#### Some Open Problems Linked to the Cosine-Sine Decompositions

Vjeran Hari<sup>1</sup> Josip Matejaš<sup>2</sup>

<sup>1</sup>Faculty of Science, Department of Mathematics, University of Zagreb, hari@math.hr <sup>2</sup>Faculty of Economics and Business, University of Zagreb, jmatejas@efzg.hr

> ApplMath 18 September 17–20, 2018, Solaris, Šibenik, Croatia

• Cosine-Sine Decomposition

# This work has been fully supported by Croatian Science Foundation under the project IP-09-2014-3670.



- Cosine-Sine Decomposition
- Known Algorithms

This work has been fully supported by Croatian Science Foundation under the project IP-09-2014-3670.



- Cosine-Sine Decomposition
- Known Algorithms
- A New Approach

# This work has been fully supported by Croatian Science Foundation under the project IP-09-2014-3670.



- Cosine-Sine Decomposition
- Known Algorithms
- A New Approach
- Some Applications

# This work has been fully supported by Croatian Science Foundation under the project IP-09-2014-3670.



- Cosine-Sine Decomposition
- Known Algorithms
- A New Approach
- Some Applications
- Solving 4 Symmetric Eigenproblem with 6 Rotations

This work has been fully supported by Croatian Science Foundation under the project IP-09-2014-3670.



### Cosine-Sine Decomposition (CSD) of Orthogonal Matrix Q

Let Q be orthogonal matrix of order n and let

$$Q = \left[ \begin{array}{cc} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \\ I & n-I \end{array} \right] \left\{ \begin{array}{c} I \\ I \\ n-I \end{array} \right]$$

be the partition of Q defined by l,  $1 \le l \le n-1$ .

(1)

Let Q be orthogonal matrix of order n and let

$$Q = \begin{bmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \\ I & n-I \end{bmatrix} \stackrel{\} I}{n-I}$$
(1)

be the partition of Q defined by I,  $1 \le l \le n-1$ .

The Cosine-Sine decomposition of Q is read

$$Q = \begin{bmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{bmatrix} = \begin{bmatrix} U_1 & \\ & U_2 \end{bmatrix} \begin{bmatrix} C & -S \\ S & C \end{bmatrix} \begin{bmatrix} V_1 & \\ & V_2 \end{bmatrix}'$$

C, S diagonal, ,  $C^2 + S^2 = I$ ,  $U_1$ ,  $U_2$ ,  $V_1$ ,  $V_2$  orthogonal.

#### A Bit of History

 C. C. Paige, M. Wei, History and Generality of the CS Decomposition, Linear Algebra and its Appl. 208 (1994) 303-326

#### A Bit of History

- C. C. Paige, M. Wei, History and Generality of the CS Decomposition, Linear Algebra and its Appl. 208 (1994) 303-326
- G. W. Stewart, Computing the CS decomposition of a partitioned orthogonal matrix, Numer. Math. 40 (1982) 297-306
- C. Van Loan. Computing the CS and the generalized singular value decompositions, Numer. Math. 46(4) (1985) 479491

#### A Bit of History

- C. C. Paige, M. Wei, History and Generality of the CS Decomposition, Linear Algebra and its Appl. 208 (1994) 303-326
- G. W. Stewart, Computing the CS decomposition of a partitioned orthogonal matrix, Numer. Math. 40 (1982) 297-306
- C. Van Loan. Computing the CS and the generalized singular value decompositions, Numer. Math. 46(4) (1985) 479491
- B. D. Sutton, Computing the complete CS decomposition, Numer. Algorithms 50 (209) 3365
- B. D. Sutton, Stable computation of the CS decomposition: simultaneous bidiagonalization, SIAM J. Matrix Anal. Appl. 33 (2012) 121
- D. Calvetti, L. Reichel, H. Xu, A CS decomposition for orthogonal matrices with application to eigenvalue computation, Linear Algebra and its Appl. 476 (2015) 10.1016/j.laa.2015.03.007

Z. Bai, The CSD, GSVD, their Applications and Computations 1999 (preprint)

Z. Bai, The CSD, GSVD, their Applications and Computations 1999 (preprint)

In matrix theory, CSD is used

- to define canonical angles between two subspaces of R<sup>n</sup>
- in the theory of orthogonal projections
- in solving GSVD
- in accelerating block Jacobi methods
- in quantum compiling

• . . .

$$Q_{11} = U_{11}C_1V_{11}^T, \qquad Q_{22} = U_{22}C_2V_{22}^T$$

$$Q_{11} = U_{11}C_1V_{11}', \qquad Q_{22} = U_{22}C_2V_{22}'$$
$$U = \begin{bmatrix} U_{11} & O \\ O & U_{22} \end{bmatrix}, \quad V = \begin{bmatrix} V_{11} & O \\ O & V_{22} \end{bmatrix}.$$

$$Q_{11} = U_{11}C_1V_{11}', \qquad Q_{22} = U_{22}C_2V_{22}'$$

$$U = \begin{bmatrix} U_{11} & O \\ O & U_{22} \end{bmatrix}, \quad V = \begin{bmatrix} V_{11} & O \\ O & V_{22} \end{bmatrix}.$$

We have

$$W = U^T Q V = \left[ egin{array}{cc} C_1 & W_{12} \ W_{21} & C_2 \end{array} 
ight],$$

where

$$W_{12} = U_{11}^T Q_{12} V_{22}, \qquad W_{21} = U_{22}^T Q_{21} V_{11}.$$

and  $C_1$  and  $C_2$  are diagonal.

(2)

We can assume

$$C_1 = \text{diag } (\gamma_1, \dots, \gamma_l), \qquad C_2 = \text{diag } (\gamma_{l+1}, \dots, \gamma_n)$$
  
$$\gamma_1 \ge \gamma_2 \ge \dots \ge \gamma_l, \qquad \gamma_{l+1} \ge \gamma_{l+2} \ge \dots \ge \gamma_n.$$

We can assume

$$C_1 = \text{diag } (\gamma_1, \dots, \gamma_l), \qquad C_2 = \text{diag } (\gamma_{l+1}, \dots, \gamma_n)$$
  
$$\gamma_1 \ge \gamma_2 \ge \dots \ge \gamma_l, \qquad \gamma_{l+1} \ge \gamma_{l+2} \ge \dots \ge \gamma_n.$$

#### Lemma

Let n = 2I. Then  $C_1 = C_2$  and  $W_{12}$ ,  $W_{21}$  are block diagonal. If  $\gamma_n > 0$ then  $W_{21} = -W_{12}^T$ . Otherwise  $W_{21}$  and  $-W_{12}^T$  can differ in the last diagonal blocks. In the special case when  $C_2 = O$  or  $C_1 = O$  these blocks are the whole matrices  $W_{12}$  and  $W_{21}$ .

#### Theorem

Let W be orthogonal matrix satisfying the above relations. If  $2I \ge n$  then

$$W = \begin{bmatrix} I \\ C \\ S_2 \end{bmatrix} \left\{ \begin{array}{c} 2l - n \\ r - l \\ r - l \end{array} \right\}$$

If 2l < n, then

$$W = \begin{bmatrix} C & S_1 \\ I & I \\ S_2 & C \end{bmatrix} \begin{cases} I & I \\ I & I \\$$

where *C* is diagonal with nonnegative diagonal elements arranged nonincreasingly,  $S_1$  and  $S_2$  are block-diagonal such that each diagonal block of  $S_1$  and of  $S_2$  is some multiple of an orthogonal matrix. The relation  $S_1 = -S_2^T$  holds, except possibly for the last diagonal block. If all diagonal elements of *C* are distinct,  $S_1$ and  $S_2$  are diagonal and  $S_1^2 = S_2^2 = I - C^2$  holds.

