

Tracking dominant symmetric matrices (including a new matrix factorization)

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We want to approximate an $N \times N$ indefinite symmetric matrix H by a rank r factorization

$$H \approx U M U^T$$

where $U^T U = I_r$ and M is allowed to be indefinite as well

The optimal approximation is known

- ▶ $\Lambda(M)$ contains the r largest eigenvalues of H (in modulus)
- ▶ $\text{Im}(U)$ is a basis for the corresponding eigenspace

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Goal :

Iterative procedure for large dense matrices in $\mathcal{O}(Nnr)$ complexity

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Iterative procedure for large dense matrices in $\mathcal{O}(Nnr)$ complexity ($r \ll N$ is the rank of M and $n \leq N$ is the window size of the method)

"Sweeping" through H

We show only the columns and rows of U and H that are involved

$$\begin{bmatrix} \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \end{bmatrix} \quad \begin{bmatrix} \times & \times & \times & \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times & \times & \times & \times \end{bmatrix}$$

Rank $r = 3$ and we will use window size $n = 6$

step 1

$$\begin{bmatrix} \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \end{bmatrix} \begin{bmatrix} \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times \end{bmatrix}$$

Start with leading $n \times n$ subproblem ($n = 6$ is the window size)

step 2

$$\begin{bmatrix} \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \end{bmatrix} \begin{bmatrix} \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \end{bmatrix}$$

Expand

step 2

$$\begin{bmatrix} \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \end{bmatrix} \begin{bmatrix} \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \end{bmatrix}$$

Expand also U (rank increases by 2)

step 3

$$\begin{bmatrix} \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \end{bmatrix} \begin{bmatrix} \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \end{bmatrix}$$

Downdate rank ...

step 4

$$\begin{bmatrix} \times & \times & \times \\ \times & \times & \times \\ \color{red}{\times} & \color{red}{\times} & \color{red}{\times} \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \end{bmatrix} \begin{bmatrix} \times & \times & \color{red}{\times} & \times & \times & \times & \times \\ \times & \times & \color{red}{\times} & \times & \times & \times & \times \\ \color{red}{\times} & \color{red}{\times} & \color{red}{\times} & \color{red}{\times} & \color{red}{\times} & \color{red}{\times} & \color{red}{\times} \\ \times & \times & \color{red}{\times} & \times & \times & \times & \times \\ \times & \times & \color{red}{\times} & \times & \times & \times & \times \\ \times & \times & \color{red}{\times} & \times & \times & \times & \times \\ \times & \times & \color{red}{\times} & \times & \times & \times & \times \end{bmatrix}$$

... and also **downsize window**

step 4

$$\begin{bmatrix} \times & \times & \times \\ \times & \times & \times \\ \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \end{bmatrix} \begin{bmatrix} \times & \times & & \times & \times & \times & \times \\ \times & \times & & \times & \times & \times & \times \\ \\ \times & \times & & \times & \times & \times & \times \\ \times & \times & & \times & \times & \times & \times \\ \times & \times & & \times & \times & \times & \times \\ \times & \times & & \times & \times & \times & \times \end{bmatrix}$$

step 5

$$\begin{bmatrix} \times & \times & \times \\ \times & \times & \times \\ \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \end{bmatrix} \begin{bmatrix} \times & \times & & \times & \times & \times & \times & \times \\ \times & \times & & \times & \times & \times & \times & \times \\ \\ \times & \times & & \times & \times & \times & \times & \times \\ \times & \times & & \times & \times & \times & \times & \times \\ \times & \times & & \times & \times & \times & \times & \times \\ \times & \times & & \times & \times & \times & \times & \times \\ \times & \times & & \times & \times & \times & \times & \times \end{bmatrix}$$

Expand

step 6

$$\begin{bmatrix} \times & \times & \times \\ \times & \times & \times \\ \\ \times & \times & \times \\ \color{red}{\times} & \color{red}{\times} & \color{red}{\times} \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \end{bmatrix} \begin{bmatrix} \times & \times & \times & \color{red}{\times} & \times & \times & \times \\ \times & \times & \times & \color{red}{\times} & \times & \times & \times \\ \\ \times & \times & \times & \color{red}{\times} & \times & \times & \times \\ \color{red}{\times} & \color{red}{\times} & \color{red}{\times} & \color{red}{\times} & \color{red}{\times} & \color{red}{\times} & \color{red}{\times} \\ \times & \times & \times & \color{red}{\times} & \times & \times & \times \\ \times & \times & \times & \color{red}{\times} & \times & \times & \times \\ \times & \times & \times & \color{red}{\times} & \times & \times & \times \end{bmatrix}$$

