

# Second Order Refinements for the Classical Capacity of Quantum Channels

(arXiv:1308.6503)

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ISIT  
June 30, 2014

# Information Processing with Finite Resources

- Information theory usually treats the asymptotic limit where resources are unrestricted (e.g. the number of sequential channel uses is arbitrarily large).
- This is often a good approximation as classical computers can deal with large amounts of data easily.
- However, it fails for time-sharing in wireless networks.
- Quantum computers can only cope with a comparably small amount of data coherently for the foreseeable future.

## Today's Question

How much information can we transmit reliably over a noisy quantum channel when sender and receiver have access to a small-scale quantum computer?

## Coding over Quantum Channels

- Let  $\mathcal{W} : \mathcal{X} \rightarrow \mathcal{S}$  be a map to quantum states on a finite-dimensional Hilbert space, denoted  $\mathcal{S}$ .
- Here,  $\mathcal{X}$  could be a discrete set (classical-quantum channel) or a continuous set of quantum states.
- The  $n$ -fold repetition of this channel,  $\mathcal{W}^n : \mathcal{X}^n \rightarrow \mathcal{S}^n$ , acts as

$$\mathcal{W}^n(\vec{x}) = \mathcal{W}(x_1) \otimes \mathcal{W}(x_2) \otimes \dots \otimes \mathcal{W}(x_n)$$

for some  $n$ -tuple  $\vec{x} = (x_1, x_2, \dots, x_n)$ .

- Thus,  $\mathcal{W}^n$  only accepts product states. (But our results also apply for separable input states.)
- We are interested in how much classical information we can transmit over this channel.

## Coding over Quantum Channels

- A code  $\mathcal{C} = (\mathcal{M}, e, d)$  for  $\mathcal{W}$  consists of a set of messages,  $\mathcal{M}$ , an encoder  $e : \mathcal{M} \rightarrow \mathcal{X}$ , and a decoding POVM  $d = \{D_m\}$ .
- The *average* probability of error is defined as

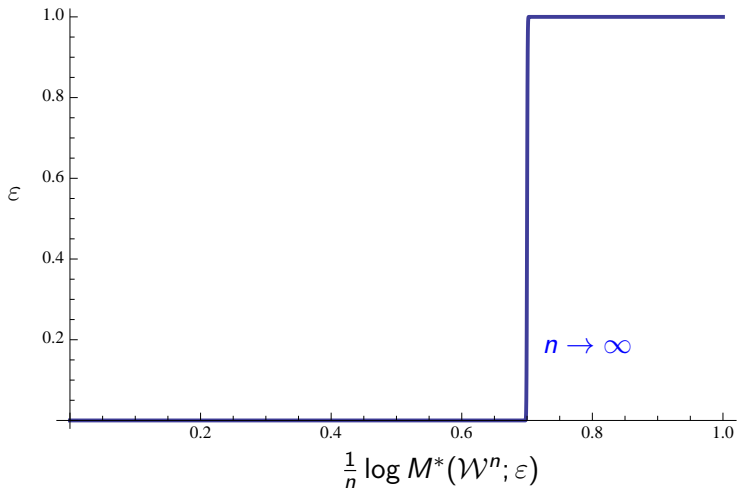
$$p_{\text{err}}(\mathcal{C}, \mathcal{W}) := 1 - \frac{1}{|\mathcal{M}|} \sum_{m \in \mathcal{M}} \text{tr}(\mathcal{W}(e(m))D_m).$$

- We are interested in the maximum size of a code with error at most  $\varepsilon$ , i.e.

