



Bounds on Information Combining With Quantum Side Information

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Basic question

Given random variables X_1 and X_2 :

▶ What do we know about $X_1 + X_2$ and in particular $H(X_1 + X_2)$?



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Best known instance: Entropy power inequalities

$$e^{2H(X_1+X_2)} \ge e^{2H(X_1)} + e^{2H(X_2)}$$

Adding quantum side information is very difficult!



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Adding quantum side information is very difficult!

Here simplest setting: binary random variables.

Outline



- 1 Classical Information Combining
- 2 Quantum Information Combining
- 3 Conjectured Bounds
- 4 Application to polar codes
- 5 Wrap-up

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Without conditioning



$$X_{1} \sim \begin{bmatrix} p \\ 1-p \end{bmatrix}, \quad X_{2} \sim \begin{bmatrix} q \\ 1-q \end{bmatrix}$$

$$\downarrow \downarrow$$

$$X_{1} + X_{2} \sim \begin{bmatrix} pq + (1-p)(1-q) \\ p(1-q) + q(1-p) \end{bmatrix} \equiv \begin{bmatrix} p \star q \\ 1-p \star q \end{bmatrix}$$

Therefore

$$H(X_1 + X_2) = h(h^{-1}(H(X_1)) * h^{-1}(H(X_2))$$

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With conditioning



Classical bounds on information combining.

Write
$$H(X_i|Y_i) = H_i$$
,

$$h(h^{-1}(H_1) \star h^{-1}(H_2)) \leq H(X_1 + X_2 | Y_1 Y_2) \leq \log 2 - \frac{(\log 2 - H_1)(\log 2 - H_2)}{\log 2}$$

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With
$$H_1 = H_2 = H$$
,

$$0.799 \frac{H(\log 2 - H)}{\log 2} \le h(h^{-1}(H) \star h^{-1}(H)) - H$$
$$\le H(X_1 + X_2 | Y_1 Y_2) - H$$
$$\le \frac{H(\log 2 - H)}{\log 2}$$

Main ingredient



$$g_c(H_1, H_2) := h(h^{-1}(H_1) * h^{-1}(H_2))$$

$$H(X_{1} + X_{2}|Y_{1}Y_{2})$$

$$= \sum_{y_{1},y_{2}} p_{Y_{1}=y_{1}} p_{Y_{2}=y_{2}} H(X_{1} + X_{2}|Y_{1} = y_{1}Y_{2} = y_{2})$$

$$= \sum_{y_{1},y_{2}} p_{Y_{1}=y_{1}} p_{Y_{2}=y_{2}} h(h^{-1}(H(X_{1}|Y_{1} = y_{1})) * h^{-1}(H(X_{2}|Y_{2} = y_{2})))$$

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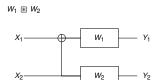


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Channel picture





Notation:

$$H(X_i|Y_i) = H(W_i)$$

 $H(X_1 + X_2|Y_1Y_2) = H(W_1 \otimes W_2)$

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Channel Duality



For every channel W we can define a dual channel W^{\perp} .

Additional uncertainty relation

$$H(W) = \log 2 - H(W^{\perp})$$

and symmetry relation

$$H(W_1 \otimes W_2) - (H(W_1) + H(W_2))/2$$

= $H(W_1^{\perp} \otimes W_2^{\perp}) - (H(W_1^{\perp}) + H(W_2^{\perp}))/2$.

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Based on results in Renes, IEEE Trans. 64, 577 (2018), arXiv:1701.05583

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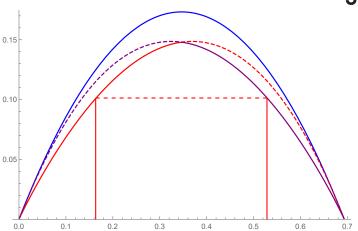
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Channel Duality





CQMI



Conditional Quantum Mutual Information

$$H(X_1 + X_2|B_1B_2) - H_1 = I(X_1 + X_2 : X_2|B_1B_2)$$

Lower bounds on CQMI

$$I(A:C|B)_{\tau} \geq -2\log F(\tau_{ACB}, \mathcal{R}'_{B\to AB}(\tau_{CB}))$$

CQMI



Conditional Quantum Mutual Information

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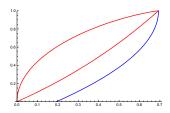
Concavity of von Neumann Entropy



Let $\rho_i \in \mathcal{B}(\mathbb{C}^d)$ and $\{p_i\}_{i=1}^n$ be a probability distribution.

$$H\left(\sum_{i=1}^{n} p_{i} \rho_{i}\right) - \sum_{i=1}^{n} p_{i} H(\rho_{i})$$

