

Lecture 31
04/09/12

Recall that for a complex inner product space V ,

$$N \text{ normal} \iff N = UDV^{-1}$$

↓ ↗
orthonormal diagonal matrix of λ -values.
 EIGENVECTORS OF N

($N^*N = NN^*$)

SPECIAL CASE:

$$L \text{ self-adjoint} \iff L = UDU^{-1}$$

↓
 ($L^* = L$) ↗
real diagonal matrix of λ -values

If V real inner product space,

$$S \text{ symmetric} \iff S = ODO^{-1}$$

↓ ↓
 ($S^T = S$) real matrices.

Q: What are properties of U ?

ISOMETRIES (7.4):

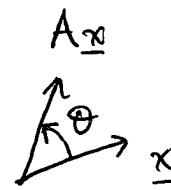
Def. U is an isometry if it preserves length — i.e.,

$$\|Ux\| = \|x\| \quad \text{for all } x \in V.$$

NOTATION: If V complex, U is called unitary.
 " " " REAL, " " " " ORTHOGONAL.

Ex $V = \mathbb{R}^2$, $A = \begin{pmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{pmatrix}$ $\subset \mathbb{L}^2$

$$\underline{x} = (x_1, x_2)^T$$



$$\|A\underline{x}\|^2 = \|(cx_1 - sx_2, sx_1 + cx_2)^T\|^2$$

$$= c^2 x_1^2 + s^2 x_2^2 + s^2 x_1^2 + c^2 x_2^2$$

$$= x_1^2 + x_2^2$$

$$= \|\underline{x}\|^2, \text{ where } c = \cos \theta, s = \sin \theta$$

$\Rightarrow A$ isometry (i.e., A orthonormal matrix).

Remark: In fact, for any real space V , there is an orthonormal basis \mathcal{B} of V such that for an orthonormal matrix A ,

$$[A]_{\mathcal{B}} = \begin{pmatrix} B_1 & & 0 \\ & B_2 & \\ 0 & & \ddots & B_k \end{pmatrix}, \text{ where each block } B_i$$

is either $\begin{pmatrix} 1 \\ 1 \end{pmatrix}$, $\begin{pmatrix} -1 \\ -1 \end{pmatrix}$, or $\begin{pmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{pmatrix}$ for some $\theta \in (0, \pi)$.

unchanged reflection rotation in plane

Thm. These are equivalent (i.e., (i)-(iv) and (i')-(iv') are same):

(i) V isometry

(i') V^* isometry

(ii) $\langle V_x | V_y \rangle = \langle x | y \rangle$ for all $x, y \in V$

(ii') $\langle V_x^* | V_y^* \rangle = \langle x | y \rangle$ for all $x, y \in V$

$$(iii) U^*U = I$$

(iv) if $\mathcal{E} = \{\underline{e}_i\}$ orthonormal

$$[U]_g = (U_{\underline{e}_1}, \dots, U_{\underline{e}_n})$$

has orthonormal columns

$$\left(\begin{array}{ccc} \xrightarrow{\underline{e}_i} & \rightarrow & \xleftarrow{U_{\underline{e}_i}} \end{array} \right)$$

$$(iii') UVU^* = I$$

(iv') if $\mathcal{E} = \{\underline{e}_i\}$ orthonormal

$$[U^*]_g = (U_{\underline{e}_1}^*, \dots, U_{\underline{e}_n}^*)$$

has orthonormal columns.

IN ADDITION:

$$(a) U \text{ is invertible and } U^{-1} = U^*.$$

$$\left(\begin{array}{l} \text{pf. } \|U\underline{x}\| = \|\underline{x}\| \Rightarrow U\underline{x} = 0 \text{ iff } \underline{x} = 0 \\ \Rightarrow \text{Ker}(U) = \{0\} \Rightarrow U \text{ invertible.} \\ U^*U = I \Rightarrow U^{-1} = U^*. \end{array} \right)$$