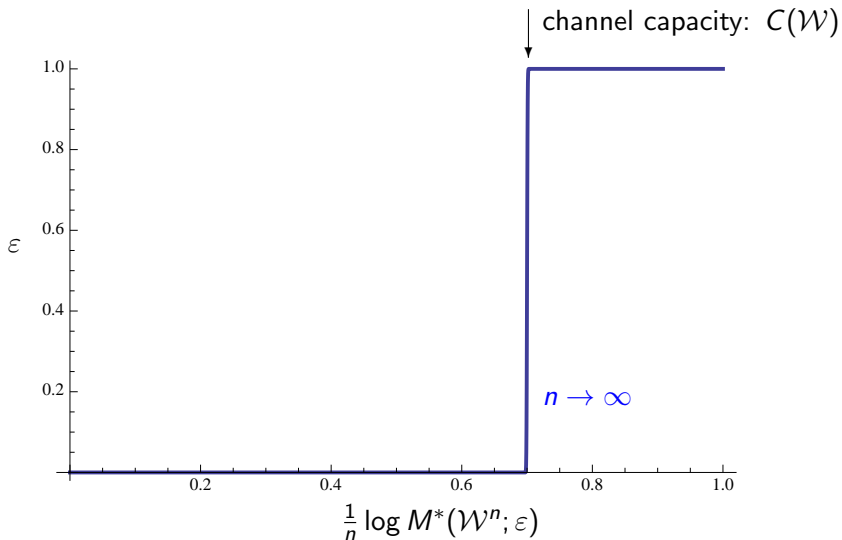
$$M^*(\mathcal{W}; \varepsilon) := \max \{k \in \mathbb{N} \mid \exists \mathcal{C} : |\mathcal{M}| = k \wedge p_{\text{err}}(\mathcal{C}, \mathcal{W}) \leq \varepsilon\}.$$

- We want to investigate  $M^*(\mathcal{W}^n; \varepsilon)$  as a function of  $n$  and  $\varepsilon$ .

