

Computing secret key rates

TELECOM
Paris



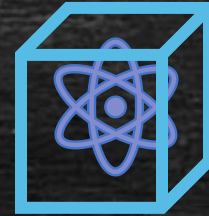
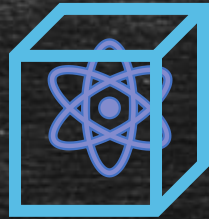
Les Diablerets QKD Summer School 2026

Peter Brown

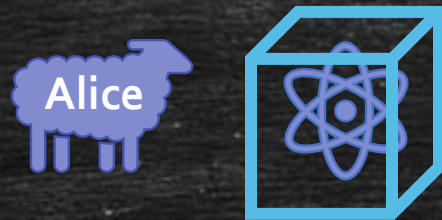


Inria

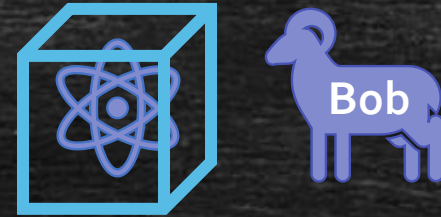
The key-rate problem



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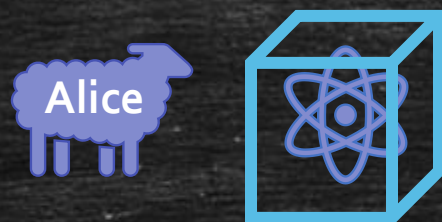
1001101...



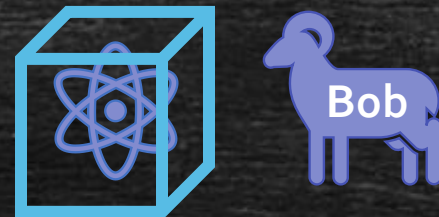
1001111...

1. They generate raw keys using their devices.

The key-rate problem



1001101...



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2. They correct errors (*information reconciliation*)

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3. They extract randomness (*privacy amplification*)

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Cost: $leak_{EC}$

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Key rate: $\min_{\text{attacks}} H(Z|E) - leak_{EC}$ bits per round

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Cost: $leak_{EC}$

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The entropy optimization problem

Want to study the following problem

$$\min_{\text{attacks}} H(Z|E)$$

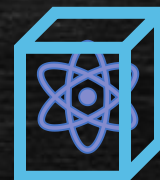
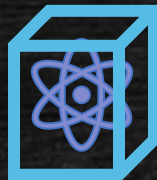
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Set of "attacks" depends on security model and protocol:

Device dependent



Characterized system
E.g. Known POVMs / state

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Partially characterized system
E.g. Known dimension

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Device independent



Fully uncharacterized system
E.g. We know it is quantum

The entropy optimization problem II

Things look difficult

$$\min_{\text{attacks}} H(Z|E)$$

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Must assume Eve knows the
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Our computers work with limited memory / time...

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 - Is there a (small) finite dimensional representation?
- Conditional entropy is concave

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Not nice (for minimizing)

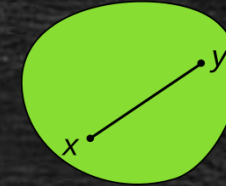
A Tool: Convex Optimisation

Convexity I

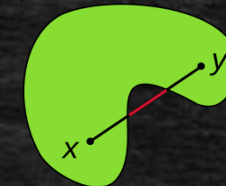
Definition:

A set X is convex if for all $x, y \in X$ and $\lambda \in [0, 1]$ we have

$$\lambda x + (1 - \lambda)y \in X.$$



Convex



Nonconvex

Examples:

- Quantum states

$$\mathcal{S} = \{ \rho \mid \rho \succeq 0, \text{Tr}[\rho] = 1 \}$$

- Quantum measurements

$$\mathcal{M} = \left\{ (M_1, \dots, M_n) \mid \forall i \ M_i \succeq 0, \sum_k M_k = \mathbb{I} \right\}$$

Convexity II

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Definition:

A function $f : X \rightarrow \mathbb{R}$ is convex if for all $x, y \in X$ and $\lambda \in [0, 1]$ we have

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Examples:

- Surprisal $-\log(x)$
- Trace norm $\|X\|_1$
- Negative entropy $-H(A|B)$

Convex Optimisation

$$\begin{array}{ll} \min & f(x) \\ \text{s.t.} & x \in X \end{array}$$

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Theorem:

If $f : X \rightarrow \mathbb{R}$ is convex and X is convex, then any *local minimum* is also a global minimum.

