

Lecture 5

①

continuing w/ Chap. 2

functions of Hermitian operators

Let $f: \mathbb{R} \rightarrow \mathbb{R}$ be a real-valued function w/ domain $\text{dom}(f)$

For Hermitian $X = \sum_k \lambda_k |\psi_k\rangle\langle\psi_k|$
we define

$$f(X) = \sum_{k: \lambda_k \in \text{dom}(f)} f(\lambda_k) |\psi_k\rangle\langle\psi_k|$$

consistent w/ Taylor expansion
for analytic functions

$$\text{suppose } f(z) = \sum_{l=0}^{\infty} a_l z^l$$

(2)

Then given $X = U D U^\dagger$
 $\uparrow$ diagonal

$$X^l = (U D U^\dagger)^l = U D^l U^\dagger$$

$$\Rightarrow f(X) = \sum_{l=0}^{\infty} \alpha_l X^l$$

$$= \sum_{l=0}^{\infty} \alpha_l U D^l U^\dagger$$

$$= U \left(\sum_{l=0}^{\infty} \alpha_l D^l \right) U^\dagger$$

$$= U f(D) U^\dagger$$

$\downarrow$

$\uparrow$
function applied to
diagonal
entries
individually

$$= \sum_k f(\lambda_k) |\psi_k\rangle \langle \psi_k|$$

3

Consequence:

if U is unitary, then

$$f(UXU^\dagger) = U f(X) U^\dagger$$

Examples of functions: x^α , $\log x$
(used throughout, for Rényi & von Neumann entropies)

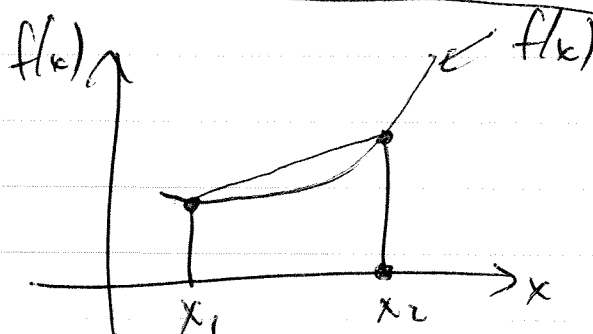
operator convex, concave, & monotone functions

f is operator convex if

$$f(\lambda X + (1-\lambda)Y) \leq \lambda f(X) + (1-\lambda)f(Y)$$

$\forall$ Hermitian X, Y & $\lambda \in [0,1]$

graph of
convex
function



function always
lies below
chord connecting
two points

④

operator convexity is stronger
than ordinary convexity

examples of operator convex functions:

x^α for $\alpha \in [-1, 0) \cup [1, 2]$ & $x \in [0, \infty)$

$x \log x$ for $x \in [0, \infty)$

f is operator concave if
 $-f$ is operator convex.

f is operator monotone if
 $X \leq Y \Rightarrow f(X) \leq f(Y)$
for all Hermitian X & Y

f is operator anti-monotone if
 $-f$ is operator monotone

5

These concepts are used in the proofs of data-processing inequalities for q_c relative entropies.

Norms

norm $\ni$ a function $\|\cdot\|: \mathcal{H} \rightarrow \mathbb{R}$ that satisfies

1) Non-negativity:

$$\|\psi\rangle\| \geq 0 \quad \forall |\psi\rangle \in \mathcal{H} \quad \neq$$

$$\|\psi\rangle\| = 0 \quad \Leftrightarrow \quad |\psi\rangle = 0$$

2) Scaling / homogeneity

For all $\alpha \in \mathbb{C} \quad \neq \quad |\psi\rangle \in \mathcal{H}$,

$$\|\alpha|\psi\rangle\| = |\alpha| \|\psi\rangle\|$$

⑥

3) Triangle inequality?

$$\forall |\psi\rangle, |\phi\rangle \in \mathcal{H}$$

$$\| |\psi\rangle + |\phi\rangle \| \leq \| |\psi\rangle \| + \| |\phi\rangle \|$$

consequence of 2) + 3):

every norm is convex

$$\| (\lambda |\psi\rangle + (1-\lambda) |\phi\rangle) \| \leq \lambda \| |\psi\rangle \| + (1-\lambda) \| |\phi\rangle \|$$

$$\forall |\psi\rangle, |\phi\rangle \in \mathcal{H} \quad \forall \lambda \in [0, 1]$$

Norms for the Hilbert space of linear operators:

For all $X \in \mathcal{L}(\mathcal{H})$, Schatten α -norm

$$\|X\|_\alpha = (\text{Tr}[|X|^\alpha])^{1/\alpha}$$

$$\forall \alpha \in [1, \infty)$$

(7)

where $|X| = \sqrt{X^*X}$

$$\|X\|_\infty = \lim_{\alpha \rightarrow \infty} \|X\|_\alpha$$

can show that

$$\|X\|_\alpha = \left(\sum_{k=1}^r s_k^\alpha \right)^{1/\alpha}$$

where $\{s_k\}_{k=1}^r$ is set of singular values of X .