Hari (University of Zagreb)

**CSD** Open Problems

$$\begin{split} C &= \text{diag} \left( \gamma^{(1)} I_{n_1}, \dots, \gamma^{(p-1)} I_{n_{p-1}}, \gamma^{(p)} I_{n_p} \right), \\ S_2 &= \text{diag} \left( \sigma^{(1)} S_{11}, \dots, \sigma^{(p-1)} S_{p-1,p-1}, \sigma^{(p)} S_{pp} \right), \\ S_1 &= \text{diag} \left( -\sigma^{(1)} S_{11}^T, \dots - \sigma^{(p-1)} \tilde{S}_{p-1,p-1}^T, -\sigma^{(p)} \tilde{S}_{pp}^T \right), \end{split}$$

To obtain the CSD of Q, we make the block-diagonal orthogonal matrices

$$\begin{array}{lll} \tilde{U} & = & \left[ \begin{array}{c} I_0 & & \\ & \operatorname{diag}(S_{11}, \ldots, S_{pp}) \end{array} \right], \\ \tilde{V} & = & \left[ \begin{array}{c} I_0 & & \\ & \operatorname{diag}(S_{11}^T, \ldots \tilde{S}_{pp}^T) \end{array} \right], \end{array}$$

where  $I_0$  stands for  $I_{2l-n}$   $(I_{n-2l})$  provided that 2l > n (2l < n). It does not exist when 2l = n. Then make the transformation  $\tilde{W} = \tilde{U}^T W \tilde{V}$ . The matrix  $\tilde{W}$  has the same form as W in Theorem 2, but C (resp.  $S_2$ ,  $S_1$ ) is replaced by  $\Gamma$ , (resp.  $\Sigma$ ,  $-\Sigma$ ). Here

$$\Gamma = \operatorname{diag}(\gamma^{(1)}I_{n_1}, \dots, \gamma^{(p)}I_{n_p}), \quad \Sigma = \operatorname{diag}(\sigma^{(1)}I_{n_1}, \dots, \sigma^{(p)}I_{n_p}),$$

#### Computing CSD in Finite Arithmetic

#### Computing CSD in Finite Arithmetic

In computer we rarely have orthogonal matrix Q, rather we have  $\tilde{Q}$  which is almost orthogonal.

• Usually,  $\tilde{Q}$  computed as product of Householder reflectors or plane rotations

#### Computing CSD in Finite Arithmetic

- Usually,  $\tilde{Q}$  computed as product of Householder reflectors or plane rotations
- Just storing a matrix in the computer generates small relative errors in the matrix elements

- Usually,  $\tilde{Q}$  computed as product of Householder reflectors or plane rotations
- Just storing a matrix in the computer generates small relative errors in the matrix elements
- $\tilde{Q}^{T}\tilde{Q}$  and  $\tilde{Q}\tilde{Q}^{T}$  are close to identity

- Usually,  $\tilde{Q}$  computed as product of Householder reflectors or plane rotations
- Just storing a matrix in the computer generates small relative errors in the matrix elements
- $\tilde{Q}^{T}\tilde{Q}$  and  $\tilde{Q}\tilde{Q}^{T}$  are close to identity
- Our goal here is to compute an approximate CS decomposition of  $\tilde{Q}$  which is as accurate as the data warrant

- Usually,  $\tilde{Q}$  computed as product of Householder reflectors or plane rotations
- Just storing a matrix in the computer generates small relative errors in the matrix elements
- $\tilde{Q}^{T}\tilde{Q}$  and  $\tilde{Q}\tilde{Q}^{T}$  are close to identity
- Our goal here is to compute an approximate CS decomposition of Q
   Which
   is as accurate as the data warrant
- To this end  $\tilde{Q}$  is partitioned, as earlier, so that the diagonal blocks are of order l and n l.

- Usually,  $\tilde{Q}$  computed as product of Householder reflectors or plane rotations
- Just storing a matrix in the computer generates small relative errors in the matrix elements
- $\tilde{Q}^{T}\tilde{Q}$  and  $\tilde{Q}\tilde{Q}^{T}$  are close to identity
- Our goal here is to compute an approximate CS decomposition of  $\tilde{Q}$  which is as accurate as the data warrant
- To this end  $\tilde{Q}$  is partitioned, as earlier, so that the diagonal blocks are of order l and n l.
- We assume that the two initial diagonalizations of the diagonal blocks Q
  <sub>11</sub> and Q
  <sub>22</sub> are already performed, so that these diagonal blocks are diagonal. By W we denote the computed version of W from the preceding section

Since  $\tilde{W}$  is almost orthogonal, we can assume

$$\tilde{W}^T \tilde{W} = I + E, \quad \tilde{W} \tilde{W}^T = I + F, \quad \|E\|_2 \le \varepsilon, \ \|F\|_2 \le \varepsilon$$

 $\varepsilon$  is a small number, typically like  $\mathcal{O}(n\mathbf{u})$  or  $\mathcal{O}(n^2\mathbf{u})$ , where  $\mathbf{u}$  denotes the unit roundoff of the finite arithmetic used in the computation. The bound  $\varepsilon$  measures how close to orthogonality is  $\tilde{W}$ .

We assume

$$\tilde{W} = \begin{bmatrix} \Gamma^+ & \Psi^T & Y^T \\ \Phi & I - \Delta' & 0 \\ X & 0 & \Gamma^- \end{bmatrix}$$

• 
$$\Gamma^+$$
 and  $\Gamma^-$  are of order /

We assume

$$\tilde{W} = \begin{bmatrix} \Gamma^+ & \Psi^T & Y^T \\ \Phi & I - \Delta' & 0 \\ X & 0 & \Gamma^- \end{bmatrix}$$

- $\Gamma^+$  and  $\Gamma^-$  are of order *I*
- the central term is written in the form  $I \Delta'$  because we have  $\Psi \Psi^T + (I - \Delta')^2 \approx I.$

So, we expect that the diagonal elements of  $\Delta'$  are nonnegative.

We assume

$$\tilde{W} = \begin{bmatrix} \Gamma^+ & \Psi^T & Y^T \\ \Phi & I - \Delta' & 0 \\ X & 0 & \Gamma^- \end{bmatrix}$$

- $\Gamma^+$  and  $\Gamma^-$  are of order *I*
- the central term is written in the form  $I-\Delta'$  because we have  $\Psi\Psi^T+(I-\Delta')^2\approx I.$

So, we expect that the diagonal elements of  $\Delta'$  are nonnegative. Set

$$\Gamma = \frac{1}{2}(\Gamma^+ + \Gamma^-)$$

then we have

$$\Gamma^+ = \Gamma(I + \Delta), \quad \Gamma^- = \Gamma(I - \Delta)$$

and we can assume

$$\|\Gamma\Delta\|_2 \leq \varepsilon_1, \ \|\Delta'\|_2 \leq \varepsilon_1.$$

$$\tilde{W} = \begin{bmatrix} \Gamma^+ & \Psi^{\prime} & Y^{\prime} \\ \Phi & I - \Delta^{\prime} & 0 \\ X & 0 & \Gamma^- \end{bmatrix}$$
$$\Gamma = \frac{1}{2}(\Gamma^+ + \Gamma^-), \quad \Gamma^+ = \Gamma(I + \Delta), \quad \Gamma^- = \Gamma(I - \Delta)$$

We can assume

$$\|\Gamma\Delta\|_2 \leq \varepsilon_1, \ \|\Delta'\|_2 \leq \varepsilon_1.$$

Here,  $\varepsilon_1$  is a modest multiple of **u**. Why?

$$\tilde{W} = \begin{bmatrix} \Gamma^+ & \Psi^{\prime} & Y^{\prime} \\ \Phi & I - \Delta^{\prime} & 0 \\ X & 0 & \Gamma^- \end{bmatrix}$$
$$\Gamma = \frac{1}{2}(\Gamma^+ + \Gamma^-), \quad \Gamma^+ = \Gamma(I + \Delta), \quad \Gamma^- = \Gamma(I - \Delta)$$

We can assume

$$\|\Gamma\Delta\|_2 \leq \varepsilon_1, \ \|\Delta'\|_2 \leq \varepsilon_1.$$

Here,  $\varepsilon_1$  is a modest multiple of **u**. Why?

