# Mathematics for Machine Learning

## — Linear Algebra: Singular Value Decomposition & Matrix Approximation

Joseph Chuang-Chieh Lin

Department of Computer Science & Information Engineering,
Tamkang University

Fall 2023

# Credits for the resource

- The slides are based on the textbooks:
  - *Marc Peter Deisenroth, A. Aldo Faisal, and Cheng Soon Ong: Mathematics for Machine Learning. Cambridge University Press. 2020.*
  - *Howard Anton, Chris Rorres, Anton Kaul: Elementary Linear Algebra. Wiley. 2019.*
- We could partially refer to the monograph:
  *Francesco Orabona: A Modern Introduction to Online Learning.*
  *https://arxiv.org/abs/1912.13213*

# Outline

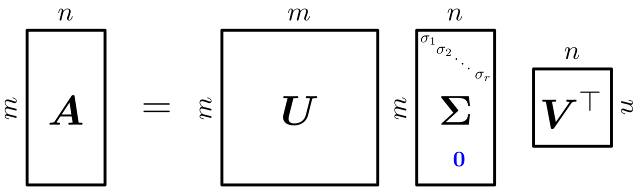
# Outline

# Why Singular Value Decomposition?

- It can be applied to all matrices (not only to square matrices).
- It always exists.

# Illustration

$\boldsymbol{A} \in \mathbb{R}^{m \times n}$, $\text{rank}(\boldsymbol{A}) = r \leq \min(m, n)$:

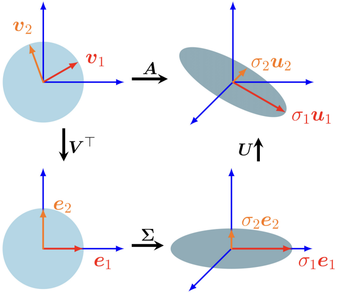



- $\boldsymbol{U} \in \mathbb{R}^{m \times m}$ with orthogonal columns vectors $\boldsymbol{u}_i$, $i = 1, \ldots, m$.
- $\boldsymbol{V} \in \mathbb{R}^{n \times n}$ with orthogonal columns vectors $\boldsymbol{v}_j$, $j = 1, \ldots, n$.
- $\boldsymbol{\Sigma} \in \mathbb{R}^{m \times n}$ with $\Sigma_{ii} = \sigma_i \geq 0$ and $\Sigma_{ij} = 0$ for $i \neq j$.
  - $\sigma_i$: singular values; $\sigma_1 \geq \sigma_2 \geq \ldots \geq \sigma_r \geq 0$.
  - $\boldsymbol{u}_i$: left-singular vectors;
    $\boldsymbol{v}_j$: right-singular vectors;

# Illustration & Example

$$\boldsymbol{A} = \begin{bmatrix} 1 & -0.8 \\ 0 & 1 \\ 1 & 0 \end{bmatrix} = \boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^\top$$

$$= \begin{bmatrix} -0.79 & 0 & -0.62 \\ 0.38 & -0.78 & -0.49 \\ -0.48 & -0.62 & 0.62 \end{bmatrix} \begin{bmatrix} 1.62 & 0 \\ 0 & 1.0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} -0.78 & 0.62 \\ -0.62 & -0.78 \end{bmatrix}$$



# Exercise

**Exercise**

Prove that for an $\boldsymbol{A} \in \mathbb{R}^{m \times n}$, $\boldsymbol{A}\boldsymbol{A}^\top$ and $\boldsymbol{A}^\top\boldsymbol{A}$ have the same nonzero eigenvalues.

# Outline

# SVD & Eigendecomposition

- Recall the eigendecomposition of a symmetric positive definite matrix

$$\boldsymbol{S} = \boldsymbol{S}^\top = \boldsymbol{P}\boldsymbol{D}\boldsymbol{P}^\top.$$

# SVD & Eigendecomposition

- Recall the eigendecomposition of a symmetric positive definite matrix

$$\boldsymbol{S} = \boldsymbol{S}^\top = \boldsymbol{P}\boldsymbol{D}\boldsymbol{P}^\top.$$

with the corresponding SVD

$$\boldsymbol{S} = \boldsymbol{U}\Sigma\boldsymbol{V}^\top$$

so $\boldsymbol{U} = \boldsymbol{P} = \boldsymbol{V}$, $\boldsymbol{D} = \Sigma$.

