

# Device-independent lower bounds on the conditional von Neumann entropy

Peter Brown, Hamza Fawzi and Omar Fawzi

arXiv:2106.13692

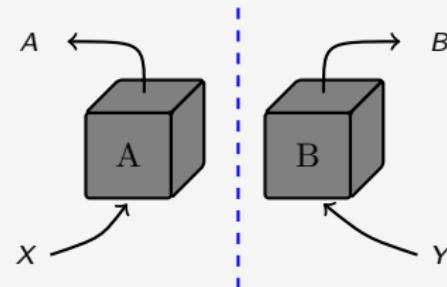
April 05 2022

Code available: [github.com/peterjbrown519/DI-rates](https://github.com/peterjbrown519/DI-rates)



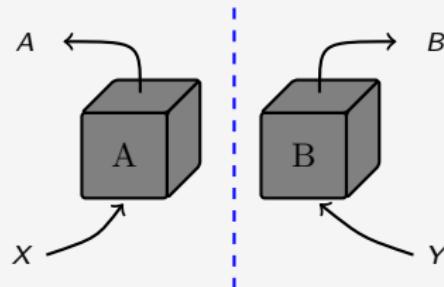
# Motivation – Device-independence

## Bell-nonlocality



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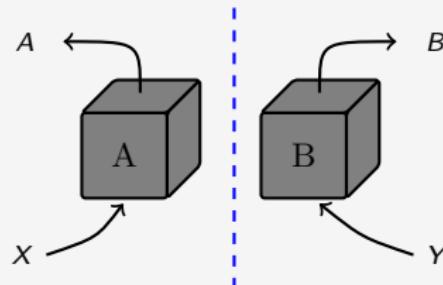
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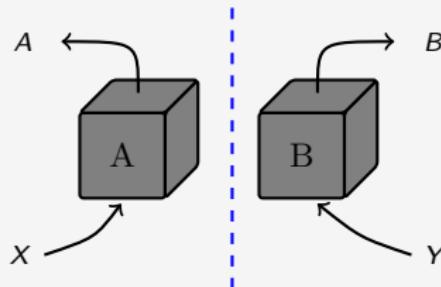
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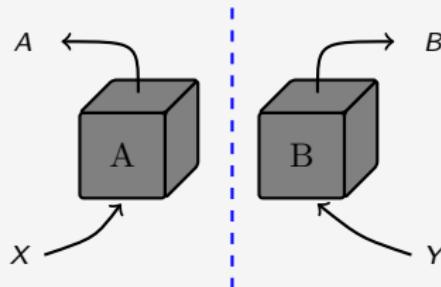
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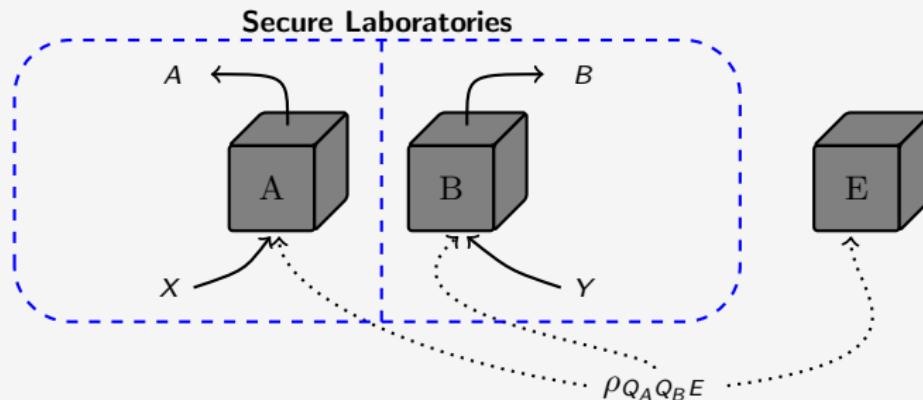
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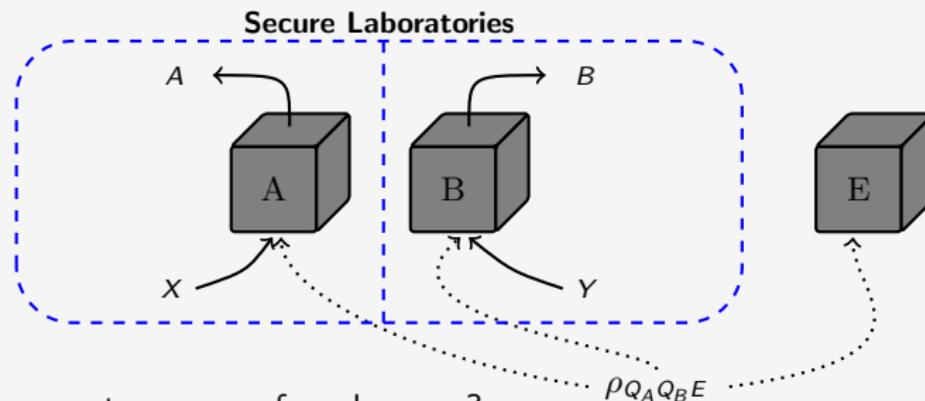
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Main focus of this work

## Randomness generated per round

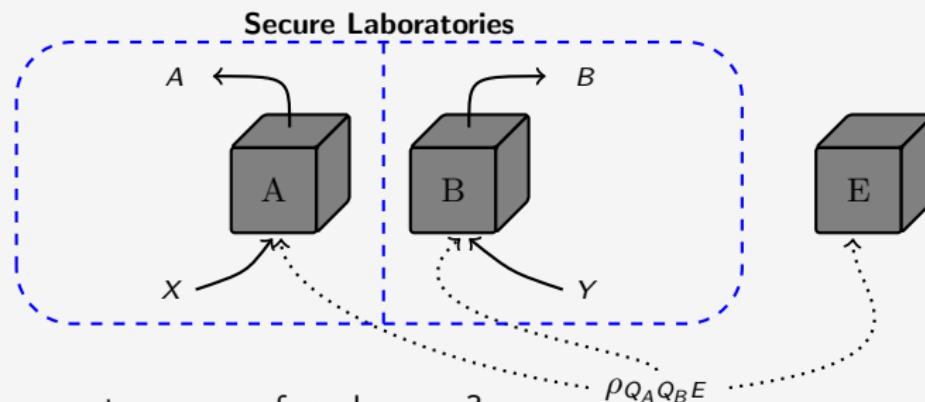


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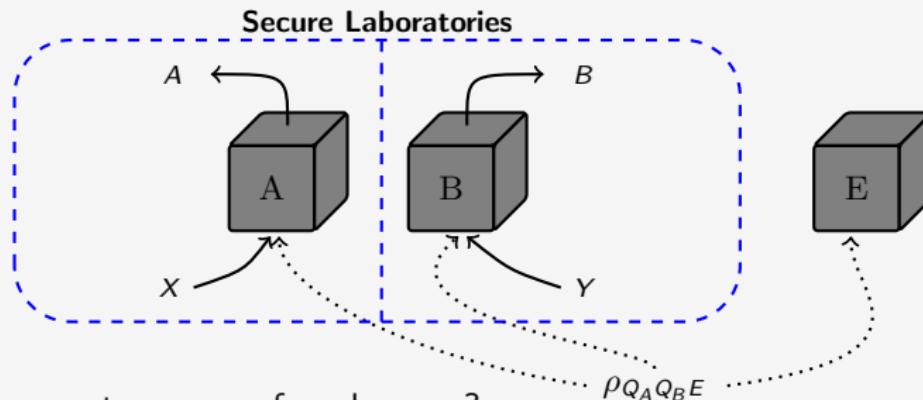
- Randomness expansion

