



# Quantum Multi-Hypothesis Testing

## A new take on an old problem

KOENRAAD M.R. AUDENAERT

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June 26, 2012

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Joint unpublished work with Milan Mosonyi (Bristol).

Preprint with lots of [TODO] markers available on request.

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# Hypothesis testing

- The problem:
  - Given a system in an unknown quantum state;
  - I tell you it comes from a given set of  $r$  density matrices  $\{\rho_i\}_{i=1}^r$ ;
  - Figure out which of the  $r$  density matrices is the true one, using a well-chosen measurement.
- What is the optimal measurement, what is the optimal error probability?

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# 1. Classical communication over a quantum channel

The most natural setting for the hypothesis testing problem

Allows me to stay in the closet

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# Classical communication

- Classical Communication = passing a message from one point (space/time) to another using a physical information carrier.
- Message: sequence of symbols from an alphabet  $\{1, 2, \dots, r\}$ .
- Basic communication system:



- Source: produces symbols
- Transmitter: symbol values  $\rightarrow$  values of physical property
- Channel: passes information carrier from sender to receiver; adds noise
- Receiver: values of physical property  $\rightarrow$  symbol values

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# Quantum communication

- Quantum Communication = passing a message from one point (space/time) to another using a quantum state.
- Message: sequence of symbols from an alphabet  $\{1, 2, \dots, r\}$ .
- Basic communication system:



- Source: produces symbols
- Transmitter: symbol values  $\rightarrow$  quantum states: *signal states*
- Quantum Channel: CPTP map
- Receiver: quantum measurement

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# The problem of communication: Noise

- Noise = Nature modifying the physical properties of the carrier, causing communication errors.
- Noise makes the symbols less distinguishable, destroying information.
- Good communication design: reduce amount of noise (technology issues), and *amount of errors caused by noise*: optimal choice of signal states, optimal measurement
- Optimality expressed in terms of a mathematical model.
- In this talk: signal states given, measurement to be optimised.

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# Mathematical model



- **Source:**

- Emits symbols from the alphabet  $\{1, 2, \dots, r\}$ .
- Each symbol modelled as i.i.d. random variable  $I$  with probability distribution  $p_I(i)$ ,  $i \in \{1, 2, \dots, r\}$ .

- **Transmitter:**

- Translates symbols  $i$  to signal states  $\sigma_i$ .



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# Mathematical model

$\boxed{\text{Source}} \rightarrow I \rightarrow \boxed{\text{Xmitter}} \rightarrow \sigma \rightarrow \boxed{\text{Channel}} \rightarrow \rho \rightarrow \boxed{\text{Receiver}} \rightarrow J \rightarrow \boxed{\text{Recipient}}$

- **Noisy quantum channel:**

- State coming out of the channel ( $\rho$ ) will be different from what got in ( $\sigma$ ).
- Channel modelled as CPTP map  $\Phi$ .

- **Transmitter + noisy channel:**

- Combined model:  $i \mapsto \Phi(\sigma_i) =: \rho_i$ .

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# Mathematical model

Source  $\rightarrow I \rightarrow$  Xmitter  $\rightarrow \sigma \rightarrow$  Channel  $\rightarrow \rho \rightarrow$  Receiver  $\rightarrow J \rightarrow$  Recipient

- **Receiver:**

- Has to “guess”  $i$  from state  $\rho_i$ .
- Should be designed so that the probability of guessing incorrectly is minimal.
- Need to incorporate receiver imperfections as well, e.g. receiver noise.
- Model: POVM  $\{E_j\}_{j=1}^r$
- Produces outcome  $j$  with probability (Born rule)  $p_j(\rho) = \text{Tr } E_j \rho$ .

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# Success Probability

- The quality of a receiver is determined by the probability that it chooses the correct answer; i.e.  $j = i$ .
- Probability that receiver outputs  $j$  given that source produced  $i$ :

$$p_{J|I}(j|i) = \text{Tr } \rho_i E_j.$$

- Success probability given symbol  $i$  is

$$p_{J|I}(i|i) = \text{Tr } \rho_i E_i.$$

- *Average success probability*  $p_s$ :

$$p_s = \sum_{i=1}^r p_I(i) p_{J|I}(i|i).$$

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# All together now...