ΓΔ has as diagonal elements the means of the absolute errors of the singular values of *Q*<sub>11</sub> and *Q*<sub>22</sub> and they are tiny.

$$\tilde{W} = \begin{bmatrix} \Gamma^+ & \Psi^{\prime} & Y^{\prime} \\ \Phi & I - \Delta^{\prime} & 0 \\ X & 0 & \Gamma^- \end{bmatrix}$$
$$\Gamma = \frac{1}{2}(\Gamma^+ + \Gamma^-), \quad \Gamma^+ = \Gamma(I + \Delta), \quad \Gamma^- = \Gamma(I - \Delta)$$

We can assume

$$\|\Gamma\Delta\|_2 \leq \varepsilon_1, \ \|\Delta'\|_2 \leq \varepsilon_1.$$

Here,  $\varepsilon_1$  is a modest multiple of **u**. Why?

- ΓΔ has as diagonal elements the means of the absolute errors of the singular values of Q
  <sub>11</sub> and Q
  <sub>22</sub> and they are tiny.
- We have assumed the same bound for  $\|\Gamma\Delta\|_2$  and for  $\|\Delta'\|_2$  because  $\Delta'$  and  $\Gamma^-$  are parts of the same SVD computation of  $\tilde{Q}_{22}$ .
$$\tilde{W} = \begin{bmatrix} \Gamma^+ & \Psi^T & Y^T \\ \Phi & I - \Delta' & 0 \\ X & 0 & \Gamma^- \end{bmatrix}$$

#### Lemma

The following assertions hold.

$$\|\Phi\|_2 \leq \sqrt{\varepsilon} \quad and \quad \|\Psi\|_2 \leq \sqrt{\varepsilon}.$$
 (3)

(ii) For all *i*, *j*, such that  $\gamma_i \neq \gamma_j$ ,

$$x_{ij} = rac{\xi_{ij}}{\gamma_i - \gamma_j}$$
 and  $y_{ij} = rac{\eta_{ij}}{\gamma_i - \gamma_j}$ ,  $|\xi_{ij}| \le |\varepsilon|$ ,  $|\eta_{ij}| \le |\varepsilon|$ . (4)

$$ilde{W} = \left[ egin{array}{ccc} {\sf \Gamma}^+ & {\Psi}^{\mathcal{T}} & {Y}^{\mathcal{T}} \ {\Phi} & {\it I} - {\Delta}' & 0 \ X & 0 & {\Gamma}^- \end{array} 
ight]$$

These results are analogous to those of Lemma 1 and theorem 2. They tell us that tiny gap between successive diagonals of  $\Gamma$  can make the appropriate off-diagonal elements of X and Y large. Hence, in order to compute the CS decomposition we shall have to work on X and Y.

$$\tilde{W} = \begin{bmatrix} \Gamma^+ & \Psi^T & Y^T \\ \Phi & I - \Delta' & 0 \\ X & 0 & \Gamma^- \end{bmatrix}$$

These results are analogous to those of Lemma 1 and theorem 2. They tell us that tiny gap between successive diagonals of  $\Gamma$  can make the appropriate off-diagonal elements of X and Y large. Hence, in order to compute the CS decomposition we shall have to work on X and Y.

We know that the possible large elements in X and Y form a small diagonal block (in earlier notation: a diagonal submatrix -Y<sub>i</sub><sup>T</sup> in X and Y<sub>i</sub> in Y) which is close to a multiple of orthogonal matrix

$$\tilde{W} = \begin{bmatrix} \Gamma^+ & \Psi^T & Y^T \\ \Phi & I - \Delta' & 0 \\ X & 0 & \Gamma^- \end{bmatrix}$$

These results are analogous to those of Lemma 1 and theorem 2. They tell us that tiny gap between successive diagonals of  $\Gamma$  can make the appropriate off-diagonal elements of X and Y large. Hence, in order to compute the CS decomposition we shall have to work on X and Y.

- We know that the possible large elements in X and Y form a small diagonal block (in earlier notation: a diagonal submatrix -Y<sub>i</sub><sup>T</sup> in X and Y<sub>i</sub> in Y) which is close to a multiple of orthogonal matrix
- Note that the QL, QR, LQ, RQ factorizations of an almost diagonal matrix actually almost diagonalizes it

$$\tilde{W} = \begin{bmatrix} \Gamma^+ & \Psi^T & Y^T \\ \Phi & I - \Delta' & 0 \\ X & 0 & \Gamma^- \end{bmatrix}$$

These results are analogous to those of Lemma 1 and theorem 2. They tell us that tiny gap between successive diagonals of  $\Gamma$  can make the appropriate off-diagonal elements of X and Y large. Hence, in order to compute the CS decomposition we shall have to work on X and Y.

- We know that the possible large elements in X and Y form a small diagonal block (in earlier notation: a diagonal submatrix - Y<sub>i</sub><sup>T</sup> in X and Y<sub>i</sub> in Y) which is close to a multiple of orthogonal matrix
- Note that the QL, QR, LQ, RQ factorizations of an almost diagonal matrix actually almost diagonalizes it
- Therefore, we can make the QL factorization of X,  $X = Q_X L_X$  and of Y,  $Y = Q_Y L_Y = Q_Y R^T$  and transform  $\tilde{W}$  appropriately

$$\tilde{W}' = \begin{bmatrix} I & O \\ O & Q_X^T \end{bmatrix} \tilde{W} \begin{bmatrix} I & O \\ O & Q_Y \end{bmatrix} = \begin{bmatrix} \Gamma(I + \Delta) & \Psi^T & R \\ \Phi & I - \Delta' & O \\ L_X & O & Q_X^T \Gamma(I - \Delta)Q_Y \end{bmatrix}.$$

$$\tilde{W}' = \begin{bmatrix} I & O \\ O & Q_X^T \end{bmatrix} \tilde{W} \begin{bmatrix} I & O \\ O & Q_Y \end{bmatrix} = \begin{bmatrix} \Gamma(I + \Delta) & \Psi^T & R \\ \Phi & I - \Delta' & O \\ L_X & O & Q_X^T \Gamma(I - \Delta)Q_Y \end{bmatrix}.$$

 If the norm of Y is close to u, the Q<sub>Y</sub> becomes dependent on the errors in *W* which are also of that order of magnitude

$$\tilde{W}' = \begin{bmatrix} I & O \\ O & Q_X^T \end{bmatrix} \tilde{W} \begin{bmatrix} I & O \\ O & Q_Y \end{bmatrix} = \begin{bmatrix} \Gamma(I + \Delta) & \Psi^T & R \\ \Phi & I - \Delta' & O \\ L_X & O & Q_X^T \Gamma(I - \Delta)Q_Y \end{bmatrix}.$$

- If the norm of Y is close to u, the Q<sub>Y</sub> becomes dependent on the errors in *W* which are also of that order of magnitude
- In that case, the same is true for  $Q_X$  since  $||X|| \approx ||Y||$ . This can make  $Q_X^T \Gamma(I \Delta)Q_Y$  to be far from  $\Gamma$ . Therefore, we shall follow another way.

$$\tilde{W}' = \begin{bmatrix} I & O \\ O & Q_X^T \end{bmatrix} \tilde{W} \begin{bmatrix} I & O \\ O & Q_Y \end{bmatrix} = \begin{bmatrix} \Gamma(I + \Delta) & \Psi^T & R \\ \Phi & I - \Delta' & O \\ L_X & O & Q_X^T \Gamma(I - \Delta)Q_Y \end{bmatrix}.$$

- If the norm of Y is close to u, the Q<sub>Y</sub> becomes dependent on the errors in *W* which are also of that order of magnitude
- In that case, the same is true for  $Q_X$  since  $||X|| \approx ||Y||$ . This can make  $Q_X^T \Gamma(I \Delta) Q_Y$  to be far from  $\Gamma$ . Therefore, we shall follow another way.
- We split  $\Gamma = \operatorname{diag} (\gamma_1, \ldots, \gamma_l)$  into two parts,

$$\Gamma = \begin{bmatrix} \Gamma_1 & O \\ O & \Gamma_2 \end{bmatrix}, \quad \Gamma_1 = \operatorname{diag}(\gamma_1, \ldots, \gamma_m), \quad 0 \leq m \leq l,$$

where *m* is the largest index for which  $\gamma_m \ge \frac{\sqrt{2}}{2}$ ,  $0 \le m \le l$ , holds. Thus, if  $\gamma_l \ge \sqrt{2}/2$ , then  $\Gamma = \Gamma_1$  and if  $\gamma_1 < \sqrt{2}/2$ , then  $\Gamma = \Gamma_2$ .