$$H(AB|X = x^*, Y = y^*, E)$$

- QKD

$$H(A|X = x^*, E) - H(A|X = x^*, Y = y^*, B)$$

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Want device-independent lower bounds

## Device-independent lower bounds

Fix some linear constraint(s)  $C$  on  $p_{AB|XY}$ . E.g.

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- Our new approach
  - Define a sequence

$$H_m(\rho) = \inf_{Z_1, \dots, Z_m \in B(H)} \text{Tr} [\rho \, q(Z_1, \dots, Z_m)] \quad (1)$$

such that  $H_m \leq H$  and  $H_m \rightarrow H$  as  $m \rightarrow \infty$ .

- **close to optimal / more efficient / wider scope**

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### Goal:

Search for variational bounds on entropies with an NPO form.

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Rule of thumb:

$H_{\min}$  applicable  $\implies$  Our bounds applicable  
(not iff)

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### The goal

Derive something of the form

$$D(\rho\|\sigma) \leq c_m + \sup_Z \text{Tr} [\rho p_m(Z)] + \text{Tr} [\sigma q_m(Z)]$$

with  $p_m$  and  $q_m$  some polynomials and with the RHS converging as  $m \rightarrow \infty$ .

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$$\ln(x) = \int_0^1 \frac{x-1}{t(x-1)+1} dt \geq \sum_{i=1}^m w_i f_{t_i}(x)$$

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## Main Result

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and RHS converges as  $m \rightarrow \infty$ .

## Application: Device-independence

- 1 Approximate von Neumann entropy with  $m$ -th level variational form

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- NPA hierarchy converges as  $\|Z\|$  can be bounded.

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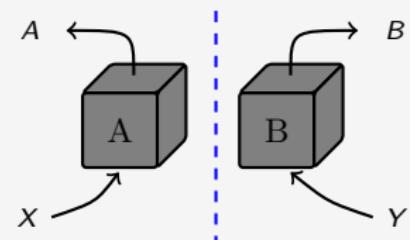
Drop  $\otimes$  and impose  $[M, Z] = 0$ .

### Remarks

- Can now be easily relaxed to an NPO and solved using NPA [PNA10].
- NPA hierarchy converges as  $\|Z\|$  can be bounded.
- Similar results for  $H(AB|X = x, Y = y, Q_E)$  or  $H(A|XQ_E)$  and others.

## Results

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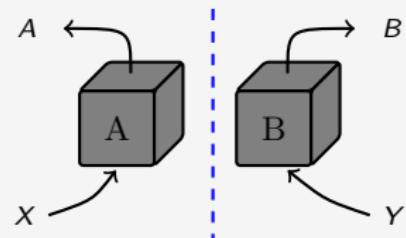
- Looked at different constraint sets  $C$ :

- CHSH score

$$\frac{1}{4} \sum_{xy=a \oplus b} p(ab|xy) \geq \omega$$

- Full distribution

$$p(ab|xy) = c_{abxy} \quad \forall(a, b, x, y)$$



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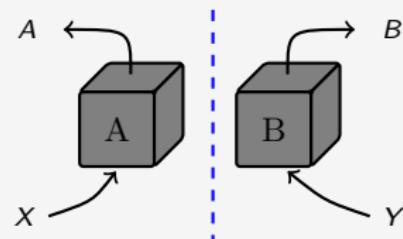
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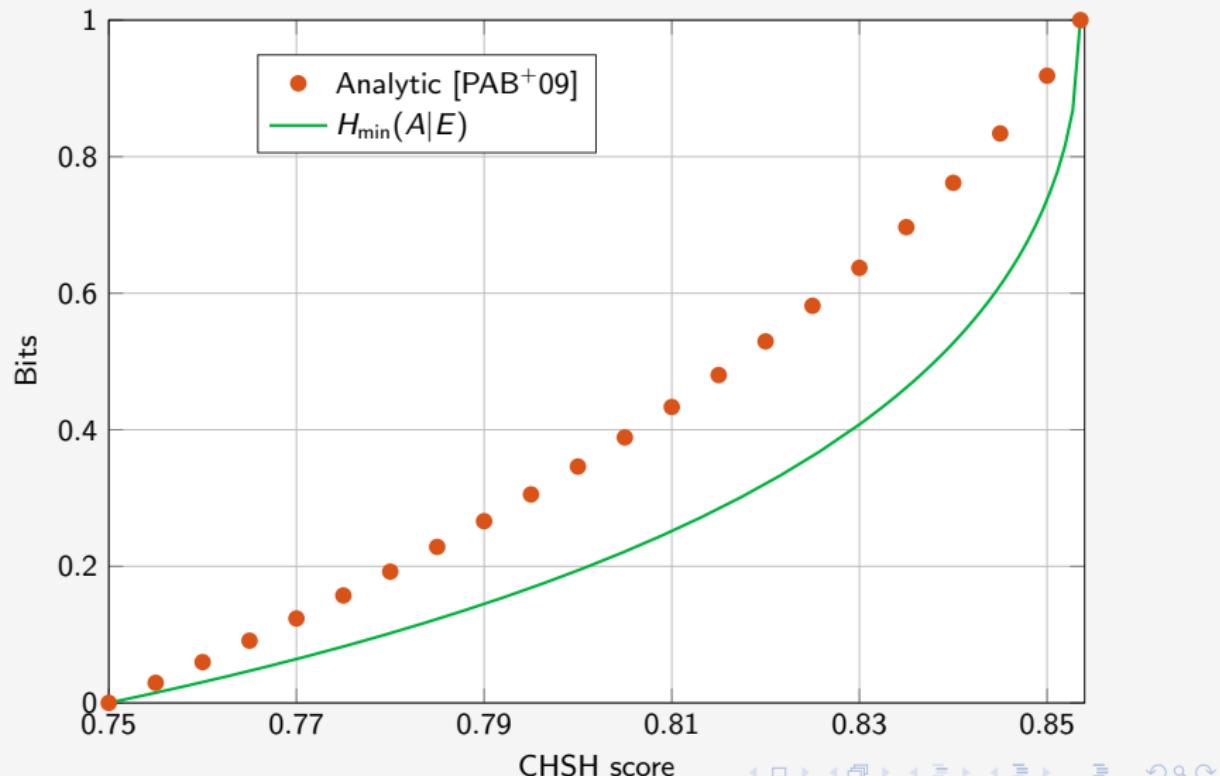
- Investigated *detection efficiency* noise model.