Downdate and downsize

step 7

$$\begin{bmatrix} \times & \times & \times \\ \times & \times & \times \\ \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \\ \\ \end{bmatrix} \begin{bmatrix} \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times \\ \\ \times & \times & \times & \times & \times & \times \\ \\ \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times \\ \\ \end{bmatrix}$$

step 8

The diagram illustrates two 6x4 grids of 'x' marks. The left grid contains 24 black 'x' marks. The right grid contains 24 'x' marks, with 16 black and 8 blue. The blue 'x' marks are located in the bottom row of the right grid.

Expand

step 9

$$\begin{bmatrix} \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \end{bmatrix} \begin{bmatrix} \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \end{bmatrix}$$

Downdate and downsize

step 10

[illegible]

step 11

$$\begin{bmatrix} \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \end{bmatrix} \begin{bmatrix} \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times & \times \end{bmatrix}$$

Expand

step 12

$$\begin{bmatrix} \times & \times & \times \\ \times & \times & \times \\ \color{red}{\times} & \color{red}{\times} & \color{red}{\times} \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \end{bmatrix} \begin{bmatrix} \times & \times & \color{red}{\times} & \times & \times & \times & \times \\ \times & \times & \color{red}{\times} & \times & \times & \times & \times \\ \color{red}{\times} & \color{red}{\times} & \color{red}{\times} & \color{red}{\times} & \color{red}{\times} & \color{red}{\times} & \color{red}{\times} \\ \times & \times & \color{red}{\times} & \times & \times & \times & \times \\ \times & \times & \color{red}{\times} & \times & \times & \times & \times \\ \times & \times & \color{red}{\times} & \times & \times & \times & \times \\ \times & \times & \color{red}{\times} & \times & \times & \times & \times \end{bmatrix}$$

Downdate and **downsize**

step 13

$$\begin{bmatrix} \times & \times & \times \\ \times & \times & \times \\ & & \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \\ \times & \times & \times \end{bmatrix} \quad \begin{bmatrix} \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times \\ & & & & & \\ \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times & \times \end{bmatrix}$$

Applications

- ▶ Tracking indefinite matrix problems
- ▶ Updating in sequential quadratic programming
- ▶ Updating saddle point problems

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Tools

- ▶ Updating increases $r \rightarrow r + 2$ and $n \rightarrow n + 1$
- ▶ Downdating restores the rank r (reduce by 2 again)
- ▶ Downsizing restores the window size n (optional)

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- ▶ deflating eigenvalues from a block diagonal is expensive because of the updating of D_{bl}

An anti-triangular decomposition

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Theorem

Every $n \times n$ symmetric matrix H has a factorization $H = U M U^T$ where

$$M = \left[\begin{array}{cccc} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & Y^T \\ 0 & 0 & X & Z^T \\ 0 & Y & Z & W \end{array} \right] \begin{array}{l} \} n_0 \\ \} n_1 \\ \} n_2 \\ \} n_1 \end{array}, \quad X = e L L^T$$

where $U^T U = I_n$, $e = \pm 1$, $Y \in \mathbb{R}^{n_1 \times n_1}$, $L \in \mathbb{R}^{n_2 \times n_2}$ and $r = 2n_1 + n_2$

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$$\text{Ex : } T = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \times \\ 0 & 0 & 0 & 0 & 0 & \times \\ 0 & 0 & 0 & \times & \times & \times \\ 0 & 0 & 0 & \times & \times & \times \\ 0 & 0 & 0 & \times & \times & \times \\ 0 & 0 & \times & \times & \times & \times \\ 0 & \times & \times & \times & \times & \times \end{bmatrix}$$

Properties

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- ▶ $\ln M_+ = (n_1 + n_2, n_1, n - r)$ and $\ln M_- = (n_1, n_1 + n_2, n - r)$

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- ▶ U is rectangular when removing zero rows/columns in M
- ▶ The decomposition of a dense matrix requires $\mathcal{O}(n^3)$ flops

