

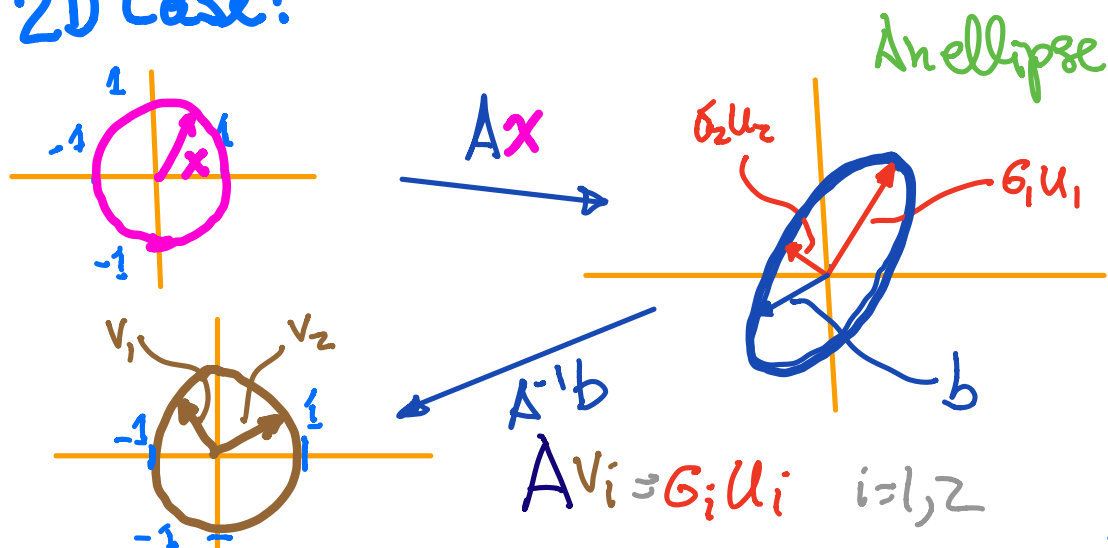
SVD: $A = U \Sigma V^*$ $A \in \mathbb{C}^{m \times n}$
 $(U \Sigma V^T \text{ if } A \in \mathbb{R}^{m \times n})$

$$\begin{cases} A A^* U = U \Sigma \Sigma^* & (\text{Left}) \\ A^* A V = V \Sigma^* \Sigma & (\text{Right}) \end{cases}$$

both are e' value problems with
e' values $\sigma_1^2, \sigma_2^2, \dots, \sigma_r^2$ //

Observation pick $\{x: \|x\|_2 = 1, x \in \mathbb{R}^n\}$
& $A \in \mathbb{R}^{m \times n}$ then $Ax = b \in \mathbb{R}^m$ is a vector set
that traces out a hyperellipse.

2D Case:



If A has rank $r \Rightarrow r \sigma_i$'s are nonzero
 σ_i are called the singular values of A

$\begin{matrix} \uparrow \\ m \\ \downarrow \end{matrix} \begin{bmatrix} \xrightarrow{n} \\ \vdots \\ A \\ \vdots \end{bmatrix}$ at most n will be nonzero

The Hyperellipse: Consider $r = n$
 $\times$ the semiaxis have lengths $\sigma_1 \geq \sigma_2 \dots \sigma_n > 0$

n LEFT singular vectors of $A: \{u_1, u_2, \dots, u_n\}$
 u_i 's are unit, orthogonal. These are
the semiaxes directions of hyperellipse.

n RIGHT singular vectors $\{v_1, v_2, \dots, v_n\}$
 $V = \{v_1, v_2, \dots, v_n\}$ if $S \in V$ then
 $TS = AS \in \{u_1, u_2, \dots, u_n\}$

//

REDUCED SVD:

$$Av_j = \sigma_j u_j \quad 1 \leq j \leq n$$

$$\Delta V = \hat{V} \hat{\Sigma}$$

Full SVD

$$A \in \mathbb{C}^{m \times n}$$

$$V \in \mathbb{C}^{m \times m}$$

$$V \in \mathbb{C}^{n \times n}$$

$$\Sigma \in \mathbb{R}^{m \times n}$$

unitary spaces $\mathbb{C}^m$

$$1) \mathbb{C}^n$$

singular values along diagonal //

What if is not full rank? Not a problem:

$$\begin{bmatrix} A \end{bmatrix}_{m \times n} = \begin{bmatrix} U \end{bmatrix}_{m \times n} \begin{bmatrix} \Sigma \end{bmatrix}_{n \times n} \begin{bmatrix} V^* \end{bmatrix}_{n \times n}$$

Diagram illustrating the SVD decomposition of a matrix A (size $m \times n$) into U (size $m \times n$), Σ (size $n \times n$), and V^* (size $n \times n$). The matrix Σ is shown with diagonal elements $\sigma_1, \sigma_2, \dots, \sigma_r, 0, \dots, 0$ and a zero block $\emptyset$ below the diagonal. The rank r is indicated by a double-headed arrow under the first r columns of U and the first r rows of Σ . The dimension n is indicated by a double-headed arrow above V^* and below Σ .