NOTE: This means that the singular thm. can be written as

$$N \text{ norm} \Leftrightarrow N = UDU^*$$

$$\left(\begin{array}{l} L \text{ self-adjoint} \Leftrightarrow L = UDU^* \\ \quad \quad \quad \text{column.} \\ S \text{ symmetric} \Leftrightarrow S = ODOT \\ \quad \quad \quad \text{row.} \end{array} \right)$$

(b) All entries of U have magnitude $|\lambda| = 1$
(so if U orthonormal $\lambda = \pm 1$).

$$\left(\begin{array}{l} \text{pf. } \|U\underline{x}\| = \|\underline{x}\| \\ \|\lambda\underline{x}\| = |\lambda| \|\underline{x}\| \Rightarrow |\lambda| = 1. \end{array} \right)$$

$$(c) |\det U| = 1$$

$$\left(\text{Pf. } |\det U| = |\lambda_1 \cdots \lambda_n| = 1. \right)$$

Pf. of Thm. :

$$\begin{aligned} \text{(i)} \Rightarrow \text{(ii)} : \text{ If } V \text{ real, } \langle \underline{x} | \underline{y} \rangle &= \frac{\|\underline{x} + \underline{y}\|^2 - \|\underline{x} - \underline{y}\|^2}{4} \quad \text{PARALLELGRAM IDENTITY} \\ \Rightarrow \langle U\underline{x} | U\underline{y} \rangle &= \frac{\|U(\underline{x} + \underline{y})\|^2 - \|U(\underline{x} - \underline{y})\|^2}{4} \\ &= \frac{\|\underline{x} + \underline{y}\|^2 - \|\underline{x} - \underline{y}\|^2}{4} \\ &= \langle \underline{x} | \underline{y} \rangle. \end{aligned}$$

similarly if V complex..

$$\text{(ii)} \Rightarrow \text{(iii)} : \langle (U^*U - I)\underline{x} | \underline{y} \rangle = \langle U\underline{x} | U\underline{y} \rangle - \langle \underline{x} | \underline{y} \rangle = 0.$$

$$\text{Let } \underline{y} = (U^*U - I)\underline{x} \Rightarrow \|U^*U - I)\underline{x}\| = 0 \quad \text{for all } \underline{x} \in V$$

$$\Rightarrow U^*U = I.$$

$$\text{(iii)} \Rightarrow \text{(iv)} : \langle U\underline{e}_i | U\underline{e}_j \rangle = \langle U^*U\underline{e}_i | \underline{e}_j \rangle = \langle \underline{e}_i | \underline{e}_j \rangle = 0.$$

$$\text{(iv)} \Rightarrow \text{(i)} : \underline{x} = \sum_{i=1}^n x_i \underline{e}_i$$

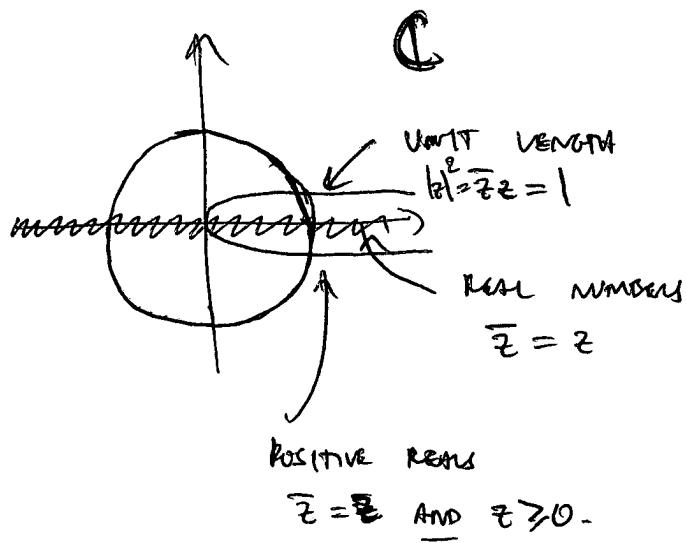
$$\Rightarrow \|U\underline{x}\|^2 = \langle U\underline{x} | U\underline{x} \rangle = \sum_{i=1}^n \sum_{j=1}^n \langle U\underline{e}_i | U\underline{e}_j \rangle$$

