

Distance measures between states

Def.: The trace distance between two states ρ and σ in $S(A)$ is defined by

$$\Delta(\rho, \sigma) = \frac{1}{2} \underbrace{\|\rho - \sigma\|_1}_{\sum_i |\lambda_i|}, \quad \text{where } \lambda_i \text{ eigenvalues of } \rho - \sigma$$
$$= \frac{1}{2} \operatorname{Tr} |\rho - \sigma|.$$

Rk: - $\Delta(\rho, \rho) = 0$, $\Delta(\rho, \sigma) \leq \frac{1}{2} (\|\rho\|_1 + \|\sigma\|_1) = 1$.

- Invariant under unitary

$$\Delta(U\rho U^*, U\sigma U^*) = \Delta(\rho, \sigma)$$

- For $\rho = \sum_a P(a) |a\rangle\langle a|$

$$\sigma = \sum_a Q(a) |a\rangle\langle a|$$

$$\Delta(\rho, \sigma) = \frac{1}{2} \underbrace{\sum_a |P(a) - Q(a)|}_{\text{called total variation distance between } P \text{ and } Q}$$

- Data processing \Leftrightarrow important property for any quantum channel E distance measure.

$$\Delta(E(\rho), E(\sigma)) \leq \Delta(\rho, \sigma)$$

Operational interpretation: distinguishing states.

Hypotheses System A is either in:

$$H_0 : \rho_0$$

$$H_1 : \rho_1$$

Question: Minimum probability of error?

Strategy given by a POVM: E_0, E_1

$$\begin{matrix} \text{if} \\ H_0 \end{matrix} \quad \begin{matrix} \text{if} \\ H_1 \end{matrix}$$

Prior: H_0 with probability $\frac{1}{2}$.
 H_1 with probability $\frac{1}{2}$.

$$\text{Error probability} = \underbrace{\frac{1}{2} \text{Tr}(E_1 \rho_0)}_{\substack{\text{state is } \rho_0 \\ \text{but we wrongly say } H_1 \\ \text{"Type I" error}}} + \underbrace{\frac{1}{2} \text{Tr}(E_0 \rho_1)}_{\substack{\text{state is } \rho_1 \\ \text{but wrongly say } H_0 \\ \text{"Type II" error}}}$$

Often H_0 and H_1 play asymmetric role.

Proposition: The minimum error probability over all possible strategies is $\frac{1}{2} - \frac{1}{2} \Delta(\rho_0, \rho_1)$.

Rk: Hypothesis testing can also be considered in different regimes e.g. fix Type I error $\leq \epsilon$ and minimize Type II error.

(also called divergence).

Def: The hypothesis testing relative entropy with parameter $\varepsilon \in [0, 1]$ is defined by

$$D_H^\varepsilon(\rho \| \sigma) = \max_{0 \leq E \leq I} -\log \text{Tr}(E\rho)$$

$\text{Tr}(E\rho) \geq 1-\varepsilon$

Rk: - $D_H^\varepsilon(\rho \| \sigma) \in [0, +\infty]$.
 E_0 corresponds to E_0 ,
 $E_1 = I - E_0 = I - E$.

- $2^{-D_H^\varepsilon(\rho \| \sigma)}$ is the minimum Type II error if Type I error $\leq \varepsilon$.

- For $\varepsilon = 1$, $D_H^1(\rho \| \sigma) = +\infty$ (not interesting) -
- For $\varepsilon = 0$, $D_H^0(\rho \| \sigma) = -\log \text{Tr}(\Pi_\rho \sigma)$

where Π_ρ := projector onto the support of ρ

$$:= \sum_{i: \lambda_i \neq 0}^I |e_i x_i\rangle \langle e_i| \quad \text{where } \rho = \sum_i \lambda_i |e_i x_i\rangle \langle e_i|$$

↑ eigen decomposition.

- For $\rho = \sigma$, $D_H^\varepsilon(\rho \| \rho) = -\log(1-\varepsilon)$.
 ≈ 0 if ε small.
- For ρ and σ having orthogonal supports, i.e., $\rho\sigma = 0$
 $D_H^\varepsilon(\rho \| \sigma) = +\infty$

Further remarks about $D_H^\varepsilon(\rho \parallel \sigma)$

- In general, no closed form expression but

$$\min_{\sigma \in E \leq I} \text{Tr}(\sigma) \quad \text{subject to } \text{Tr}(\sigma) \geq 1 - \varepsilon$$

is a convex optimization program, more specifically
it is a **semi-definite program**.
can be computed efficiently for small dimension.

