Merged Talk:

A Hierarchy of Information Quantities for Finite Block Length Analysis of Quantum Tasks

> <u>Marco Tomamichel</u>\*, Masahito Hayashi<sup>†\*</sup> arXiv: 1208.1478

Second Order Asymptotics for Quantum Hypothesis Testing

> Ke Li\* arXiv: 1208.1400

\*CQT, National University of Singapore <sup>†</sup>Graduate School of Mathematics, Nagoya University

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Theory A predicts that System is in state  $\rho$ .

Theory *B* predicts that System is in state  $\sigma$ .

- Devise a *test*, a POVM  $\{Q, 1-Q\}$  with  $0 \le Q \le 1$ .
- If Q clicks, you accept the null hypothesis.

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This is fatal — you will write a crackpot paper!

• We are interested in the minimal  $\beta$  that can be achieved if  $\alpha$  is required to be smaller than a given constant,  $\varepsilon$ , i.e. the SDP

$$\beta_{\rho,\sigma}^{\varepsilon} := \min_{\substack{0 \le Q \le 1 \\ \alpha(Q) \le \varepsilon}} \beta(Q) = \min_{\substack{0 \le Q \le 1 \\ \operatorname{tr}(\rho Q) \ge 1 - \varepsilon}} \operatorname{tr}(\sigma Q).$$

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• The additive normalization  $\log(1-\varepsilon)$  ensures (Dupuis+'12)

$$D_h^{\varepsilon}(
ho\|\sigma) \ge 0$$
 and  $D_h^{\varepsilon}(
ho\|\sigma) = 0 \iff 
ho = \sigma.$ 

• It also satisfies data-processing,  $D_h^{\varepsilon}(\rho \| \sigma) \ge D_h^{\varepsilon}(\mathcal{E}(\rho) \| \mathcal{E}(\sigma))$ .

• We consider *n* independent repetitions of the experiment, i.e. the states  $\rho^{\otimes n}$  and  $\sigma^{\otimes n}$ .

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• This was recently improved (Audenaert, Mosonyi & Verstraete'12)

$$D_h^{\varepsilon}(\rho^{\otimes n} \| \sigma^{\otimes n}) \le nD(\rho \| \sigma) + O(\sqrt{n}) \quad \text{and} \\ D_h^{\varepsilon}(\rho^{\otimes n} \| \sigma^{\otimes n}) \ge nD(\rho \| \sigma) - O(\sqrt{n}).$$

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• Our goal is to investigate the second order term,  $O(\sqrt{n})$ .

For two states  $\rho$ ,  $\sigma$  with  $\operatorname{supp}\{\sigma\} \supseteq \operatorname{supp}\{\rho\}$ , and  $0 < \varepsilon < 1$ , we find  $D_h^{\varepsilon}(\rho^{\otimes n} \| \sigma^{\otimes n}) \le nD(\rho \| \sigma) + \sqrt{nV(\rho \| \sigma)} \Phi^{-1}(\varepsilon) + 2\log n + O(1)$ , and  $D_h^{\varepsilon}(\rho^{\otimes n} \| \sigma^{\otimes n}) \ge nD(\rho \| \sigma) + \sqrt{nV(\rho \| \sigma)} \Phi^{-1}(\varepsilon) - O(1)$ .

• D and V are the mean and variance of  $\log \rho - \log \sigma$  under  $\rho$ , i.e.  $V(\rho \| \sigma) := \operatorname{tr} \left( \rho \left( \log \rho - \log \sigma - D(\rho \| \sigma) \right)^2 \right).$ 

•  $\Phi$  is the cumulative normal distribution function, and  $\Phi^{-1}(\varepsilon)$  is



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• We also have bounds on the constant terms, enabling us to calculate upper and lower bounds on  $D_h^{\varepsilon}(\rho^{\otimes n} || \sigma^{\otimes n})$  for finite *n*.

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- Classically, the result is known to hold with both logarithmic terms equal to  $\frac{1}{2} \log n$  (e.g. Strassen'62,Polyanskiy,Poor&Verdú'10).
- One ingredient of both proof is the *Berry-Essèen theorem*, which quantizes the convergence of the distribution of a sum of i.i.d. random variables to a normal distribution.
- Intuitively, our results can be seen as a quantum, entropic formulation of the *central limit theorem*.

# Smooth Entropies

• We also investigate the smooth min-entropy (Renner'05), where it was known (T,Colbeck&Renner'09) that

$$\begin{split} & H^{\varepsilon}_{\min}(A^n|B^n)_{\rho^{\otimes n}} \leq nH(A|B)_{\rho} + O(\sqrt{n}), \quad \text{and} \\ & H^{\varepsilon}_{\min}(A^n|B^n)_{\rho^{\otimes n}} \geq nH(A|B)_{\rho} - O(\sqrt{n}). \end{split}$$

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where  $H(A|B)_{\rho} = D(\rho_{AB} \| 1_A \otimes \rho_B)$  and  $V(A|B)_{\rho} = V(\rho_{AB} \| 1_A \otimes \rho_B)$ .

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 Both hypothesis testing and smooth entropies have various applications in information theory, some of which we explore next.