- Independent probability  $\eta \in [0, 1]$  that each device succeeds.
- Device failures recorded as a particular outcome.



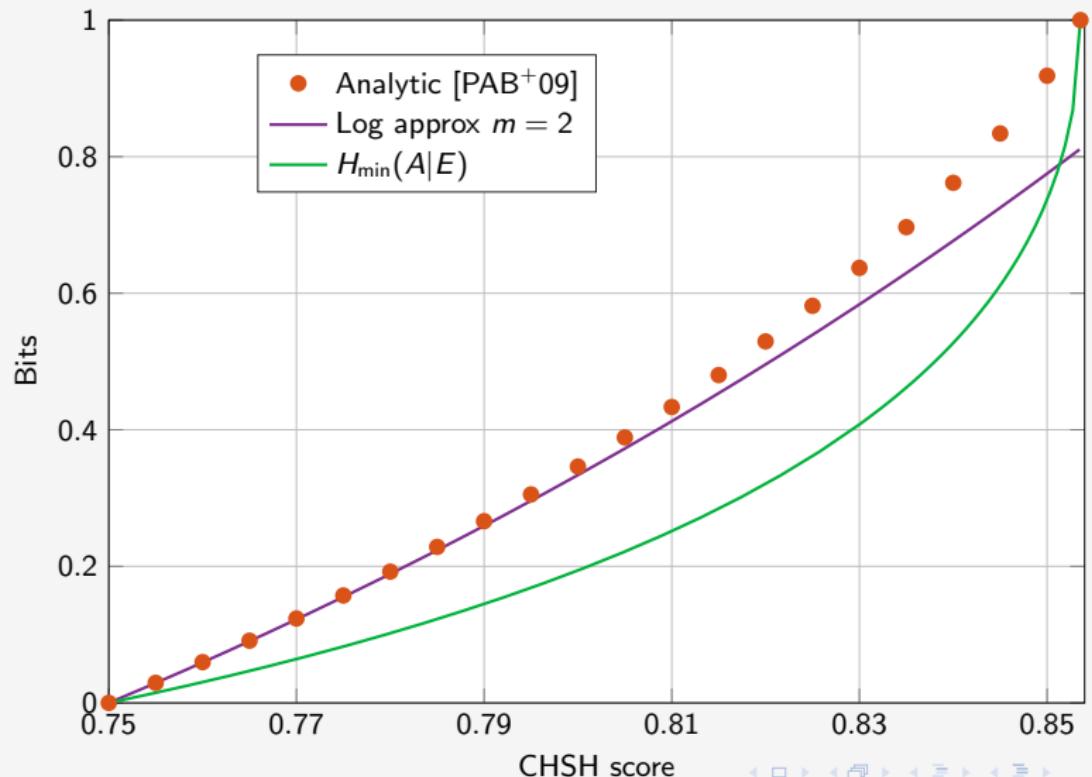
# Results I – Recovering tight bounds for the CHSH game