Basic Properties of Schatten Norm

Monotonicity:

$$\alpha \geq \beta$$

$$\Rightarrow \|X\|_\alpha \leq \|X\|_\beta$$

monotonically non-increasing
w/ α

Isometric invariance:

$$\|X\|_\alpha = \|UXV^*\|_\alpha \quad \forall \text{ isometries } U, V$$

8

Duality:

$$\|X\|_\alpha = \sup_{Y \neq 0} \left\{ \frac{|\text{Tr}[Y+X]|}{\|Y\|_\beta, \frac{1}{\alpha} + \frac{1}{\beta} = 1} \right\}$$

$\Rightarrow$ Hölder's inequality:

$$|\text{Tr}[Z^+ X]| \leq \|X\|_\alpha \|Z\|_\beta$$

where $\alpha, \beta \in [1, \infty]$ satisfy

$$\frac{1}{\alpha} + \frac{1}{\beta} = 1$$

can prove that

$$\|X\|_\infty = S_{\max}$$

$\nearrow$

largest singular value
of X

9

Trace Norm ($\alpha=1$)

$$\|X\|_1 = \sum_{k=1}^n s_k$$

↑
sum of singular
values

If X is Hermitian, then

$$\|X\|_1 = \sum_k |\lambda_k|$$

↑
eigenvalues

If X is positive semidefinite, then

$$\|X\|_1 = \text{Tr}[X]$$

(10)

Variational characterization of
trace norm

$$\|x\|_1 = \sup_{Y \neq 0, \|Y\|_\infty \leq 1} |\text{Tr}[Yx]|$$

$$\text{Also, } \|x\|_1 = \sup_{\substack{U \\ \uparrow \\ \text{isometry}}} |\text{Tr}[Ux]|$$

we have

$$\|x\|_\infty \leq \|x\|_1 \leq d \|x\|_\infty$$

Operator Jensen Inequality

(11)

Let f be a continuous function.
The following are equivalent:

1) f is operator convex

$$\begin{aligned} 2) \quad & f\left(\sum_k A_k^+ X_k A_k\right) \\ & \leq \sum_k A_k^+ f(X_k) A_k \end{aligned}$$

$\forall$ Hermitian X_k &

$\{A_k\}_k$ satisfying $\sum_k A_k^+ A_k = I$

$$3) \quad f(V + XV) \leq V + f(X)V$$

$\forall$ Hermitian X &

isometry V .

(12)

$2 \Rightarrow 1$ easy. pick

$$A_1 = \sqrt{r} I, X_1 = X,$$

$$A_2 = \sqrt{1-r} I, X_2 = Y$$

$$\Rightarrow f(rX + (1-r)Y) \leq r f(X) + (1-r) f(Y)$$

$3 \Rightarrow 2$ more interesting

$$\text{Set } X = \sum_k X_k \otimes |k\rangle\langle k|$$

$$V = \sum_k A_k \otimes |k\rangle$$

$$V^\dagger V = I \text{ follows from } \sum_k A_k^\dagger A_k = I$$

$$\text{Also } V^\dagger X V = \sum_k A_k^\dagger X_k A_k$$

$$f(X) = f\left(\sum_k X_k \otimes |k\rangle\langle k|\right) = \sum_k f(X_k) \otimes |k\rangle\langle k|$$

(13)

$$\text{Then } V^\dagger f(x) V = \sum_k A_k^\dagger f(x_k) A_k$$

for others, see book

Superoperators

Linear operation that acts on
linear operators.

$$N: L(H_A) \rightarrow L(H_B)$$

satisfies

$$N(\alpha X + \beta Y) = \alpha N(X) + \beta N(Y)$$

$$\forall \alpha, \beta \in \mathbb{C} \text{ \& } X, Y \in L(H_A).$$

For every superoperator, $\exists n \in \mathbb{N}$ \&
sets $\{K_i\}_{i=1}^n$ \& $\{L_i\}_{i=1}^n$ s.t.

$$N(X) = \sum_{i=1}^n K_i X L_i^\dagger$$

(14)

identity denoted by
 id & satisfies

$$\text{id}(x) = x \quad \forall x \in L(H)$$

Given superoperators N & M ,
their tensor product is given by

$N \otimes M$ & satisfies

$$(N \otimes M)(x \otimes y) = N(x) \otimes M(y)$$

Hermiticity preserving superoperator

N is H.P. if

$N(x)$ is Hermitian $\forall$ Hermitian x .