$$\tilde{W}' = \begin{bmatrix} I & O \\ O & Q_X^T \end{bmatrix} \tilde{W} \begin{bmatrix} I & O \\ O & Q_Y \end{bmatrix} = \begin{bmatrix} \Gamma(I + \Delta) & \Psi^T & R \\ \Phi & I - \Delta' & O \\ L_X & O & Q_X^T \Gamma(I - \Delta)Q_Y \end{bmatrix}.$$

- If the norm of Y is close to u, the Q<sub>Y</sub> becomes dependent on the errors in *W* which are also of that order of magnitude
- In that case, the same is true for  $Q_X$  since  $||X|| \approx ||Y||$ . This can make  $Q_X^T \Gamma(I \Delta) Q_Y$  to be far from  $\Gamma$ . Therefore, we shall follow another way.
- We split  $\Gamma = \operatorname{diag} (\gamma_1, \ldots, \gamma_l)$  into two parts,

$$\Gamma = \left[ \begin{array}{cc} \Gamma_1 & O \\ O & \Gamma_2 \end{array} \right], \quad \Gamma_1 = \text{diag} \ (\gamma_1, \ldots, \gamma_m), \quad 0 \leq m \leq l,$$

where *m* is the largest index for which  $\gamma_m \ge \frac{\sqrt{2}}{2}$ ,  $0 \le m \le I$ , holds. Thus, if  $\gamma_I \ge \sqrt{2}/2$ , then  $\Gamma = \Gamma_1$  and if  $\gamma_1 < \sqrt{2}/2$ , then  $\Gamma = \Gamma_2$ .

• Although the story complicates, now we can make sharp estimates for almost all blocks appearing in  $\tilde{W}'$ .

• In today's CPU and GPU eigenvalue and singular value computation, very efficient and accurate are the block diagonalization methods. They are generalizations of the element-wise Jacobi methods. Instead of annihilating two off-diagonal elements, they annihilate two off-diagonal blocks.

- In today's CPU and GPU eigenvalue and singular value computation, very efficient and accurate are the block diagonalization methods. They are generalizations of the element-wise Jacobi methods. Instead of annihilating two off-diagonal elements, they annihilate two off-diagonal blocks.
- The dimension of these blocks depends on the available cache memory of the computing machine. Typically these blocks are of order 16–256. For the annihilation of these blocks one employs a special method that is referred to as kernel algorithm.

- In today's CPU and GPU eigenvalue and singular value computation, very efficient and accurate are the block diagonalization methods. They are generalizations of the element-wise Jacobi methods. Instead of annihilating two off-diagonal elements, they annihilate two off-diagonal blocks.
- The dimension of these blocks depends on the available cache memory of the computing machine. Typically these blocks are of order 16–256. For the annihilation of these blocks one employs a special method that is referred to as kernel algorithm.
- So, the kernel algorithm diagonalizes a symmetric matrix of order 32–512. Typically, an element-wise Jacobi method is used.

- In today's CPU and GPU eigenvalue and singular value computation, very efficient and accurate are the block diagonalization methods. They are generalizations of the element-wise Jacobi methods. Instead of annihilating two off-diagonal elements, they annihilate two off-diagonal blocks.
- The dimension of these blocks depends on the available cache memory of the computing machine. Typically these blocks are of order 16–256. For the annihilation of these blocks one employs a special method that is referred to as kernel algorithm.
- So, the kernel algorithm diagonalizes a symmetric matrix of order 32–512. Typically, an element-wise Jacobi method is used.
- The kernel algorithm can be made more efficient if instead of two off-diagonal elements it annihilates two blocks of small order 2–4. If the blocks are of order 2 then there is a need for a simple, efficient and accurate eigenvalue algorithm for a symmetric matrix of order 4.

- In today's CPU and GPU eigenvalue and singular value computation, very efficient and accurate are the block diagonalization methods. They are generalizations of the element-wise Jacobi methods. Instead of annihilating two off-diagonal elements, they annihilate two off-diagonal blocks.
- The dimension of these blocks depends on the available cache memory of the computing machine. Typically these blocks are of order 16–256. For the annihilation of these blocks one employs a special method that is referred to as kernel algorithm.
- So, the kernel algorithm diagonalizes a symmetric matrix of order 32–512. Typically, an element-wise Jacobi method is used.
- The kernel algorithm can be made more efficient if instead of two off-diagonal elements it annihilates two blocks of small order 2–4. If the blocks are of order 2 then there is a need for a simple, efficient and accurate eigenvalue algorithm for a symmetric matrix of order 4.
- We shall show how the CSD can be used to shed some light how to the construction 6 plane rotations that diagonalize the given 4 × 4 symmetric matrix.

Hari (University of Zagreb)

**CSD** Open Problems

Let

$$A = \begin{bmatrix} A_{11} & A_{12} \\ A_{12}^T & A_{22} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{12} & a_{22} & a_{23} & a_{24} \\ a_{13} & a_{23} & a_{33} & a_{34} \\ a_{14} & a_{24} & a_{34} & a_{44} \end{bmatrix},$$

be a symmetric matrix of order 4 and let Q be orthogonal and such that

 $A = Q \Lambda Q^{\tau}.$ 

Recall the CSD of Q with n = 4, l = 2

$$Q = \begin{bmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{bmatrix} = \begin{bmatrix} U_1 \\ U_2 \end{bmatrix} \begin{bmatrix} C & -S \\ S & C \end{bmatrix} \begin{bmatrix} V_1 \\ V_2 \end{bmatrix}^T = UGV^T$$

C, S diagonal, ,  $C^2 + S^2 = I$ ,  $U_1$ ,  $U_2$ ,  $V_1$ ,  $V_2$  orthogonal.

• Let  $D_U$ ,  $D_V$  be special 4  $\times$  4 diagonal matrices of signs

- Let  $D_U$ ,  $D_V$  be special  $4 \times 4$  diagonal matrices of signs
- Let  $D_U$  contain the signs of the diagonal elements of U

- Let  $D_U$ ,  $D_V$  be special  $4 \times 4$  diagonal matrices of signs
- Let  $D_U$  contain the signs of the diagonal elements of U
- Let  $D_V$  contain the signs of the diagonal elements of  $VD_U$

- Let  $D_U$ ,  $D_V$  be special  $4 \times 4$  diagonal matrices of signs
- Let  $D_U$  contain the signs of the diagonal elements of U
- Let  $D_V$  contain the signs of the diagonal elements of  $VD_U$
- Then  $ilde{U} = U D_U$  has nonnegative diagonal, so  $ilde{U} = R_1 R_2$

- Let  $D_U$ ,  $D_V$  be special  $4 \times 4$  diagonal matrices of signs
- Let  $D_U$  contain the signs of the diagonal elements of U
- Let  $D_V$  contain the signs of the diagonal elements of  $VD_U$
- Then  $ilde{U} = U D_U$  has nonnegative diagonal, so  $ilde{U} = R_1 R_2$
- $R_1$  and  $R_2$  are plane rotations with angles in  $[-\pi/2,\pi/2]$

- Let  $D_U$ ,  $D_V$  be special  $4 \times 4$  diagonal matrices of signs
- Let  $D_U$  contain the signs of the diagonal elements of U
- Let  $D_V$  contain the signs of the diagonal elements of  $VD_U$
- Then  $ilde{U} = U D_U$  has nonnegative diagonal, so  $ilde{U} = R_1 R_2$
- $R_1$  and  $R_2$  are plane rotations with angles in  $[-\pi/2,\pi/2]$
- Then  $\tilde{V} = D_V V D_U$  has nonnegative diagonal, so  $\tilde{V}^T = R_5 R_6$

- Let  $D_U$ ,  $D_V$  be special  $4 \times 4$  diagonal matrices of signs
- Let  $D_U$  contain the signs of the diagonal elements of U
- Let  $D_V$  contain the signs of the diagonal elements of  $VD_U$
- Then  $ilde{U} = U D_U$  has nonnegative diagonal, so  $ilde{U} = R_1 R_2$
- $R_1$  and  $R_2$  are plane rotations with angles in  $[-\pi/2,\pi/2]$
- Then  $\tilde{V} = D_V V D_U$  has nonnegative diagonal, so  $\tilde{V}^T = R_5 R_6$
- $R_5$  and  $R_6$  are plane rotations with angles in  $[-\pi/2,\pi/2]$