Bounding  $\inf H(A|X = 0, Q_E)$



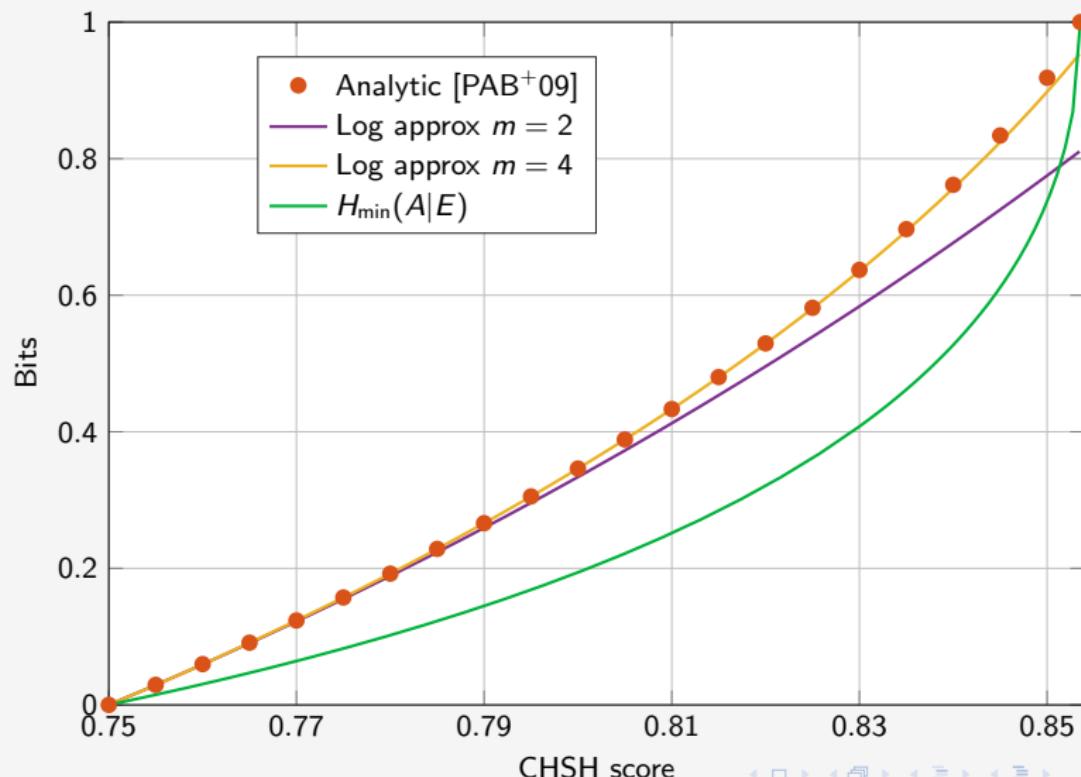
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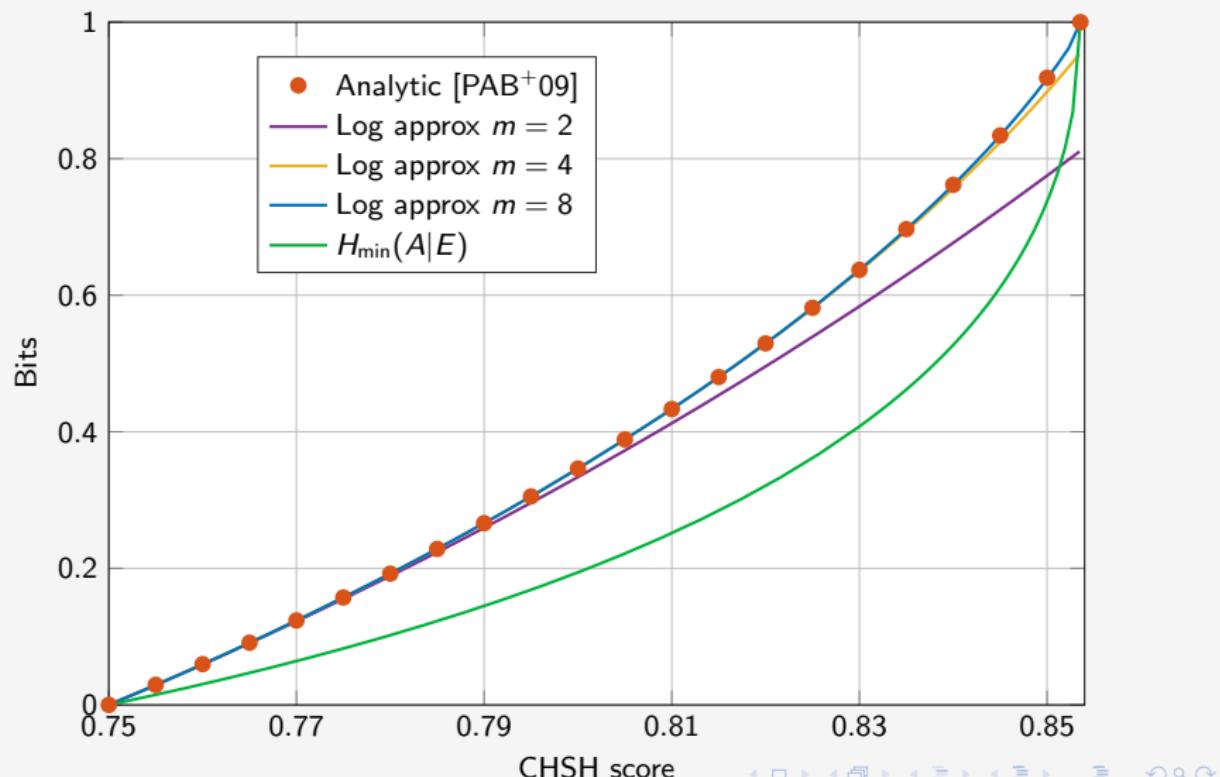
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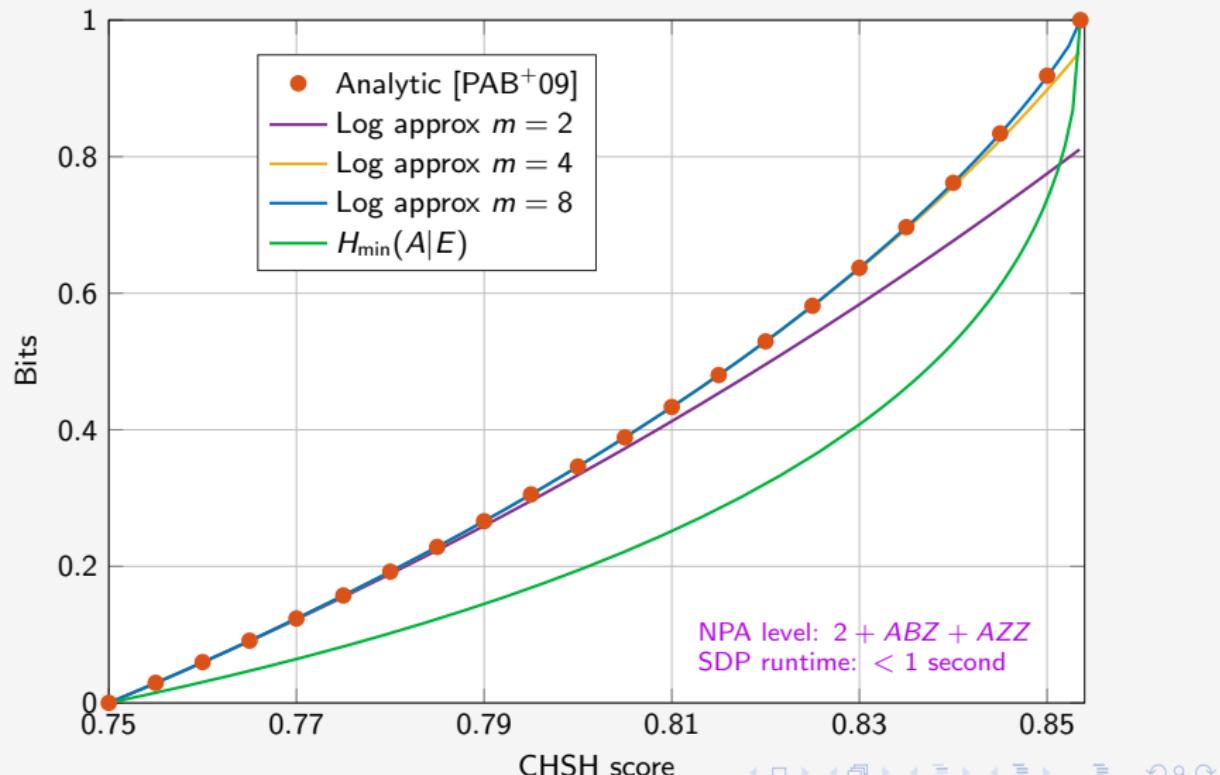
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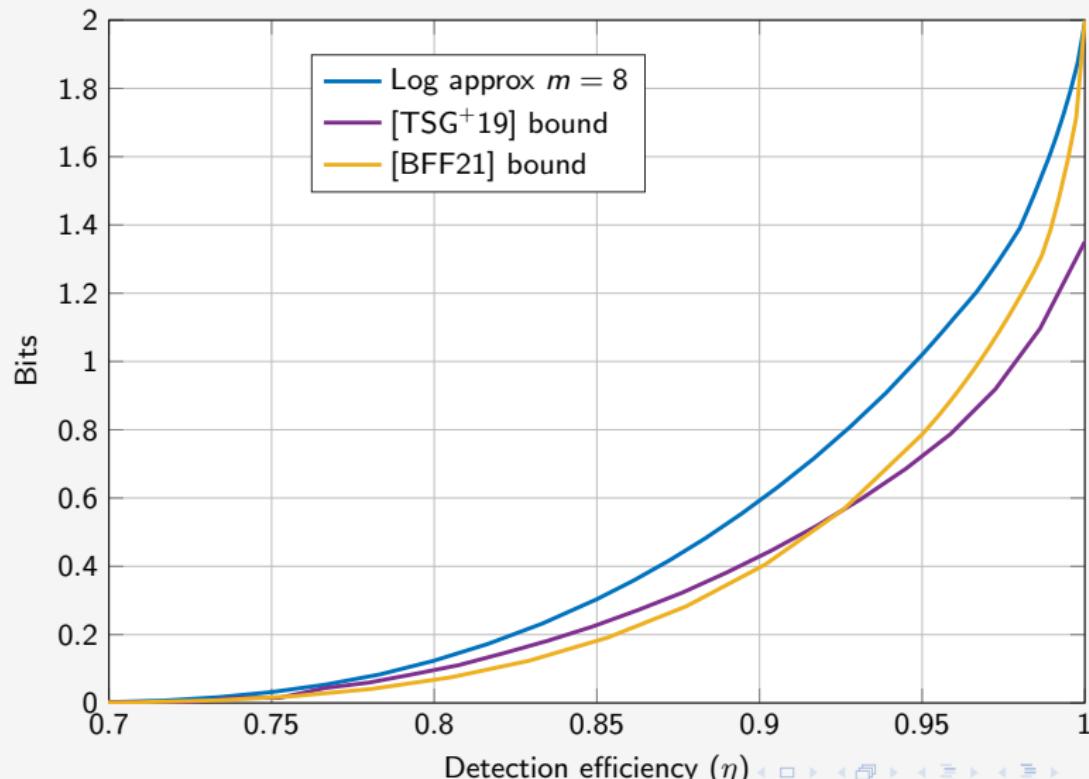
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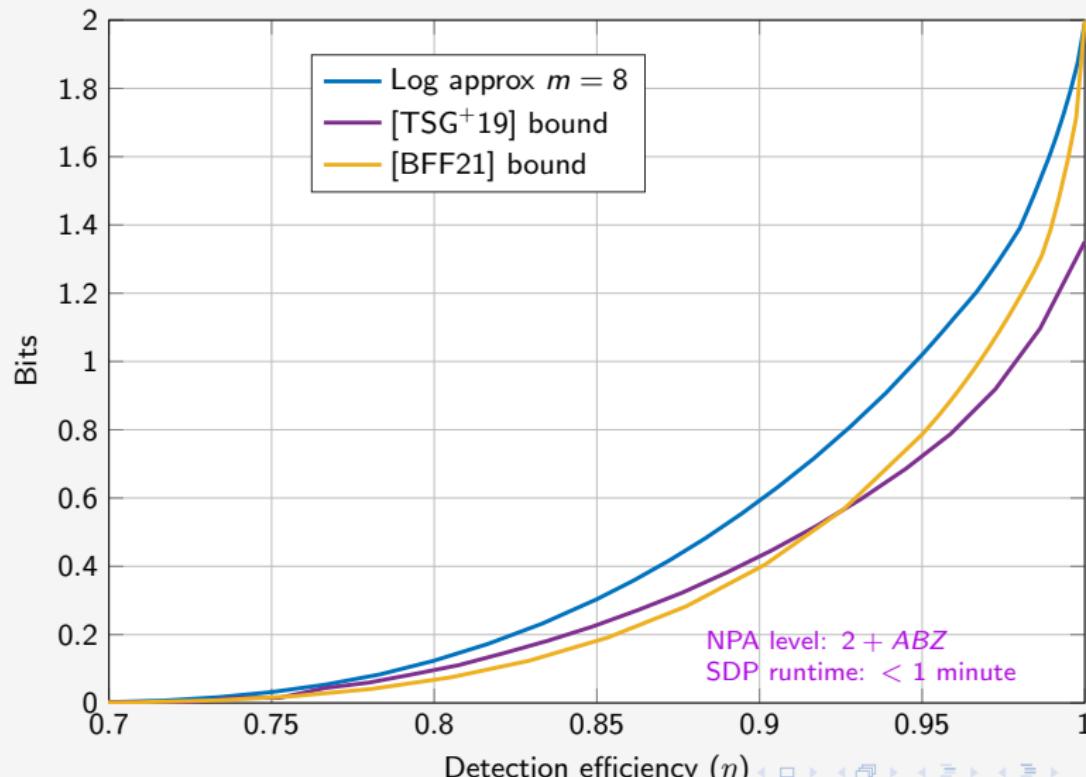