# The Overall Idea

- Computing the SVD of $\boldsymbol{A} \in \mathbb{R}^{m \times n} \Leftrightarrow$ Finding two sets of orthonormal bases $U = (\mathbf{u}_1, \ldots, \mathbf{u}_m)$ and $V = (\mathbf{v}_1, \ldots, \mathbf{v}_n)$ respectively.
- Images of $\boldsymbol{A}\mathbf{v}_i$'s form a set of orthogonal vectors.

# The first step: Constructing the right-singular vectors

- **Recall:** Eigenvectors of a *symmetric* matrix form an orthonormal basis (The Spectral theorem).
- Also, we can always construct a symmetric, positive semidefinite matrix $\boldsymbol{A}^\top \boldsymbol{A} \in \mathbb{R}^{n \times n}$ from any matrix $\boldsymbol{A} \in \mathbb{R}^{m \times n}$.
- Thus,

$$\boldsymbol{A}^\top \boldsymbol{A} = \boldsymbol{P}\boldsymbol{D}\boldsymbol{P}^\top = \boldsymbol{P} \begin{bmatrix} \lambda_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \lambda_n \end{bmatrix} \boldsymbol{P}^\top,$$

where $\boldsymbol{P}$ is orthogonal and composed of orthonormal eigenbasis.

⋆ $\lambda_i \geq 0$ are the eigenvalues of $\boldsymbol{A}^\top \boldsymbol{A}$.

# The first step (2/2)

- Assume the SVD of $\boldsymbol{A}$ exists.

$$\boldsymbol{A}^\top \boldsymbol{A} = (\boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^\top)^\top (\boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^\top) = \boldsymbol{V}\boldsymbol{\Sigma}^\top \boldsymbol{U}^\top \boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^\top$$

where $\boldsymbol{U}$, $\boldsymbol{V}$ are orthonormal matrices

# The first step (2/2)

- Assume the SVD of $\boldsymbol{A}$ exists.

$$\boldsymbol{A}^\top \boldsymbol{A} = (\boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^\top)^\top (\boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^\top) = \boldsymbol{V}\boldsymbol{\Sigma}^\top \boldsymbol{U}^\top \boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^\top$$

where $\boldsymbol{U}, \boldsymbol{V}$ are orthonormal matrices $\quad (\because \boldsymbol{U}^\top \boldsymbol{U} = \boldsymbol{I})$.

# The first step (2/2)

- Assume the SVD of $\boldsymbol{A}$ exists.

$$\boldsymbol{A}^\top \boldsymbol{A} = (\boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^\top)^\top(\boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^\top) = \boldsymbol{V}\boldsymbol{\Sigma}^\top \boldsymbol{U}^\top \boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^\top$$

where $\boldsymbol{U}, \boldsymbol{V}$ are orthonormal matrices $(\because \boldsymbol{U}^\top \boldsymbol{U} = \boldsymbol{I})$. So,

# The first step (2/2)

- Assume the SVD of $\boldsymbol{A}$ exists.

$$\boldsymbol{A}^\top \boldsymbol{A} = (\boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^\top)^\top(\boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^\top) = \boldsymbol{V}\boldsymbol{\Sigma}^\top\boldsymbol{U}^\top\boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^\top$$

where $\boldsymbol{U}, \boldsymbol{V}$ are orthonormal matrices $(\because \boldsymbol{U}^\top\boldsymbol{U} = \boldsymbol{I})$. So,

$$\boldsymbol{A}^\top \boldsymbol{A} = \boldsymbol{V}\boldsymbol{\Sigma}^\top\boldsymbol{\Sigma}\boldsymbol{V}^\top = \boldsymbol{V}\begin{bmatrix} \sigma_1^2 & 0 & \\ 0 & \ddots & 0 \\ 0 & 0 & \sigma_n^2 \end{bmatrix}\boldsymbol{V}^\top$$

- Hence, we identify $\boldsymbol{V}^\top = \boldsymbol{P}^\top$ (right-singular vectors) and $\sigma_i^2 = \lambda_i$.