For $\begin{bmatrix} 0 & B^T \\ B & A \end{bmatrix}$ one just requires a QR of B to get a (permuted) M

Proof (for e=1)

$$\text{Let } U^T H U = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & Y^T \\ 0 & 0 & LL^T & Z^T \\ 0 & Y & Z & W \end{bmatrix}, \quad U = [U_1 | U_2 | U_3 | U_4] \quad \text{then}$$

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The maximal neutral subspace is not unique but

the maximal non-negative subspace containing it, is unique

(see Gohberg-Lancaster-Rodman)

Some examples

$$\text{Let } H = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & -1 \end{bmatrix}$$

$$\text{then neutral vectors are e.g. given by } u_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 1 \end{bmatrix}, \quad \begin{bmatrix} 0 \\ a \\ b \\ \sqrt{a^2 + 2b^2} \end{bmatrix}$$

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Some examples

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When all positive eigenvalues are equal and all negative eigenvalues are equal, M is unique and essentially diagonal !

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One easily obtains the rank $r + 2$ factorization $\tilde{H} = \tilde{U} \tilde{M} \tilde{U}^T$ where

$$\tilde{U} := \left[\begin{array}{c|c|c} u_{\perp} & U & \\ \hline & & 1 \end{array} \right], \quad \tilde{M} := \left[\begin{array}{c|c|c} 0 & 0 & \rho \\ \hline 0 & M_r & r \\ \hline \rho & r^T & \alpha \end{array} \right], \quad b = Ur + \rho u_{\perp}$$

comes from a Gram Schmidt orthogonalization of $[U|b]$

Updating + downdating problem

Notice that up to a symmetric permutation, \tilde{T} is anti-triangular :

$$\tilde{T} := \begin{bmatrix} 0 & 0 & 0 & 0 & \rho \\ 0 & 0 & 0 & S & r_s \\ 0 & 0 & eLL^T & W & r_w \\ 0 & S^T & W^T & G & r_g \\ \rho & r_s^T & r_w^T & r_g^T & \alpha \end{bmatrix}$$

where the matrix size n_1 increased by 1 (and the rank of \tilde{T} by 2)

We need to “chop off” \tilde{T} ’s 2 eigenvalues of smallest modulus : λ_1, λ_2
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All of these steps can be performed in $\mathcal{O}(Nr)$ flops

- ▶ Let H_v be an orthogonal (Householder) transformation such that

$$H_v \mathbf{v} = v \mathbf{e}_1, \quad v = \mp \|\mathbf{v}\|_2, \quad \tilde{U} = \begin{bmatrix} \mathbf{v}^T \\ v \end{bmatrix}$$

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- ▶ Any row of \tilde{U} can be chosen to be removed this way
- ▶ Choose the row of least norm to get a better approximation

Example (positive semi-definite)

The following matrix has rank 3

$$F(i,j) = \sum_{k=1}^3 \exp\left(-\frac{(i-\mu_k)^2 + (j-\mu_k)^2}{2\sigma_k}\right), \quad i,j = 1, \dots, 100,$$

with

$$\mu = [4 \quad 18 \quad 76], \quad \sigma = [10 \quad 20 \quad 5].$$

Let $F = Q\Lambda Q^T$ be its spectral decomposition and let $\tilde{\Delta} \in \mathbb{R}^{100 \times 100}$ be a matrix of random numbers generated by the `matlab` function `randn`, and define $\Delta = \tilde{\Delta} / \|\tilde{\Delta}\|_2$. Consider the matrix

$$H = F + \varepsilon \Delta \Delta^T, \quad \varepsilon = 1.0e-5$$

Example

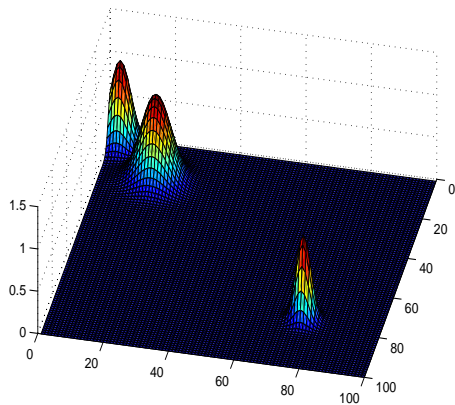


Figure: Graph of the size of the entries of the matrix H .

