

Lecture 39: Dealing with nondiagonalizable matrices. ①

(§6.7 and §7.1)

Last time: For a linear op T on a finite dim'l inner product space V , the following are equivalent:

- 1) T is an isometry, i.e. $\langle T(x), T(y) \rangle = \langle x, y \rangle$ for all $x, y \in V$.
- 2) $T \circ T^* = T^* \circ T = I_V$
- 3-4) For every (some) orthonormal basis β for V , the image $T(\beta)$ is an orthonormal basis.
- 5) $\|T(x)\| = \|x\|$ for all $x \in V$.

Def: A square matrix is unitary when $A^*A = I$ and orthogonal when $A^t A = I$.

[With respect to an orthonormal basis, an isometry has a unitary (and orthogonal if $\mathbb{F} = \mathbb{R}$) matrix.]

Thm: Suppose $A \in M_{n \times n}(\mathbb{R})$ is orthogonal. Then L_A is an isometry of $(\mathbb{R}^n, \text{dot})$.

Pf: Set $a_i = Ae_i = i^{\text{th}}$ col of A . Then $I =$

$$A^t A = \begin{pmatrix} - & a_1 & - \\ & \vdots & \\ - & a_n & - \end{pmatrix} \begin{pmatrix} | & & | \\ a_1 & \dots & a_n \\ | & & | \end{pmatrix} = G \text{ where } G_{ij} = \langle a_i, a_j \rangle$$

In particular $\{L_A(e_i)\}$ is an orthonormal basis of \mathbb{R}^n . ■■■

Cor: $A \in M_{n \times n}(\mathbb{R})$. TFAE:

- i) A is orthogonal
- ii) $A^t = A^{-1}$
- iii) the columns of A are an orthonormal basis for \mathbb{R}^n .
- iv) — rows ————— " —————
- v) L_A is an isometry of $(\mathbb{R}^n, \text{dot})$.

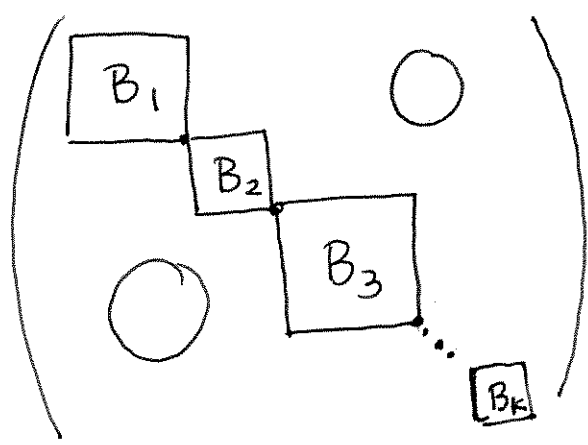
Pf: Exercise.

Restated Thm: Suppose $A \in M_{n \times n}(\mathbb{R})$ is symmetric.

Then there is an orthogonal Q with $Q^t A Q = Q^{-1} A Q$ diagonal.

What to do when $A \in M_{n \times n}(\mathbb{R})$ is not diagonalizable?

Jordan Canonical Form: Over \mathbb{C} , any square matrix is similar to one of the following form:



where each block has the form

$$\begin{pmatrix} \lambda_i & 1 & & 0 \\ & \lambda_i & \dots & 0 \\ & & \dots & \lambda_i \\ 0 & & & \lambda_i \end{pmatrix}$$

Applications:

1) Proof that any regular Markov chain converges.

Point: Blocks B with $|\lambda| < 1$ have $\lim_{n \rightarrow \infty} B^n = 0$.

2) Solving systems of linear differential equations.

Singular Value Decomposition: Work over \mathbb{R} for concreteness.

Story so far: $T: V \rightarrow V$
linear $\iff A = [T]_{\beta} \in M_{n \times n}(\mathbb{R})$

Goal: Choose β so that

$[T]_{\beta}$ is simple $\iff B = Q^{-1}AQ$
as possible. \uparrow diagonal, J.C.F., etc.

Problems: 1) To use J.C.F. need to work over \mathbb{C} .

2) What about $T: V \rightarrow W$?

In (2), there's not even any notion of an eigenvector! However we do get to choose two bases, β for V and γ for W , in order to write down $[T]_{\beta}^{\gamma}$. [This gives more flexibility

even if $W = V$ since $[T]_{\beta} = [T]_{\beta}^{\beta}$.] (5)

Thm [Probably Skip!] Suppose $T: V \rightarrow W$ is linear and V and W are finite dim'l. Then there are bases so that $[T]_{\beta}^{\gamma} = \begin{pmatrix} 1 & 0 & & 0 \\ 0 & 1 & & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & & & 0 \\ \vdots & & & \vdots \\ 0 & & & 0 \end{pmatrix}$.

