# CIS 635 Knowledge Discovery & Data Mining

Singular Value Decomposition (SVD)

# Singular Value Decomposition (SVD)

- Another Linear Dimensionality Reduction
   Technique
- Different than PCA

# PCA steps - Recall

- 1. Let assume  $D_{mxn}$  is a given data matrix
- 2. Apply standard scalar (normalization)
- 3. Estimate Covariance (matrix),  $A_{nxn}$
- Compute Eigenvalues and Eigenvectors of the Covariance Matrix by solving the linear dynamical system at the right

If **A** is a *nxn* matrix, solving this linear dynamical system will give *n* **eigenvalues**, and n associated *n* **eigenvectors** 

$$AX = \lambda X$$

$$AX - \lambda X = 0$$
or
$$(A - \lambda I) X = 0$$

- **A** is your Data Matrix (Transposed)
- SVD decomposes A into 3 matrices: U, S, V

$$A_{m\times n} = U_{m\times m} S_{m\times n} V_{n\times n}^T$$

$$\begin{pmatrix} A & U & S & V^{T} \\ x_{11} & x_{12} & x_{1n} \\ & \ddots & \\ x_{m1} & & x_{mn} \end{pmatrix} = \begin{pmatrix} u_{11} & u_{m1} \\ & \ddots \\ & u_{1m} & u_{mm} \end{pmatrix} \begin{pmatrix} \sigma_{1} & 0 \\ & \sigma_{r} \\ 0 & \ddots & 0 \end{pmatrix} \begin{pmatrix} v_{11} & v_{1n} \\ & \ddots \\ v_{n1} & v_{nn} \end{pmatrix}$$

$$m \times m \qquad m \times m \qquad m \times n \qquad n \times n$$

- A is your Data Matrix (Transposed)
- SVD decomposes A into 3 matrices: U, S, V
- Say we are given,

$$A = \left(\begin{array}{ccc} 3 & 2 & 2 \\ 2 & 3 & -2 \end{array}\right)$$

$$A_{m\times n} = U_{m\times m} S_{m\times n} V_{n\times n}^T$$

$$\begin{pmatrix} A & U & S & V^{T} \\ x_{11} & x_{12} & x_{1n} \\ & \ddots & \\ x_{m1} & & x_{mn} \end{pmatrix} = \begin{pmatrix} u_{11} & u_{m1} \\ & \ddots \\ u_{1m} & u_{mm} \end{pmatrix} \begin{pmatrix} \sigma_{1} & 0 \\ & \sigma_{r} \\ 0 & & 0 \end{pmatrix} \begin{pmatrix} v_{11} & v_{1n} \\ & \ddots \\ v_{n1} & v_{nn} \end{pmatrix}$$

$$m \times n \qquad m \times n \qquad n \times n$$

- A is your Data Matrix (Transposed)
- SVD decomposes A into 3 matrices: U, S, V
- Say we are given,

$$A = \begin{pmatrix} 3 & 2 & 2 \\ 2 & 3 & -2 \end{pmatrix}$$
 SVD solves this linear system (mxm) 
$$(AA^T - I)X = 0$$

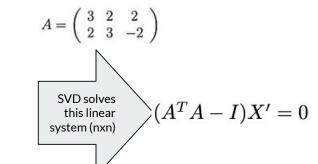
$$AA^T = \left(\begin{array}{cc} 17 & 8 \\ 8 & 17 \end{array}\right)$$

eigenvalues:  $\lambda_1 = 25$ ,  $\lambda_2 = 9$ eigenvectors

$$u_1 = \begin{pmatrix} 1/\sqrt{2} \\ 1/\sqrt{2} \end{pmatrix}$$
  $u_2 = \begin{pmatrix} 1/\sqrt{2} \\ -1/\sqrt{2} \end{pmatrix}$ 

And

- A is your Data Matrix (Transposed)
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- Say we are given,



$$A^T A = \left(\begin{array}{rrr} 13 & 12 & 2\\ 12 & 13 & -2\\ 2 & -2 & 8 \end{array}\right)$$

eigenvalues:  $\lambda_1 = 25$ ,  $\lambda_2 = 9$ ,  $\lambda_3 = 0$ eigenvectors

$$v_1 = \left( \begin{array}{c} 1/\sqrt{2} \\ 1/\sqrt{2} \\ 0 \end{array} \right) \quad v_2 = \left( \begin{array}{c} 1/\sqrt{18} \\ -1/\sqrt{18} \\ 4/\sqrt{18} \end{array} \right) \quad v_3 = \left( \begin{array}{c} 2/3 \\ -2/3 \\ -1/3 \end{array} \right)$$

- A is your Data Matrix (Transposed)
- SVD decomposes A into 3 matrices: U, S, V
- Say we are given,

$$A = \left(\begin{array}{ccc} 3 & 2 & 2 \\ 2 & 3 & -2 \end{array}\right)$$

$$A_{m\times n} = U_{m\times m} S_{m\times n} V_{n\times n}^T$$

$$A = USV^T = \begin{pmatrix} 1/\sqrt{2} & 1/\sqrt{2} \\ 1/\sqrt{2} & -1/\sqrt{2} \end{pmatrix} \begin{pmatrix} 5 & 0 & 0 \\ 0 & 3 & 0 \end{pmatrix} \begin{pmatrix} 1/\sqrt{2} & 1/\sqrt{2} & 0 \\ 1/\sqrt{18} & -1/\sqrt{18} & 4/\sqrt{18} \\ 2/3 & -2/3 & -1/3 \end{pmatrix}$$

**Full derivation** 



Notebook Link