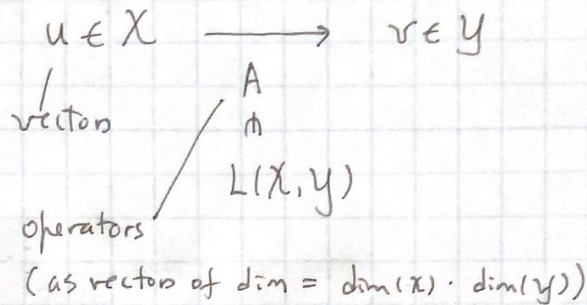


Last time:



Today: Properties of operators and matrix analysis

Sec 3.2 ① Eigenvector and eigenvalues (evecs & evals)

Def: if $A \in L(X)$, $u \in X$, $u \neq 0$, $Au = \lambda u$ for some $\lambda \in \mathbb{C}$
|
zero vector

then u is an eigenvector of A , and λ the corr eigenvalue.

Def: fix $A \in L(X)$. Consider $f(z) = \text{Det}(z \mathbb{1}_X - A)$.
|
determinant

① $f(z)$ is a polynomial in z with $\deg = \dim(X)$.

② By the unique factorization theorem on $f(z)$

$$f(z) = (z - \lambda_1)(z - \lambda_2) \dots (z - \lambda_{\dim(X)}) \quad \text{for } \lambda_i \in \mathbb{C}$$

③ $\forall i = 1, 2, \dots, \dim(X)$, $f(\lambda_i) = \text{Det}(\lambda_i \mathbb{1}_X - A) = 0$

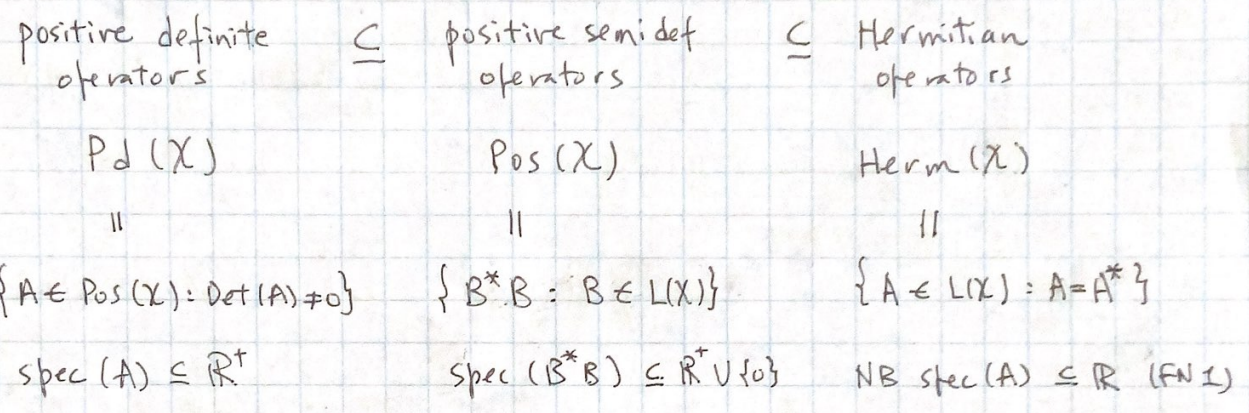
Recall $\text{Det}(M) \neq 0 \Leftrightarrow M$ invertible, so $\lambda_i \mathbb{1}_X - A$ not invertible,
 and $\exists u_i \in \text{Ker}(\lambda_i \mathbb{1}_X - A)$ so u_i, λ_i are evec, eval of A .

Def: Multiset $\{\lambda_1, \lambda_2, \dots, \lambda_{\dim(X)}\}$ is called the spectrum of A
 # times λ repeats in the set is called the multiplicity of λ .