# The second step: Constructing the left-singular vectors

- Similarly, we can always construct a symmetric, positive semidefinite matrix $\boldsymbol{A}\boldsymbol{A}^\top \in \mathbb{R}^{m \times m}$ from any matrix $\boldsymbol{A} \in \mathbb{R}^{m \times n}$.
- Thus, by assuming the SVD of $\boldsymbol{A}$ exists, we have

$$\begin{aligned} \boldsymbol{A}\boldsymbol{A}^\top &= (\boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^\top)(\boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^\top)^\top = \boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^\top\boldsymbol{V}\boldsymbol{\Sigma}^\top\boldsymbol{U}^\top \\ &= \boldsymbol{U}\begin{bmatrix} \sigma_1^2 & 0 & \\ 0 & \ddots & 0 \\ 0 & 0 & \sigma_m^2 \end{bmatrix}\boldsymbol{U}^\top \end{aligned}$$

**Note:** $\boldsymbol{A}\boldsymbol{A}^\top$ and $\boldsymbol{A}^\top\boldsymbol{A}$ have the same eigenvalues.

# The second step: Constructing the left-singular vectors

- Similarly, we can always construct a symmetric, positive semidefinite matrix $\boldsymbol{A}\boldsymbol{A}^\top \in \mathbb{R}^{m \times m}$ from any matrix $\boldsymbol{A} \in \mathbb{R}^{m \times n}$.
- Thus, by assuming the SVD of $\boldsymbol{A}$ exists, we have

$$\begin{aligned} \boldsymbol{A}\boldsymbol{A}^\top &= (\boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^\top)(\boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^\top)^\top = \boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^\top\boldsymbol{V}\boldsymbol{\Sigma}^\top\boldsymbol{U}^\top \\ &= \boldsymbol{U}\begin{bmatrix} \sigma_1^2 & 0 & \\ 0 & \ddots & 0 \\ 0 & 0 & \sigma_m^2 \end{bmatrix}\boldsymbol{U}^\top \end{aligned}$$

**Note:** $\boldsymbol{A}\boldsymbol{A}^\top$ and $\boldsymbol{A}^\top\boldsymbol{A}$ have the same eigenvalues.

$\Rightarrow$ The nonzero entries of $\boldsymbol{\Sigma}$ in the SVD for both steps must be the same.

# The last step: Link up all parts (1/2)

Images of the $\boldsymbol{v}_i$ under $\boldsymbol{A}$ must be orthogonal.

$$(\boldsymbol{A}\mathbf{v}_i)^\top(\boldsymbol{A}\mathbf{v}_j) = \mathbf{v}_i^\top(\boldsymbol{A}^\top\boldsymbol{A})\mathbf{v}_j = \mathbf{v}_i^\top(\lambda_j\mathbf{v}_j) = \lambda_j\mathbf{v}_i^\top\mathbf{v}_j = 0.$$

(For $m \geq r$) We observe that $\{\boldsymbol{A}\mathbf{v}_1, \ldots, \boldsymbol{A}\mathbf{v}_r\}$ is a basis of an $r$-dimensional subspace of $\mathbb{R}^m$.

# The last step: Link up all parts (1/2)

Images of the $\boldsymbol{v}_i$ under $\boldsymbol{A}$ must be orthogonal.

$$(\boldsymbol{A}\mathbf{v}_i)^\top(\boldsymbol{A}\mathbf{v}_j) = \mathbf{v}_i^\top(\boldsymbol{A}^\top\boldsymbol{A})\mathbf{v}_j = \mathbf{v}_i^\top(\lambda_j\mathbf{v}_j) = \lambda_j\mathbf{v}_i^\top\mathbf{v}_j = 0.$$

(For $m \geq r$) We observe that $\{\boldsymbol{A}\mathbf{v}_1, \ldots, \boldsymbol{A}\mathbf{v}_r\}$ is a basis of an $r$-dimensional subspace of $\mathbb{R}^m$.