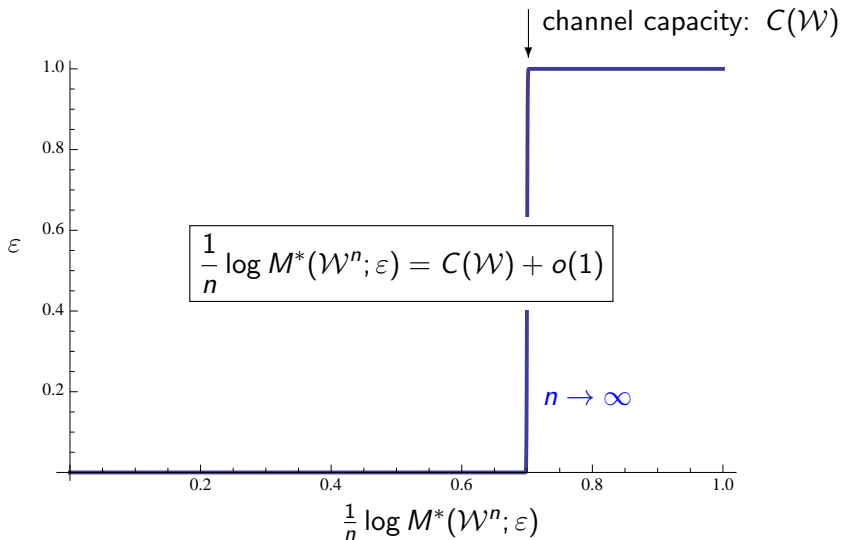
# Strong Converse



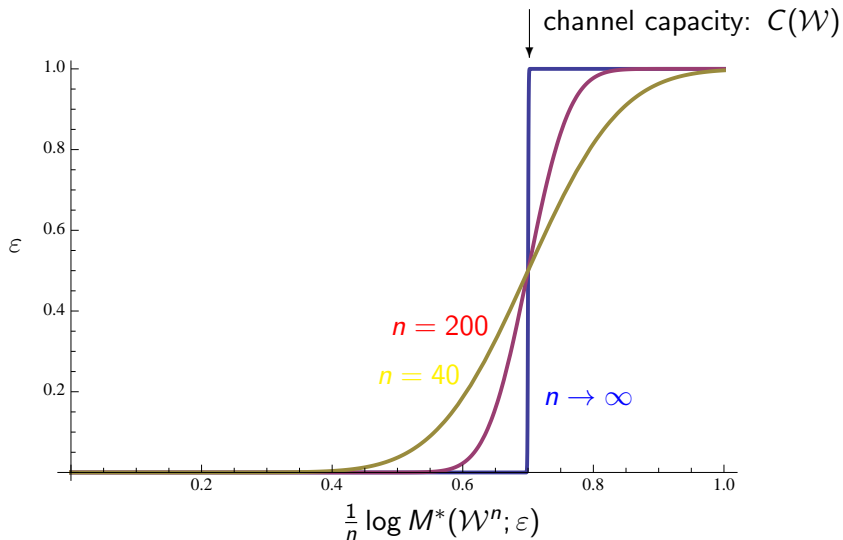
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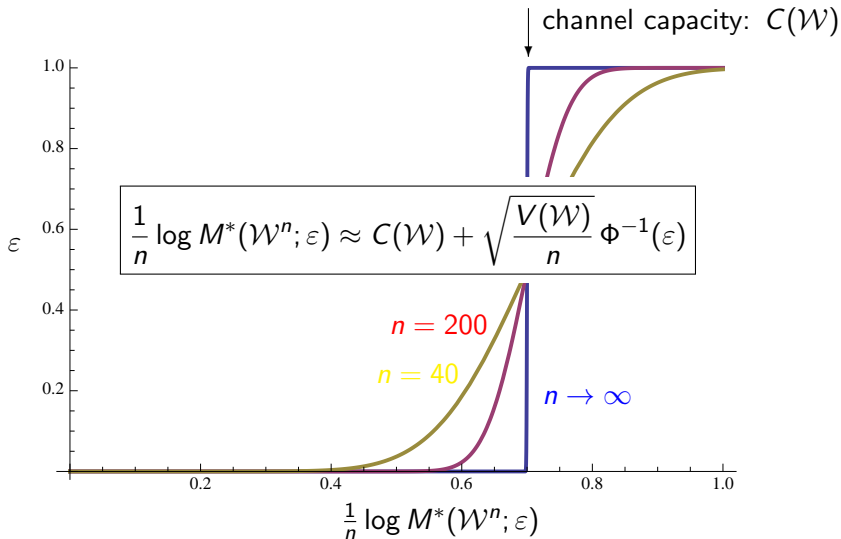


## Finite Resource Regime





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## Finite Resource Regime

- The main result of this work is to make this precise.

### Theorem

*For all channels  $\mathcal{W}$  and  $\varepsilon \in (0, 1)$ , we have*

$$\log M^*(\mathcal{W}^n; \varepsilon) = nC(\mathcal{W}) + \sqrt{nV_\varepsilon(\mathcal{W})} \Phi^{-1}(\varepsilon) + o(\sqrt{n}).$$

*(Furthermore, if  $\mathcal{X}$  is discrete and some regularity conditions apply, the remainder term is in fact  $O(\log n)$ .)*

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- The channel dispersion,  $V_\varepsilon(\mathcal{W})$  might have different values for  $\varepsilon < \frac{1}{2}$  and  $\varepsilon > \frac{1}{2}$ , but is otherwise independent of  $\varepsilon$ .

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- The parameters have a geometrical interpretation.

## History and Previous Work

- Classical Channels:
  - Strassen'62 first introduced the Gaussian approximation for (classical) discrete memoryless channels.
  - These results were recently rediscovered and strengthened by Hayashi [IEEE TIT **55**, 2009] and Polyanskiy, Poor & Verdú [IEEE TIT **56**, 2010].
- Quantum Channels:
  - We build on one-shot bounds for  $M^*(\mathcal{W}; \varepsilon)$  that are due to Hayashi & Nagaoka [IEEE TIT **49**, 2003]. (See also Wang & Renner [PRL **108**, 2012].)
  - A Gaussian approximation for quantum hypothesis testing due to T & Hayashi [IEEE TIT **59**, 2013] and Li [Ann. Stat. **42**, 2014].
  - Classical proof strategies, for example in Hayashi'09, Polyanskiy *et al.*'10 as well as T & Tan [IEEE TIT **59**, 2013].