- Quantum state: density operator (matrix)  $\rho_i$ , satisfying

$$\boxed{\forall i : \rho_i \geq 0, \text{ with } \text{Tr } \rho_i = 1.}$$

- Quantum measurement:  $r$  measurement operators  $E_j$ , satisfying

$$\boxed{\forall j : E_j \geq 0, \text{ with } \sum_{j=1}^r E_j = \mathbb{I}.}$$

- Quantum success probability (to be optimised):

$$\boxed{p_s = \sum_{i=1}^r p_I(i) \text{Tr } \rho_i E_i.}$$

- Looks like an inner product between the  $\rho_i$  and the  $E_i$ . However, optimisation is difficult because  $\rho_i$  and  $E_i$  have different normalisations.

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## 2. Optimal Quantum Receiver

What is the optimal POVM? What is the optimal success probability?

- For a binary alphabet ( $r = 2$ ) this has an analytical answer.
- For larger alphabets, no analytical answer is known, but it can be solved using numerical methods.

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# Optimal Quantum Receiver

- To keep notations simpler, I will absorb the source symbol probabilities  $p_I(i)$  into the received states  $\rho_i$  and write  $A_i := p_I(i)\rho_i$  (signal operators).
- Furthermore, I will write  $A_0 = \sum_i A_i$ .
- Thus:

$$A_i \geq 0, \quad \text{Tr } A_0 = 1.$$

- Formula for  $p_s$ , for a given POVM  $\{E_k\}$ :

$$p_s(\{E_k\}) = \sum_{k=1}^r \text{Tr } A_k E_k.$$

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# SDP Formulation

- Optimal success rate, for optimal POVM:

$$p_s^* = \max_{\{E_k\}} \left\{ \sum_{k=1}^r \text{Tr } A_k E_k; \quad E_k \geq 0, \sum_{k=1}^r E_k = \mathbb{I} \right\}.$$

- This type of maximisation is known as a semidefinite program (SDP):
  - maximisation of a linear functional
  - over variables subject to linear constraints and semidefiniteness constraints.
- (The set of feasible values of the variables is convex.)
- Efficient numerical methods exist for solving SDPs.

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# Dual Formulation

- For every SDP there exists a *dual* SDP, which gives the same answer but via a *minimisation* over a new variable (essentially a Lagrange multiplier).

- Primal SDP:

$$p_s^* = \max_{\{E_k\}} \left\{ \sum_{k=1}^r \text{Tr } A_k E_k; \quad E_k \geq 0, \sum_{k=1}^r E_k = \mathbb{I} \right\}.$$

- Dual SDP:

$$p_s^* = \min_Y \{ \text{Tr } Y; \quad \forall k : Y \geq A_k \}.$$

- See, e.g. Eldar, Megretski and Verghese, IEEE IT-49 (2003), 1007–1012.



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# Proof

Introduce  $r$  operators  $X_k \geq 0$ , one more operator  $Y$ , and define

$$\mathcal{L} = \sum_k \operatorname{Tr}(A_k E_k) + \sum_k \operatorname{Tr}(X_k E_k) + \operatorname{Tr} Y (\mathbb{I} - \sum_k E_k) = \operatorname{Tr} Y + \sum_k \operatorname{Tr} E_k (A_k + X_k - Y).$$

Then,  $\mathcal{L} \geq \sum_k \operatorname{Tr}(A_k E_k) = p_s(\{E_k\})$ , so that

$$p_s^* \leq \max_{E_k} \left\{ \mathcal{L}; E_k \geq 0, \sum_{k=1}^r E_k = \mathbb{I} \right\} \leq \max_{E_k} \{ \mathcal{L} \} = \begin{cases} \operatorname{Tr} Y, & Y = A_k + X_k \\ +\infty, & \text{otherwise.} \end{cases}$$

The positivity condition on the  $X_k$  can be replaced by requiring that  $Y \geq A_k$ , for all  $k$ . Hence

$$p_s^* \leq \begin{cases} \operatorname{Tr} Y, & Y \geq A_k \\ +\infty, & \text{otherwise,} \end{cases} \quad \forall Y.$$