Thm: $\text{Tr}(A) = \sum_{\lambda \in \text{spec}(A)} \lambda$

$\text{Det}(A) = \prod_{\lambda \in \text{spec}(A)} \lambda$

Salt 2 Consider $L(X)$:



Ex: read 1.4.4

(an change $B \in L(X)$ to $B \in L(X, Y)$ for some Y .)

Ex: read 1.4.2

Ex: read 1.4.3

Notation: $A \geq 0$ if $A \in \text{Pos}(X)$
 $A \geq B$ if $A - B \in \text{Pos}(X)$
(the CES X is omitted)

eg lec 1, register $\leftrightarrow X = \mathbb{C}^2$
states $\leftrightarrow D(X) = \{\rho \in \text{Pos}(X) : \text{Tr} \rho = 1\}$.
density operators in X

PZLN

FN 1: $\langle u, v \rangle = \langle v, u \rangle$, so if $A = A^*$, $Au = \lambda u$, then

$\lambda \langle u, u \rangle = \langle u, Au \rangle = \langle A^*u, u \rangle = \langle Au, u \rangle = \overline{\langle u, Au \rangle} = \overline{\lambda \langle u, u \rangle}$

but $\langle u, u \rangle$ positive real \downarrow , $\lambda = \bar{\lambda}$. (why we need $u \neq 0$)

Def: A projector (or projection, orthogonal projection, projection operator) is an operator $P \in \text{Pos}(X)$ satisfying $P^2 = P$ (equivalently $\text{spec}(P) = \{0, 1\}$)

Def: For a subspace $V \subseteq X$, $\Pi_V =$ projector whose image is V .

Def: $A \in L(X, Y)$ is an isometry if $\forall u \in X, \|Au\| = \|u\|$.

Thm: $A \in L(X, Y)$ is an isometry

$(\Rightarrow) A^*A = \mathbb{1}_X$

$(\Leftrightarrow) \langle Au, Av \rangle = \langle u, v \rangle \quad \forall u, v \in X. \quad (\text{Pf: Ex})$

Def: $A \in L(X)$ normal if $AA^* = A^*A$.

eg all Hermitian operators are normal.

Sec 15 (3) The spectral theorem and functions of normal operators.

Thm (the spectral thm) If X CES, $A \in L(X)$ normal with distinct eigenvalues $\lambda_1, \dots, \lambda_k$, then $\exists!$ projector $P_1, \dots, P_k \in \text{Pos}(X)$ st.

↑
unique

① $P_i P_j = 0$ if $i \neq j$

② $P_1 + \dots + P_k = \mathbb{1}_X$

③ $\text{rank}(P_i) = \text{multiplicity of } \lambda_i$

④ $\sum_{i=1}^k \lambda_i P_i = A$

⑤ if $\text{spec}(A) = \{\lambda_1, \lambda_2, \dots, \lambda_k, \dots, \lambda_{\dim(X)}\}$, then \exists o.n. basis $\{x_i\}$ for X

s.t. $\sum_{i=1}^n \lambda_i x_i x_i^* = A$

the spectral decompositions, ④ unique, ⑤ not nec.

Thm let $A, B \in L(X)$ be commuting normal operators.

Then \exists o.n. basis $\{x_i\}$ of X s.t.

$$A = \sum_{i=1}^n \lambda_i x_i x_i^*, \quad B = \sum_{i=1}^n \mu_i x_i x_i^*$$

are spec decoms of A, B respectively.

Def: If $A \in L(X)$ normal with spec decomp $A = \sum_{i=1}^k \lambda_i P_i$,

then a function $f: \mathbb{C} \rightarrow \mathbb{C}$ can be extended to A as $f(A) = \sum_{i=1}^k f(\lambda_i) P_i$.

eg. if $A \in Pd(X)$, then $\log(A) = \sum_{i=1}^k \log(\lambda_i) P_i$.

eg. if $A \in Pos(X)$, then $A^{\frac{1}{2}} = \sum_{i=1}^k \lambda_i^{\frac{1}{2}} P_i$.