- Let  $D_U$ ,  $D_V$  be special  $4 \times 4$  diagonal matrices of signs
- Let  $D_U$  contain the signs of the diagonal elements of U
- Let  $D_V$  contain the signs of the diagonal elements of  $VD_U$
- Then  $ilde{U} = U D_U$  has nonnegative diagonal, so  $ilde{U} = R_1 R_2$
- $R_1$  and  $R_2$  are plane rotations with angles in  $[-\pi/2,\pi/2]$
- Then  $\tilde{V} = D_V V D_U$  has nonnegative diagonal, so  $\tilde{V}^T = R_5 R_6$
- $R_5$  and  $R_6$  are plane rotations with angles in  $[-\pi/2,\pi/2]$
- $R_1$  and  $R_5$  ( $R_2$  and  $R_6$ ) rotate in the (1,2)-plane ((3,4)-plane)

Note that

$$Q = UGV^{T} = UD_{U}(D_{U}GD_{U})(D_{V}VD_{U})^{T}D_{V} = \tilde{U}\tilde{G}\tilde{V}^{T}D_{V}$$

Note that

$$Q = UGV^{T} = UD_{U}(D_{U}GD_{U})(D_{V}VD_{U})^{T}D_{V} = \tilde{U}\tilde{G}\tilde{V}^{T}D_{V}$$

Note also that

$$\tilde{G} = \left[ \begin{array}{cc} C & -D_1 S D_2 \\ D_2 S D_1 & C \end{array} \right] = R_3 R_4$$

The plane rotations  $R_3$  and  $R_4$  rotate in the (1,3) and (2,4) planes with angles in  $[-\pi/2, \pi/2]$ .

Note that

$$Q = UGV^{T} = UD_{U}(D_{U}GD_{U})(D_{V}VD_{U})^{T}D_{V} = \tilde{U}\tilde{G}\tilde{V}^{T}D_{V}$$

Note also that

$$\tilde{G} = \left[ \begin{array}{cc} C & -D_1 S D_2 \\ D_2 S D_1 & C \end{array} \right] = R_3 R_4$$

The plane rotations  $R_3$  and  $R_4$  rotate in the (1,3) and (2,4) planes with angles in  $[-\pi/2, \pi/2]$ .

This way we have obtained

$$Q = R_1 R_2 R_3 R_4 R_5 R_6 D_V.$$

Hence

$$\begin{split} \Lambda &= Q^T A Q = D_V R_6^T R_5^T R_4^T R_3^T R_2^T R_1^T A R_1 R_2 R_3 R_4 R_5 R_6 D_V \\ &= R_6^T R_5^T R_4^T R_3^T R_2^T R_1^T A R_1 R_2 R_3 R_4 R_5 R_6. \end{split}$$

Recall

$$A = \left[ \begin{array}{ccc} A_{11} & A_{12} \\ A_{12}^T & A_{22} \end{array} \right] = \left[ \begin{array}{cccc} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{12} & a_{22} & a_{23} & a_{24} \\ \hline a_{13} & a_{23} & a_{33} & a_{34} \\ a_{14} & a_{24} & a_{34} & a_{44} \end{array} \right],$$

 $\Lambda = (R_5 R_6)^T (R_3 R_4)^T (R_1 R_2)^T A (R_1 R_2) (R_3 R_4) (R_5 R_6).$ 

Recall

$$A = \left[ \begin{array}{ccc} A_{11} & A_{12} \\ A_{12}^{T} & A_{22} \end{array} \right] = \left[ \begin{array}{cccc} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{12} & a_{22} & a_{23} & a_{24} \\ \hline a_{13} & a_{23} & a_{33} & a_{34} \\ a_{14} & a_{24} & a_{34} & a_{44} \end{array} \right],$$

 $\Lambda = (R_5 R_6)^T (R_3 R_4)^T (R_1 R_2)^T A (R_1 R_2) (R_3 R_4) (R_5 R_6).$ 

The rotations within each parenthesis commute. We can conclude:

• Since  $R_5$  and  $R_6$  rotate in (1,2) and (3,4) planes they cannot change  $||A_{12}||_F$ 

Recall

$$A = \left[ \begin{array}{ccc} A_{11} & A_{12} \\ A_{12}^{T} & A_{22} \end{array} \right] = \left[ \begin{array}{cccc} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{12} & a_{22} & a_{23} & a_{24} \\ \hline a_{13} & a_{23} & a_{33} & a_{34} \\ a_{14} & a_{24} & a_{34} & a_{44} \end{array} \right],$$

 $\Lambda = (R_5 R_6)^T (R_3 R_4)^T (R_1 R_2)^T A (R_1 R_2) (R_3 R_4) (R_5 R_6).$ 

- Since  $R_5$  and  $R_6$  rotate in (1,2) and (3,4) planes they cannot change  $||A_{12}||_F$
- Since  $R_1$  and  $R_2$  rotate in (1,2) and (3,4) planes they cannot change  $||A_{12}||_F$

Recall

$$A = \left[ \begin{array}{ccc} A_{11} & A_{12} \\ A_{12}^{T} & A_{22} \end{array} \right] = \left[ \begin{array}{cccc} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{12} & a_{22} & a_{23} & a_{24} \\ \hline a_{13} & a_{23} & a_{33} & a_{34} \\ a_{14} & a_{24} & a_{34} & a_{44} \end{array} \right],$$

 $\Lambda = (R_5 R_6)^T (R_3 R_4)^T (R_1 R_2)^T A (R_1 R_2) (R_3 R_4) (R_5 R_6).$ 

- Since  $R_5$  and  $R_6$  rotate in (1,2) and (3,4) planes they cannot change  $||A_{12}||_F$
- Since  $R_1$  and  $R_2$  rotate in (1,2) and (3,4) planes they cannot change  $||A_{12}||_F$
- So, the product  $R_3R_4$  has the task to zero  $A_{12}$

Recall

$$A = \left[ \begin{array}{ccc} A_{11} & A_{12} \\ A_{12}^{T} & A_{22} \end{array} \right] = \left[ \begin{array}{cccc} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{12} & a_{22} & a_{23} & a_{24} \\ \hline a_{13} & a_{23} & a_{33} & a_{34} \\ a_{14} & a_{24} & a_{34} & a_{44} \end{array} \right],$$

 $\Lambda = (R_5 R_6)^T (R_3 R_4)^T (R_1 R_2)^T A (R_1 R_2) (R_3 R_4) (R_5 R_6).$ 

- Since  $R_5$  and  $R_6$  rotate in (1,2) and (3,4) planes they cannot change  $||A_{12}||_F$
- Since  $R_1$  and  $R_2$  rotate in (1,2) and (3,4) planes they cannot change  $||A_{12}||_F$
- So, the product  $R_3R_4$  has the task to zero  $A_{12}$
- Hence the task of  $R_5$  and  $R_6$  is to annihilate (1, 2)- and (3, 4)-elements

Recall

$$A = \left[ \begin{array}{ccc} A_{11} & A_{12} \\ A_{12}^{T} & A_{22} \end{array} \right] = \left[ \begin{array}{cccc} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{12} & a_{22} & a_{23} & a_{24} \\ \hline a_{13} & a_{23} & a_{33} & a_{34} \\ a_{14} & a_{24} & a_{34} & a_{44} \end{array} \right],$$

 $\Lambda = (R_5 R_6)^T (R_3 R_4)^T (R_1 R_2)^T A (R_1 R_2) (R_3 R_4) (R_5 R_6).$ 

- Since  $R_5$  and  $R_6$  rotate in (1,2) and (3,4) planes they cannot change  $||A_{12}||_F$
- Since  $R_1$  and  $R_2$  rotate in (1,2) and (3,4) planes they cannot change  $||A_{12}||_F$
- So, the product  $R_3R_4$  has the task to zero  $A_{12}$
- Hence the task of  $R_5$  and  $R_6$  is to annihilate (1, 2)- and (3, 4)-elements
- Therefore, we can choose  $R_5$  and  $R_6$  as simple Jacobi rotations