Minimising over  $Y$  yields the best upper bound on  $p_s^*$ :

$$p_s^* \leq \min_{Y \geq A_k} \{ \operatorname{Tr} Y; Y \geq A_k \}.$$

One can show that equality can be achieved (under certain mild technical conditions). □

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# LUB

- The optimal  $Y$  in

$$p_s^* = \min_Y \{ \text{Tr } Y; \quad \forall k : Y \geq A_k \}.$$

can be interpreted as some sort of *least upper bound* (LUB) on the  $A_k$ .

- Henceforth I will write

$$p_s^* = \text{Tr LUB}(A_1, \dots, A_r),$$

with

$$\text{LUB}(A_1, \dots, A_r) = \text{argmin}_Y \{ \text{Tr } Y; \quad \forall k : Y \geq A_k \}.$$

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# LUB: properties

- For diagonal  $A_i$ , LUB is just the entrywise maximum.
- $\text{LUB}(A, B, C) \neq \text{LUB}(A, \text{LUB}(B, C))$ ;
- However,  $\text{Tr LUB}(A, B, C) \leq \text{Tr LUB}(A, \text{LUB}(B, C))$ .
- $\text{Tr}(\text{LUB}(A, B) + \text{LUB}(C, D)) \geq \text{Tr LUB}(A + C, A + D, B + C, B + D)$ .
- $\text{LUB}(A_1, \dots, A_r) + B = \text{LUB}(A_1 + B, \dots, A_r + B)$ .
- $\text{LUB}(A, 0) = A_+$ .

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# GLB

- I will also need the *greatest lower bound* (GLB):

$$\text{GLB}(A_1, \dots, A_r) = \operatorname{argmax}_Y \{ \operatorname{Tr} Y; \quad \forall k : Y \leq A_k \}.$$

- Property:  $\text{GLB}(A_1, \dots, A_r) = -\text{LUB}(-A_1, \dots, -A_r)$ .
- $A, B \geq 0$  does *not* imply  $\text{GLB}(A, B) \geq 0$ , only  $\operatorname{Tr} \text{GLB}(A, B) \geq 0$ .

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# Solution of binary case

- The case  $r = 2$  can be solved analytically (Holevo, Helstrom 1973).

$$\begin{aligned} p_s(\{E, \mathbb{I} - E\}) &= \text{Tr}(A_1 E + A_2(\mathbb{I} - E)) \\ &= \text{Tr} A_2 + \text{Tr}((A_1 - A_2)E). \end{aligned}$$

- Choose as  $E$  the *projector* on the support of  $(A_1 - A_2)_+$ .
- The  $p_s$  of this POVM, which is a lower bound on  $p_s^*$ , is:

$$p_s^* \geq p_s(\{E, \mathbb{I} - E\}) = \text{Tr} A_2 + \text{Tr}(A_1 - A_2)_+.$$

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# Solution of binary case

- Now consider the dual problem,  $p_s^* = \min_Y \{\text{Tr } Y : Y \geq A_k\}$ .
- Let us choose

$$Y = (A_1 + A_2 + |A_1 - A_2|)/2 = A_2 + (A_1 - A_2)_+ = A_1 + (A_2 - A_1)_+.$$

- This is clearly an upper bound ( $Y \geq A_k$ ), hence

$$p_s^* \leq \text{Tr } Y = \text{Tr } A_2 + \text{Tr}(A_1 - A_2)_+.$$

- Now note: this is the same expression as in the lower bound.

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## Solution of binary case

- Thus, we have equality; the chosen  $E$  is optimal, and so is  $Y$ :

$$Y = \text{LUB}(A_1, A_2) = A_2 + (A_1 - A_2)_+.$$

- Hence, we have

$$p_s^* = \text{Tr LUB}(A_1, A_2) = \text{Tr}(A_2 + (A_1 - A_2)_+).$$

- The optimal error probability  $p_e^* = 1 - p_s^*$  can be expressed in terms of GLB.