NB: $\sum_{i=1}^n f(\lambda_i) x_i x_i^* = \sum_{i=1}^k f(\lambda_i) P_i$, i.e. ④⑤ give the same $f(A)$

Qn: what about $A \in L(X, Y)$, $\dim(X) \neq \dim(Y)$?

Sec 2.1 Thm (singular-value thm): $A \in L(X, Y)$, $A \neq 0$, $r = \text{rank}(A) \geq 1$.

$\exists s_1, \dots, s_r \in \mathbb{R}^+$, o.n sets $\{x_1, \dots, x_r\} \subseteq X$, $\{y_1, \dots, y_r\} \subseteq Y$

s.t. $A = \sum_{i=1}^r s_i y_i x_i^* \quad \left(\sum_{i=1}^r s_i |y_i\rangle \langle x_i| \right)$

Singular values.

left - right - singular vectors.

Singular value decomposition SVD

Obs For $A \in L(X, Y)$, $A = \sum_{i=1}^r s_i y_i x_i^*$ SVD

$AA^* = \sum_{i=1}^r s_i^2 y_i y_i^*$ and $A^*A = \sum_{i=1}^r s_i^2 x_i x_i^*$ are spec decoms.

Recipe for SVD = ① find AA^* and its spectral decomp $\sum_{i=1}^r \lambda_i y_i y_i^*$

② find x_i 's st. $A = \sum_{i=1}^r \sqrt{\lambda_i} y_i x_i^*$

or find A^*A & spec decomp, and find y_i 's.

Cor of SVD: if $A \in L(X, Y)$, $A = \sum_{i=1}^r s_i y_i x_i^*$ SVD

then $B = \sum_{i=1}^r s_i^{-1} x_i y_i^*$ satisfies $BA = \mathbb{1}_{\text{Im}(A)}$

Moore-Penrose pseudo-inverse of A. Sec 2.1.1.

Sec 2.3 ④ Schatten norms of operators

Def: $\forall A \in L(X, Y)$, $p \in \mathbb{R}$, $p \geq 1$,

Schatten p -norm of A: $\|A\|_p := \left(\text{Tr} \left[(A^*A)^{\frac{p}{2}} \right] \right)^{\frac{1}{p}}$

$\|A\|_\infty := \max \{ \|Au\| : u \in X, \|u\|=1 \}$

norm of function operator

Obs: if $S(A)$ = vector of singular values of A

then $\|A\|_p = \|S(A)\|_p$
p-norm on vector

Euclidean norm

Obs: $\|A\|_2 = \text{Tr}(A^*A)^{\frac{1}{2}} = \left(\sum_{a,b} |A(a,b)|^2 \right)^{\frac{1}{2}} = \text{Euclidean norm in } L(X, Y)$.

Qn: is $\|A\|_p$ the p -norm for elements of $L(X, Y)$ for $p \neq 2$?

Special Schatten p-norms:

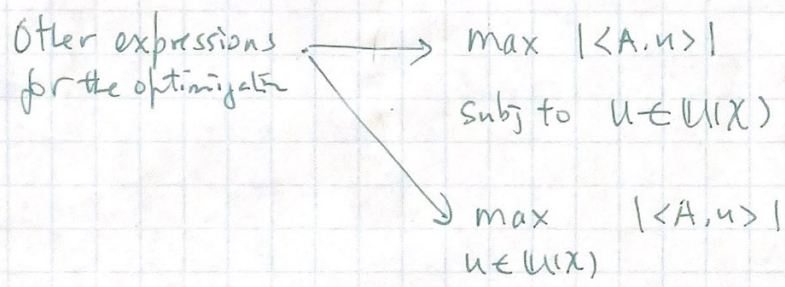
$\|\cdot\|_{tr} = \|\cdot\|_1$ trace norm