- Classical case $\rho = \sum_{x \in X} P(x) |x\rangle\langle x|$
 $\sigma = \sum_{x \in X} Q(x) |x\rangle\langle x|$.

A natural test:

For complex x , compute $\frac{P(x)}{Q(x)}$

If ≥ 1 output "P"
If ≤ 1 output "Q"
called likelihood ratio.

Prop: D_H^ε satisfies the data processing inequality
[i.e. for any quantum channel \mathcal{E} , we have
 $D_H^\varepsilon(\mathcal{E}(\rho) \parallel \mathcal{E}(\sigma)) \leq D_H^\varepsilon(\rho \parallel \sigma)$

Proof: Very intuitive: If I have a strategy to distinguish $\mathcal{E}(\rho)$ from $\mathcal{E}(\sigma)$, can distinguish ρ and σ by first applying \mathcal{E} then the strategy.

Let E be such that

$$D_H^E(E(\rho) \| E(\sigma)) = -\log \text{Tr}(E E(\sigma)) \text{ and } \text{Tr}(E E(\rho)) \geq 1 - \varepsilon$$

Note that $L(H)$ is itself a Hilbert space with inner product $\langle S, T \rangle = \text{Tr}(S^* T)$.

So $E \in L(L(H))$ has an adjoint denoted E^* , it satisfies :

$$\text{Tr}(E E(\sigma)) = \text{Tr}(E^* E(\sigma)) = \text{Tr}(E^*(E)\sigma)$$

\uparrow
 E is Hermitian

$$\text{and } \text{Tr}(E E(\rho)) = \text{Tr}(E^*(E)\rho)$$

Fact : E completely positive $\Leftrightarrow E^*$ completely positive.
 E trace preserving $\Leftrightarrow E^*$ is unital i.e.
 $E^*(I) = I$.

As a result, $E^*(E)$ satisfies

$$0 = E^*(0) \leq E^*(E) \leq E^*(I) = I.$$

and it is a feasible solution for the program for $D_H^E(E(\rho) \| \sigma)$

$$\text{So } D_H^E(E(\rho) \| E(\sigma)) \leq D_H^E(\rho \| \sigma). \blacksquare$$

Special states of interest: $\rho^{\otimes n}, \sigma^{\otimes n}$
with $n \rightarrow \infty$.

Th (Quantum Stein Lemma)

Let $\epsilon \in (0, 1)$ and $\rho, \sigma \in S(A)$.

Then

$$\lim_{n \rightarrow \infty} \frac{1}{n} D_H^\epsilon(\rho^{\otimes n} \parallel \sigma^{\otimes n}) = D(\rho \parallel \sigma).$$

The quantum relative entropy

(ρ state but σ not necessarily normalized)

Def: For $\rho \in S(A), \sigma \in Pos(A)$ where A is a finite dimensional Hilbert space, the quantum relative entropy is defined by :

$$supp(\rho) = \text{Span}\{ |e_i\rangle : d_i \neq 0\}$$

if $\rho = \sum_i \lambda_i |e_i\rangle \langle e_i|$

$$D(\rho \parallel \sigma) = \begin{cases} Tr(\rho (\log \rho - \log \sigma)) & \text{if } supp(\rho) \subseteq supp(\sigma) \\ +\infty & \text{else} \end{cases}$$

Rk: * $\log \rho = \sum_i (\log \lambda_i) |e_i\rangle \langle e_i|$ for $\rho = \sum_i \lambda_i |e_i\rangle \langle e_i|$

* Classical case; i.e. ρ and σ commute

$$\rho = \sum_x P(x) |x\rangle \langle x|, \quad \sigma = \sum_x Q(x) |x\rangle \langle x|.$$

$$D(\rho \parallel \sigma) = \sum_x P(x) \log \frac{P(x)}{Q(x)}$$

called relative entropy or Kullback-Leibler divergence

Quantum relative entropy can be seen as a noncommutative generalization of KL divergence (there are others as well)

Th (Properties of the quantum relative entropy)

- We have $D(\rho \parallel \sigma) \geq 0$ for $\rho, \sigma \in S(A)$ with equality iff $\rho = \sigma$.
 - Data processing for D : for a quantum channel \mathcal{E}
- $$D(\mathcal{E}(\rho) \parallel \mathcal{E}(\sigma)) \leq D(\rho \parallel \sigma)$$

Will prove this later.