Example

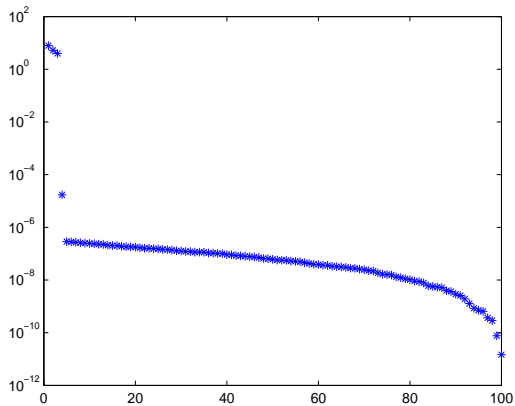


Figure: Distribution of the eigenvalues of the matrix H in logarithmic scale.

Example

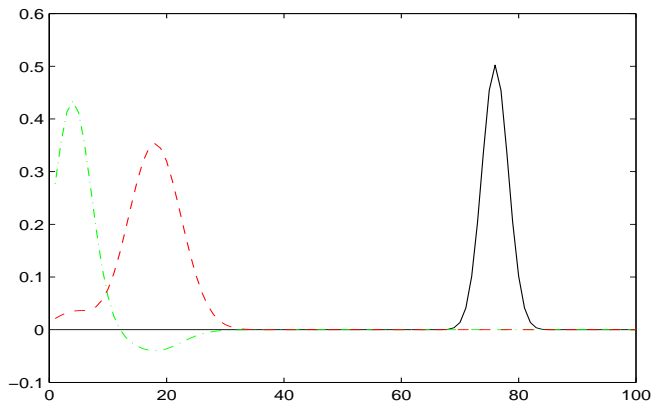


Figure: Plot of the three dominant eigenvectors of H

Example

Largest three eigenvalues of the matrix H (first column)

Largest three eigenvalues computed with our procedure
(next cols) with rank $r = 3$ and window $n = 30, 40, 50$

λ_i	$\mu_i, n = 30$	$\mu_i, n = 40$	$\mu_i, n = 50$
7.949478e0	7.375113e0	7.820407e0	7.947127e0
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The quality is improving with increasing window size n

Examples

We will consider a few examples of full decompositions
i.e. no downdating or downsizing

Ex1: $A = \text{randn}(100)$; $A = A + A'$; $\text{Inertia}(A) = (50, 0, 50)$

Ex2: $A = \text{rand}(100)$; $A = A + A'$; $\text{Inertia}(A) = (48, 0, 52)$

Ex3: A low rank

Ex4: A diagonal dominant

In each of the case we had good backward stability

$\frac{\ QMQ^T - A\ _2}{\ A\ _2}$	$\frac{\ LU - PA\ _2}{\ A\ _2}$	$\frac{\ QR - A\ _2}{\ A\ _2}$
2.49e-15	7.27e-16	1.12e-15