$\|\cdot\|_F = \|\cdot\|_2$ Frobenius norm

$\|\cdot\| = \|\cdot\|_\infty$ Spectral norm / operator norm

Thm: $\forall A \in L(X), \|A\|_1 = \max \{ \underbrace{|\langle A, u \rangle|}_{\text{objective function}} : \underbrace{u \in U(X)}_{\text{constraint}} \}$

unitary operators on X
(isometric ops from X to X)



Pf: if $A=0, \|A\|_1 = (\text{Tr } 0)^1 = 0, \text{ RHS} = 0 \therefore \text{claim is true.}$

if $A \neq 0$, use SVT and obtain SVD for A :

$A = \sum_{i=1}^r s_i y_i x_i^*$ where $r = \text{rank}(A),$
 $\{x_i\}_{i=1}^r, \{y_i\}_{i=1}^r$ orthon sets in X

• $\|A\|_1 = \sum_{i=1}^r s_i$

• On the RHS, take $u = \sum_{i=1}^r y_i x_i^* + \Pi_{\text{Ker}(A)}$

then $\langle A, u \rangle = \sum_{i=1}^r s_i \therefore \text{LHS} \leq \text{RHS.}$

• meanwhile, apply spectral decomp to $U \in U(X)$ (normal),

$$U = \sum_{j=1}^{\dim(X)} w_j w_j^* e^{i\theta_j}, \quad \{w_j\}_{j=1}^{\dim(X)} \text{ o.n. basis of } X$$

$$\langle A, U \rangle = \text{tr}(A^* U)$$

$$= \text{tr} \sum_{j=1}^{\dim(X)} \sum_{i=1}^r s_i x_i y_i^* \cdot w_j w_j^* e^{i\theta_j}$$

$$= \sum_{i=1}^r s_i \sum_{j=1}^{\dim(X)} \underbrace{(w_j^* x_i)}_{\text{coeff of } x_i \text{ in basis } \{w_j\}} \underbrace{(y_i^* w_j)}_{\text{coeff of } y_i \text{ in basis } \{w_j\}} e^{i\theta_j}$$

coeff of x_i in the basis $\{w_j\}$ in the coeff of y_i in the basis $\{w_j\}$

$$e^{i\theta_j} \langle w_j | x_i \rangle \cdot \overline{\langle w_j | y_i \rangle}$$

still the coeff of a unit vector in the $\{w_j\}$ basis.

inner product between 2 unit vectors absolute value ≤ 1

$$\therefore |\langle A, U \rangle| \leq \sum_{i=1}^r s_i | \dots | \leq \sum_{i=1}^r s_i = \text{LHS.}$$

triangle inequality over the sum over i

□

NB We will use the thm to show monotonicity of fidelity later, after defining partial tracing.

8

eg. $\forall u, v \in X$, show that $\|uu^* - vv^*\|_p = 2^{\frac{1}{p}} \sqrt{1 - |\langle u, v \rangle|^2}$

Pf Let $A = uu^* - vv^*$ ($|uxu| - |vxv|$)

$A \in \text{Herm}(X)$

$\text{tr} A = 0$, $\text{rank}(A) \leq 2$

$\text{spec}(A) = \{\lambda, -\lambda, 0, 0, \dots, 0\}$...

$$\begin{aligned}\text{tr} A^2 &= \text{tr} (|uxu| - |vxv|)(|uxu| - |vxv|) \\ &= 2 - 2|\langle u, v \rangle|^2 \\ &= 2\lambda^2\end{aligned}$$

$$\therefore \lambda = \sqrt{1 - |\langle u, v \rangle|^2}$$

$$\begin{aligned}\therefore \|A\|_p &= (\lambda^p + \lambda^p + 0^p + \dots + 0^p)^{\frac{1}{p}} = 2^{\frac{1}{p}} \lambda \\ &= 2^{\frac{1}{p}} \sqrt{1 - |\langle u, v \rangle|^2}\end{aligned}$$

Ex: Read other properties of $\|\cdot\|_p$ in Sec 2.3.1.