- Normalize the images of these right-singular vectors:

$$\mathbf{u}_i := \frac{\boldsymbol{A}\mathbf{v}_i}{\|\boldsymbol{A}\mathbf{v}_i\|} = \frac{1}{\sqrt{\lambda_i}}\boldsymbol{A}\mathbf{v}_i = \frac{1}{\sigma_i}\boldsymbol{A}\mathbf{v}_i.$$

- That is, $\boldsymbol{A}\mathbf{v}_i = \sigma_i\mathbf{u}_i$, for $i = 1, \ldots, r$.

# The last step: Link up all parts (2/2)

- Concatenate the $\mathbf{v}_i$'s as the columns of $\boldsymbol{V}$;
- Concatenate the $\mathbf{u}_i$'s as the columns of $\boldsymbol{U}$;

# The last step: Link up all parts (2/2)

- Concatenate the $\mathbf{v}_i$'s as the columns of $\boldsymbol{V}$;
- Concatenate the $\mathbf{u}_i$'s as the columns of $\boldsymbol{U}$;
- Then,

$$\boldsymbol{AV} = \boldsymbol{U\Sigma} \in \mathbb{R}^{m \times n}.$$

# The last step: Link up all parts (2/2)

- Concatenate the $\mathbf{v}_i$'s as the columns of $\boldsymbol{V}$;
- Concatenate the $\mathbf{u}_i$'s as the columns of $\boldsymbol{U}$;
- Then,

$$\boldsymbol{A}\boldsymbol{V} = \boldsymbol{U}\boldsymbol{\Sigma} \in \mathbb{R}^{m \times n}.$$

Thus,

$$\boldsymbol{A}\boldsymbol{V}\boldsymbol{V}^\top = \boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^\top$$

# The last step: Link up all parts (2/2)

- Concatenate the $\mathbf{v}_i$'s as the columns of $\boldsymbol{V}$;
- Concatenate the $\mathbf{u}_i$'s as the columns of $\boldsymbol{U}$;
- Then,

$$\boldsymbol{AV} = \boldsymbol{U\Sigma} \in \mathbb{R}^{m \times n}.$$

Thus,

$$\boldsymbol{A} = \boldsymbol{AV}\boldsymbol{V}^\top = \boldsymbol{U\Sigma}\boldsymbol{V}^\top$$

**Exercise**

Why do we have $\boldsymbol{A} = \boldsymbol{AVV}^\top$?

# Rank-$k$ Approximation

$$\hat{\boldsymbol{A}}(k) := \sum_{i=1}^{k} \sigma_i \mathbf{u}_i \mathbf{v}_i^\top = \sum_{i=1}^{k} \sigma_i \boldsymbol{A})$$

# Outline

## Example

Find the singular value decomposition of

$$\boldsymbol{A} = \begin{bmatrix} 1 & 0 & 1 \\ -2 & 1 & 0 \end{bmatrix}$$

# Outline

# Motivation

- Represent a matrix $\boldsymbol{A}$ as a sum of simpler low-rank matrices $\boldsymbol{A}_i$.
- Cheaper than computing the full SVD.
- Rank-1 matrix $\boldsymbol{A}_i \in \mathbb{R}^{m \times n}$:

$$\boldsymbol{A}_i = \mathbf{u}_i \mathbf{v}_i^\top. \quad \text{(outer product)}$$

# Motivation

- Represent a matrix $\boldsymbol{A}$ as a sum of simpler low-rank matrices $\boldsymbol{A}_i$.
- Cheaper than computing the full SVD.
- Rank-1 matrix $\boldsymbol{A}_i \in \mathbb{R}^{m \times n}$:

$$\boldsymbol{A}_i = \mathbf{u}_i \mathbf{v}_i^\top. \quad \text{(outer product)}$$

- In fact, we can derive

$$\boldsymbol{A} = \sum_{i=1}^{r} \sigma_i \mathbf{u}_i \mathbf{v}_i^\top = \sum_{i=1}^{r} \sigma_i \boldsymbol{A}_i.$$

  - Outer-product matrices $\boldsymbol{A}_i$ weighted by the $i$th singular value $\sigma_i$.