- Consider a CQ random source that outputs states  $\rho_{XE} = \sum_{x} p_{x} |x\rangle \langle x| \otimes \rho_{E}^{x}$ .
- Investigate the amount of randomness that can be extracted from X such that it is independent of E and the random seed, S.

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- For any 0  $\leq \varepsilon < 1$  and  $\rho_{\textit{XE}}$  a CQ state, we define

$$\ell^{\varepsilon}(X|E) := \max \big\{ \ell \in \mathbb{N} \, \big| \, \exists \, \mathcal{P}, \sigma_E : |Z| = 2^{\ell} \wedge au_{ZES} pprox^{\varepsilon} \, 2^{-\ell} \mathbb{1}_Z \otimes \sigma_E \otimes au_S \big\}.$$

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• This quantity can be characterized in terms of the smooth min-entropy (Renner'05). We tighten this and show

#### Theorem

Consider an i.i.d. source  $\rho_{X^n E^n} = \rho_{XE}^{\otimes n}$  and  $0 < \varepsilon < 1$ . Then,  $\ell^{\varepsilon}(X^n | E^n) = nH(X|E) + \sqrt{nV(X|E)}\Phi^{-1}(\varepsilon^2) \pm O(\log n).$ 

- Consider a CQ random source that outputs states  $\rho_{XB} = \sum_{x} p_{x} |x\rangle \langle x| \otimes \rho_{B}^{x}$ .
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- For any 0  $\leq \varepsilon < 1$  and  $ho_{XB}$  a CQ state, we define

 $m^{\varepsilon}(X|B)_{\rho} := \min \{ m \in \mathbb{N} \mid \exists \mathcal{P} : |M| = 2^{m} \land P[X \neq X'] \leq \varepsilon \}.$ 

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• This quantity can be characterized using hypothesis testing (H&Nagaoka'04). We tighten this and show

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### Example of Second Order Asymptotics

• Consider transmission of  $|0\rangle$ ,  $|1\rangle$  through a Pauli channel to B (phase and bit flip independent) with environment E. This yields the states

$$\begin{split} \rho_{XB} &= \frac{1}{2} \sum |x\rangle \langle x| \otimes \left( (1-p) |x\rangle \langle x| + p | 1-x\rangle \langle 1-x| \right), \\ \rho_{XE} &= \frac{1}{2} \sum |x\rangle \langle x| \otimes |\phi^x\rangle \langle \phi^x|, \qquad |\phi^x\rangle = \sqrt{p} |0\rangle + (-1)^x \sqrt{1-p} |1\rangle. \end{split}$$

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• Plot of first and second order asymptotic approximation of  $\frac{1}{n}\ell^{\varepsilon}(X|E)$ and  $\frac{1}{n}m^{\varepsilon}(X|B)$  for p = 0.05 and  $\varepsilon = 10^{-6}$ .

#### Example of Finite Block Length Bounds



# Different Layers of Approximation

Class	Role	Quantities
Class 1	Optimal performance of protocol.	$m^{arepsilon}(X B)_{ ho}$
	Calculation is very difficult.	$\ell^{\varepsilon}(X B)_{ ho}$ ,
Class 2	One-shot bound for general source.	$H_h^{\varepsilon}(A B)_{ ho},$
	SDP tractable for small systems.	$H^arepsilon_{\min}(A B)_ ho$
Class 3	Quantum information spectrum.	$D_{s}^{\varepsilon}( ho\ \sigma)$
Class 4	Classical information spectrum.	$D_s^{\varepsilon}(P_{0,\rho,\sigma} \  P_{1,\rho,\sigma})$
	Approximately possible for i.i.d.	
Class 5	Second order asymptotics.	nH(X B)+
	Calculation is easy for large <i>n</i> .	$\sqrt{n} s(X B) \Phi^{-1}(\varepsilon)$

Classes	Difference	Method
$1 \rightarrow 2$	$O(\log n)$	Random coding and monotonicity.
$2 \rightarrow 4$	$O(\log n)$	Relations between entropies.
$4 \rightarrow 5$	<i>O</i> (1)	Berry-Essèen Theorem.

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# Conclusion / Differences & Overlap

- The methods employed in the two papers are conceptually different.
- The approach employed by Li is more direct, leads to tighter bounds for finite *n* and better coefficients for the logarithmic term.
- The approach of T&H is more general.

Result	Т&Н	Li
2nd order asymptotics for hypothesis testing	$\checkmark$	$\checkmark$
Finite <i>n</i> bounds for hypothesis testing	$\checkmark$	$\checkmark$
2nd order asymptotics of smooth min-entropy	$\checkmark$	
Application to data compression and randomness		
extraction with quantum side information	$\checkmark$	
Hierarchy of information quantities, linking		
operational quantities, one-shot entropies and		
asymptotic analysis of quantum tasks	$\checkmark$	

 There is a difference of 2 log n between the current upper and lower bounds on D<sup>ε</sup><sub>h</sub>(ρ<sup>⊗n</sup> || σ<sup>⊗n</sup>). Is this fundamental, i.e. do there exist ρ and σ for which these bounds are tight? Or can this be further improved? (Classically, the upper and lower bounds only differ in the constant.)

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# Thank you for your attention.