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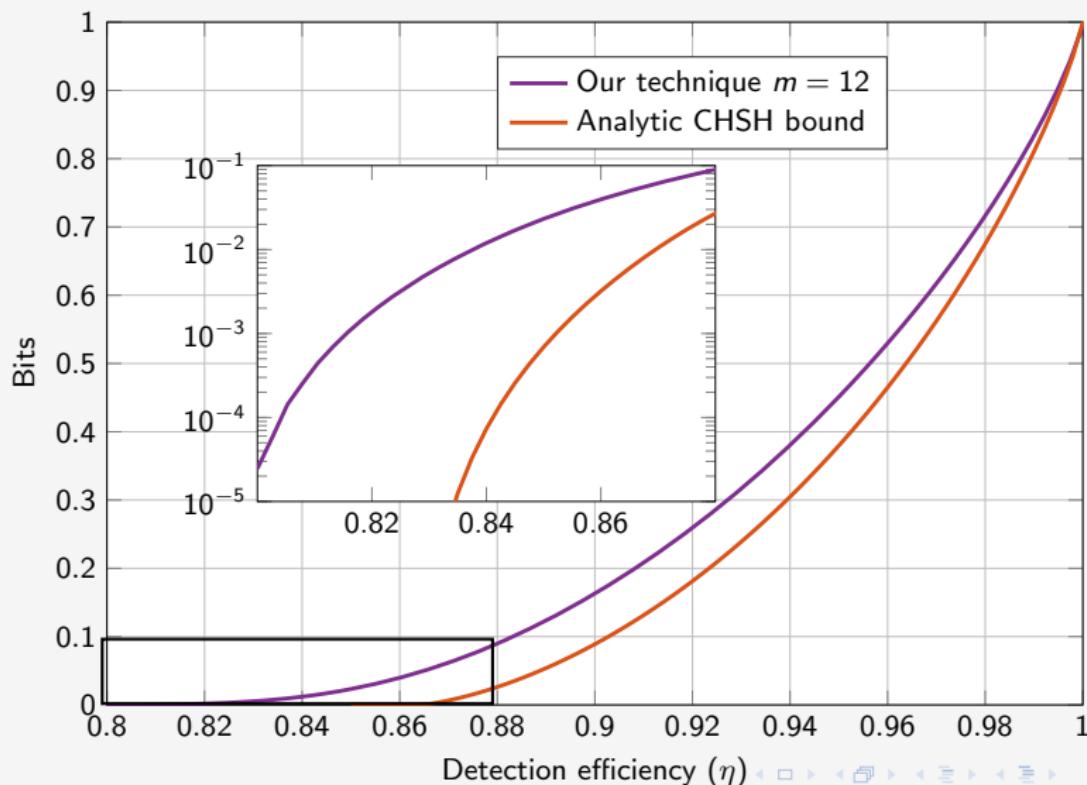
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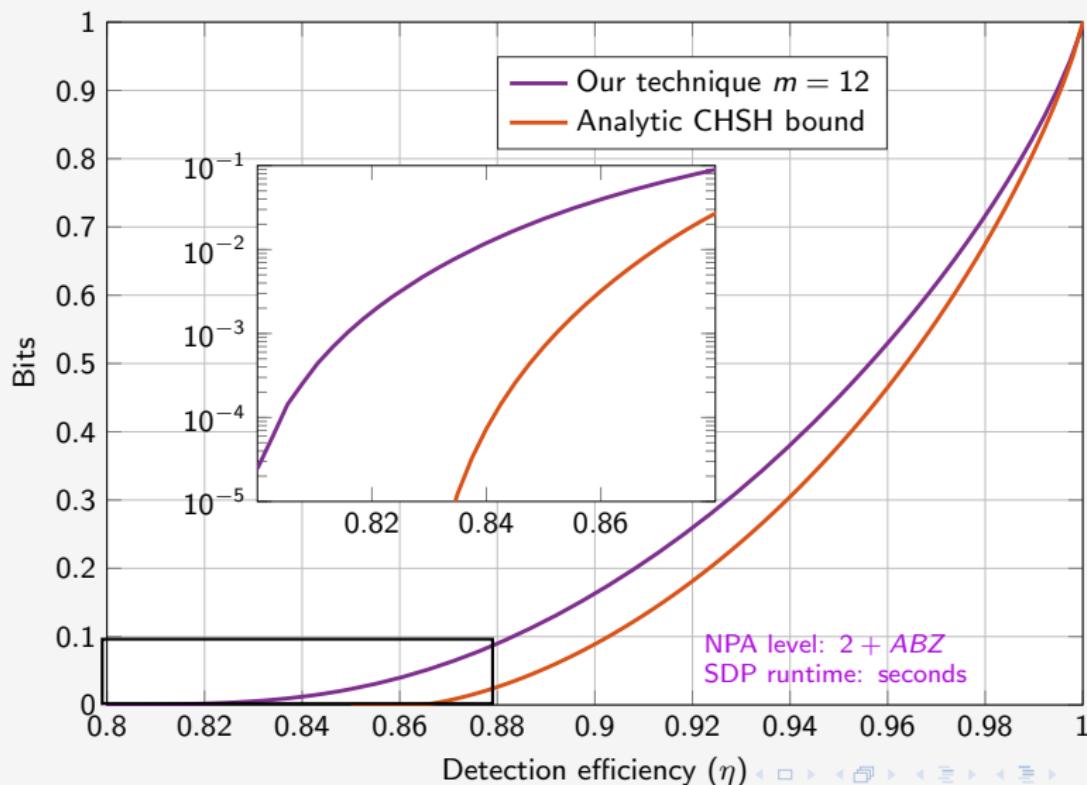
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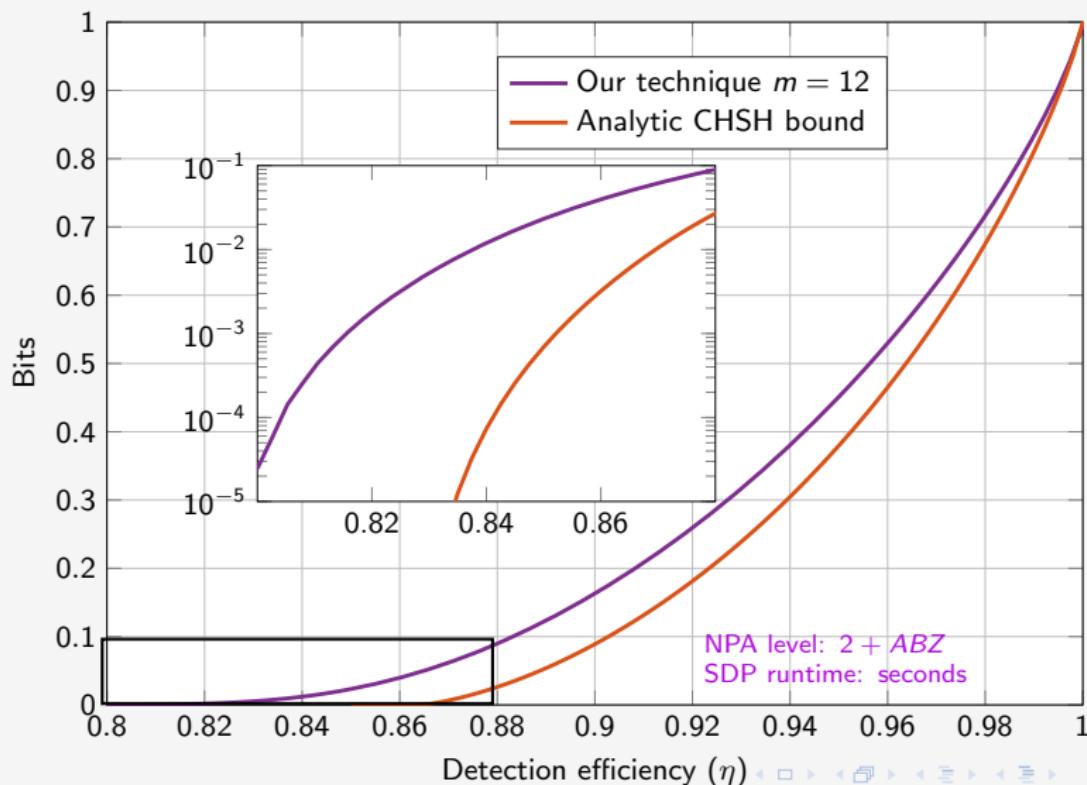
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Analytical results  
with similar thresholds [MPW21]



