

# Minimax Localization of Structural Information in Large Noisy Matrices

## Poster: W055

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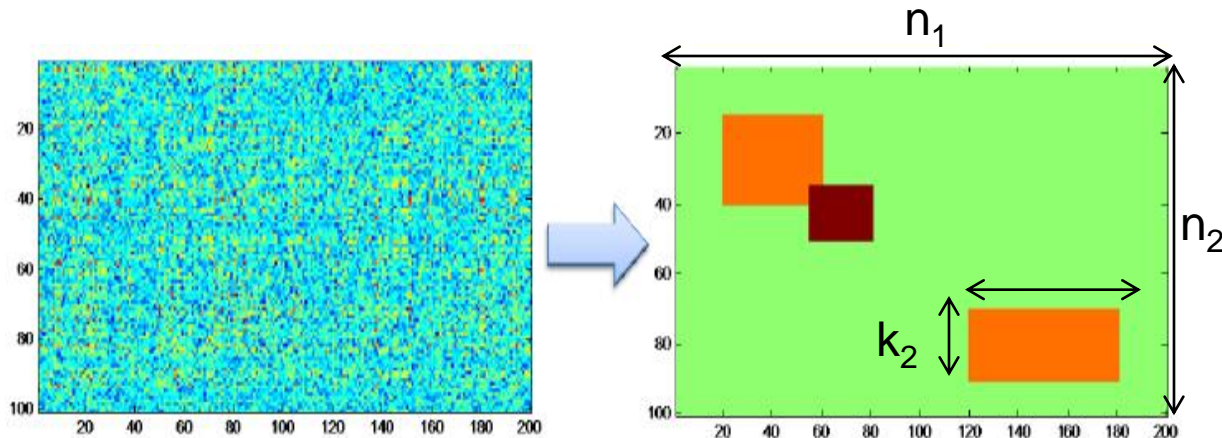


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# Identifying biclusters



**Goal:** De-noise and re-order rows/columns of the matrix to infer biclusters that are activated.

Observation model

$$\mathbf{A} = \beta \mathbf{u} \mathbf{v}^T + \mathbf{R}$$

$\mathbf{u}$  –  $k_1$  sparse unit vector  
 $\mathbf{v}$  –  $k_2$  sparse unit vector  
 $\mathbf{u}, \mathbf{v} \in \{-1, 0, 1\}$

$\mathbf{R} \sim$  i.i.d. zero-mean subgaussian( $\sigma^2$ ) perturbation

# Identifying biclusters

Information Theoretic minimax limit: If

$$\text{SNR} \quad \frac{\beta}{\sigma} \sim \sqrt{\frac{k_1 k_2 \log(n_1 n_2)}{\min(k_1, k_2)}}$$

then, for **any** biclustering procedure, the probability of failure remains bounded away from zero by a constant.

## Note:

Optimal performance achieved by scanning over all submatrices of size  $k_1 \times k_2$ .

# Computationally efficient procedures

SNR

Elementwise thresholding

Sparse Singular Value Decomposition

Row/Column Averaging

(large clusters only  $k \sim n^{1/2+\alpha}$  )

$$\left. \begin{array}{l} \text{Elementwise thresholding} \\ \text{Sparse Singular Value Decomposition} \end{array} \right\} \frac{\beta}{\sigma} \sim \sqrt{k_1 k_2 \log(n_1 n_2)}$$

$$\frac{\beta}{\sigma} \sim \frac{\sqrt{k_1 k_2 \log(n_1 n_2)}}{\min(n_1^\alpha, n_2^\alpha)}$$

## Note:

These procedures do not achieve information theoretic lower bound.