



LINEAR ALGEBRA

UE19MA251

APARNA B S

Department of Science and Humanities

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Agenda



- Problems on SVD
- SVD and Rank one matrices
- SVD and Pseudoinverse

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Problems on SVD



Find SVD of

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

The eigenvalues of

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

are $\lambda_1 = 3, \lambda_2 = 1, \lambda_3 = 0$. Hence the singular values of \mathbf{A} are

$$\sigma_1 = \sqrt{3}, \sigma_2 = 1$$

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Problems on SVD



Orthonormal eigenvectors of $(A^T A)$ are

$$v_1 = \frac{1}{\sqrt{6}} \begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix}, \quad v_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}, \quad v_3 = \frac{1}{\sqrt{3}} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

The corresponding left singular vectors of A are

$$u_1 = \frac{Av_1}{\sigma_1} = \frac{1}{\sqrt{2}} \begin{bmatrix} -1 \\ 1 \end{bmatrix}, \quad u_2 = \frac{Av_2}{\sigma_2} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

So

$$A = U\Sigma V^T = \begin{bmatrix} -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} \sqrt{3} & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \frac{1}{\sqrt{6}} & -\frac{2}{\sqrt{6}} & \frac{1}{\sqrt{6}} \\ -\frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} \end{bmatrix}$$

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Rank One matrices and SVD

Every real matrix of rank r is the sum of r real matrices of rank 1 based on singular values and singular vectors.

By SVD

$$\begin{aligned} \mathbf{A} &= \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T = \sigma_1 \mathbf{u}_1 \mathbf{v}_1^T + \cdots + \sigma_r \mathbf{u}_r \mathbf{v}_r^T \\ &= \mathbf{A}_1 + \cdots + \mathbf{A}_r \end{aligned}$$

Image approximation. For an image of size 1000×1000 , a compression rate of 90% is achieved if 50 terms are used.

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SVD and Pseudo Inverse

Let $A = U\Sigma V^T$ be an SVD of A . For a rectangular system of linear equations $Ax = b$, the least-squares solution with the minimum length is $x^+ = V\Sigma^+U^Tb$.

Pseudo-inverse. The minimum-length least-squares solution can be written as $x^+ = A^+b$, where $A^+ = V\Sigma^+U^T$. A^+ is called the **pseudo-inverse** of A .

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SVD and Pseudoinverse



The Pseudoinverse of a matrix generalizes the notion of the inverse in a similar manner that SVD generalized the diagonalization of a matrix.

Not every matrix has an inverse, but every matrix has a pseudoinverse.

Computing the pseudoinverse from SVD is simple.

If $A = U\Sigma V^*$ then $A^+ = V\Sigma^+U^*$

where Σ^+ is formed from Σ by taking the reciprocal of all the non-zero elements, leaving all the zeros alone, and making the matrix the right shape: if Σ is an m by n matrix, then Σ^+ must be an n by m matrix.

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SVD and Pseudoinverse

Consider the matrix $A = \begin{bmatrix} 2 & -1 & 0 \\ 4 & 3 & -2 \end{bmatrix}$

The Singular value decomposition of A is

$$\begin{bmatrix} \frac{1}{\sqrt{26}} & -\frac{5}{\sqrt{26}} \\ \frac{5}{\sqrt{26}} & \frac{1}{\sqrt{26}} \end{bmatrix} \begin{bmatrix} \sqrt{30} & 0 & 0 \\ 0 & 2 & 0 \end{bmatrix} \begin{bmatrix} \frac{11}{\sqrt{195}} & \frac{7}{\sqrt{195}} & -\sqrt{\frac{5}{39}} \\ -\frac{3}{\sqrt{26}} & 2\sqrt{\frac{2}{13}} & -\frac{1}{\sqrt{26}} \\ \frac{1}{\sqrt{30}} & \sqrt{\frac{2}{15}} & \sqrt{\frac{5}{6}} \end{bmatrix}$$

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The Pseudoinverse may be computed from SVD using the definition explained earlier.

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More on Pseudoinverse A^\dagger

- If A is square and nonsingular then $A^\dagger = A^{-1}$.
- A^\dagger is always defined.
- Thus A^\dagger is a generalization of usual inverse.
- If $B \in \mathbb{R}^{n,m}$ satisfies
 1. $ABA = A$
 2. $BAB = B$
 3. $(BA)^T = BA$
 4. $(AB)^T = AB$then $B = A^\dagger$.
- Thus A^\dagger is uniquely defined by these axioms.

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Example on Pseudoinverse A^\dagger .

Show that the pseudoinverse of $A = \begin{bmatrix} 1 & 1 \\ 1 & 1 \\ 0 & 0 \end{bmatrix}$ is $B = \frac{1}{4} \begin{bmatrix} 1 & 1 & 0 \\ 1 & 1 & 0 \end{bmatrix}$.

We have $BA = \frac{1}{2} \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$ and $AB = \frac{1}{2} \begin{bmatrix} 1 & 1 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$. Thus

1. $ABA = A$
2. $BAB = B$
3. $(BA)^T = BA$
4. $(AB)^T = AB$

and hence $A^\dagger = B$.



THANK YOU

Aparna B. S

Department of Science & Humanities

aparnabs@pes.edu