## Application 2: Beyond DI

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$$E(A : B) := \inf_{\text{Tr}_E[\rho_{ABE}] = \rho_{AB}} I(A : B | E).$$

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- SDP lower bounds via NPA hierarchy!

## Results - Werner state squashed entanglement

Consider a two-qubit Werner state

$$\rho = p \frac{\Pi_{\text{sym}}}{\text{Tr} [\Pi_{\text{sym}}]} + (1 - p) \frac{\Pi_{\text{asym}}}{\text{Tr} [\Pi_{\text{asym}}]}$$

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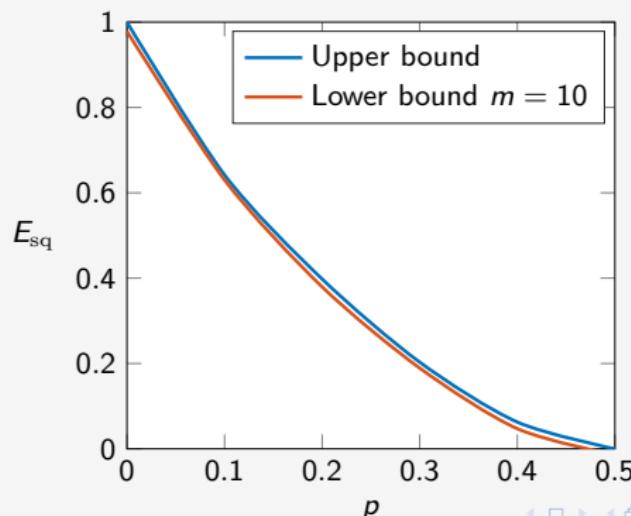
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Using variational lower bounds and heuristic upper bounds we find

$$d_A = d_B = 2$$



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Thanks for your attention

# Bibliography



Peter Brown, Hamza Fawzi, and Omar Fawzi.