## Proof Challenges

- The direct part follows from the Hayashi & Nagaoka (one-shot) bound together with the Gaussian approximation for quantum hypothesis testing. The only new ingredient here is a refined application of Carathéodory's Theorem.

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- For the converse, we analyze the one-shot bound

$$\log M^*(\mathcal{W}^n, \varepsilon) \lesssim \inf_{\sigma_n \in \mathcal{S}^{\otimes n}} \sup_{\rho_n \in \text{im}(\mathcal{W}^n)} D_h^\varepsilon(\rho_n \| \sigma_n).$$

by choosing an appropriate  $\sigma_n$  that works well for all  $\rho_n$ .

- In the classical (second order) converse proofs one usually relies on the Method of Types. This is not possible here since we allow continuous sets of channel input states.
- Instead, we span an  $\varepsilon$ -covering on the (finite-dimensional) output space to deal with codes that are far from capacity.



## Some Information Quantities

- The relative entropy is given by

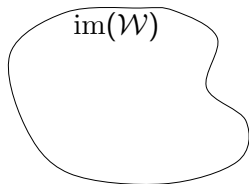
$$D(\rho\|\sigma) := \text{tr} \left( \rho (\log \rho - \log \sigma) \right).$$

- The relative entropy variance is given by

$$V(\rho\|\sigma) := \text{tr} \left( \rho (\log \rho - \log \sigma)^2 \right) - D(\rho\|\sigma)^2.$$

## Divergence Radius and Center

- Channel image:  $\text{im}(\mathcal{W}) := \{\rho \in \mathcal{S} \mid \exists x \in \mathcal{X} : \mathcal{W}(x) = \rho\}$ .



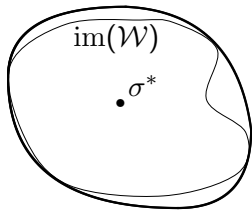
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- Divergence radius (of channel image):

$$\chi(\mathcal{W}) := \min_{\sigma \in \mathcal{S}} \max_{\rho \in \text{im}(\mathcal{W})} D(\rho \parallel \sigma)$$

- Divergence center (it is unique!):

$$\sigma^*(\mathcal{W}) := \arg \min_{\sigma \in \mathcal{S}} \max_{\rho \in \text{im}(\mathcal{W})} D(\rho \parallel \sigma)$$



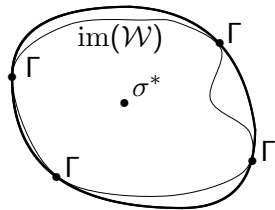
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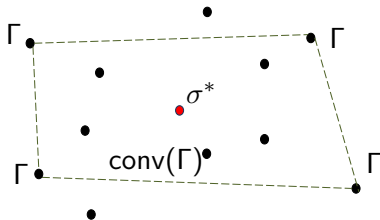
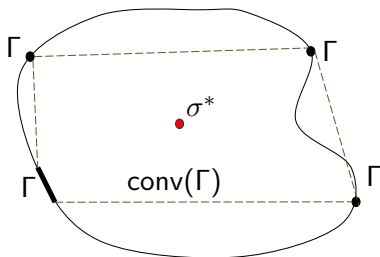
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- Peripheral Points:  $\Gamma(\mathcal{W}) := \arg \max_{\rho \in \text{im}(\mathcal{W})} D(\rho \parallel \sigma^*)$ .