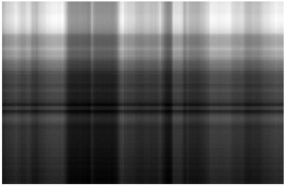
# Rank-$k$ Approximation

Up to an intermediate value $k < r$,

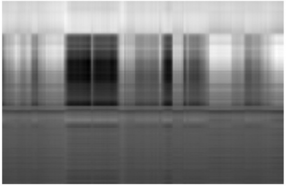
$$\hat{\boldsymbol{A}}(k) := \sum_{i=1}^{k} \sigma_i \mathbf{u}_i \mathbf{v}_i^\top = \sum_{i=1}^{k} \sigma_i \boldsymbol{A}_i$$

# Illustrating example

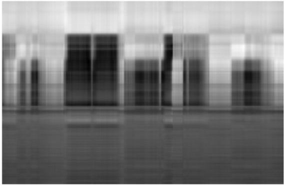
(a) Original image $\boldsymbol{A}$.



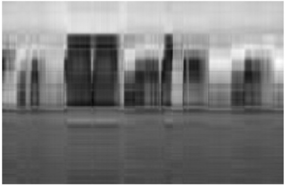
(b) Rank-1 approximation $\widehat{\boldsymbol{A}}(1)$.



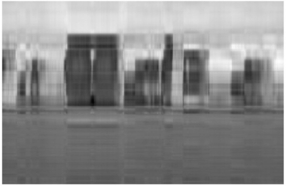
(c) Rank-2 approximation $\widehat{\boldsymbol{A}}(2)$.



(d) Rank-3 approximation $\widehat{\boldsymbol{A}}(3)$.



(e) Rank-4 approximation $\widehat{\boldsymbol{A}}(4)$.



(f) Rank-5 approximation $\widehat{\boldsymbol{A}}(5)$.

# Measure the difference b/w $\boldsymbol{A}$ and $\hat{\boldsymbol{A}}$

## Spectral Norm

For $\mathbf{x} \in \mathbb{R}^n \setminus \{\mathbf{0}\}$, the spectral norm of $\boldsymbol{A} \in \mathbb{R}^{m \times n}$ is

$$\|\boldsymbol{A}\|_2 = \max_{\mathbf{x}} \frac{\|\boldsymbol{A}\mathbf{x}\|_2}{\|\mathbf{x}\|_2}$$

# Measure the difference b/w $\boldsymbol{A}$ and $\hat{\boldsymbol{A}}$

## Spectral Norm

For $\mathbf{x} \in \mathbb{R}^n \setminus \{\mathbf{0}\}$, the spectral norm of $\boldsymbol{A} \in \mathbb{R}^{m \times n}$ is

$$\|\boldsymbol{A}\|_2 = \max_{\mathbf{x}} \frac{\|\boldsymbol{A}\mathbf{x}\|_2}{\|\mathbf{x}\|_2}$$

- Think about why we need to divide the norm $\|\mathbf{x}\|_2$.

# Theorem & Exercise

**Theorem (4.24)**

The spectral norm of $\boldsymbol{A}$ is its largest singular value $\sigma_1$.

# Eckart-Young Theorem

**Theorem [Eckart & Young 1936]**

Consider $\boldsymbol{A} \in \mathbb{R}^{m \times n}$ of rank $r$ and let $\boldsymbol{B} \in \mathbb{R}^{m \times n}$ be a matrix of rank $k$.

