

Eigen Decomposition

$$A \in \mathbb{R}^{n \times n}$$

$$A = Q \Lambda Q^{-1}$$

$$Q = \begin{bmatrix} | & | & & | \\ v_1 & v_2 & \dots & v_n \\ | & | & & | \end{bmatrix}$$

$$A v_i = \lambda_i v_i$$

$$\Lambda = \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \dots & \\ & & & \lambda_n \end{bmatrix} \quad \lambda_i \in \mathbb{C}$$

if $A \in \mathbb{R}^{n \times m}$

Singular Value Decomposition (SVD)

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

* complex conjugate transpose

transpose $\begin{bmatrix} 1 & 2 \\ 3 & 7 \\ 5 & 6 \end{bmatrix}^T = \begin{bmatrix} 1 & 3 & 5 \\ 2 & 7 & 6 \end{bmatrix}$

Complex conjugate $a + bi \rightarrow a - bi$

$a, b \in \mathbb{R}$

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

$$U \in \mathbb{C}^{n \times n}$$

$$V \in \mathbb{C}^{m \times m}$$

$$\begin{bmatrix} A \end{bmatrix} = \begin{bmatrix} U \end{bmatrix} \begin{bmatrix} \Sigma \end{bmatrix} \begin{bmatrix} V \end{bmatrix}$$

$$A = \begin{bmatrix} \hat{U} & \hat{U}^\perp \end{bmatrix} \begin{bmatrix} \hat{\Sigma} \\ 0 \end{bmatrix} V^* = \hat{U} \hat{\Sigma} V^* \quad \text{Since } \hat{\Sigma} \text{ diag}$$

the values in $\hat{\Sigma}$ are sorted

$$A^{-1} = V \hat{\Sigma}^{-1} \hat{U}^*$$

$$Ax = b \quad x = V \hat{\Sigma}^{-1} \hat{U}^* b$$

$$\hat{\Sigma} = \begin{bmatrix} \sigma_1 & & 0 \\ & \sigma_2 & \\ 0 & & \dots \\ & & & \sigma_n \end{bmatrix}$$

$$\hat{\Sigma}^{-1} = \begin{bmatrix} 1/\sigma_1 & & 0 \\ & 1/\sigma_2 & \\ 0 & & \dots \\ & & & 1/\sigma_n \end{bmatrix}$$

$$A = \begin{bmatrix} \text{matrix} \end{bmatrix} \begin{bmatrix} \hat{\Sigma} \end{bmatrix} \begin{bmatrix} V^* \end{bmatrix}$$

$$U = \begin{bmatrix} | & | & & | \\ v_1 & v_2 & \dots & v_n \\ | & | & & | \end{bmatrix}$$

Data Driven Science and Engineering

Principal Component Analysis (PCA)

$$\hat{X} = \begin{bmatrix} | & | & & | \\ x_1 & x_2 & \dots & x_n \\ | & | & & | \end{bmatrix} \quad \begin{bmatrix} \text{matrix} \end{bmatrix} \begin{bmatrix} \text{matrix} \end{bmatrix} \begin{bmatrix} \text{matrix} \end{bmatrix}$$

$\hat{X} \in \mathbb{R}^{m \times n}$

$$SVD(\hat{X} - \text{mean}(\hat{X}))$$

$$\text{mean}(\hat{X})_j = \frac{1}{n} \sum_{i=0}^n x_{ij} = \begin{bmatrix} | \\ | \\ | \end{bmatrix}$$

$$\hat{X} = \begin{bmatrix} | & | & & | \\ v_1 & v_2 & \dots & v_n \\ | & | & & | \end{bmatrix} \begin{bmatrix} \sigma_1 & & & \\ & \sigma_2 & & \\ & & \dots & \\ & & & \sigma_n \end{bmatrix} \begin{bmatrix} -v_1 \\ -v_2 \\ \vdots \\ -v_n \end{bmatrix}$$

$$\hat{X} = \hat{U} \hat{\Sigma} V^*$$

images

$$\hat{U}^* \hat{X} = \hat{U}^* \hat{U} \hat{\Sigma} V^*$$

$$\hat{U}^* \hat{X} = \hat{\Sigma} V^*$$

$$\hat{\Sigma}^{-1} \hat{U}^* \hat{X} = \hat{\Sigma}^{-1} \hat{\Sigma} V^*$$

$$= V^*$$

$$= \begin{bmatrix} -v_1 \\ -v_2 \end{bmatrix}$$