Pf (Skip!): Using the rep'l. theorem, pick a basis $\beta = \{v_1, \dots, v_n\}$ whose last k vectors are a basis for $\mathcal{N}(T)$. Again via replacement, extend $\{T(v_1), \dots, T(v_{n-k})\}$ (which is linearly independent) to a basis γ for W . Then $[T]_{\beta}^{\gamma}$ has the desired form. ▣

Singular Value Decomposition: Suppose T is a linear map between real inner product spaces V and W . Then there exist orthonormal basis β and γ so that

$$[T]_{\beta}^{\gamma} = \begin{pmatrix} \sigma_1 & & 0 & & 0 \\ & \sigma_2 & & & 0 \\ & & \ddots & & \\ & & & \sigma_r & \\ 0 & & & & 0 \\ \vdots & & & & \vdots \\ 0 & & & & 0 \end{pmatrix}$$

where $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r \geq 0$ are in \mathbb{R} .

(6)

Notes: 1) Here $r = \text{rank}(T)$.

2) It turns out ^{that} the singular values σ_i are unique.

3) Matrix form: Given $A \in M_{m \times n}(\mathbb{R})$ there exist $P \in M_{m \times m}(\mathbb{R})$ and $Q \in M_{n \times n}(\mathbb{R})$, both orthonormal, so that PAQ has the above form. (Like diagonalizing a symmetric matrix, except we do not insist that $P = Q^t = Q^{-1}$.)

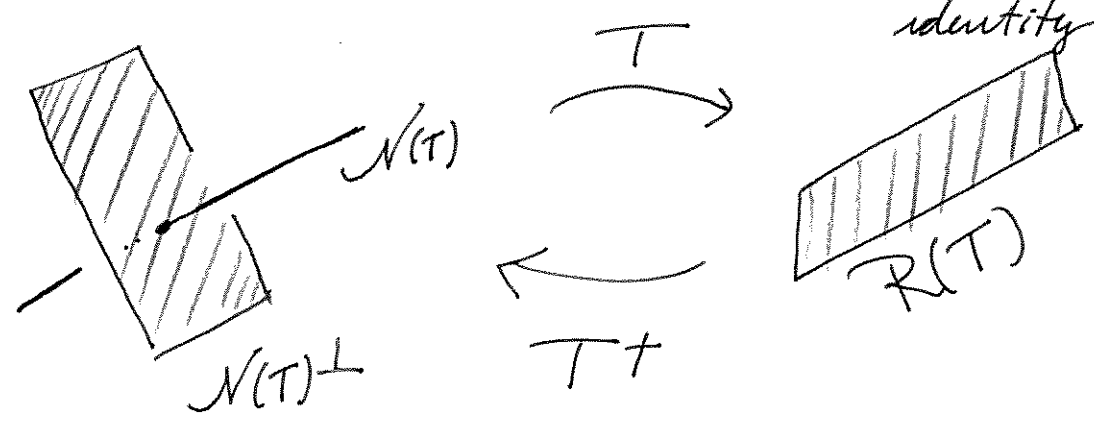
Proof idea for SVD: Diagonalize $T^* \circ T$.

[Only talked about T^* for linear ops, not general linear transformations, so just think about the case when $W = V$.]

Applications:

1) Pseudo-inverse: Given $T: V \rightarrow W$ there is a $T^\dagger: W \rightarrow V$ where

$T^+(W) = \mathcal{N}(T)^\perp$, the linear op $T \circ T^+$ is orthogonal projection onto $\mathcal{R}(T)$, and $T^+ \circ T$ is the identity on $\mathcal{N}(T)^\perp$.



Point: The restriction $L : \mathcal{N}(T)^\perp \rightarrow \mathcal{R}(T)$
 $x \rightarrow T(x)$
 is an isomorphism, and $T^+ = L^{-1} \circ \text{proj}_{\mathcal{R}(T)}$

2) Computing determinants. When A is square and invertible, $\det(A) = \pm \sigma_1 \dots \sigma_r$

Proof: By HW, $\det(\text{orthogonal}) = \pm 1$.

3) In fact, the SVD has been a key tool in scientific computing for 50+ years.