EXISTENCE & UNIQUENESS: Every $A \in \mathbb{C}^{m \times n}$ has an SVD. Further, the $\{\sigma_j\}$ are uniquely determined.

If $A \in \mathbb{C}^{n \times n}$ & $\{\sigma_j\}$ are distinct $\Rightarrow \{u_i\}$ & $\{v_i\}$ are unique, to within multiplicative constants //

LECTURES (MATRIX FACTS VIA SVD):

$$b = Ax \quad A \in \mathbb{C}^{m \times n}, b \in \mathbb{C}^m \text{ expand}$$

$$\begin{cases} b = \sum_{i=1}^m \alpha_i u_i & \{u_i\} \text{ span } \mathbb{C}^m \\ x = \sum_{i=1}^n \beta_i v_i & \{v_i\} \text{ span } \mathbb{C}^n \end{cases}$$

or

$$b = U\alpha \quad \text{and} \quad x = V\beta$$

α, β are the vectors of coefficients $\{\alpha_i\}, \{\beta_i\}$

Since U & V are Unitary

(if Q is unitary $Q^*Q = I$ i.e. $Q^* = Q^{-1}$)

$$U^*b = \alpha \quad V^*x = \beta$$

$$\text{so } b = Ax$$

$$U^*b = U^*Ax = U^*(U \Sigma V^*)x = \Sigma V^*x$$

$$\Leftrightarrow \alpha = \Sigma \beta$$

if you choose the right bases for $\mathbb{C}^m$ and $\mathbb{C}^n$
then SVD shows that the linear transformation
can be written as a diagonal map!

Relation between SVD and DIAGONALIZATION:
if A is diagonalizable

$$A = X \Lambda X^{-1}$$

X columns are e'vectors of A

Λ matrix with e'values as diagonal entries

$$\text{if } b = Ax \text{ \& } b = X\beta \quad x = X\alpha$$

$$\text{then } b = Ax \Leftrightarrow X\beta = Ax = (X \Lambda X^{-1})X\alpha$$

$$\text{or } \beta = \Lambda \alpha$$

SVD vs Diagonalization (EV)

SVD uses 2 different bases

[SVD uses orthonormal vectors
EV uses L1 vector

[Not all A have a diagonalization, even if A is square. However, all A have an SVD. //

MATRIX PROPERTIES:

let $A \in \mathbb{C}^{m \times n}$

$p \equiv \min(m, n)$

$r \leq p$ nonzero singular σ_i

$\langle x, y, \dots \rangle \equiv$ space spanned by $x, y, \dots$

Thm: $\text{rank}(A) = r$

pf: $\text{rank}(A) = \text{rank}(U \Sigma V^*) = \text{rank}(\Sigma) = r$

Thm $\text{Col}(A) = \text{range}(A) = \langle u_1, u_2, \dots, u_r \rangle$

$\text{null}(A) = \langle v_{r+1}, v_{r+2}, \dots, v_n \rangle$

Thm: $\|A\|_2 = \sigma_1$

$$\|A\|_F = \sqrt{\sigma_1^2 + \dots + \sigma_r^2}$$

Thm: $\sigma_i > 0$ are the square roots of $\lambda_i > 0$ eigenvalues of A^*A and AA^* : recall that

$$\begin{cases} A A^* U = U \Sigma \Sigma^* \\ A^* A V = V \Sigma^* \Sigma \end{cases}$$

Thm:

$$\text{If } A = A^* \text{ (Hermitian)} \Rightarrow A = Q \Lambda Q^*$$

$$\begin{matrix} & & \downarrow & \downarrow & \downarrow \\ & & U & \Sigma & V^* \end{matrix}$$

Q is complete & the entries of Λ are real //

Thm: $|\det(A)| = \prod_{i=1}^m \sigma_i$

$$\begin{aligned} |\det(U \Sigma V^*)| &= |\det U \det \Sigma \det V^*| \\ &= |\det \Sigma| \end{aligned}$$

Since Σ is diagonal then

$$\det \Sigma = \prod \text{diagonal elements of } \Sigma //$$

LOW RANK APPROXIMATIONS

Thm: A is the sum of rank 1 matrices. Follows from

$$A = \sum_{j=1}^n \sigma_j u_j v_j^* = U \Sigma V^*$$

A very useful quality of rank 1 representations of matrices is that the k^{th} partial sum has the highest possible 2-norm or F-norm:

Thm: For any $0 \leq k \leq r$ let

$$A_k \equiv \sum_{j=1}^k \sigma_j u_j v_j^*.$$

If $k = p = \min(m, n) \Rightarrow G_{k+1} = 0$.

$$\|A - A_k\|_2 = \inf_{\substack{B \in \mathbb{C}^{m \times n} \\ \text{rank}(B) \leq k}} \|A - B\|_2 = G_{k+1}$$

Thm: For any $0 \leq k \leq r$ the matrix A_k also satisfies

$$\|A - A_k\|_F = \inf_{\substack{B \in \mathbb{C}^{m \times n} \\ \text{rank}(B) \leq k}} \|A - B\|_F = \sqrt{G_{k+1}^2 + \dots + G_r^2}$$