①

So far covered:

Sec 1.3.2, 1.4, 1.5, 2.1, 2.3

Post pone:

Sec 2.2, 2.4 to later

Rest of lecture 2: Highlights of Sec 2.5
Reading Ex on what we cannot cover.

⑤ $\|\cdot\|$ any norm, take Euclidean norm for concreteness

Def: X, Y CESs, $A \subseteq X$, $f: A \rightarrow Y$ function

f is continuous (cts) at u

if $\forall \varepsilon > 0 \exists \delta > 0$ s.t. $\left[\forall v \in A \text{ s.t. } \|v - u\| < \delta \right]$

$\|f(v) - f(u)\| < \varepsilon$.

ie if v is close enough to u , then $f(v)$ is close to $f(u)$
no further than δ no further than ε

Here δ depends on ε .

Def: A set $A \subseteq X$ is compact if every sequence $\{x_n\}_{n \in \mathbb{N}} \subseteq A$ ^{set of natural numbers}
has a subsequence $\{x_{n_i}\}_{i \in \mathbb{N}}$ that converges to a point $v \in A$.
($n_1 < n_2 < \dots$)

Thm: (Heine-Borel Thm) X CES, (10)

$A \subseteq X$ is compact \Leftrightarrow ① A is closed (ie $X \setminus A$ is open.)
② A is bound (ie $\exists r$ s.t. $\forall x \in A, \|x\| < r$)

Why continuity and compactness?

They prevent a lot of "pathologies" that prevents your steps in a proof to hold.

eg If X CES, $A \subseteq X$ compact, then

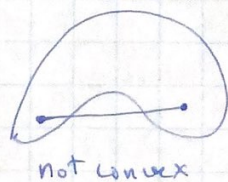
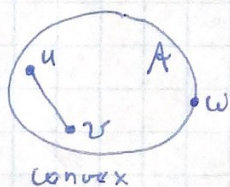
① if $f: A \rightarrow \mathbb{R}$ is continuous on A
then f attains a max and a min on A (rather than sup/inf).

② if $f: X \rightarrow Y$ is continuous on A , Y CES,
then $f(A) \subseteq Y$ is compact.

//

$$\{f(x) \in Y : x \in A\}$$

Def: X CES, $A \subseteq X$ is convex if $\forall u, v \in A, \lambda \in [0, 1]$
 $\lambda u + (1-\lambda)v \in A$



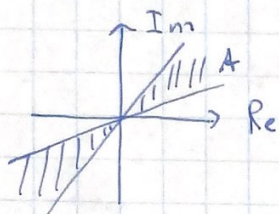
Def: for a convex set A , $w \in A$ is an extreme point of A

if " $w = \lambda u + (1-\lambda)v$ for some $u, v \in A$ " \Rightarrow $u = v = w$.

Def: $A \subseteq X$ is a cone if $\forall u \in A, \lambda \geq 0, \lambda u \in A$. Qn cone \Rightarrow convex?

Def $A \subseteq X$ is a cone if $\forall u \in A, \lambda \geq 0, \lambda u \in A$. (11)

eg. $X = \mathbb{C}$



NB cone $\not\Rightarrow$ convex.

So we say "convex cone" if the cone is convex.

Ex: show that if $A, B \subseteq X$ convex, then

$$\underline{A+B} = \{ \underline{u+v} : u \in A, v \in B \} \text{ are also convex.}$$

eg. X CES. $\text{Pos}(X)$ convex cone with only one extreme point 0.

$D(X)$ convex but not a cone, with rank 1 (pure states) being extreme points.

Def: Σ finite non-empty set.

$p \in \mathbb{R}^{\Sigma}$ prob vector if $p(a) \geq 0, \sum_{a \in \Sigma} p(a) = 1$.

