

## 1. Basics

1. For the following matrices compute the eigenvalues, their algebraic and geometric multiplicities, their eigenvectors and, if needed, their generalized eigenvectors.

$$A = \begin{bmatrix} 2 & 1 \\ 4 & -1 \end{bmatrix}, \quad B = \begin{bmatrix} 1 & -2 \\ 2 & 1 \end{bmatrix}, \quad C = \begin{bmatrix} 2 & 1 \\ -1 & 4 \end{bmatrix}, \quad D = \begin{bmatrix} 1 & 0 & 0 \\ 3 & 3 & -4 \\ -2 & 1 & -2 \end{bmatrix},$$

$$E = \begin{bmatrix} 3 & -10 & -10 \\ 0 & 3 & 0 \\ 0 & -5 & -2 \end{bmatrix}, \quad F = \begin{bmatrix} 2 & 2 & 1 \\ 0 & 2 & 1 \\ 0 & -1 & 0 \end{bmatrix}$$

2. „The big Six Matrix Decompositions“

Repeat the properties of the following matrix factorizations:

- 2.1. Cholesky-Decomposition
- 2.2. (Pivotised) LU-Decomposition
- 2.3. QR-Decomposition
- 2.4. Spectral Decomposition
- 2.5. Schur-Decomposition
- 2.6. Singular Value Decomposition (SVD)

Think about existence and uniqueness. Which algorithms you know for the decompositions ?

3. Show the uniqueness of the sparse QR-Decomposition  $A = Q_1 R_1$ , if  $A \in \mathbb{R}^{m \times n} (m > n)$  has full column rank.  $Q_1 \in \mathbb{R}^{m \times n}$  has orthonormal columns and  $R_1 \in \mathbb{R}^{n \times n}$  is a upper triangular matrix. Moreover,  $R_1$  comes from the lower triangular factor  $G$  from the Cholesky-Decomposition of  $A^T A$  by the identity  $R_1 = G^T$ .
4. For  $A \in \mathbb{R}^{m \times n}$  with  $s = \text{rank}(A)$  we have the Singular Value Decomposition (SVD)

$$A = U \Sigma V^T$$

with orthonormal  $U = [u_1, \dots, u_m] \in \mathbb{R}^{m \times m}$  and orthonormal  $V = [v_1, \dots, v_n] \in \mathbb{R}^{n \times n}$ .

Proof that:

- a) If  $k < s$  and  $A_k = \sum_{i=1}^k \sigma_i u_i v_i^T$ , then:

$$\min_{\text{rank}(B)=k} \|A - B\|_2 = \|A - A_k\|_2 = \sigma_{k+1}$$

- b)

$$\begin{aligned} \ker(A) &= \text{span}\{v_{s+1}, \dots, v_n\} \\ \text{im}(A) &= \text{span}\{u_1, \dots, u_s\} \end{aligned}$$

- c)

$$\|A\|_F = \sqrt{\sigma_1^2 + \dots + \sigma_s^2}$$