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# GLB

- Define the *complementary* states

$$\bar{A}_k := \sum_{j:j \neq k} A_j = A_0 - A_k.$$

- Then

$$\begin{aligned} p_e^* = 1 - p_s^* &= \text{Tr } A_0 - \text{Tr LUB}(A_1, \dots, A_r) \\ &= \text{Tr } A_0 + \text{Tr GLB}(-A_1, \dots, -A_r) \\ &= \text{Tr GLB}(A_0 - A_1, \dots, A_0 - A_r) \\ &= \text{Tr GLB}(\bar{A}_1, \dots, \bar{A}_r) \\ &= \min_{\{E_k\}} \sum_k \text{Tr } \bar{A}_k E_k \end{aligned}$$

- For  $r = 2$ ,  $\bar{A}_1 = A_2$  and  $\bar{A}_2 = A_1$ , hence  $P_e^* = \text{Tr GLB}(A_2, A_1)$  and

$$\text{GLB}(A_1, A_2) = A_2 - (A_1 - A_2)_+.$$



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# General case

- No analytical solutions for  $\text{LUB}(A_1, \dots, A_r)$ , nor for  $p_s^*$  are known for  $r > 2$ .
- Can be solved in specific cases. Numerical methods needed for the general case.
- What if we want to answer questions of a general nature? What if the dimension  $d$  becomes too high for numerics?
- In particular, what can we say about the *asymptotic behaviour* of the error probability?

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### 3. Asymptotic error rate

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# Asymptotic error rate

- In the case of classical communication, we can reduce the error by sending the same symbol  $n$  times, make  $n$  measurements and then do a majority vote on the  $n$  outcomes.
- We can do something similar in the quantum case.
- Here the transmitter-channel produces, for input symbol  $i$ ,  $n$  identical quantum systems each described by the same density operator  $\rho_i$ , i.e. it produces  $n$  copies of  $\rho_i$ .
- In the quantum case, the optimal strategy is *not* to perform measurements on each copy of  $\rho_i$ , but to store these  $n$  copies and make a single measurement on the composite system as a whole.
- This composite system is described by the  $n$ -fold Kronecker product

$$\rho_i^{\otimes n} := \rho_i \otimes \dots \otimes \rho_i.$$

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# Asymptotic error rate

- The formula for the optimal success probability  $p_s^*$  remains the same, but the operators  $A_k$  are replaced by  $A_{k,n} = p_k \rho_k^{\otimes n}$ .

$$p_{s,n}^* = \max_{\{E_k\}} \sum_k \text{Tr} A_{k,n} E_k = \text{Tr LUB}(\{A_{k,n}\}).$$

- The error probability  $p_{e,n}^* = 1 - p_{s,n}^*$  decreases exponentially with  $n$ :

$$p_{e,n}^* \approx \exp(-Rn).$$

- One defines the *asymptotic error rate* as follows:

$$R = \lim_{n \rightarrow \infty} -\frac{1}{n} \log p_{e,n}^*.$$

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# Quantum Chernoff Divergence

- There is a simple formula in the case of  $r = 2$ , (generalising a similar formula valid in the classical setting, due to Chernoff (1952)):

$$R = -\log \min_{0 \leq s \leq 1} \text{Tr} \rho_1^s \rho_2^{1-s}.$$

- This was recently generalised to vN algebras by Y Ogata.
- This quantity is now known as the Chernoff divergence of  $\rho_1$  and  $\rho_2$ ,  $C(\rho_1, \rho_2)$ .
- It quantifies the distinguishability of  $\rho_1$  and  $\rho_2$ .

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# Quantum Chernoff Divergence

- For larger  $r$ , it is believed that the asymptotic error rate is equal to the *smallest pairwise* quantum Chernoff divergence.

$$R = C := \min_{j < k} C(\rho_j, \rho_k).$$

- In the classical case, this was proved by Salikhov (1973).
- Nussbaum and Szkola (2010) have shown this to be true in the quantum case when all density operators have rank 1 (pure states).
- The general case is still an open problem.
- Nussbaum and Szkola showed that  $R \leq C$ .
- To show also that  $R \geq C$ , good upper bounds on the optimal error probability are required.

