

- New concepts:
  - An orthogonal eigenvalue-revealing decomposition: Schur
  - Computability
  - Non-computability of polynomial roots
  - The need for an additional orthogonal decomposition
  - Interpreting the eigenvalue decomposition
  - Motivating the singular value decomposition
  - The singular value decomposition (SVD)



- Review of already encountered matrix decompositions:
  - $LU = A$  factorization (Gaussian elimination), used to solve linear systems (compute coordinates in new basis)
  - $QR = A$  factorization (Gram-Schmidt algorithm), used to solve least squares problems (compute best possible approximation)
  - $AX = X\Lambda$ , eigenproblem. If  $X$  nonsingular, eigendecomposition  $X\Lambda X^{-1} = A$  (reduction to diagonal form)
- Additional matrix decompositions:
  - $QTQ^T = A$ , Schur decomposition (reduction to triangular form)
  - $PJP^{-1} = A$ , Jordan decomposition (reduction to disjoint eigenspaces)
  - $U\Sigma V^T = A$ , singular value decomposition (SVD, reduction to diagonal form, but with different bases in the domain, codomain)

**Theorem.** (Schur) Any square matrix  $A \in \mathbb{R}^{m \times m}$  can be decomposed as  $A = QTQ^T$ , with  $T \in \mathbb{R}^{m \times m}$  upper triangular ( $t_{ij} = 0$  for  $i > j$ ) and  $Q \in \mathbb{R}^{m \times m}$  orthogonal ( $QQ^T = I$ ).

- The eigenvalues of  $T$  triangular are its diagonal elements
- $A$  is similar to  $T$ :  $Ax = \lambda x \Rightarrow Ty = \lambda y$  and  $y = Q^T x$

Computability.

- roots of first degree polynomial:  $p_1(x) = ax + b = 0 \Rightarrow x = -b/a$  ( $a \neq 0$ )
- roots of second degree polynomial:  $p_2(x) = ax^2 + bx + c \Rightarrow$

$$x_{1,2} = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

- roots of third degree polynomial (Cardano's formulas ~1520's)
- roots of fourth degree polynomial (Ferrari's formulas ~1540's, irrespective of Inquisitor Torquemada forbidding Valmes such knowledge)
- fifth degree polynomial: no formula possible (Galois, Abel Ruffini, 1820's)



- If  $A \in \mathbb{R}^{m \times m}$  is normal ( $AA^T = A^T A$ ) then it has an orthogonal eigendecomposition  $\exists Q$ ,  $A = Q \Lambda Q^T$ ,  $QQ^T = Q^T Q = I$
- How does  $b = Ax$  work?

$$b = Ax = Q \Lambda Q^T x = Q \Lambda y = Q w$$

$$c = Q^T b \Leftrightarrow Qc = Ib, y = Q^T x \Leftrightarrow Qy = Ix$$

- In the  $I = [e_1 \dots e_m]$  basis set  $b = x_1 a_1 + \dots + x_m a_m$  implies all components of  $a_1, \dots, a_m$  influence each component of  $b$

$$b_i = \sum_{j=1}^m a_{ij} x_j$$

- In the  $Q$  basis set  $w = \Lambda y$ , component  $i$  of  $w$  influenced only by component  $i$  of  $y$

$$w_i = \lambda_i y_i$$



- For  $A \in \mathbb{R}^{m \times n}$ ,  $b = Ax$ , a mapping from  $\mathbb{R}^n$  to  $\mathbb{R}^m$  try to define:
  - an orthonormal basis  $V$  in  $\mathbb{R}^n$ ,  $V \in \mathbb{R}^{n \times n}$ ,  $VV^T = V^T V = I_n$

$$Ix = Vy \Rightarrow y = V^T x$$

- an orthonormal basis  $U$  in  $\mathbb{R}^m$ ,  $U \in \mathbb{R}^{m \times m}$ ,  $UU^T = U^T U = I_m$

$$Ib = Uc \Rightarrow c = U^T b$$

- impose that the action of  $A$  in the new bases is a simple component scaling

$$c = \Sigma y \Rightarrow U^T b = \Sigma V^T x \Rightarrow b = U \Sigma V^T x \Rightarrow$$

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

- Note that  $\Sigma \in \mathbb{R}^{m \times n}$

**Theorem.** (SVD) For any  $A \in \mathbb{R}^{m \times n}$ ,  $A = U \Sigma V^T$ , with  $U \in \mathbb{R}^{m \times m}$ ,  $V \in \mathbb{R}^{n \times n}$  orthogonal,  $\Sigma \in \mathbb{R}_+^{m \times n}$  pseudo-diagonal  $\Sigma = \text{diag}(\sigma_1, \dots, \sigma_r, \dots, 0)$ ,  $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r > 0$ ,  $r \leq \min(m, n)$ .  $r = \text{rank}(A)$ .

The SVD is determined by eigendecomposition of  $A^T A$ , and  $A A^T$

- $A^T A = (U \Sigma V^T)^T (U \Sigma V^T) = V (\Sigma^T \Sigma) V^T$ , an eigendecomposition of  $A^T A$ . The columns of  $V$  are eigenvectors of  $A^T A$  and called *right singular vectors* of  $A$
- $A A^T = (U \Sigma V^T)(U \Sigma^T V^T)^T = U (\Sigma \Sigma^T) U^T$ , an eigendecomposition of  $A A^T$ . The columns of  $U$  are eigenvectors of  $A A^T$  and called *left singular vectors* of  $A$
- The matrix  $\Sigma$  has zero elements except for the diagonal that contains  $\sigma_i$ , the *singular values* of  $A$ , computed as the square roots of the eigenvalues of  $A^T A$  (or  $A A^T$ )

The theorem also holds for complex matrices with transposition replaced by taking the adjoint,  $A \in \mathbb{C}^{m \times n}$ ,  $A = U \Sigma V^*$ , with  $U \in \mathbb{C}^{m \times m}$ ,  $V \in \mathbb{C}^{n \times n}$  unitary.

- SVD of  $\mathbf{A} \in \mathbb{R}^{m \times n}$  reveals:  $\text{rank}(\mathbf{A})$ , bases for  $C(\mathbf{A})$ ,  $N(\mathbf{A}^T)$ ,  $C(\mathbf{A}^T)$ ,  $N(\mathbf{A})$

$$\begin{matrix} m \\ \mathbf{A} \\ n \end{matrix} = \begin{matrix} m \\ \mathbf{U} \\ m \end{matrix} \begin{matrix} m \\ \mathbf{\Sigma} \\ n \end{matrix} \begin{matrix} m \\ \mathbf{V}^T \\ n \end{matrix}$$

$$\mathbf{A} = \begin{pmatrix} \mathbf{u}_1 & \dots & \mathbf{u}_r & \mathbf{u}_{r+1} & \dots & \mathbf{u}_m \end{pmatrix} \begin{pmatrix} \sigma_1 & & & & & \\ & \ddots & & & & \\ & & \sigma_r & & & \\ & & & 0 & & \\ & & & & \ddots & \end{pmatrix} \begin{pmatrix} \mathbf{v}_1^T \\ \vdots \\ \mathbf{v}_r^T \\ \mathbf{v}_{r+1}^T \\ \vdots \\ \mathbf{v}_n^T \end{pmatrix}$$