$$= x_1^2 + \dots + x_n^2 = \|\underline{x}\|^2.$$

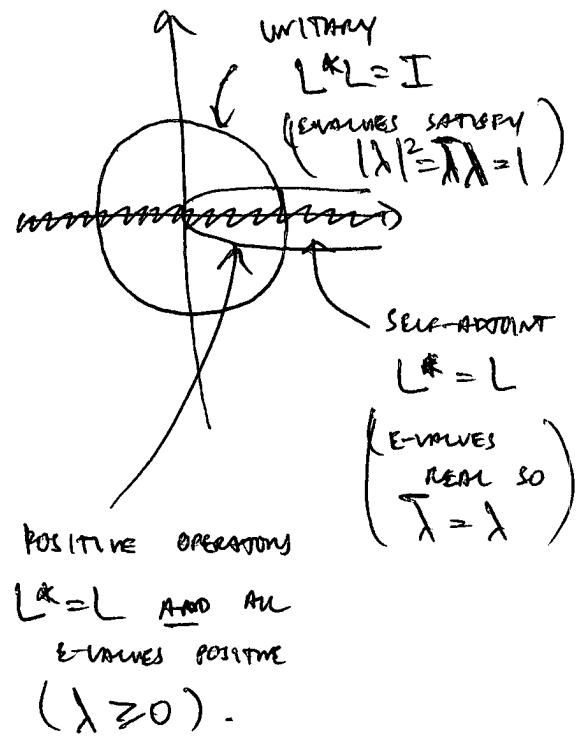
(i) \Leftrightarrow (ii): easy to show.

TO SUMMARIZE: THERE IS A nice Analogy BETWEEN
COMPLEX NUMBERS AND LINEAR OPERATORS!

Complex Numbers



Linear Operators



Polar Representation: For any z ,

$$z = \frac{z}{|z|} |z| = \left(\frac{z}{|z|} \right) \sqrt{\bar{z}z}$$

UNIT LENGTH POSITIVE REAL

Polar Decomposition: For any L ,

$$L = U \sqrt{L^* L}$$

↑
unitary positive operator.

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Positive operators:

DEF. L positive if it is self-adjoint and all its eigenvalues are ≥ 0 . We denote this by $L \geq 0$.

(Note: we allow eigenvalues to be zero.)

Rmkn: L positive $\Leftrightarrow L^* = L$ and $\langle Lx | Lx \rangle \geq 0$ for all $x \in V$.

Thm. If $L \geq 0$, there is a unique operator $B \geq 0$ such that $B^2 = L$. In particular,

$$B = U D^{1/2} U^*, \text{ where } L = U D U^*$$

$$\begin{pmatrix} \sqrt{\lambda_1} & & \\ & \ddots & \\ & & \sqrt{\lambda_n} \end{pmatrix} \quad \begin{pmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{pmatrix}$$

$$\begin{aligned} \underline{\text{Pr}} \quad B^2 &= (\underbrace{U D^{1/2} U^*}_{= I})(U D^{1/2} U^*) = U D^{1/2} D^{1/2} U^* \\ &= U D U^* = L. \end{aligned}$$

Uniqueness easy.

Ex. suppose $A \in M_{2,2}(\mathbb{C})$ has e-values

$$\lambda_1 = 9, \quad \lambda_2 = 4 \quad \text{w/ corresponding E-vectors} \\ \underline{\xi}_1 = \begin{pmatrix} i \\ 1 \end{pmatrix}, \quad \underline{\xi}_2 = \begin{pmatrix} -i \\ 1 \end{pmatrix}.$$

Q1: what is A ?

A1: since $\langle \underline{\xi}_1 | \underline{\xi}_2 \rangle = (-i, 1)(-i, 1)^T = 0$,

A has orthonormal E-vectors and REAL E-values

$\Rightarrow A$ self-adjoint.

$$\Rightarrow A = UDU^* = \begin{pmatrix} i & -i \\ 1 & 1 \end{pmatrix} \begin{pmatrix} 9 & 0 \\ 0 & 4 \end{pmatrix} \begin{pmatrix} -i & 1 \\ i & 1 \end{pmatrix} \\ = \begin{pmatrix} 13 & 5i \\ -5i & 13 \end{pmatrix}.$$

Q2: what is \sqrt{A} ?

