

Mathematics for Machine Learning

— Linear Algebra: Singular Value Decomposition & Matrix Approximation

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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

- 1 Singular Value Decomposition (SVD)
 - Construction of the SVD
 - Example
- 2 Matrix Approximation

Outline

1 Singular Value Decomposition (SVD)

- Construction of the SVD
- Example

2 Matrix Approximation

Why Singular Value Decomposition?

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

Illustration

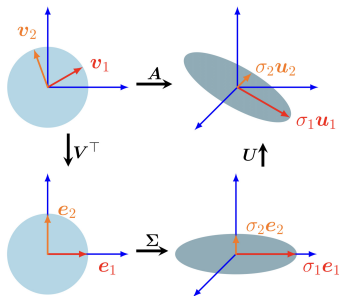
$$\mathbf{A} \in \mathbb{R}^{m \times n}, \text{rank}(\mathbf{A}) = r \leq \min(m, n):$$

$$\begin{array}{c} n \\ \boxed{\mathbf{A}} \\ m \end{array} = \begin{array}{c} m \\ \boxed{\mathbf{U}} \end{array} \begin{array}{c} n \\ \boxed{\begin{array}{c} \sigma_1 \quad \sigma_2 \quad \dots \quad \sigma_r \\ \Sigma \\ 0 \end{array}} \\ m \end{array} \begin{array}{c} n \\ \boxed{\mathbf{V}^\top} \\ n \end{array}$$

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

Illustration & Example

$$\begin{aligned}
 \mathbf{A} &= \begin{bmatrix} 1 & -0.8 \\ 0 & 1 \\ 1 & 0 \end{bmatrix} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T \\
 &= \begin{bmatrix} -0.79 & 0 & -0.62 \\ 0.38 & -0.78 & -0.49 \\ -0.48 & -0.62 & 0.62 \end{bmatrix} \begin{bmatrix} 1.62 & 0 \\ 0 & 1.0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} -0.78 & 0.62 \\ -0.62 & -0.78 \end{bmatrix}
 \end{aligned}$$



Exercise

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

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SVD & Eigendecomposition

- Recall the eigendecomposition of a symmetric positive definite matrix

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

SVD & Eigendecomposition

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with the corresponding SVD

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

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

The Overall Idea

- Computing the SVD of $\mathbf{A} \in \mathbb{R}^{m \times n} \Leftrightarrow$ Finding two sets of orthonormal bases $U = (\mathbf{u}_1, \dots, \mathbf{u}_m)$ and $V = (\mathbf{v}_1, \dots, \mathbf{v}_n)$ respectively.
- Images of $\mathbf{A}\mathbf{v}_i$'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 $\mathbf{A}^\top \mathbf{A} \in \mathbb{R}^{n \times n}$ from any matrix $\mathbf{A} \in \mathbb{R}^{m \times n}$.
- Thus,

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

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

★ $\lambda_i \geq 0$ are the eigenvalues of $\mathbf{A}^\top \mathbf{A}$.

The first step (2/2)

- Assume the SVD of \mathbf{A} exists.

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

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where \mathbf{U} , \mathbf{V} are orthonormal matrices ($\therefore \mathbf{U}^\top \mathbf{U} = \mathbf{I}$).

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

- Hence, we identify $\mathbf{V}^\top = \mathbf{P}^\top$ (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 $\mathbf{A}\mathbf{A}^\top \in \mathbb{R}^{m \times m}$ from any matrix $\mathbf{A} \in \mathbb{R}^{m \times n}$.
- Thus, by assuming the SVD of \mathbf{A} exists, we have

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

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

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

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

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

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

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- Normalize the images of these right-singular vectors:

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

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

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

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

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

Thus,

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

Exercise

Why do we have $\mathbf{A} = \mathbf{A}\mathbf{V}\mathbf{V}^{\top}$?

Rank- k Approximation

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

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Example

Find the singular value decomposition of

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

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Motivation

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

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

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- In fact, we can derive

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

- Outer-product matrices \mathbf{A}_i weighted by the i th singular value σ_i .

Rank- k Approximation

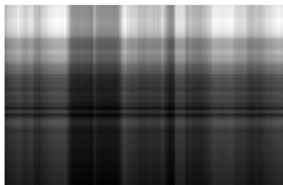
Up to an intermediate value $k < r$,

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

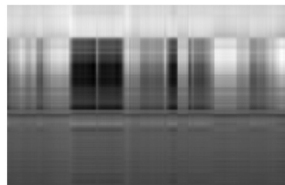
Illustrating example



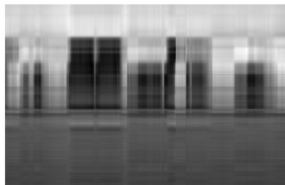
(a) Original image A .



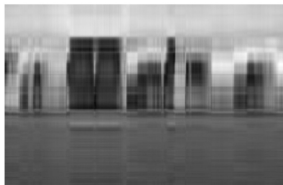
(b) Rank-1 approximation $\hat{A}(1)$.



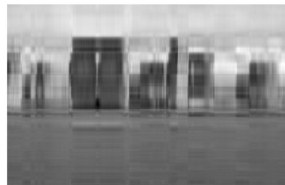
(c) Rank-2 approximation $\hat{A}(2)$.



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



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



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

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

Spectral Norm

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

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

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

Theorem & Exercise

Theorem (4.24)

The spectral norm of \mathbf{A} is its largest singular value σ_1 .

Eckart-Young Theorem

Theorem [Eckart & Young 1936]

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

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

$$\hat{\mathbf{A}}(k) = \arg \min_{\text{rank}(\mathbf{B})=k} \|\mathbf{A} - \mathbf{B}\|_2,$$

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

Physical meaning:

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

Sketch of the Proof (1/2)

Note that

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

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

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

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

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

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

Discussions