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# 4,3,2,...

- There are some weaker results that indicate that the pairwise Chernoff divergence can not be too different from  $R$ .
- First, Nussbaum and Szkola proved  $R \geq C/(r(r-1)/2)$ .
- We were then able to improve the lower bound to  $R \geq C/4$ .
- After that, Nussbaum and Szkola improved it further to  $R \geq C/3$ .
- Earlier this year we showed  $R \geq C/2$ .
- Proof involves: Tyson's bound, Lieb's theorem, Hölder's inequality

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# Tyson's bound

- Bound on the optimal error probability:  $P_e^* \leq 2(1 - \text{Tr}(\sum_i A_i^2)^{1/2})$ .
- *Proof.* Choose a special POVM in the primal SDP:  $E_k = S^{-1/2} A_k^2 S^{-1/2}$ , with  $S := \sum_j A_j^2$ . By Hölder's inequality:

$$\begin{aligned} \text{Tr } A_k^2 S^{-1/2} &= \|A_k S^{-1/2} A_k\|_1 \\ &= \|(A_k S^{-1/2} A_k^{1/2}) A_k^{1/2}\|_1 \\ &\leq \|A_k S^{-1/2} A_k^{1/2}\|_2 \|A_k^{1/2}\|_2 \\ &= (\text{Tr } E_k A_k)^{1/2} (\text{Tr } A_k)^{1/2} \\ &\leq (\text{Tr } A_k + \text{Tr } E_k A_k)/2. \end{aligned}$$

Sum over  $k$  yields  $\text{Tr } S^{1/2} \leq (1 + P_s(E))/2$ , hence  $2(1 - \text{Tr } S^{1/2}) \geq P_e(E) \geq P_e^*$ .  $\square$



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# Proof of C/2 bound

- Lieb's theorem:  $\text{Tr}(B^r C^{1-r})$  is jointly concave in  $B$  and  $C$ , for  $0 < r \leq 1$ ; that is, for  $n$  PSD matrices  $B_j$  and  $C_j$ ,

$$\text{Tr} \sum_j B_j^r C_j^{1-r} \leq \text{Tr} \left( \sum_j B_j \right)^r \left( \sum_j C_j \right)^{1-r}$$

- Put  $r = 2/3$ ,  $B_j = A_j^{1/2}$ ,  $C_j = A_j^2$ :

$$1 = \text{Tr} \sum_j A_j^{1/3} A_j^{2/3} \leq \text{Tr} \left( \sum_j A_j^{1/2} \right)^{2/3} \left( \sum_j A_j^2 \right)^{1/3}$$

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# Proof of C/2 bound

- Applying Hölder's inequality with well-chosen parameters:

$$\text{Tr } XY \leq \|XY\|_1 \leq \|X\|_3 \|Y\|_{3/2},$$

$$\begin{aligned} 1 &\leq \left\| \left( \sum_j A_j^{1/2} \right)^{2/3} \right\|_3 \left\| \left( \sum_j A_j^2 \right)^{1/3} \right\|_{3/2} \\ &= \left( \text{Tr} \left( \sum_j A_j^{1/2} \right)^2 \right)^{1/3} \left( \text{Tr} \left( \sum_j A_j^2 \right)^{1/2} \right)^{2/3}. \end{aligned}$$

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# Proof of C/2 bound

- Taking the 3/2 power and rearranging then yields

$$\begin{aligned}\mathrm{Tr}\left(\sum_j A_j^2\right)^{1/2} &\geq \left(\mathrm{Tr}\left(\sum_j A_j^{1/2}\right)^2\right)^{-1/2} = \left(\sum_{j,k} \mathrm{Tr} A_j^{1/2} A_k^{1/2}\right)^{-1/2} \\ &= \left(1 + 2 \sum_{j < k} \mathrm{Tr} A_j^{1/2} A_k^{1/2}\right)^{-1/2} \geq 1 - \sum_{j < k} \mathrm{Tr} A_j^{1/2} A_k^{1/2},\end{aligned}$$

where in the last line we exploited the inequality  $(1 + x)^{-1/2} \geq 1 - x/2$ .