Recall

$$A = \begin{bmatrix} A_{11} & A_{12} \\ A_{12}^{T} & A_{22} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{12} & a_{22} & a_{23} & a_{24} \\ \hline a_{13} & a_{23} & a_{33} & a_{34} \\ a_{14} & a_{24} & a_{34} & a_{44} \end{bmatrix},$$

 $\Lambda = (R_5 R_6)^T (R_3 R_4)^T (R_1 R_2)^T A (R_1 R_2) (R_3 R_4) (R_5 R_6).$ 

The rotations within each parenthesis commute. We can conclude:

- Since  $R_5$  and  $R_6$  rotate in (1,2) and (3,4) planes they cannot change  $||A_{12}||_F$
- Since  $R_1$  and  $R_2$  rotate in (1,2) and (3,4) planes they cannot change  $||A_{12}||_F$
- So, the product  $R_3R_4$  has the task to zero  $A_{12}$
- Hence the task of  $R_5$  and  $R_6$  is to annihilate (1, 2)- and (3, 4)-elements
- Therefore, we can choose  $R_5$  and  $R_6$  as simple Jacobi rotations
- The role of  $R_1$  and  $R_2$  is to prepare the matrix, in such a way that  $R_3$  and  $R_4$  can accomplish their task

Hari (University of Zagreb)

**CSD** Open Problems

$$A = \left[ \begin{array}{ccc} A_{11} & A_{12} \\ A_{12}^{T} & A_{22} \end{array} \right] = \left[ \begin{array}{cccc} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{12} & a_{22} & a_{23} & a_{24} \\ \hline a_{13} & a_{23} & a_{33} & a_{34} \\ a_{14} & a_{24} & a_{34} & a_{44} \end{array} \right],$$

Let us rename

$$A \leftarrow (R_3R_4)^T (R_1R_2)^T A (R_1R_2) (R_3R_4).$$
$$A = \left[ \begin{array}{ccc} A_{11} & A_{12} \\ A_{12}^{\mathsf{T}} & A_{22} \end{array} \right] = \left[ \begin{array}{cccc} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{12} & a_{22} & a_{23} & a_{24} \\ \hline a_{13} & a_{23} & a_{33} & a_{34} \\ a_{14} & a_{24} & a_{34} & a_{44} \end{array} \right],$$

Let us rename

$$A \leftarrow (R_3R_4)^T (R_1R_2)^T A(R_1R_2) (R_3R_4).$$

• Since  $R_3$  does not affect/change  $a_{24}$ ,  $R_4$  must be Jacobi rotation

$$A = \left[ \begin{array}{ccc} A_{11} & A_{12} \\ A_{12}^T & A_{22} \end{array} \right] = \left[ \begin{array}{cccc} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{12} & a_{22} & a_{23} & a_{24} \\ \hline a_{13} & a_{23} & a_{33} & a_{34} \\ a_{14} & a_{24} & a_{34} & a_{44} \end{array} \right],$$

$$A \leftarrow (R_3R_4)^T (R_1R_2)^T A(R_1R_2) (R_3R_4).$$

- Since  $R_3$  does not affect/change  $a_{24}$ ,  $R_4$  must be Jacobi rotation
- Since  $R_4$  does not affect/change  $a_{13}$ ,  $R_3$  must be Jacobi rotation

$$A = \begin{bmatrix} A_{11} & A_{12} \\ A_{12}^T & A_{22} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{12} & a_{22} & a_{23} & a_{24} \\ \hline a_{13} & a_{23} & a_{33} & a_{34} \\ a_{14} & a_{24} & a_{34} & a_{44} \end{bmatrix},$$

$$A \leftarrow (R_3R_4)^T (R_1R_2)^T A(R_1R_2) (R_3R_4).$$

- Since  $R_3$  does not affect/change  $a_{24}$ ,  $R_4$  must be Jacobi rotation
- Since  $R_4$  does not affect/change  $a_{13}$ ,  $R_3$  must be Jacobi rotation
- Since  $R_5R_6$  annihilates  $a_{14}$  and  $a_{23}$   $R_5$  or/and  $R_6$  must be Givens rotation(s)

$$A = \begin{bmatrix} A_{11} & A_{12} \\ A_{12}^T & A_{22} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{12} & a_{22} & a_{23} & a_{24} \\ \hline a_{13} & a_{23} & a_{33} & a_{34} \\ a_{14} & a_{24} & a_{34} & a_{44} \end{bmatrix},$$

$$A \leftarrow (R_3R_4)^T (R_1R_2)^T A(R_1R_2) (R_3R_4).$$

- Since  $R_3$  does not affect/change  $a_{24}$ ,  $R_4$  must be Jacobi rotation
- Since  $R_4$  does not affect/change  $a_{13}$ ,  $R_3$  must be Jacobi rotation
- Since  $R_5R_6$  annihilates  $a_{14}$  and  $a_{23}$   $R_5$  or/and  $R_6$  must be Givens rotation(s)
- Since  $R_3R_4 = R_4R_3$  the angle of  $R_3(R_4)$  does not depend on that of  $R_4(R_3)$

$$A = \begin{bmatrix} A_{11} & A_{12} \\ A_{12}^T & A_{22} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{12} & a_{22} & a_{23} & a_{24} \\ \hline a_{13} & a_{23} & a_{33} & a_{34} \\ a_{14} & a_{24} & a_{34} & a_{44} \end{bmatrix},$$

$$A \leftarrow (R_3R_4)^T (R_1R_2)^T A(R_1R_2) (R_3R_4).$$

- Since  $R_3$  does not affect/change  $a_{24}$ ,  $R_4$  must be Jacobi rotation
- Since  $R_4$  does not affect/change  $a_{13}$ ,  $R_3$  must be Jacobi rotation
- Since  $R_5R_6$  annihilates  $a_{14}$  and  $a_{23}$   $R_5$  or/and  $R_6$  must be Givens rotation(s)
- Since  $R_3R_4 = R_4R_3$  the angle of  $R_3$  ( $R_4$ ) does not depend on that of  $R_4$  ( $R_3$ )
- Once we know  $R_1$  and  $R_2$ , we are done since all later rotations are Jacobi rotations. However, for  $R_3$  and  $R_4$  we must allow for the larger interval  $[-\pi/2, \pi/2]$  for the angles.

We have made a simple experiment in MATLAB to check the role of the rotations  $R_1 - R_6$ . We shall explain the details by describing the steps of the experiment.

We have made a simple experiment in MATLAB to check the role of the rotations  $R_1 - R_6$ . We shall explain the details by describing the steps of the experiment.

• Everything starts with the symmetric matrix A,

$$A = \left[ \begin{array}{rrrrr} 0 & 2 & 3 & 4 \\ 2 & 3 & 4 & 5 \\ 3 & 4 & 5 & 6 \\ 4 & 5 & 6 & 8 \end{array} \right]$$

We have made a simple experiment in MATLAB to check the role of the rotations  $R_1 - R_6$ . We shall explain the details by describing the steps of the experiment.

• Everything starts with the symmetric matrix A,

$$A = \left[ \begin{array}{rrrr} 0 & 2 & 3 & 4 \\ 2 & 3 & 4 & 5 \\ 3 & 4 & 5 & 6 \\ 4 & 5 & 6 & 8 \end{array} \right]$$

Using the commands: digits(dg); AA = vpa(sym(A,'f'))
 A is converted to symbolic type, so we can apply to it variable precision arithmetic (vpa). We set dg= 80.

We have made a simple experiment in MATLAB to check the role of the rotations  $R_1 - R_6$ . We shall explain the details by describing the steps of the experiment.