## Peripheral Decompositions of the Divergence Center

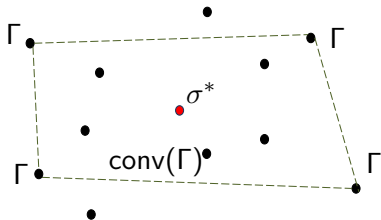
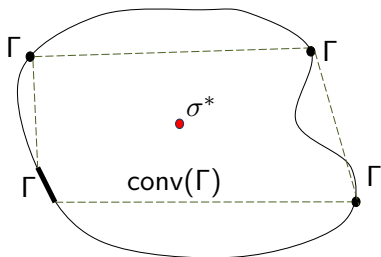
- The center  $\sigma^*(\mathcal{W})$  lies in the convex hull of  $\Gamma(\mathcal{W})$ . (This is intuitive, but not trivial, since  $D(\cdot\|\cdot)$  is not a metric.)



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- The center  $\sigma^*(\mathcal{W})$  lies in the convex hull of  $\Gamma(\mathcal{W})$ . (This is intuitive, but not trivial, since  $D(\cdot\|\cdot)$  is not a metric.)
- We consider the set  $\Pi$  of valid decompositions of  $\sigma^*$  using points in  $\Gamma$ .
- $P \in \Pi$  implies

$$\sum_{\rho \in \Gamma} P(\rho)\rho = \sigma^*.$$



## From Divergence Center to Holevo's Formula

- Let  $P$  be any distribution over the set of output states  $\mathcal{S}$ .
- Using a minimax theorem, we find Holevo's expression:

$$\begin{aligned}\chi(\mathcal{W}) &= \max_P \left\{ \sum_{\rho} P(\rho) D\left(\rho \parallel \sum_{\rho} P(\rho)\rho\right) \right\} \\ &= \max_P \left\{ H\left(\sum_{\rho} P(\rho)\rho\right) - \sum_{\rho} P(\rho)H(\rho) \right\}\end{aligned}$$

Thus, in particular

$$\chi(\mathcal{W}) = \sum_{\rho \in \Gamma} P(\rho) D(\rho \parallel \sigma^*(\mathcal{W})), \quad \forall P \in \Pi.$$

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- The argument of the maximization is a mutual information.
- The decompositions  $P \in \Pi$  correspond to signaling ensembles that achieve capacity.



# Channel Capacity

- The HSW theorem due to Holevo [IEEE TIT **44**, 1998], and Schumacher & Westmoreland [Phys. Rev. A **56**, 1997] implies

$$\lim_{\varepsilon \searrow 0} \lim_{n \rightarrow \infty} \frac{1}{n} \log M^*(\mathcal{W}^n; \varepsilon) = \chi(\mathcal{W}).$$

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- The strong converse due to Winter [IEEE TIT **45**, 1999] and Ogawa & Nagaoka [IEEE TIT **45**, 1999] yields

$$\lim_{n \rightarrow \infty} \frac{1}{n} \log M^*(\mathcal{W}^n; \varepsilon) = \chi(\mathcal{W}), \quad \forall \varepsilon \in (0, 1).$$

- Thus,  $C(\mathcal{W}) = \chi(\mathcal{W})$ .

## Peripheral Information Variance

- To investigate the finite block length behavior, we define

$$v_{\min}(\mathcal{W}) := \min_{P \in \Pi} \left\{ \sum_{\rho \in \text{im}(\mathcal{W})} P(\rho) V(\rho \| \sigma^*(\mathcal{W})) \right\}, \quad \text{and}$$

$$v_{\max}(\mathcal{W}) := \max_{P \in \Pi} \left\{ \sum_{\rho \in \text{im}(\mathcal{W})} P(\rho) V(\rho \| \sigma^*(\mathcal{W})) \right\}.$$

- We find that

$$V_{\varepsilon}(\mathcal{W}) = \begin{cases} v_{\min}(\mathcal{W}) & \text{if } \varepsilon < \frac{1}{2} \\ v_{\max}(\mathcal{W}) & \text{else} \end{cases}.$$

- At  $\varepsilon = \frac{1}{2}$  the sign of  $\Phi^{-1}(\varepsilon)$  changes, thus the preferred signaling ensemble changes with it.