Def: A convex combination of points in A is a finite sum

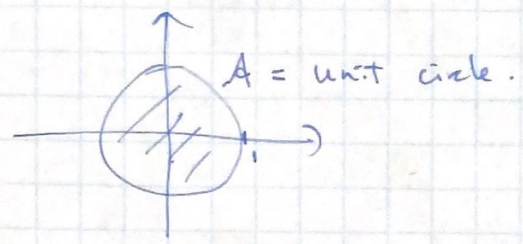
$$\sum_{a \in \Sigma} p(a) u_a$$

where $\{u_a : a \in \Sigma\} \subseteq A, p$ prob vector.

Def: Convex Hull of a set $A \subseteq X$, denote $\text{conv}(A)$ is the intersection of all convex sets containing A .

Thm: $\text{conv}(A) =$ convex combinations of points in A .

eg. $X = \mathbb{C}$

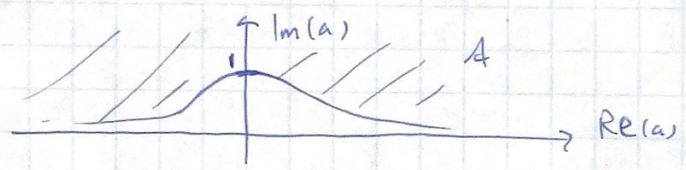


Note A infinite but $\text{conv}(A)$ is the entire disc; each ^{interior} point is convex combination of 2 extreme points.

Thm if A is compact, then $\text{conv}(A)$ is compact.

N.B If A is closed, $\text{conv}(A)$ may or may not be closed.

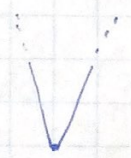
eg. $X = \mathbb{C}$, $A = \{ a \in \mathbb{C} : \text{Im}(a) \geq \frac{1}{1 + [\text{Re}(a)]^2} \}$



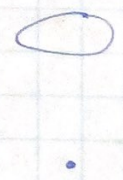
Thm (Krein-Milman): if A compact and convex,
then $A = \text{convex hull of its extreme points.}$

eg. the convex cone \neq convex hull of its extreme points.

↑
closed
convex
not bound



the truncated cone is convex hull of its extreme points.

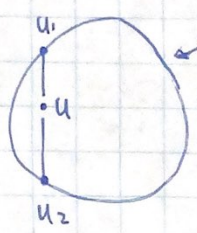


Three thms on convex sets in real Euclidean spaces ($\mathbb{R}^k \sim \mathbb{R}^{|\Sigma|}$):

• Thm 2.6 (Carathéodory's theorem)

If $A \subseteq \mathbb{R}^k$, $u \in \text{conv}(A)$, then $u = \sum_{a=1}^{k+1} p(a) u_a$ where $\{u_a\}_{a=1}^{k+1} \subseteq A$.

eg. $k=2$

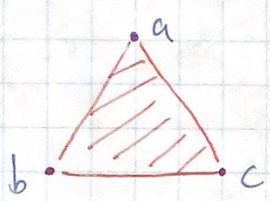


$A = \text{unit circle}$, $\text{conv}(A) = \text{unit disc}$

Each $u = \text{conv comb of } k=2 \text{ points in } A$.

(better than CT)

eg. $k=2$, $A = \{a, b, c\}$, $\text{conv}(A) = \text{triangle}$.



Each interior point is a convex combination of 3 points in A .

• Thm 2.7 (Sion's minmax theorem)

If $A, B \subseteq \mathbb{R}^k$ are compact and convex

$$\text{then } \min_{u \in A} \max_{v \in B} \langle u, v \rangle = \max_{v \in B} \min_{u \in A} \langle u, v \rangle$$

• Thm 2.8 (Separating hyperplane theorem)

If $A \subseteq \mathbb{R}^k$ is closed and convex, and $u \in \mathbb{R}^k \setminus A$,

then $\exists v \in \mathbb{R}^k$ s.t. $\langle v, w \rangle > \langle v, u \rangle$ for all $w \in A$.