Then for any $k \leq r$ with $\hat{\boldsymbol{A}}(k) = \sum_{i=1}^{k} \sigma_1 \mathbf{u}_i \mathbf{v}_i^\top$, it holds that

$$\hat{\boldsymbol{A}}(k) = \underset{\operatorname{rank}(\boldsymbol{B})=k}{\arg\min} \|\boldsymbol{A} - \boldsymbol{B}\|_2,$$

$$\|\boldsymbol{A} - \hat{\boldsymbol{A}}(k)\|_2 = \sigma_{k+1}.$$

Physical meaning:

- We can view the rank-$k$ approximation as a projection of the matrix $\boldsymbol{A}$ onto a lower-dimensional space of rank-at-most-$k$ matrices.
- The approximation error: the next singular value (i.e., $\sigma_{k+1}$)!

# Sketch of the Proof (1/2)

Note that

$$\boldsymbol{A} - \hat{\boldsymbol{A}}(k) = \sum_{i=k+1}^{r} \sigma_i \mathbf{u}_i \mathbf{v}_i^{\top}.$$

By Theorem 4.24, we have $\|\boldsymbol{A} - \hat{\boldsymbol{A}}(k)\|_2 = \sigma_{k+1}$ (spectral norm).

# Sketch of the Proof (1/2)

Note that

$$\boldsymbol{A} - \hat{\boldsymbol{A}}(k) = \sum_{i=k+1}^{r} \sigma_i \mathbf{u}_i \mathbf{v}_i^\top.$$

By Theorem 4.24, we have $\|\boldsymbol{A} - \hat{\boldsymbol{A}}(k)\|_2 = \sigma_{k+1}$ (spectral norm).

But why $\hat{\boldsymbol{A}}$ is the *best* approximation in some sense?

# Sketch of the Proof (1/2)

Note that

$$\boldsymbol{A} - \hat{\boldsymbol{A}}(k) = \sum_{i=k+1}^{r} \sigma_i \mathbf{u}_i \mathbf{v}_i^\top .$$

By Theorem 4.24, we have $\|\boldsymbol{A} - \hat{\boldsymbol{A}}(k)\|_2 = \sigma_{k+1}$ (spectral norm).

But why $\hat{\boldsymbol{A}}$ is the *best* approximation in some sense?

Assume that $r > k$ and there is another $\boldsymbol{B}$ with $\text{rank}(\boldsymbol{B}) \leq k$, such that

$$\|\boldsymbol{A} - \boldsymbol{B}\|_2 < \|\boldsymbol{A} - \hat{\boldsymbol{A}}(k)\|_2.$$

# Sketch of the Proof (2/2)

Note that $\dim(\mathrm{null}(\boldsymbol{B})) \geq n - k$.

# Sketch of the Proof (2/2)

Note that $\dim(\text{null}(\boldsymbol{B})) \geq n - k$.

There exists an $\geq (n - k)$-dimensional null space $Z \subseteq \mathbb{R}^n$ such that

$$\mathbf{x} \in Z, \; \boldsymbol{B}\mathbf{x} = \mathbf{0}.$$

# Sketch of the Proof (2/2)

Note that $\dim(\text{null}(\boldsymbol{B})) \geq n - k$.

There exists an $\geq (n-k)$-dimensional null space $Z \subseteq \mathbb{R}^n$ such that

$$\mathbf{x} \in Z,\ \boldsymbol{B}\mathbf{x} = \mathbf{0}.$$

$\Rightarrow \|\boldsymbol{A}\mathbf{x}\|_2 = \|(\boldsymbol{A} - \boldsymbol{B})\mathbf{x}\|_2$

# Sketch of the Proof (2/2)

Note that $\dim(\text{null}(\boldsymbol{B})) \geq n - k$.

There exists an $\geq (n-k)$-dimensional null space $Z \subseteq \mathbb{R}^n$ such that

$$\mathbf{x} \in Z, \ \boldsymbol{B}\mathbf{x} = \mathbf{0}.$$

$\Rightarrow \|\boldsymbol{A}\mathbf{x}\|_2 = \|(\boldsymbol{A} - \boldsymbol{B})\mathbf{x}\|_2 \leq \|\boldsymbol{A} - \boldsymbol{B}\|_2 \|\mathbf{x}\|_2$

# Sketch of the Proof (2/2)

Note that $\dim(\text{null}(\boldsymbol{B})) \geq n - k$.