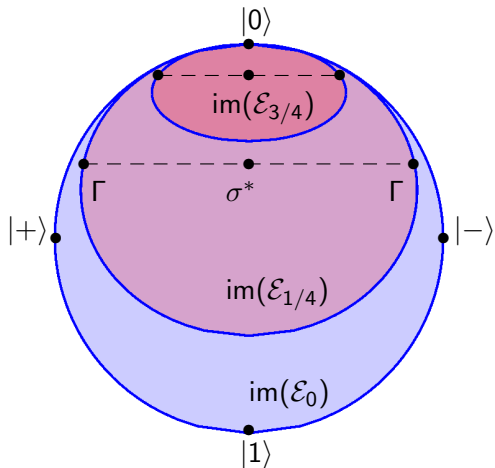
## Example: Amplitude Damping Channel

- The amplitude damping channel for  $\gamma \in [0, 1]$  is given by

$$\mathcal{E}_\gamma : \rho \mapsto \begin{pmatrix} 1 & 0 \\ 0 & \sqrt{1-\gamma} \end{pmatrix} \rho \begin{pmatrix} 1 & 0 \\ 0 & \sqrt{1-\gamma} \end{pmatrix} + \begin{pmatrix} 0 & \sqrt{\gamma} \\ 0 & 0 \end{pmatrix} \rho \begin{pmatrix} 0 & 0 \\ \sqrt{\gamma} & 0 \end{pmatrix}.$$

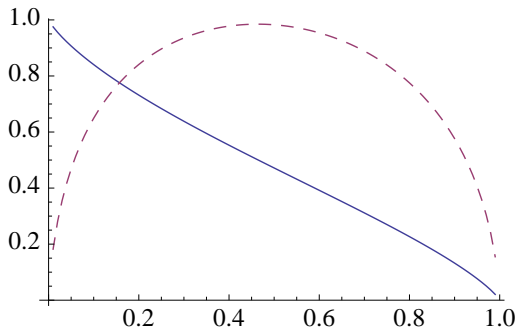
- It models the relaxation to a ground state—here  $|0\rangle$ —in an open quantum system.

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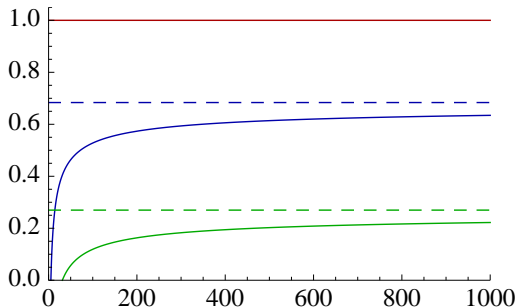
Projection of channel image onto the xz-plane of the Bloch sphere.

## Example: Amplitude Damping Channel



Divergence radius,  $\chi(\mathcal{E}_\gamma)$  (in bits, solid line), and peripheral information variance,  $v_{\min}(\mathcal{E}_\gamma) = v_{\max}(\mathcal{E}_\gamma)$  (in bits<sup>2</sup>, dashed line), as a function of  $\gamma$ .

## Example: Amplitude Damping Channel



Gaussian approximation for  $\frac{1}{n} \log M^*(\mathcal{E}_\gamma^n, \varepsilon)$  for  $\varepsilon = 1\%$ ,  $\gamma \in \{0, \frac{1}{4}, \frac{3}{4}\}$  (top to bottom) as a function of  $n$ . The dashed lines correspond to the asymptotic limit.

## Summary

For all channels  $\mathcal{W}$  and  $\varepsilon \in (0, 1)$ , we have

$$\log M^*(\mathcal{W}^n; \varepsilon) = nC(\mathcal{W}) + \sqrt{nV_\varepsilon(\mathcal{W})} \Phi^{-1}(\varepsilon) + o(\sqrt{n}),$$

where  $C(\mathcal{W})$  and  $V_\varepsilon(\mathcal{W})$  are given by simple single-letter formulas and have a geometrical interpretation.