- In combination with Tyson's bound this yields

$$P_e^* \leq 2\left(1 - \mathrm{Tr}\left(\sum_i A_i^2\right)^{1/2}\right) \leq 2 \sum_{j < k} \mathrm{Tr} A_j^{1/2} A_k^{1/2}$$

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# Proof of C/2 bound

- It can be shown that

$$\text{Tr } \rho_j^{1/2} \rho_k^{1/2} \leq \sqrt{\min_s \text{Tr } \rho_j^s \rho_k^{1-s}} = \exp(-C(\rho_j, \rho_k)/2).$$

- Thus

$$P_e^* \leq 2 \sum_{j < k} \sqrt{p_j p_k} \exp(-C(\rho_j, \rho_k)/2).$$

- The asymptotic error rate is therefore bounded below by the minimal Chernoff distance *times one half*. □

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## 4. Other bounds on the optimal error probability

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# Pairwise discrimination

- We need bounds on the optimal error probability for discriminating between  $r$  operators  $A_k$  in terms of the *pairwise* optimal error probabilities.
- Define

$$P_{s,2}^* = \frac{1}{r-1} \sum_{k,l: k < l} \text{Tr LUB}(A_k, A_l)$$
$$P_{e,2}^* = \frac{1}{r-1} \sum_{k,l: k < l} \text{Tr GLB}(A_k, A_l).$$

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# Pairwise discrimination

- The importance of the quantity  $P_{e,2}^*$  comes from the fact that its asymptotic rate equals the smallest pairwise Chernoff divergence.
- Indeed, the rate of the term  $\text{Tr GLB}(A_k, A_l)$  is given by  $C(\rho_k, \rho_l)$ , hence the rate of the sum  $\sum_{k,l}$  is the smallest of these rates.
- It is very easily shown that

$$P_s^* \leq P_{s,2}^*, \quad \text{so that } P_e^* \geq P_{e,2}^*.$$

- This provides an alternative proof that  $R \leq C := \min_{k < l} C(\rho_k, \rho_l)$ .

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# Nottingham, here is a problem

- Numerical results indicate that there is a constant  $c$  (which may depend on  $r$ ) such that

$$P_e^* \leq c P_{e,2}^*.$$

- Open question: prove this!
- If  $P_e^*$  differs from  $P_{e,2}^*$  only by a constant, independent of the dimension, hence independent of  $n$ , then it must have the same rate.
- **Problem 1.** Show that there is a constant  $c$ , independent of the dimension of the  $A_i$ , but possibly depending on  $r$ , such that

$$1 - \text{Tr LUB}(A_1, \dots, A_r) = \text{Tr GLB}(\bar{A}_1, \dots, \bar{A}_r) \leq c \sum_{k,l: k < l} \text{Tr GLB}(A_k, A_l) \quad ?$$



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## Problem 2

- I was able to show:

$$1 - \text{Tr LUB}(A_1, \dots, A_r) \leq \sum_k \text{Tr GLB}(A_k, \bar{A}_k).$$

- Proof relies on the following proposition:

Let  $\{P_i\}$  be a set of  $r$  projectors and let  $P_0 = \sum_i P_i$ , then the set  $(2P_i - P_0)_+$  forms an incomplete POVM.

- **Problem 2.** Show that there is a constant  $c'$  such that

$$\sum_k \text{Tr GLB}(A_k, \bar{A}_k) \leq c' \sum_{k,l: k < l} \text{Tr GLB}(A_k, A_l) \quad ?$$

- This would imply a positive answer to Problem 1.

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# Thank You!

Homework questions:

Prove

$$1 - \text{Tr LUB}(A_1, \dots, A_r) = \text{Tr GLB}(\bar{A}_1, \dots, \bar{A}_r) \leq c \sum_{k,l: k < l} \text{Tr GLB}(A_k, A_l)$$

$$\sum_k \text{Tr GLB}(A_k, \bar{A}_k) \leq c' \sum_{k,l: k < l} \text{Tr GLB}(A_k, A_l).$$