There exists an $\geq (n-k)$-dimensional null space $Z \subseteq \mathbb{R}^n$ such that

$$\mathbf{x} \in Z, \ \boldsymbol{B}\mathbf{x} = \mathbf{0}.$$

$$\Rightarrow \|\boldsymbol{A}\mathbf{x}\|_2 = \|(\boldsymbol{A}-\boldsymbol{B})\mathbf{x}\|_2 \leq \|\boldsymbol{A}-\boldsymbol{B}\|_2\|\mathbf{x}\|_2 < \sigma_{k+1}\|\mathbf{x}\|_2. \quad \cdots (\dagger)$$

# Sketch of the Proof (2/2)

Note that $\dim(\mathrm{null}(\boldsymbol{B})) \geq n - k$.

There exists an $\geq (n-k)$-dimensional null space $Z \subseteq \mathbb{R}^n$ such that

$$\mathbf{x} \in Z, \ \boldsymbol{B}\mathbf{x} = \mathbf{0}.$$

$\Rightarrow \|\boldsymbol{A}\mathbf{x}\|_2 = \|(\boldsymbol{A} - \boldsymbol{B})\mathbf{x}\|_2 \leq \|\boldsymbol{A} - \boldsymbol{B}\|_2 \|\mathbf{x}\|_2 < \sigma_{k+1} \|\mathbf{x}\|_2. \quad \cdots (\dagger)$

However, there exists a $(k+1)$-dimensional subspace $Y$ spanned by $\mathbf{v}_1, \ldots, \mathbf{v}_{k+1}$.

# Sketch of the Proof (2/2)

Note that $\dim(\text{null}(\boldsymbol{B})) \geq n - k$.

There exists an $\geq (n-k)$-dimensional null space $Z \subseteq \mathbb{R}^n$ such that

$$\mathbf{x} \in Z,\ \boldsymbol{B}\mathbf{x} = \mathbf{0}.$$

$\Rightarrow \|\boldsymbol{A}\mathbf{x}\|_2 = \|(\boldsymbol{A} - \boldsymbol{B})\mathbf{x}\|_2 \leq \|\boldsymbol{A} - \boldsymbol{B}\|_2 \|\mathbf{x}\|_2 < \sigma_{k+1} \|\mathbf{x}\|_2. \quad \cdots (\dagger)$

However, there exists a $(k+1)$-dimensional subspace $Y$ spanned by $\mathbf{v}_1, \ldots, \mathbf{v}_{k+1}$.

Note that for $\mathbf{x} \in Y$, $\|\boldsymbol{A}\mathbf{x}\|_2 \geq \sigma_{k+1} \|\mathbf{x}\|_2. \quad \cdots (\ddagger)$ (Exercise!)

# Sketch of the Proof (2/2)

Note that $\dim(\text{null}(\boldsymbol{B})) \geq n - k$.

There exists an $\geq (n-k)$-dimensional null space $Z \subseteq \mathbb{R}^n$ such that

$$\mathbf{x} \in Z,\ \boldsymbol{B}\mathbf{x} = \mathbf{0}.$$

$\Rightarrow \|\boldsymbol{A}\mathbf{x}\|_2 = \|(\boldsymbol{A} - \boldsymbol{B})\mathbf{x}\|_2 \leq \|\boldsymbol{A} - \boldsymbol{B}\|_2 \|\mathbf{x}\|_2 < \sigma_{k+1} \|\mathbf{x}\|_2. \quad \cdots (\dagger)$

However, there exists a $(k+1)$-dimensional subspace $Y$ spanned by $\mathbf{v}_1, \ldots, \mathbf{v}_{k+1}$.

Note that for $\mathbf{x} \in Y$, $\|\boldsymbol{A}\mathbf{x}\|_2 \geq \sigma_{k+1} \|\mathbf{x}\|_2. \quad \cdots (\ddagger)$ (Exercise!)

But by the Dimension Theorem (rank-nullity theorem), there must be $\mathbf{x} \in Y \cap Z$. $(\Rightarrow\!\Leftarrow)$

# Discussions