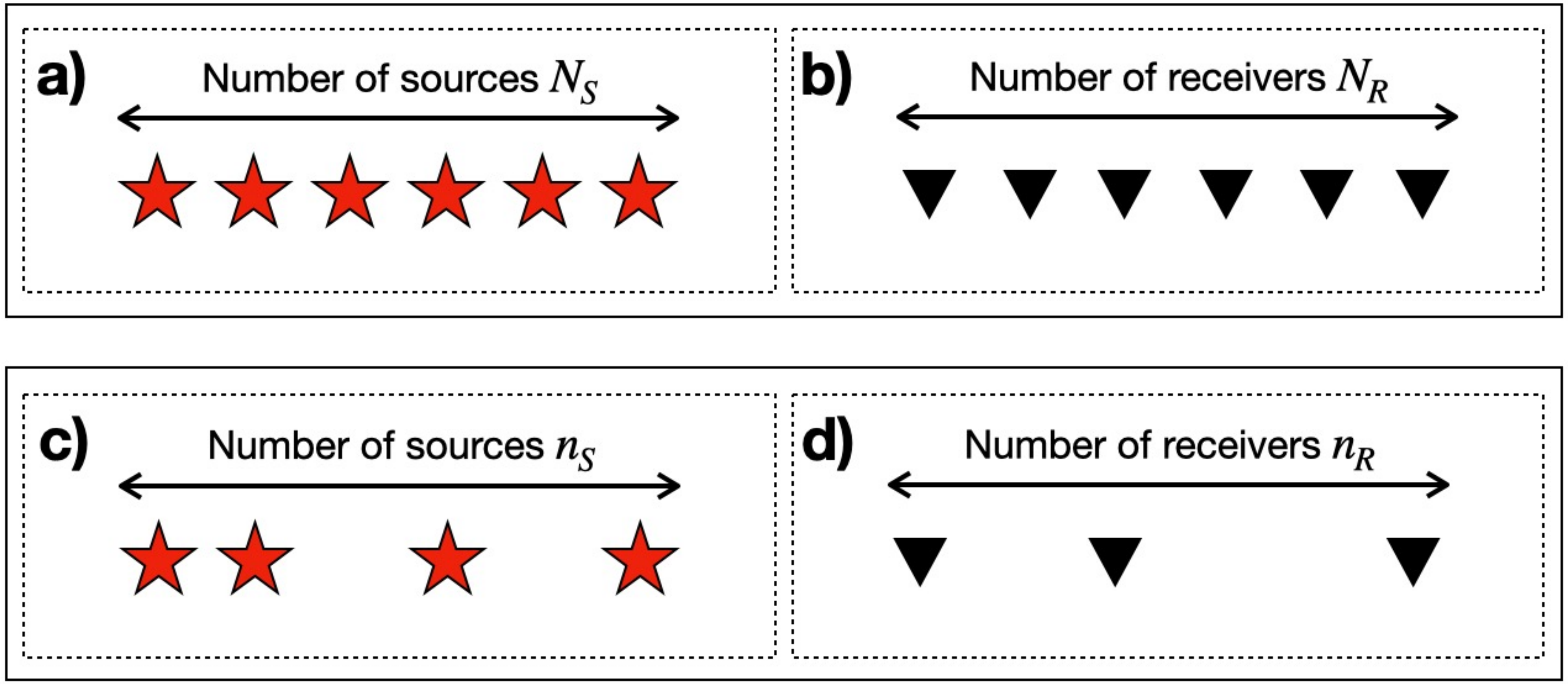
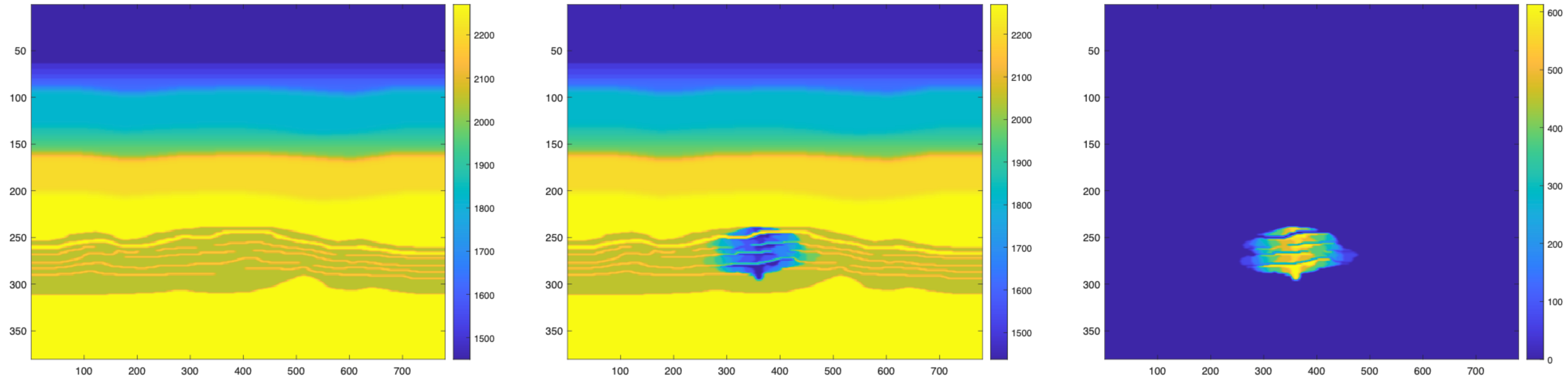