Computing conditional entropies for quantum correlations.

*Nature communications*, 12(1):1–12, 2021.



Matthias Christandl, Artur Ekert, Michal Horodecki, Paweł Horodecki, Jonathan Oppenheim, and Renato Renner.

Unifying classical and quantum key distillation.

In *Theory of Cryptography Conference*, pages 456–478. Springer, 2007.



Matthias Christandl.

The structure of bipartite quantum states-insights from group theory and cryptography.

*arXiv preprint quant-ph/0604183*, 2006.



Matthias Christandl, Norbert Schuch, and Andreas Winter.

Entanglement of the antisymmetric state.

*Communications in Mathematical Physics*, 311(2):397–422, 2012.



Matthias Christandl and Andreas Winter.

“squashed entanglement”: an additive entanglement measure.

*Journal of mathematical physics*, 45(3):829–840, 2004.



Federico Grasselli, Gláucia Murta, Hermann Kampermann, and Dagmar Bruß.

In preparation.

2021.



Michele Masini, Stefano Pironio, and Erik Woodhead.

Simple and practical diqkd security analysis via bb84-type uncertainty relations and pauli correlation constraints.

*arXiv preprint arXiv:2107.08894*, 2021.



Stefano Pironio, Antonio Acín, Nicolas Brunner, Nicolas Gisin, Serge Massar, and Valerio Scarani.

Device-independent quantum key distribution secure against collective attacks.

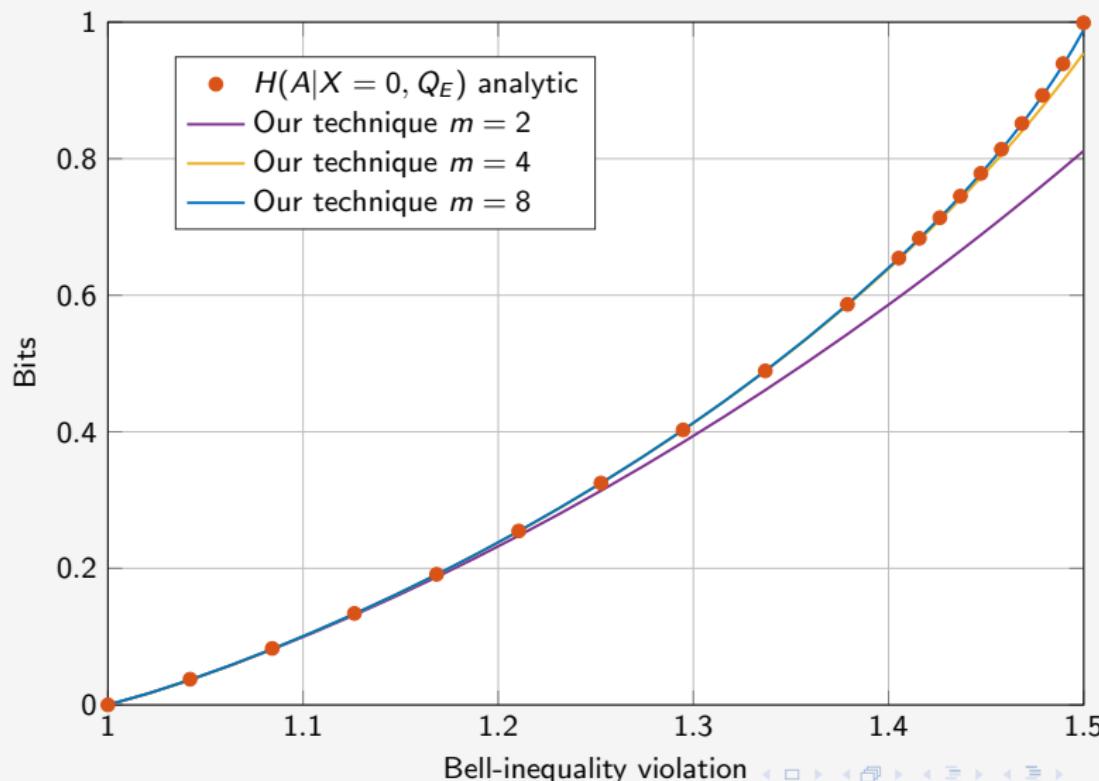
*New Journal of Physics*, 11(4):045021, 2009.



Stefano Pironio, Miguel Navascués, and Antonio Acín.

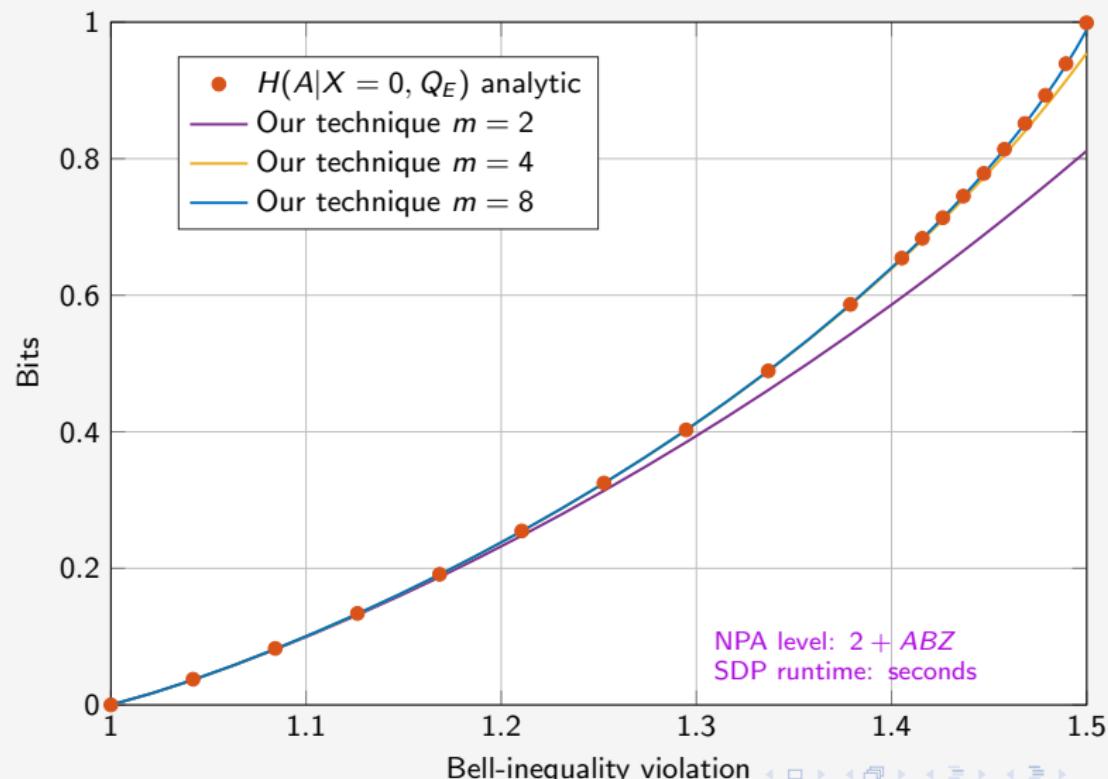
## Bonus results – DICKA setting (Holz inequality)