A2: since $A \geq 0$, \sqrt{A} exists.

$$\sqrt{A} = U D^{\frac{1}{2}} U^* = \begin{pmatrix} i & -i \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \sqrt{9} & 0 \\ 0 & \sqrt{4} \end{pmatrix} \begin{pmatrix} -i & 1 \\ i & 1 \end{pmatrix} \\ = \begin{pmatrix} 5 & i \\ -i & 5 \end{pmatrix}.$$

Note: \sqrt{A} is determined by e-values of A , not
by individual entries a_{ij} !

(3)

WE WILL USE POSITIVE OPERATORS TO INTRODUCE ONE OF THE MOST USEFUL MATRIX DECOMPOSITIONS, CALLED SINGULAR VALUE DECOMPOSITION (SVD).

MOTIVATION: SO FAR WE HAVE INTRODUCED SEVERAL DECOMPOSITIONS.

A diagonalizable

$$A = PDP^{-1}$$

\nearrow E-vectors \nwarrow DIAGONAL OF E-values

GENERAL $A \in M_{n,n}(\mathbb{C})$

$$A = \tilde{P} \tilde{\Delta} \tilde{P}^{-1}$$

\nearrow E-vectors AND GENERALIZED E-VECTORS

BLOCK DIAGONAL

JORDAN DECOMPOSITION

A normal

$$A = UDU^*$$

\nearrow ORTHONORMAL E-VECTORS \nwarrow DIAGONAL OF E-values

GENERAL $A \in M_{n,n}(\mathbb{C})$

$$A = UTU^*$$

\nearrow ORTHONORMAL BASIS \nwarrow UPPER TRIANGULAR w/ E VALUES ALONG DIAGONAL

SCHUR DECOMPOSITION

GENERAL $A \in M_{n,n}(\mathbb{C})$

$$A = U \Sigma V^*$$

\nearrow UNITARY \nwarrow UNITARY

\nearrow DIAGONAL MATRIX OF SINGULAR VALUES

SINGULAR VALUE DECOMPOSITION

THAT IS,

Q: Can we find two orthonormal bases E and F
 — such that $[A]_{EF}$ is diagonal?

A: Yes, for any A . Then \cup will have columns
 from E , \vee columns from F , and $\Sigma = [A]_{EF}$.

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Singular value decomposition (SVD):

For any $A \in M_{n,n}(\mathbb{C})$,

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

$$\left\{ \begin{array}{l} \Sigma = \text{diag}(\sigma_1, \dots, \sigma_n), \quad \sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_n \geq 0 \\ \qquad \qquad \qquad \text{SINGULAR VALUES} \\ \qquad \qquad \qquad (\text{EVALUES OF } \sqrt{A^*A} \text{ OR } \sqrt{AA^*}) \\ \hline U \\ V \end{array} \right.$$

Unitary (orthonormal e-vectors of $\sqrt{A^*A}$)
 Unitary (orthonormal e-vectors of $\sqrt{AA^*}$)

NOTE: A^*A AND AA^* ARE POSITIVE OPERATORS SINCE THEY
 ARE SELF-ADJOINT AND HAVE ALL EIGENVALUES POSITIVE (≥ 0).
 TO SEE THIS, NOTE THAT $(A^*A)^* = A^*A^{**} = A^*A$. AND IF
 λ IS AN E-VALUE w/ E-VECTOR v FOR A^*A , THEN

$$\begin{aligned} \lambda \|v\|^2 &= \lambda \langle v | v \rangle = \langle v | \lambda v \rangle = \langle v | A^*A v \rangle \\ &= \langle A v | A v \rangle \quad (\text{BY PROPERTIES OF ADJOINT.}) \\ &= \|Av\|^2 \Rightarrow \lambda \geq 0. \end{aligned}$$

Q: why SVD?