Time Lapse Application

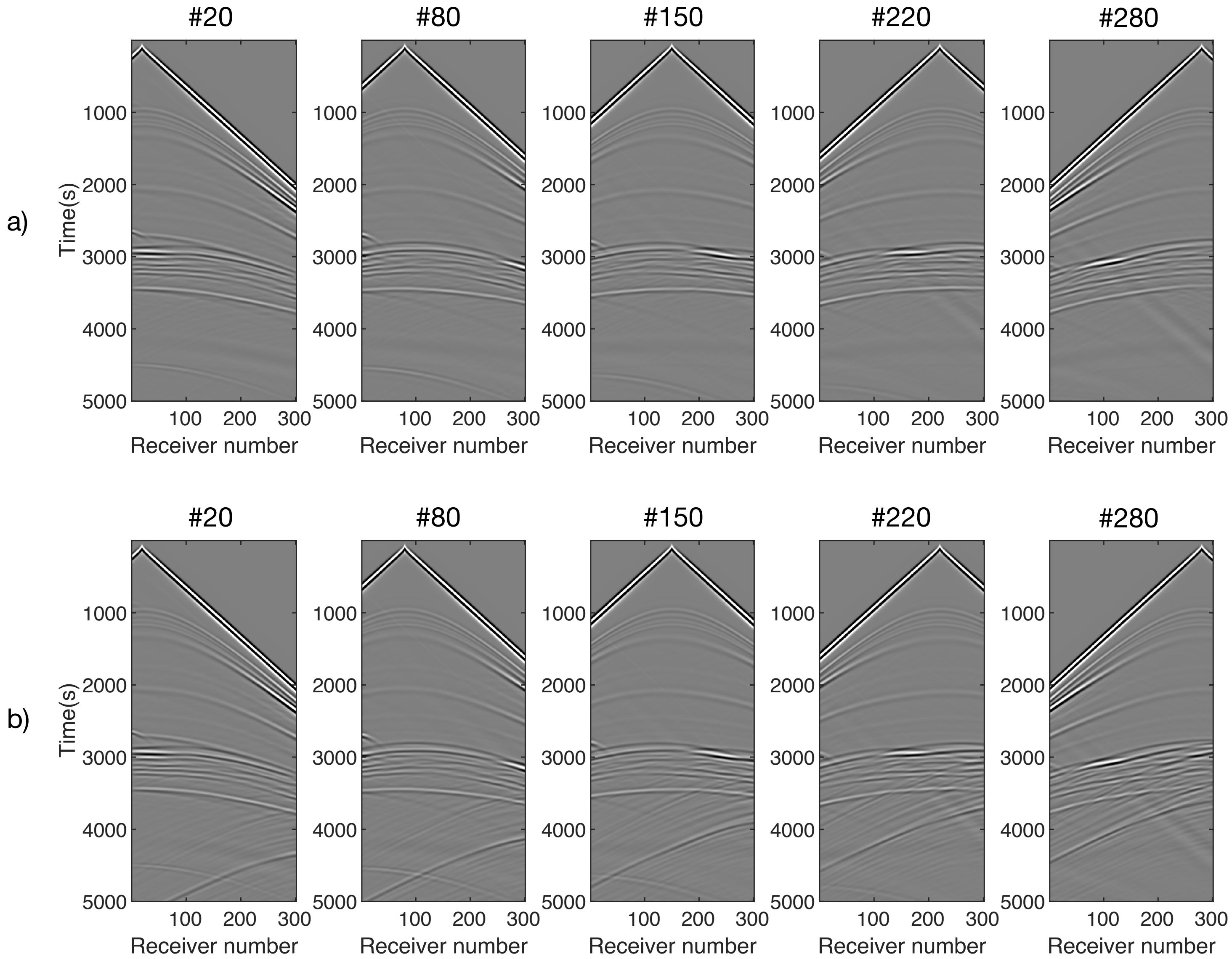
Sleipner Model

Set up:

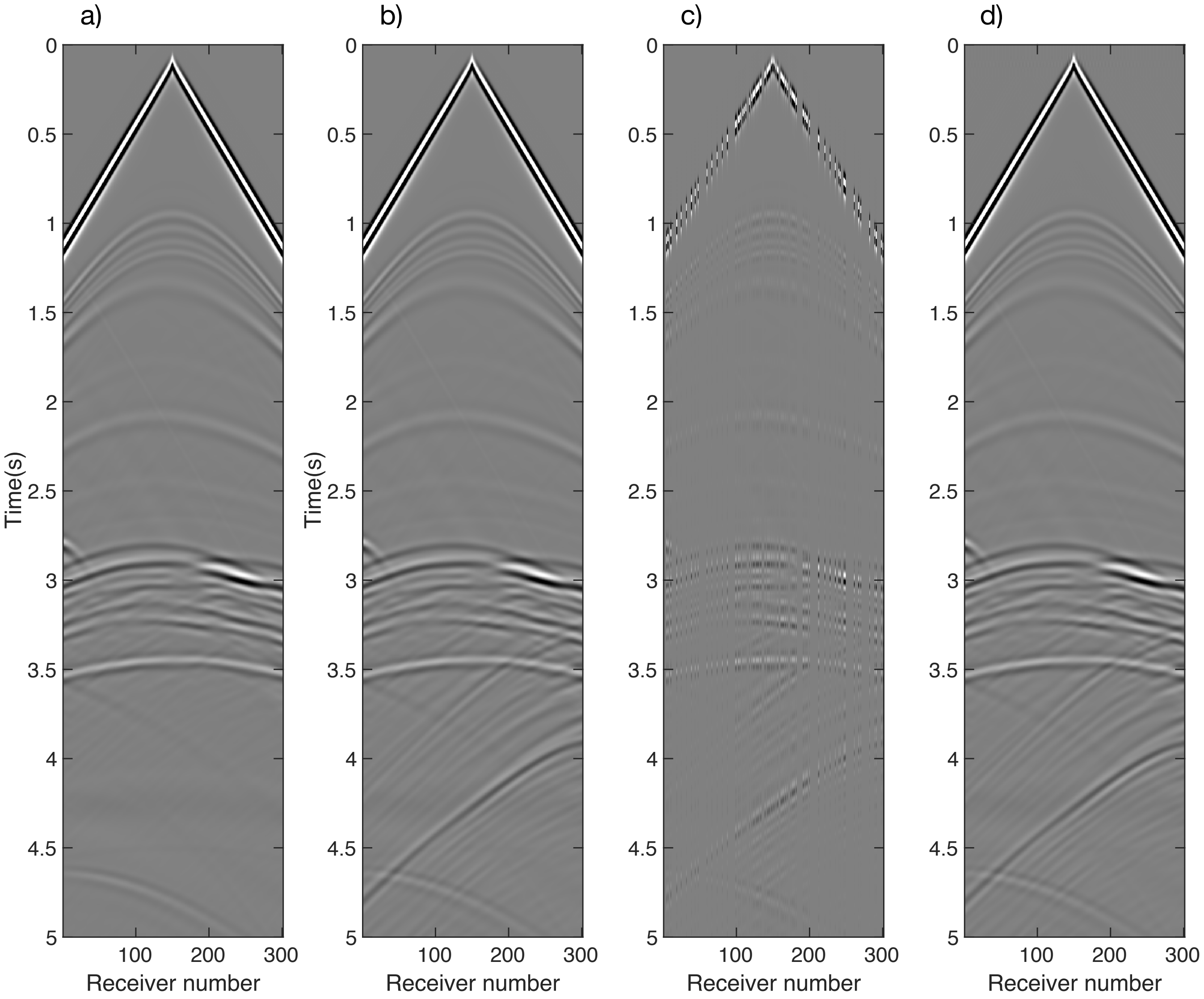
- Two set of shot gathers generated by finite-difference modelling for both the base model and the monitor model;
- 300 receivers & 300 shots.



Difference Panel



Optimal Reconstruction



Conclusions

Conclusions

- In this study, we adopted the optimal sensor selection method for seismic acquisition design.
- POD is used to extract the basis from the training dataset, and optimal acquisition geometry is determined via the QR decomposition with column pivoting.
- I tested the method on optimal receivers and sources selection examples, and synthetic data example demonstrates that using fewer sensors when given the condition that the dataset is low rank, the reconstructed result can be promising. Further, random or erratic noise, can be removed simultaneously with reconstruction.
- The time-lapse example results reveal that a previously obtained dense base survey can optimize the monitoring design.

Acknowledgments

- Sponsors of the Signal Analysis and Imaging Group at the University of Alberta

Thank you!