D can be used to define the von Neumann entropy:

Def.: For a state $\rho_{AB} \in S(A \otimes B)$ we define

- $H(A)_{\rho} := -D(\rho_A \parallel I_A)$ Recall $\rho_A = \text{Tr}_B(\rho_{AB})$
↑ entropy sign. ↑ not normalized.
- $H(A|B)_{\rho} := -D(\rho_{AB} \parallel I_A \otimes \rho_B)$. von Neumann entropy.
↑ conditional entropy
- $I(A:B)_{\rho} := D(\rho_{AB} \parallel \rho_A \otimes \rho_B)$.
↑ mutual information

Proof of Stein lemma:

Recall statement:

$$\lim_{n \rightarrow \infty} \frac{1}{n} D_H^E(P^{\otimes n} \| \sigma^{\otimes n}) = D(P \| \sigma)$$

* Achievability: \geq (have to give a strategy)

Let us start with the case where P and σ commute.

$$P = \sum_x P(x) |x\rangle\langle x| \quad \sigma = \sum_x Q(x) |x\rangle\langle x|.$$

$$P^{\otimes n} = \sum_{x_1 \dots x_n} P(x_1) \dots P(x_n) |x_1 x_2 \dots x_n x_n\rangle\langle x_1 x_2 \dots x_n x_n|$$

$$\sigma^{\otimes n} = \sum_{x_1 \dots x_n} Q(x_1) \dots Q(x_n) |x_1 x_2 \dots x_n x_n\rangle\langle x_1 x_2 \dots x_n x_n|.$$

Will define a test for this hypothesis testing problem.

Given X_1, \dots, X_n

$$\text{Compute } R = \frac{P(X_1)P(X_2) \dots P(X_n)}{Q(X_1)Q(X_2) \dots Q(X_n)}$$

$$\text{If } \frac{1}{n} \log R \geq D(P \| Q) - \delta$$

$\delta > 0$ is a parameter,
will let $\delta \rightarrow 0$ at
the end.

Return "Samples from P".

Else Return "Samples from Q".

In quantum notation corresponds to:

$$E = \sum_{x_1 \dots x_n} |x_1 \dots x_n X x_1 \dots x_n\rangle\langle x_1 \dots x_n|$$

$$\text{it clearly depends on } n \uparrow$$

$$x_1 \dots x_n : \frac{P(x_1) \dots P(x_n)}{Q(x_1) \dots Q(x_n)} \geq 2^{n(D(P \| Q) - \delta)}$$

Analysis of this test.

* If samples are from P . (Hypothesis 0)

$$\begin{aligned} & \underset{\substack{P \\ X_1 \dots X_n \sim P}}{\Pr} \left\{ \frac{1}{n} \log R \geq D(P||Q) - \delta \right\} \quad (= \text{Tr}(E_P^{\otimes n})) \\ &= \Pr \left\{ \frac{1}{n} \sum_{i=1}^n \log \frac{P(X_i)}{Q(X_i)} \geq D(P||Q) - \delta \right\} \end{aligned}$$

$$\text{But } \underset{X_i \sim P}{\mathbb{E}} \left\{ \log \frac{P(X_i)}{Q(X_i)} \right\} = \sum_x P(x) \log \frac{P(x)}{Q(x)} = D(P||Q).$$

So by the law of large numbers

$$\xrightarrow[n \rightarrow \infty]{\quad} 1$$

The constraint $\text{Tr}(E_P^{\otimes n}) \geq 1 - \varepsilon$ satisfied for large enough n .

* If samples are from Q . (Hypothesis 1)

$$\begin{aligned} & \underset{\substack{P \\ X_1 \dots X_n \sim Q}}{\Pr} \left\{ \frac{1}{n} \log R \geq D(P||Q) - \delta \right\} = \sum'_{x_1, \dots, x_n} Q(x_1) \dots Q(x_n) \\ & \quad \frac{1}{n} \sum'_i \log \frac{P(x_i)}{Q(x_i)} \geq D(P||Q) - \delta \\ &= \sum'_{x_1, \dots, x_n} Q(x_1) \dots Q(x_n) \cdot \\ & \quad Q(x_1) \dots Q(x_n) \leq 2^{-n(D(P||Q) - \delta)} \frac{P(x_1) \dots P(x_n)}{P(x_1) \dots P(x_n)} \\ &\leq 2^{-n(D(P||Q) - \delta)} \sum'_{x_1, \dots, x_n} P(x_1) \dots P(x_n) \\ &\leq 2^{-n(D(P||Q) - \delta)} \end{aligned}$$

So

$$-\log \text{Tr}(E^{\otimes n}) \geq n(D(P||Q) - \delta)$$

and $\frac{1}{n} D_H^\varepsilon(E^{\otimes n} || \sigma^{\otimes n}) \geq D(P||Q) - \delta$
for large enough n .