• Everything starts with the symmetric matrix A,

$$A = \left[ \begin{array}{rrrr} 0 & 2 & 3 & 4 \\ 2 & 3 & 4 & 5 \\ 3 & 4 & 5 & 6 \\ 4 & 5 & 6 & 8 \end{array} \right]$$

- Using the commands: digits(dg); AA = vpa(sym(A,'f'))
   A is converted to symbolic type, so we can apply to it variable precision arithmetic (vpa). We set dg= 80.
- Using the command [Qv, Dv] = eig(AA); the eigenvector matrix Qv and the eigenvalue diagonal matrix Dv are computed in vpa with 80 decimal digits

• Using the commands: D = double(Dv); Q = double(Qv); these vpa matrices are converted to double. Here are Q and D:

2.931093180703362e-01	-8.798579328718921 e-02	-2.278262800852170e-01	9.243595696169855e-01
4.193767196696980e-01	1.911371496763030e-01	8.815256669327826e-01	1.024805130325522e-01
5.289096009714916e-01	7.298536860359306e-01	-3.873541839913629e-01	-1.937136214217473e-01
6.771002353120279e-01	-6.504142427507317e-01	-1.447909554690162e-01	-3.123013983025982e-01

1.751525068292106e-01	0	0	0
0	3.389366899857361e-01	0	0
0	0	-9.579649901340663e-02	0
0	0	0	-1.758390873893391e+00

• Using the commands: D = double(Dv); Q = double(Qv); these vpa matrices are converted to double. Here are Q and D:

2.931093180703362e-01	-8.798579328718921e-02	-2.278262800852170e-01	9.243595696169855e-01
4.193767196696980e-01	1.911371496763030e-01	8.815256669327826e-01	1.024805130325522e-01
5.289096009714916e-01	7.298536860359306e-01	-3.873541839913629e-01	-1.937136214217473e-01
6.771002353120279e-01	-6.504142427507317e-01	-1.447909554690162e-01	-3.123013983025982e-01

1.751525068292106e-01	0	0	0
0	3.389366899857361e-01	0	0
0	0	-9.579649901340663e-02	0
0	0	0	-1.758390873893391e+00

• Thus Q is the eigenvector matrix for A which is accurate to the last decimal digit

• Using the commands: D = double(Dv); Q = double(Qv); these vpa matrices are converted to double. Here are Q and D:

2.931093180703362e-01	-8.798579328718921e-02	-2.278262800852170e-01	9.243595696169855e-01
4.193767196696980e-01	1.911371496763030e-01	8.815256669327826e-01	1.024805130325522e-01
5.289096009714916e-01	7.298536860359306e-01	-3.873541839913629e-01	-1.937136214217473e-01
6.771002353120279e-01	-6.504142427507317e-01	-1.447909554690162e-01	-3.123013983025982e-01

1.751525068292106e-01	0	0	0
0	3.389366899857361e-01	0	0
0	0	-9.579649901340663e-02	0
0	0	0	-1.758390873893391e+00

- Thus Q is the eigenvector matrix for A which is accurate to the last decimal digit
- Indeed, we have checked the orthogonality of *Q*:

 $\|Q^T Q - I_4\|_2 = 2.470193220159530e-16, \quad \|QQ^T - I_4\|_2 = 2.489175293808355e-16$ 

• Using the commands: D = double(Dv); Q = double(Qv); these vpa matrices are converted to double. Here are Q and D:

2.931093180703362e-01	-8.798579328718921e-02	-2.278262800852170e-01	9.243595696169855e-01
4.193767196696980e-01	1.911371496763030e-01	8.815256669327826e-01	1.024805130325522e-01
5.289096009714916e-01	7.298536860359306e-01	-3.873541839913629e-01	-1.937136214217473e-01
6.771002353120279e-01	-6.504142427507317e-01	-1.447909554690162e-01	-3.123013983025982e-01

1.751525068292106e-01	0	0	0
0	3.389366899857361e-01	0	0
0	0	-9.579649901340663e-02	0
0	0	0	-1.758390873893391e+00

- Thus Q is the eigenvector matrix for A which is accurate to the last decimal digit
- Indeed, we have checked the orthogonality of *Q*:

 $\|Q^T Q - I_4\|_2 = 2.470193220159530e-16, \quad \|QQ^T - I_4\|_2 = 2.489175293808355e-16$ 

• The remaining computation is performed in double

$$Q = \left[ \begin{array}{cc} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{array} \right]$$

Next, we compute the matrix W. First compute the SVDs of the diagonal blocks

$$Q_{11} = U_{11}C_1V_{11}^T, \qquad Q_{22} = U_{22}C_2V_{22}^T$$

$$Q = \left[ \begin{array}{cc} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{array} \right]$$

Next, we compute the matrix W. First compute the SVDs of the diagonal blocks

$$Q_{11} = U_{11}C_1V_{11}^T, \qquad Q_{22} = U_{22}C_2V_{22}^T$$

Then form the block diagonal U and V

$$U = \left[ \begin{array}{cc} U_{11} & O \\ O & U_{22} \end{array} \right], \quad V = \left[ \begin{array}{cc} V_{11} & O \\ O & V_{22} \end{array} \right].$$

$$Q = \left[ \begin{array}{cc} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{array} \right]$$

Next, we compute the matrix W. First compute the SVDs of the diagonal blocks

$$Q_{11} = U_{11}C_1V_{11}^T, \qquad Q_{22} = U_{22}C_2V_{22}^T$$

Then form the block diagonal U and V

$$U = \begin{bmatrix} U_{11} & O \\ O & U_{22} \end{bmatrix}, \quad V = \begin{bmatrix} V_{11} & O \\ O & V_{22} \end{bmatrix}.$$

and also

$$W = U^{T} Q V = \begin{bmatrix} C_1 & W_{12} \\ W_{21} & C_2 \end{bmatrix},$$
(5)

where

$$W_{12} = U_{11}^T Q_{12} V_{22}, \qquad W_{21} = U_{22}^T Q_{21} V_{11}.$$

and  $C_1$  and  $C_2$  are diagonal.

• We have obtained: W is to working accuracy G, the central matrix in CSD!

- We have obtained: W is to working accuracy G, the central matrix in CSD!
- Then we employ the procedure which transforms  $2 \times 2$  reflectors into rotations with angles from the interval  $[-\pi/2, \pi/2]$

- We have obtained: W is to working accuracy G, the central matrix in CSD!
- Then we employ the procedure which transforms  $2 \times 2$  reflectors into rotations with angles from the interval  $[-\pi/2, \pi/2]$
- This makes the decomposition  $Q = \tilde{U}\tilde{G}\tilde{V}D_V$ . Here are  $\tilde{U}$ ,  $\tilde{G}$ ,  $\tilde{V}$ ,  $D_V$ :

ſ	5.057945141284034e-01	-8.626539917473362e-01	0	0 ]
	8.626539917473362e-01	5.057945141284033e-01	0	0
	0	0	8.012598003675062e-01	-5.983165820157615e-01
l	0	0	5.983165820157615e-01	8.012598003675064e-01
		- 1		
L	5.240444959932522e-01	0	-8.516908865422823e-01	-1.110223024625157e-16
ł	2.775557561562891e-17	1.773194331327221e-01	-5.551115123125783e-17	9.841533511772902e-01
l	8.516908865422820e-01	-1.387778780781446e-16	5.240444959932518e-01	0
L	5.551115123125783e-17	-9.841533511772899e-01	1.387778780781446e-17	1.773194331327220e-01
ſ	9.732572143939268e-01	-2.297180764114445e-01	0	0 ]
	2.297180764114445e-01	9.732572143939268e-01	0	0
	0	0	7.575733907232336e-01	-6.527499962988148e-01
l	0	0	6.527499962988148e-01	7.575733907232336e-01
		$ \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ \hline 0 & 0 \\ 0 & 0 \end{bmatrix} $	$ \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ \hline -1 & 0 \\ 0 & -1 \end{bmatrix} $	

Now is the time to "extract" the 6 rotations from the CSD

- Now is the time to "extract" the 6 rotations from the CSD
- To ensure the best orthogonality of the rotations we make a procedure that takes the mean of two diagonal elements and similar for the off-diagonal elements. So, each "updated rotation" will have equal diagonal and opposite off-diagonal elements