(15)

Adjoint of a superoperatorAdjoint N^+ of N is

unique superoperator satisfying

$$\langle Y, N(X) \rangle = \langle N^+(Y), X \rangle$$

$$\forall X, Y$$

can show that

$$N^+(Y) = \sum_{i=1}^n K_i^+ Y L_i$$

$$\text{if } N(X) = \sum_{i=1}^n K_i X L_i^+$$

 N is trace preserving if

$$\text{Tr}[N(X)] = \text{Tr}[X] \quad \forall X \in L(\mathcal{H})$$

 N is unital if $N(I_A) = I_B$

(16)

can show that

N is trace preserving iff
 N^+ is unital.

Analysis

meaning of $\lim_{n \rightarrow \infty} s_n = l$:

$\forall \varepsilon > 0 \exists n_\varepsilon \in \mathbb{N}$ such that
 $\forall n \geq n_\varepsilon, |s_n - l| < \varepsilon$

Infimum

Let $E \subset \mathbb{R}$

x is a lower bound for E
if $y \geq x \forall y \in E$.

Infimum is the greatest lower
bound.

(17)

Example:

$$E = \left\{ \frac{1}{n} \right\}_{n \in \mathbb{N}}$$

$$\inf E = 0 \quad \text{but } 0 \notin E.$$

supremum

x is an upper bound for E
if $y \leq x$.

supremum is the least upper
bound.

we often use the following
common abbreviations:

$$\inf_{x \in S} F(x) = \inf \{ F(x) : x \in S \}$$

where S is a subset
of $L(H)$

$$\sup_{x \in S} F(x) = \sup \{ F(x) : x \in S \}$$

(18)

limit of a sequence need not exist

e.g. $+1, -1, +1, -1, \dots$

nice to have a substitute:

$\liminf$ & $\limsup$

$\liminf$

s is an asymptotic lower bound for sequence $\{s_n\}_{n \in \mathbb{N}}$

if $\forall \varepsilon > 0 \exists n_\varepsilon \in \mathbb{N}$ s.t.

$$\forall n \geq n_\varepsilon \quad s_n > s - \varepsilon$$

limit inferior is greatest asymptotic lower bound.

$$\liminf_{n \rightarrow \infty} s_n$$

19

lim sup

~~s~~ s is an asymptotic upper bound
for sequence $\{s_n\}_{n \in \mathbb{N}}$

if $\forall \epsilon > 0, \exists n_\epsilon \in \mathbb{N}$ s.t.

$$\forall n \geq n_\epsilon \quad s_n \leq s + \epsilon$$

limit superior is least
asymptotic upper bound

$$\limsup_{n \rightarrow \infty} s_n$$

we always have

$$\liminf_{n \rightarrow \infty} s_n \leq \limsup_{n \rightarrow \infty} s_n$$

If opposite inequality holds, then

$$\liminf_{n \rightarrow \infty} s_n = \limsup_{n \rightarrow \infty} s_n = \lim_{n \rightarrow \infty} s_n$$

Compact sets

subset S is compact if every sequence of elements in S has a ~~sub~~sequence that converges to an element in S .

For compact sets, infimum & supremum always exist and are contained in the set.
So

$$\inf_{x \in S} f(x) = \min_{x \in S} f(x) \quad \checkmark$$

$$\sup_{x \in S} f(x) = \max_{x \in S} f(x)$$

for compact S & continuous f .

Convex set

subset C is convex if

$$\forall u, v \in C \text{ and } \lambda \in [0, 1]$$

$$\lambda u + (1-\lambda)v \in C$$

Given a set $\{v_x\}_x$,

$$\sum_x p(x) v_x \text{ is called a}$$

convex combination of $\{v_x\}$

where $p(x)$ is a prob. dist.

convex hull is the convex set

of all convex combinations
of vectors in a set.

Minimax Theorem

Suppose we have

$$\inf_{x \in S} \sup_{y \in S'} F(x, y)$$

can think of this in

terms of a two-player game
 & a payoff / cost function.

we always have

$$\begin{aligned} & \sup_{y \in S'} \inf_{x \in S} F(x, y) \\ & \leq \inf_{x \in S} \sup_{y \in S'} F(x, y) \end{aligned}$$

going second in a game gives
 an advantage.

(23)

When does the reverse inequality hold?

minimax theorem (simple version)

If S & S' are compact & convex & F is continuous, convex in x for fixed y , concave in y for fixed x , then

$$\sup_{y \in S'} \inf_{x \in S} F(x, y) = \inf_{x \in S} \sup_{y \in S'} F(x, y)$$

$\Rightarrow$ no benefit to playing

second. Both players just employ optimal strategies