Works for any $\delta > 0$ so we have

$$\lim_{n \rightarrow \infty} \frac{1}{n} D_H^\varepsilon(E^{\otimes n} || \sigma^{\otimes n}) \geq D(P||Q).$$

Considered general case E, σ not commuting.

Pinching

general technique to reduce general case to commuting.

Given $\sigma = \sum_{\lambda \in \text{Spec}(\sigma)} \lambda \Pi_\lambda$, let $P_\sigma(S) = \sum \Pi_\lambda S \Pi_\lambda$.

Two important properties:

- $P_\sigma(S)$ commutes with σ
- $\rho \geq 0$, $P_\sigma(\rho) \geq \frac{1}{|\text{Spec}(\sigma)|} \rho$ number of distinct eigenvalues

$$\begin{aligned} D_H^\varepsilon(E^{\otimes n} || \sigma^{\otimes n}) &\geq D_H^\varepsilon(P_{\sigma^{\otimes n}}(\rho^{\otimes n}) || P_{\sigma^{\otimes n}}(\rho^{\otimes n})) \\ &= D_H^\varepsilon(P_{\sigma^{\otimes n}}(\rho^{\otimes n}) || \sigma^{\otimes n}) \end{aligned}$$

↑
commute!
Common eigenbasis \rightarrow corresponds to
distributions $P := \text{eigenvalues of } P_{\sigma^{\otimes n}}(E^{\otimes n})$
 $Q := \text{eigenvalues of } \sigma^{\otimes n}$.

$$D_H^\varepsilon(P_{\sigma^{\otimes n}}(\rho^{\otimes n}) || \sigma^{\otimes n}) = D_H^\varepsilon(P || Q)$$

We have $\lim_{m \rightarrow \infty} \frac{1}{m} D_H^\varepsilon(P^{\otimes m} || Q^{\otimes m}) \geq D(P||Q)$

As a result

$$\frac{1}{nm} D_H^{\mathcal{E}} \left(P_{\otimes n}(\rho^{\otimes n})^{\otimes m} \middle\| (\sigma^{\otimes n})^{\otimes m} \right) = \frac{1}{m} \cdot \frac{1}{n} D_H^{\mathcal{E}} \left(P^{\otimes m} \middle\| Q^{\otimes m} \right)$$

$$\xrightarrow[m \rightarrow \infty]{} \frac{1}{m} D(P \middle\| Q)$$

$$= \frac{1}{m} D(P_{\otimes n}(\rho^{\otimes n}) \middle\| \sigma^{\otimes n})$$

Now use $P_{\otimes n}(\rho^{\otimes n}) \geq \frac{1}{|\text{spec}(\sigma^{\otimes n})|} \sigma^{\otimes n}$

Elements in $\text{spec}(\sigma^{\otimes n})$ are of the form $\prod_{i=1}^n d_i$ with $d_i \in \text{spec}(\sigma)$
But $|\text{spec}(\sigma)| \leq d$ ($= \dim A$)

So $|\text{spec}(\sigma^{\otimes n})| \leq (n+1)^{d-1}$ (each eigenvalue appears a number of times between 0 and n)

$$\begin{aligned} D(P_{\otimes n}(\rho^{\otimes n}) \middle\| \sigma^{\otimes n}) &= \text{Tr}(P_{\otimes n}(\rho^{\otimes n}) \log P_{\otimes n}(\rho^{\otimes n}) - P_{\otimes n}(\rho^{\otimes n}) \log \sigma^{\otimes n}) \\ &= \text{Tr}(\rho^{\otimes n} P_{\otimes n}(\log P_{\otimes n}(\rho^{\otimes n})) - \rho^{\otimes n} \log \sigma^{\otimes n}) \\ &= \text{Tr}(\rho^{\otimes n} \log P_{\otimes n}(\rho^{\otimes n}) - \rho^{\otimes n} \log \sigma^{\otimes n}) \\ &\stackrel{\log \text{ is operator monotone}}{\geq} \text{Tr}(\rho^{\otimes n} \log \sigma^{\otimes n} - \rho^{\otimes n} \log \sigma^{\otimes n}) - \log |\text{spec}(\sigma^{\otimes n})| \end{aligned}$$

Thus:

$$\frac{1}{n} D(P_{\otimes n}(\rho^{\otimes n}) \middle\| \sigma^{\otimes n}) \geq \frac{1}{n} D(\rho^{\otimes n} \middle\| \sigma^{\otimes n}) - \frac{1}{n} \log |\text{spec}(\sigma^{\otimes n})|$$

$$\geq D(\rho \middle\| \sigma) - \underbrace{\frac{1}{n} \log(n+1)^{d-1}}_{\xrightarrow[n \rightarrow \infty]{} 0}.$$

Note that $D(\rho^{\otimes n} || \sigma^{\otimes n}) = n D(\rho || \sigma)$.