A: we will see later that SVD is useful in applications involving large, high-dimensional data sets.

It is not as useful for dynamic applications since

$$A^k = (U\Sigma V^*)^k = U\Sigma V^* U\Sigma V^* \dots U\Sigma V^* \\ \neq U\Sigma^k V^*. \quad (\text{unless } U=V,$$

in which case this
is the same as
Jordan form.)

Remark:

1) A^*A and AA^* have same eigenvalues!

pf. $A^*A \underline{\lambda} = \lambda \underline{\lambda} \Rightarrow AA^*(\underbrace{A\underline{\lambda}}_{\text{call } \underline{u}}) = \lambda(\underbrace{A\underline{\lambda}}_{\text{call } \underline{u}})$

$$AA^* \underline{\lambda} = \lambda \underline{\lambda} \Rightarrow A^*A(\underbrace{A^*\underline{\lambda}}_{\text{call } \underline{v}}) = \lambda(\underbrace{A^*\underline{\lambda}}_{\text{call } \underline{v}})$$

2) $r \leq \text{rank}(A) = \# \text{ of } \underline{\text{nonzero }} \sigma_i^i \text{'s.}$

pf. $\text{rank}(A) = \text{rank}([A]_{EF}) = \text{rank}(\Sigma) \\ = \# \text{ nonzero } \sigma_i^i \text{'s}$

where E, F are columns of U, V .

Procedure to find SVD :

- ① Find nonzero eigenvalues $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_r > 0$, $r \leq n$.
or A^*A and corresponding eigenvectors $\{v_i\}_{i=1}^r$.
- ② Let $\sigma_i = \sqrt{\lambda_i}$, $i=1, \dots, r$. THESE ARE THE EVALUES
of $\sqrt{A^*A}$ (or of $\sqrt{AA^*}$) — THAT IS, THE SINGULAR VALUES
of A .
- ③ Let $\underline{u}_i = \frac{1}{\sigma_i} A v_i$, $i=1, \dots, r$. THESE ARE THE
orthonormal eigenvectors of AA^* .
(To see this, note that $\langle A v_i | A v_j \rangle = \langle A^* A v_i | v_j \rangle$
 $= \begin{cases} \sigma_i^2 & \text{if } i=j \\ 0 & \text{else} \end{cases} \Rightarrow \{\underline{u}_i\}$ orthonormal.)
- ④ If necessary: For remaining columns
 v_{r+1}, \dots, v_n (eigenvectors of A^*A w/e-value 0, i.e.,
in $\text{Ker}(A^*A)$)
 u_{r+1}, \dots, u_n (eigenvectors of AA^* w/e-value 0, i.e.,
in $\text{Ker}(AA^*)$)
 USE GRAM-SCHMIDT. THAT IS, find a basis for $\text{Ker}(A^*A)$
and orthonormalize to get $\{v_i\}_{i=r+1}^n$, and similarly
find a basis for $\text{Ker}(AA^*)$ and orthonormalize to get $\{\underline{u}_i\}_{i=r+1}^n$.

BK find SVD of $A = \begin{pmatrix} 2 & 2 \\ -1 & 1 \end{pmatrix}$.

$$\textcircled{1} \quad A^*A = \begin{pmatrix} 2 & -1 \\ 2 & 1 \end{pmatrix} \begin{pmatrix} 2 & 2 \\ -1 & 1 \end{pmatrix} = \begin{pmatrix} 5 & 3 \\ 3 & 5 \end{pmatrix} \Rightarrow \lambda_1 = 8, \lambda_2 = 2$$

$$\Rightarrow \sqrt{\lambda_1} = \sqrt{8}, \sqrt{\lambda_2} = \sqrt{2} \quad (\text{Trace} = 10, \det = 16)$$

$$\textcircled{2} \quad \Rightarrow \sigma_1 = \sqrt{8}, \sigma_2 = \sqrt{2}.$$

Corresponding eigenvectors of A^*A are $v_1 = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 1 \end{pmatrix}, v_2 = \frac{1}{\sqrt{2}} \begin{pmatrix} -1 \\ 1 \end{pmatrix}$