- Now is the time to "extract" the 6 rotations from the CSD
- To ensure the best orthogonality of the rotations we make a procedure that takes the mean of two diagonal elements and similar for the off-diagonal elements. So, each "updated rotation" will have equal diagonal and opposite off-diagonal elements
- We have checked

$$\|Q - R_q R_2 R_3 R_4 R_5 R_6 D_V\|_2 = 3.885944763273228e - 16$$

- Now is the time to "extract" the 6 rotations from the CSD
- To ensure the best orthogonality of the rotations we make a procedure that takes the mean of two diagonal elements and similar for the off-diagonal elements. So, each "updated rotation" will have equal diagonal and opposite off-diagonal elements
- We have checked  $\|Q R_q R_2 R_3 R_4 R_5 R_6 D_V\|_2 = 3.885944763273228e 16$
- Next, we successively apply these 6 rotations  $R_1-R_6$  to the symmetric matrix A. We shall have 6 steps to display, each one of the form

$$A^{(k)} = R_k^T A^{(k-1)} R_k, \quad k = 1, 2, 3, 4, 5, 6, \quad A^{(0)} = A$$

# Step 1 $A^{(1)} = R_1^T A R_1$

		Γ0	2	3	4 -	]		
	Λ —	2	3	4	5			
	A =	3	4	5	6			
		4	5	6	8			
	- 5.057945141284034e-	-01	-8.	6265	3991	7473362e-01	0	0 ]
P	8.626539917473362e-	-01	5.	0579	4514	1284033e-01	0	0
$n_1 -$		0				0	1	0
	-	0				0	0	1
$A^{(1)} = R_1^{\mathcal{T}} A R_1$								

- 3.977818354899925e+00	3.322893319398632e-01	4.967999509374554e+00	6.336448015250294e+00
3.322893319398633e-01	-9.778183548999233e-01	-5.647839187283954e-01	-9.216433963473283e-01
4.967999509374554e+00	-5.647839187283954e-01	5.000000000000000e+00	6.00000000000000e+00
6.336448015250294e+00	-9.216433963473283e-01	6.000000000000000e+00	8.00000000000000e+00

 $A^{(1)}$ 

3.977818354899925e+00	3.322893319398632e-01	4.967999509374554e+00	6.336448015250294e+00
3.322893319398633e-01	-9.778183548999233e-01	-5.647839187283954e-01	-9.216433963473283e-01
4.967999509374554e+00	-5.647839187283954e-01	5.00000000000000e+00	6.00000000000000e+00
6.336448015250294e+00	-9.216433963473283e-01	6.000000000000000e+00	8.00000000000000e+00

	1	0	0	0
P _	0	1	0	0
$\kappa_2 =$	0	0	8.012598003675062e-01	-5.983165820157615e-01
	0	0	5.983165820157615e-01	8.012598003675064e-01

$$A^{(2)} = R_2^T A^{(1)} R_2$$

3	.977818354899925e+00	3.322893319398632e-01	7.771860213712436e+00	2.104704585833569e+00
3	3.322893319398633e-01	-9.778183548999233e-01	-1.003973176711023e+00	-4.005562199362495e-01
7	.771860213712436e+00	-1.003973176711023e+00	1.182683249769528e+01	3.142428287407269e+00
2	.104704585833569e+00	-4.005562199362495e-01	3.142428287407268e+00	1.173167502304712e+00

 $A^{(2)}$ 

3.977818354899925e+00	3.322893319398632e-01	7.771860213712436e+00	2.104704585833569e+00
3.322893319398633e-01	-9.778183548999233e-01	-1.003973176711023e+00	-4.005562199362495e-01
7.771860213712436e+00	-1.003973176711023e+00	1.182683249769528e+01	3.142428287407269e+00
2.104704585833569e+00	-4.005562199362495e-01	3.142428287407268e+00	1.173167502304712e+00

[	5.240444959932520e-01	0	-8.516908865422821e-01	0		
$R_3 =$	0	1	0	0		
	8.516908865422821e-01	0	5.240444959932520e-01	0		
	0	0	0	1		
$A^{(3)} = R_3^T A^{(2)} R_3$						

1.660884981522208e+01	-6.809404094573227e-01	-3.552713678800501e-15	3.779336387895281e+00
-6.809404094573226e-01	-9.778183548999233e-01	-8.091344130886772e-01	-4.005562199362495e-01
-2.664535259100376e-15	-8.091344130886771e-01	-8.041989626268715e-01	-1.457854665489189e-01
3.779336387895281e+00	-4.005562199362495e-01	-1.457854665489193e-01	1.173167502304712e+00

Hari (University of Zagreb)

 $A^{(3)}$ 

1.660884981522208e+01	-6.809404094573227e-01	-3.552713678800501e-15	3.779336387895281e+00
-6.809404094573226e-01	-9.778183548999233e-01	-8.091344130886772e-01	-4.005562199362495e-01
-2.664535259100376e-15	-8.091344130886771e-01	-8.041989626268715e-01	-1.457854665489189e-01
3.779336387895281e+00	-4.005562199362495e-01	-1.457854665489193e-01	1.173167502304712e+00

	1	0	0	0	
P	0	1.773194331327221e-01	0	9.841533511772900e-01	
N4 —	0	0	1	0	
	0	-9.841533511772900e-01	0	1.773194331327221e-01	

 $A^{(4)} = R_4^T A^{(3)} R_4$ 

1.660884981522208e+01	$-3.840190538775552e{+}00$	-3.552713678800501e-15	5.551115123125783e-16
$-3.840190538775552e{+}00$	1.245337557684717e+00	1.637578961322106e-15	-2.775557561562891e-16
-2.664535259100376e-15	1.221245327087672e-15	-8.041989626268715e-01	-8.221629404815349e-01
6.661338147750939e-15	-2.498001805406602e-16	-8.221629404815352e-01	-1.049988410279928e+00

 $A^{(4)}$ 

1.660884981522208e+01	$-3.840190538775552e{+}00$	-3.552713678800501e-15	5.551115123125783e-16
$-3.840190538775552e{+}00$	1.245337557684717e+00	1.637578961322106e-15	-2.775557561562891e-16
-2.664535259100376e-15	1.221245327087672e-15	-8.041989626268715e-01	-8.221629404815349e-01
6.661338147750939e-15	-2.498001805406602e-16	-8.221629404815352e-01	-1.049988410279928e+00

	9.732572143939268 <i>e</i> - 01	2.297180764114445e - 01	0	0	
$R_5 =$	-2.297180764114445 <i>e</i> - 01	9.732572143939268 <i>e</i> - 01	0	0	
	0	0	1	0	
	0	0	0	1	
		_ / \			

 $A^{(5)} = R_5^T A^{(4)} R_5$ 

6.040258585524866e-16	-3.833885707535341e-15	4.440892098500626e-16	1.751525068292106e+01
-1.426139932733765e-16	7.776629859117751e-16	3.389366899857359e-01	5.412337245047638e-16
-8.221629404815349e-01	-8.041989626268715e-01	5.764939108819395e-16	-2.873820291291477e-15
-1.049988410279928e+00	-8.221629404815352e-01	-9.009684930535088e-17	7.057031579426399e-16

 $A^{(5)}$ 

1.751	525068292106e+01	4.440892098500626e-16	-3.833885707535341e-15	6.040258585524866e-16
5.41	2337245047638e-16	3.389366899857359e-01	7.776629859117751e-16	-1.426139932733765e-16
-2.87	3820291291477e-15	5.764939108819395e-16	-8.041989626268715e-01	-8.221629404815349e-01
7.05	7031579426399e-16	-9.009684930535088e-17	-8.221629404815352e-01	-1.049988410279928e+00

$$R_6 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ \hline 0 & 0 & 7.575733907232336e-01 & 6.527499962988148e-01 \\ 0 & 0 & -6.527499962988148e-01 & 7.575733907232336e-01 \end{bmatrix}$$

 $A^{(6)} = R_6^T A^{(5)} R_6$ 

1.751525068292106e+01	4.440892098500626e-16	-3.298727672037416e-15	-2.044974963655654e-15
5.412337245047638e-16	3.389366899857359e-01	6.822280686584934e-16	3.995789447269441e-16
-2.637777516138035e-15	4.955471648487312e-16	-9.579649901340658e-02	1.526556658859590e-16
-1.341264250297271e-15	3.080514225727404e-16	-2.220446049250313e-16	-1.758390873893392e + 00