See movies

Random example

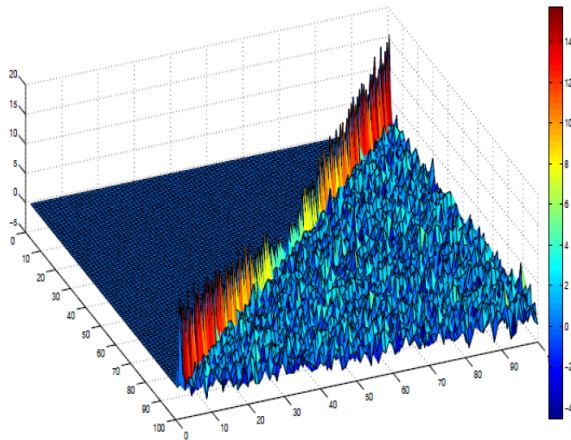


Figure: A random matrix $A = B + B^T$ with B generated by `randn(100, 100)`

Random example

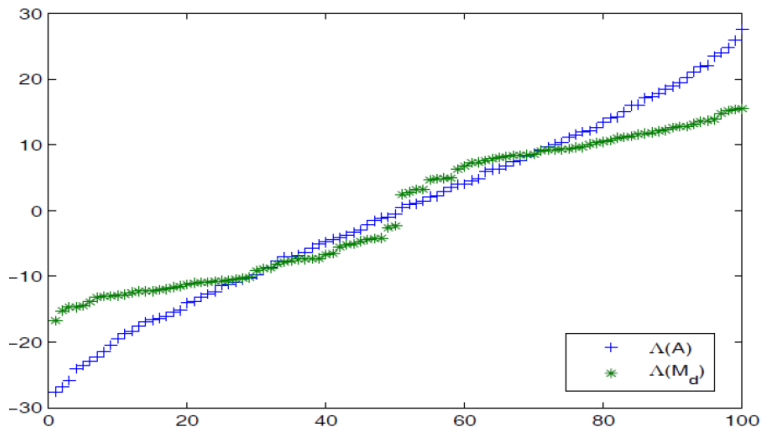


Figure: Eigenvalues and estimates based on the diagonal and anti-diagonal

Clustered example

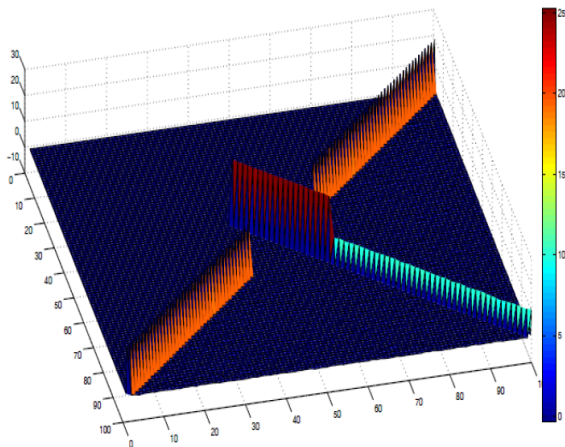


Figure: Matrix with a cluster of positive and a cluster of negative eigenvalues, generated by $A = U \text{diag}(-60I_{40}, 40I_{60}) U^T + E$ with $\|E\| \leq 1$

Clustered example

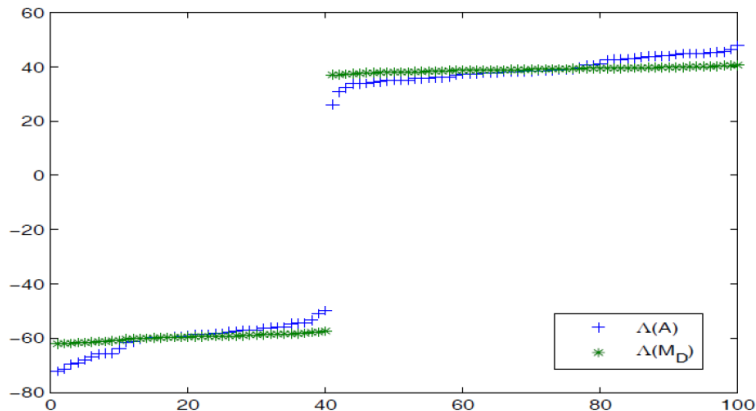


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- ▶ An efficient algorithm for computing incrementally the dominant eigenspace of a symmetric matrix
- ▶ The overall complexity of the incremental updating technique to compute an $N \times r$ basis matrix U for the dominant eigenspace of H , is reduced to $\mathcal{O}(N^2r)$
- ▶ When using both incremental updating and downsizing to compute the dominant eigenspace of \hat{H}_n (an $n \times n$ principal submatrix of H_N), the complexity is reduced to $\mathcal{O}(Nnr)$.

Chahlaoui, Gallivan, Van Dooren, *An incremental method for computing dominant singular subspaces*, SIMAX, 2001

Hoegaerts, De Lathauwer, Goethals, Suykens, Vandewalle, De Moor, *Efficiently updating and tracking the dominant kernel principal components* Neural Networks, 2007.

Mastronardi, Tyrtishnikov, Van Dooren, *A fast algorithm for updating and downsizing the dominant kernel principal components*, SIMAX, 2010

Baker, Gallivan, Van Dooren, *Low-rank incremental methods for computing dominant singular subspaces*, accepted, Lin. Alg. Appl., 2011

Mastronardi, Van Dooren, *Anti-triangular factorizations of symmetric matrices*, in preparation, 2011