 $\geq H(\{p_{i}\}) - \log\left(1 + 2\sum_{1 \leq i < j \leq n} \sqrt{p_{i} p_{j}} F(\rho_{i}, \rho_{j})\right).$



giQ

Here for the simple $H_1 = H_2 = H$ case:

$$H(X_{1} + X_{2}|B_{1}B_{2}) - H$$

$$= I(A : C|B)_{T} QCMI$$

$$\geq -2 \log F(\tau_{ACB}, \mathcal{R}'_{B \to AB}(\tau_{CB})) Fawzi - Renner$$

$$\geq -2 \log \cos \left[\frac{1}{2} \arccos[f^{2}] - \frac{1}{2} \arccos f\right] \Delta - ineq.$$

$$\geq -2 \log \cos \left[\frac{1}{2} \arccos[(1 - 2h_{2}^{-1}(\log 2 - H))^{2}] Concavity$$

$$-\frac{1}{2} \arccos[1 - 2h_{2}^{-1}(\log 2 - H)]$$

$$\Rightarrow \begin{cases} 0.083 \cdot \frac{H}{1 - \log H}, H \leq \frac{1}{2} \log 2 \\ 0.083 \cdot \frac{1}{1 \log^{2}(\log^{2} H)}, H > \frac{1}{2} \log 2. \end{cases} Duality/Simplify$$

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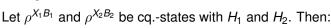
$$\begin{split} H(X_{1} + X_{2} | B_{1}B_{2}) - H &= I(A : C | B)_{\tau} & QCMI \\ \geq -2 \log F(\tau_{ACB}, \mathcal{R}'_{B \to AB}(\tau_{CB})) & Fawzi - Renner \\ \geq -2 \log \cos \left[\frac{1}{2} \arccos[f^{2}] - \frac{1}{2} \arccos f \right] & \Delta - ineq. \\ \geq -2 \log \cos \left[\frac{1}{2} \arccos[(1 - 2h_{2}^{-1}(\log 2 - H))^{2}] & Concavity \\ & - \frac{1}{2} \arccos[1 - 2h_{2}^{-1}(\log 2 - H)] \right] \\ \Rightarrow & \begin{cases} 0.083 \cdot \frac{H}{1 - \log H}, & H \leq \frac{1}{2} \log 2 \\ 0.083 \cdot \frac{\log 2 - H}{1 \log |\log 2|H|}, & H > \frac{1}{2} \log 2. \end{cases} & Duality/Simplify \end{split}$$

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Conjectured Bounds



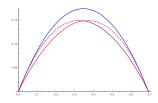


$$H(X_1 + X_2 | B_1 B_2) - (H_1 + H_2)$$

$$\geq \begin{cases} h(h^{-1}(H_1) * h^{-1}(H_2)) - (H_1 + H_2) & H_1 + H_2 \leq \log 2 \\ h(h^{-1}(\log 2 - H_1) * h^{-1}(\log 2 - H_2)) - \log 2 & H_1 + H_2 \geq \log 2 \end{cases}$$

and

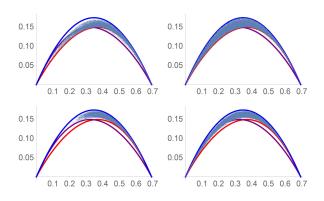
$$H(X_1 + X_2 | B_1 B_2) \le \log 2 - \frac{(\log 2 - H_1)(\log 2 - H_2)}{\log 2}.$$



Evidence



- States with Equality.
- Numerics:



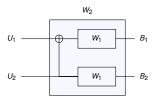
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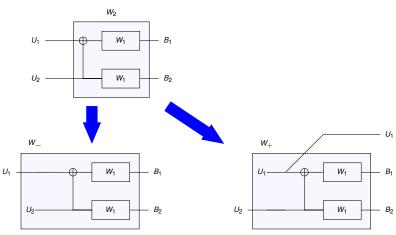
What are polar codes?



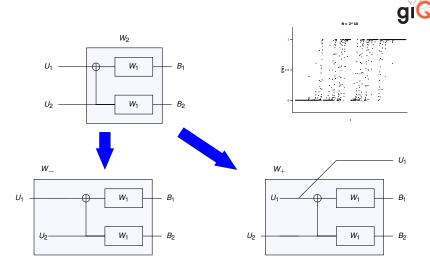


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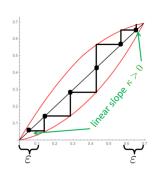


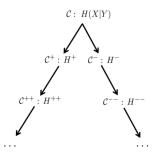
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Speed of Polarization



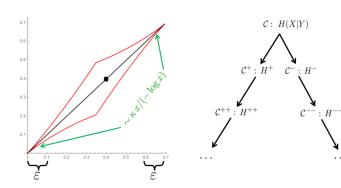




steps to reach $[0, \epsilon] \cup [\log 2 - \epsilon, \log 2]$: $n \approx \frac{1}{\kappa} \log \frac{1}{\epsilon}$ \Rightarrow Rate $R = I(W) - \epsilon$ with polynomial blocklength $\approx poly(1/\epsilon)$.

Speed of Polarization





steps to reach $[0, \epsilon] \cup [\log 2 - \epsilon, \log 2]$: $n \approx \frac{1}{\kappa} (\log \frac{1}{\epsilon})^2$ \Rightarrow Rate $R = I(W) - \epsilon$ with subexponential blocklength $\approx (1/\epsilon)^{\log(1/\epsilon)}$.

Non-stationary channels



Also:

Bounds for $H_1 \neq H_2$ give

- a conceptually simple proof of polarization (without martingales),
- that also works for non-stationary channels.

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Wrap-up



- **■** Lower bound on $H(X_1 + X_2|B_1B_2)$.
- Conjectures for optimal lower and upper bounds.
- Applications to Polar codes.

To do

- Prove conjectures!
 - Especially linear behavior!
- Extensions to other input alphabets
- Much more!

Wrap-up



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Recovery bounds