Indeed: if $\rho = \sum'_x d_x |x\rangle\langle x|$ for a basis $\{|x\rangle\}$

$$\rho^{\otimes n} = \sum_{x_1 \dots x_n} d_{x_1} d_{x_2} \dots d_{x_n} |x_1 \dots x_n \rangle \langle x_1 \dots x_n|$$

$$\begin{aligned} \log(\rho^{\otimes n}) &= \sum'_{x_1 \dots x_n} \sum'_{i=1}^n \log d_i |x_1 \dots x_n \rangle \langle x_1 \dots x_n| \\ &= \sum_{i=1}^n I_{A_i} \otimes \dots \otimes I_{A_{i-1}} \otimes (\log(\rho_{A_i})) \otimes I_{A_{i+1}} \otimes \dots \otimes I_{A_n} \end{aligned}$$

* Converse:

Will only prove

$$\lim_{\epsilon \rightarrow 0} \lim_{n \rightarrow \infty} \frac{1}{n} D_H^\epsilon(\rho^{\otimes n} || \sigma^{\otimes n}) \leq D(\rho || \sigma)$$

General quantum case

The statement is that it holds for any $\epsilon \in (0, 1)$

Let E be such that $\text{Tr}(E \rho^{\otimes n}) \geq 1 - \epsilon$.

We apply the data processing inequality for the quantum channel

$$\mathcal{E}: L(A^{\otimes n}) \rightarrow L(\mathbb{C}^2)$$

$$\begin{aligned} T &\mapsto |\text{0x0}| \text{Tr}(ET) \\ &\quad + |\text{1x1}| \text{Tr}((I-E)T). \end{aligned}$$

$$\mathcal{E}(\rho^{\otimes n}) = |\text{0x0}| \text{Tr}(E \rho^{\otimes n}) + |\text{1x1}| (1 - \text{Tr}(E \rho^{\otimes n}))$$

$$\mathcal{E}(\sigma^{\otimes n}) = |\text{0x0}| \text{Tr}(E \sigma^{\otimes n}) + |\text{1x1}| (1 - \text{Tr}(E \sigma^{\otimes n}))$$

We have on one side :

$$D(\rho^{\otimes n} \parallel \sigma^{\otimes n}) = n D(\rho \parallel \sigma).$$

- But

$$\begin{aligned} D(\rho^{\otimes n} \parallel \sigma^{\otimes n}) &\stackrel{\text{data processing}}{\geq} D(E(\rho^{\otimes n}) \parallel E(\sigma^{\otimes n})) \\ &= \text{Tr}(E_{\rho^{\otimes n}}) \log \frac{\text{Tr}(E_{\rho^{\otimes n}})}{\text{Tr}(E_{\sigma^{\otimes n}})} + (1 - \text{Tr}(E_{\rho^{\otimes n}})) \log \frac{1 - \text{Tr}(E_{\rho^{\otimes n}})}{1 - \text{Tr}(E_{\sigma^{\otimes n}})} \\ &\geq -1 - \text{Tr}(E_{\rho^{\otimes n}}) \log \text{Tr}(E_{\sigma^{\otimes n}}) \end{aligned}$$

\triangleq elementary inequalities

$$\therefore -\log \text{Tr}(E_{\sigma^{\otimes n}}) \leq \frac{n D(\rho \parallel \sigma) + 1}{\text{Tr}(E_{\rho^{\otimes n}})} \leq \frac{n D(\rho \parallel \sigma) + 1}{1 - \varepsilon}$$

$$\frac{1}{n} D_H^{\varepsilon}(\rho^{\otimes n} \parallel \sigma^{\otimes n}) \leq \frac{D(\rho \parallel \sigma)}{1 - \varepsilon} + \frac{1}{(1 - \varepsilon) \cdot n}$$

letting $n \rightarrow \infty$ then $\varepsilon \rightarrow 0$, we get the desired result. \blacksquare

Rk : D_H^{ε} is called a "one-shot entropy" measure as it has an operational interpretation for any states. Many others : $H_{\min}^{\varepsilon} \leftarrow$ Cryptography.
 \vdots "worst case" entropy.

- The usual relative entropy D and corresponding von Neumann entropy H only has an operational interpretation in an iid (independent identically distributed) or average setting.