↗ ↘
orthogonal.

$$\textcircled{3} \quad \frac{1}{\sigma_1} A v_1 = u_1 = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

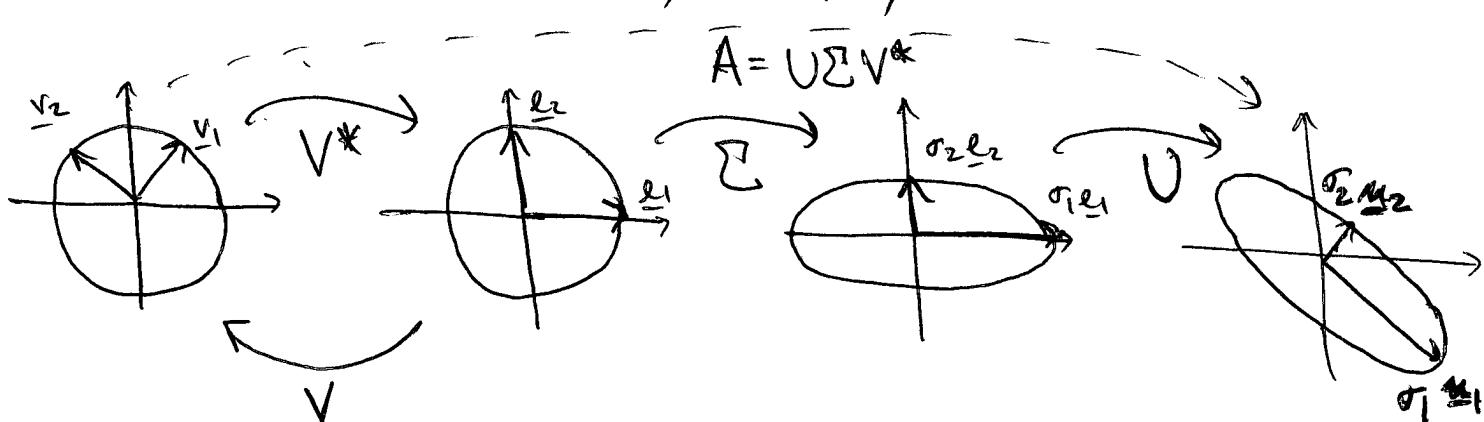
$$\frac{1}{\sigma_2} A v_2 = u_2 = \begin{pmatrix} 0 \\ 1 \end{pmatrix} \quad \text{orthogonal.}$$

$$\Rightarrow A = U \Sigma V^*$$

$$\left(\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} \sqrt{8} & 0 \\ 0 & \sqrt{2} \end{pmatrix} \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & 1 \\ -1 & 1 \end{pmatrix} \right)$$

Geometry of SVD: every linear transformation is given by a rotation, stretch, and another rotation.

For ex., $w \in \mathbb{R}^2$,



Q: Why does A^*A play a role to begin with?

From the geometric picture we see that any linear transformation is a mapping from the unit sphere to an ellipse (a hyperellipse in higher dimensions).

We seek \underline{x} 's such that $\|\underline{x}\|=1$ and $A\underline{x}$ has maximal (or minimal) length.

Let $Q(\underline{x}) = \|A\underline{x}\|^2$. Then, we seek solutions \underline{x} that

$$\left\{ \begin{array}{l} \text{extremize } Q(\underline{x}) = \|A\underline{x}\|^2 = \langle A\underline{x} | A\underline{x} \rangle = \langle \underline{x} | A^*A\underline{x} \rangle \\ \text{w/ constraint } \|\underline{x}\|=1. \end{array} \right.$$

Using Lagrange multipliers to solve this constrained maximization/minimization problem, we get that solutions satisfy

$$A^*A\underline{x} = \lambda \underline{x} \quad \text{for some } \lambda$$

\curvearrowleft LAGRANGE MULTIPLIER

\Rightarrow i.e., look at eigenvectors of A^*A !