

Eigendecomposition, SVD, and Power Iterations

Objectives

- Define eigenvectors and eigenvalues
- Relate the eigendecomposition to SVD
- Power iterations for computing eigenvector with largest eigenvalue

Eigendecomposition applies to square matrices 2

Eigenvector \underline{e}_i , eigenvalue λ_i , \underline{B} ($k \times k$)

$$\underline{B} \underline{e}_i = \lambda_i \underline{e}_i \quad \text{matrix mult} \leftrightarrow \text{scalar mult}$$

$$\underline{e}_i \longrightarrow \boxed{\underline{B}} \longrightarrow \lambda_i \underline{e}_i \quad i = 1, 2, \dots, k$$

- k eigenvalues, possibly complex valued
- Distinct $\lambda_i \Rightarrow$ linearly independent \underline{e}_i
- Symmetric $\underline{B} \Rightarrow k$ orthonormal \underline{e}_i $\underline{E} \underline{E}^T = \underline{E}^T \underline{E} = \underline{I}$

$$\underline{B} \underline{e}_i = \lambda_i \underline{e}_i \Rightarrow \underline{B} [\underline{e}_1 \underline{e}_2 \dots \underline{e}_k] = [\underline{e}_1 \underline{e}_2 \dots \underline{e}_k] \begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_k \end{bmatrix}$$

$$\underline{B} \underline{E} = \underline{E} \underline{\Lambda} \Rightarrow \underline{B} = \underline{E} \underline{\Lambda} \underline{E}^T = \sum_{i=1}^k \lambda_i \underline{e}_i \underline{e}_i^T$$

Symmetric PSD matrices and SVD 3

$$\underline{A} = [\underline{a}_1 \ \underline{a}_2 \ \dots \ \underline{a}_m] = \begin{bmatrix} \underline{x}_1^T \\ \underline{x}_2^T \\ \vdots \\ \underline{x}_N^T \end{bmatrix} = \underline{U} \underline{\Sigma} \underline{V}^T \quad (N \times m, N > m)$$

full SVD

1) $\underline{B} = \underline{A} \underline{A}^T = \sum_{i=1}^m \underline{a}_i \underline{a}_i^T$

$$\underline{B} = \underline{U} \underline{\Sigma} \underline{V}^T \underline{V} \underline{\Sigma}^T \underline{U}^T = \underline{U} \underline{\Sigma} \underline{\Sigma}^T \underline{U}^T = \underline{U} \begin{bmatrix} \sigma_1^2 & & & 0 \\ & \ddots & & \\ & & \sigma_m^2 & \\ 0 & & 0 & \ddots & 0 \end{bmatrix} \underline{U}^T$$

left SV of $\underline{A} \Leftrightarrow$ eigenvectors \underline{B}

$$\lambda_i = \begin{cases} \sigma_i^2 & i=1, 2, \dots, m \\ 0 & i=m+1, \dots, N \end{cases}$$

2) $\underline{B} = \underline{A}^T \underline{A} = \sum_{i=1}^N \underline{x}_i \underline{x}_i^T$

$$= \underline{V} \underline{\Sigma}^T \underline{U}^T \underline{U} \underline{\Sigma} \underline{V}^T = \underline{V} \underline{\Sigma}^T \underline{\Sigma} \underline{V}^T = \underline{V} \begin{bmatrix} \sigma_1^2 & & & 0 \\ & \ddots & & \\ & & \sigma_m^2 & \\ 0 & & 0 & \ddots \end{bmatrix} \underline{V}^T$$

right SV of $\underline{A} \Leftrightarrow$ eigenvectors \underline{B} , $\lambda_i = \sigma_i^2, i=1, 2, \dots, m$

Power iteration for computing 1st principal component ⁴

$\underline{A} : N \times M, N \gg M$ want \underline{v}_1 1st principal component
right SV of \underline{A} , eigenvector of $\underline{B} = \underline{A}^T \underline{A}$ ($M \times M$)

Power Iteration

pick \underline{c}_0 (random)
for $k=1, 2, \dots$ to converge

$$\underline{c}_k = \underline{B} \underline{c}_{k-1} / \|\underline{B} \underline{c}_{k-1}\|_2$$

end

$$\underline{v}_1 = \underline{c}_{\text{end}}$$

$$\underline{B} \underline{c}_{k-1} = \underbrace{\underline{B} \cdot \underline{B} \cdots \underline{B}}_{k \text{ times}} \underline{c}_0 = \underline{B}^k \underline{c}_0$$

$$\underline{B}^k = \underbrace{\underline{V} \underline{\Lambda} \underline{V}^T \underline{V} \underline{\Lambda} \underline{V}^T \cdots \underline{V} \underline{\Lambda} \underline{V}^T}_{k \text{ times}} \\ = \underline{V} \underline{\Lambda}^k \underline{V}^T$$

$$\text{Let } \underline{c}_0 = \underline{V} \underline{g} = \underline{V} \begin{bmatrix} g_1 \\ g_2 \\ \vdots \\ g_m \end{bmatrix}$$

$$\underline{B}^k \underline{c}_0 = \underline{V} \underline{\Lambda}^k \underline{V}^T \underline{V} \underline{g} \\ = \underline{V} \underline{\Lambda}^k \underline{g}$$

Power iteration...

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$$\underline{C}_k = \underline{B}\underline{C}_{k-1} / \|\underline{B}\underline{C}_{k-1}\|_2 = \underline{V}\underline{\Lambda}^k \underline{g} / \|\underline{V}\underline{\Lambda}^k \underline{g}\|_2$$

$$\underline{V}\underline{\Lambda}^k \underline{g} = [\underline{v}_1 \ \underline{v}_2 \ \dots \ \underline{v}_m] \begin{bmatrix} \lambda_1^k & & 0 \\ & \lambda_2^k & \\ 0 & & \ddots \\ & & & \lambda_m^k \end{bmatrix} \begin{bmatrix} g_1 \\ g_2 \\ \vdots \\ g_m \end{bmatrix} \quad \text{but } \frac{\lambda_i}{\lambda_1} < 1$$

$$= \lambda_1^k g_1 \underline{V} \begin{bmatrix} 1 & & 0 \\ (\frac{\lambda_2}{\lambda_1})^k & \ddots & \\ 0 & & (\frac{\lambda_m}{\lambda_1})^k \end{bmatrix} \begin{bmatrix} 1 \\ g_2/g_1 \\ \vdots \\ g_m/g_1 \end{bmatrix} \quad \text{so } \left(\frac{\lambda_i}{\lambda_1}\right)^k \rightarrow 0$$

$$\underline{V}\underline{\Lambda}^k \underline{g} \rightarrow \lambda_1^k g_1 \underline{V} \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & \ddots & & 0 \\ 0 & & \ddots & \\ 0 & 0 & \dots & 0 \end{bmatrix} \begin{bmatrix} 1 \\ \vdots \end{bmatrix} = \lambda_1^k g_1 \underline{v}_1$$

$$\underline{C}_k \rightarrow \frac{\lambda_1^k g_1 \underline{v}_1}{\|\lambda_1^k g_1 \underline{v}_1\|_2} = \frac{\underline{v}_1}{\|\underline{v}_1\|_2} = \underline{v}_1$$

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