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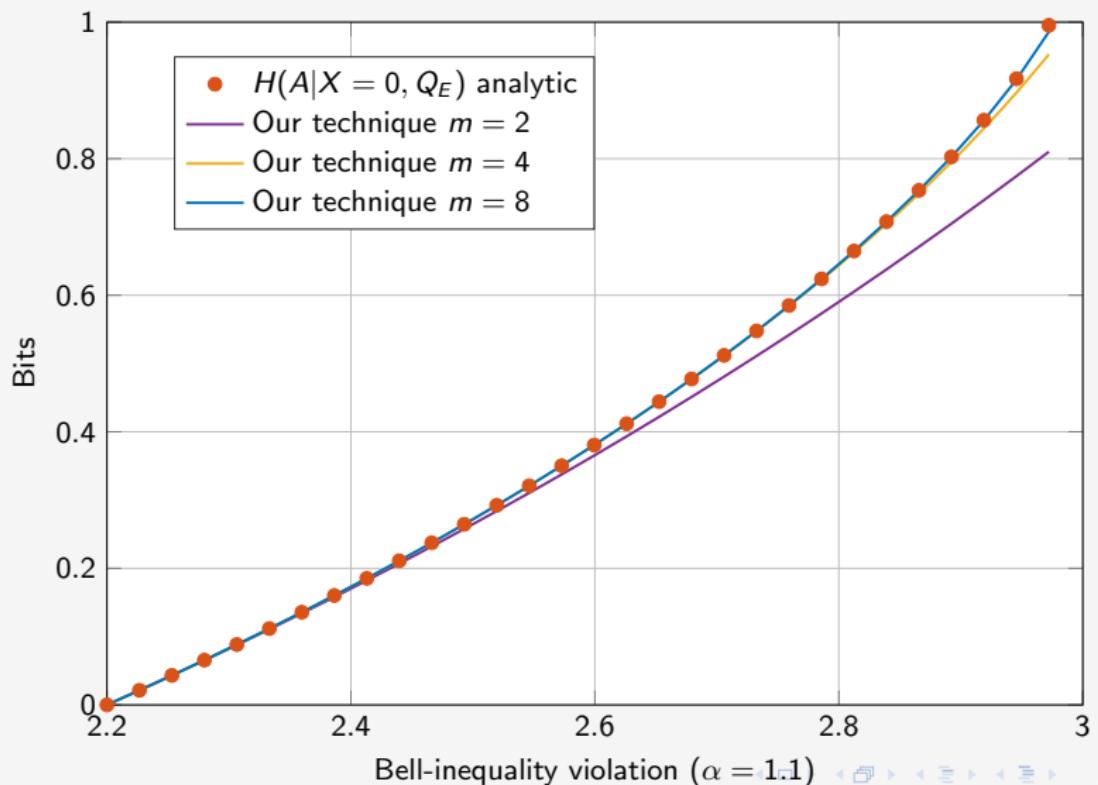
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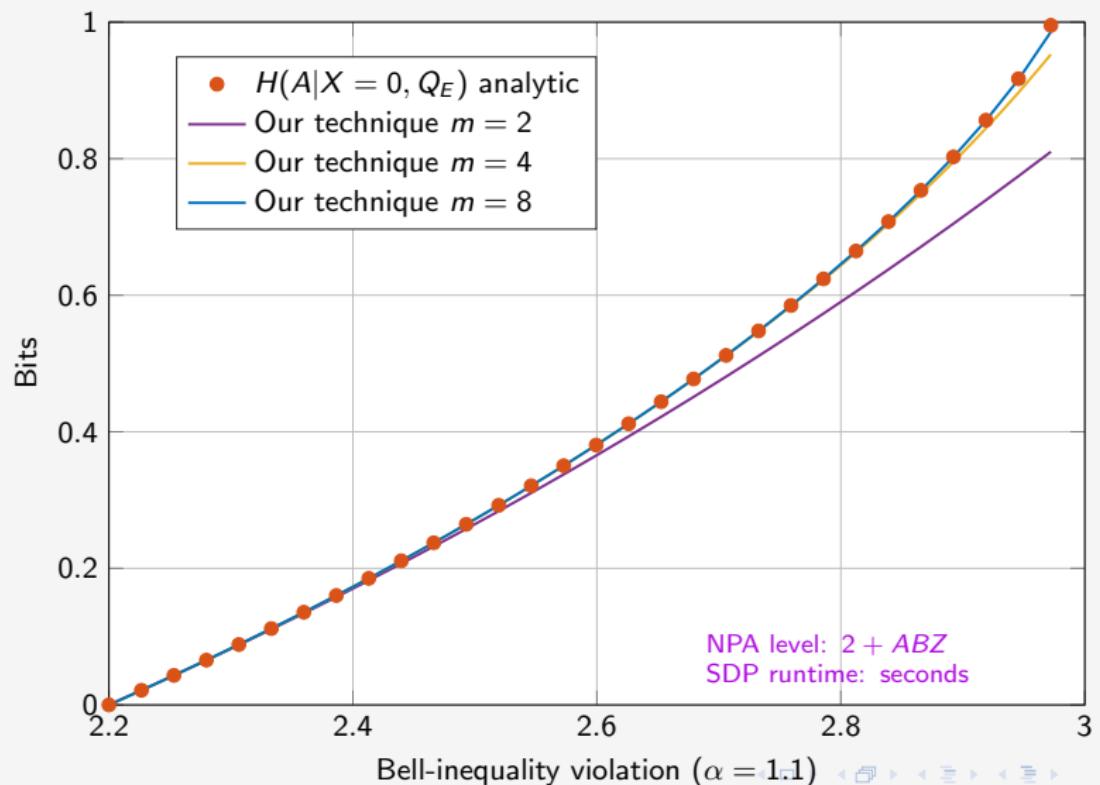
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