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Convexity does not imply efficiency though!

Semidefinite programming

Efficiently solvable convex optimisation problems exist:

$$\begin{aligned} \min_X \quad & \text{Tr}[CX] \\ \text{s.t.} \quad & \text{Tr}[F_i X] = b_i \quad \forall i \\ & X \succeq 0 \end{aligned}$$

Semidefinite programming

Efficiently solvable convex optimisation problems exist:

$$\begin{aligned} \min_X \quad & \text{Tr}[CX] && \text{Linear objective function} \\ \text{s.t.} \quad & \text{Tr}[F_i X] = b_i \quad \forall i \\ & X \succeq 0 \end{aligned}$$

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Linear objective function

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Linear (in)equalities

$$X \succeq 0$$

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Example (Min-entropy):

Given a cq-state

$$\rho_{AE} = \sum_a p(a) |a\rangle\langle a| \otimes \rho_a$$

we have

$$H_{\min}(A|E) = -\log P_{\text{guess}}(A|E)$$

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$$H_{\min}(A|E) = -\log P_{\text{guess}}(A|E)$$

$$P_{\text{guess}}(A|E) = \max_{\{M_a\}_a} \sum_a p(a) \operatorname{Tr}[M_a \rho_a]$$

$$\text{s.t. } \sum_a M_a = \mathbb{I}$$

$$M_a \succeq 0 \quad \forall a$$

Core idea

Try to transform to a convex problem

$$\min_{\text{attacks}} H(Z|E) \quad \longrightarrow \quad \begin{array}{ll} \min & f(x) \\ \text{s.t.} & x \in X \end{array}$$

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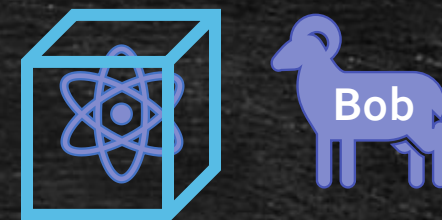
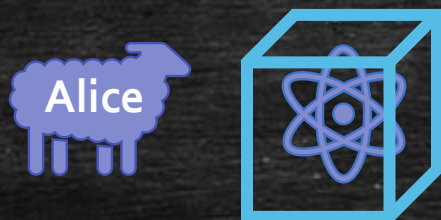
$$\begin{array}{ll} \min & f(x) \\ \text{s.t.} & x \in X \end{array}$$

- Guaranteed optima
- Efficient (hopefully)
- Existing numerical software

Device-dependent rates

Hidden convexity

Device-dependent QKD – Eve's attacks



Device-dependent QKD – Eve's attacks



Eve can manipulate the transmitted state

$$\rho_{Q_A Q_B E}$$

Device-dependent QKD – Eve's attacks



Eve can manipulate the transmitted state

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State at end of round

$$\rho_{ABPE} = (\mathcal{K} \otimes \mathcal{I}_E)(\rho_{Q_A Q_B E})$$

Device-dependent QKD – Eve's attacks



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$$\text{Tr}[(M_{ax} \otimes N_{by})\rho_{Q_A Q_B}] = p(a, b, x, y)$$

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Prepare and measure

$$\text{Tr}_{Q_B E}[\rho_{Q_A Q_B E}] = \rho_{Q_A}$$

DD-QKD key rate problem



How much certifiable randomness does Alice generate in one-round?

$$\min_{\text{Attacks}} H(A|PE)$$

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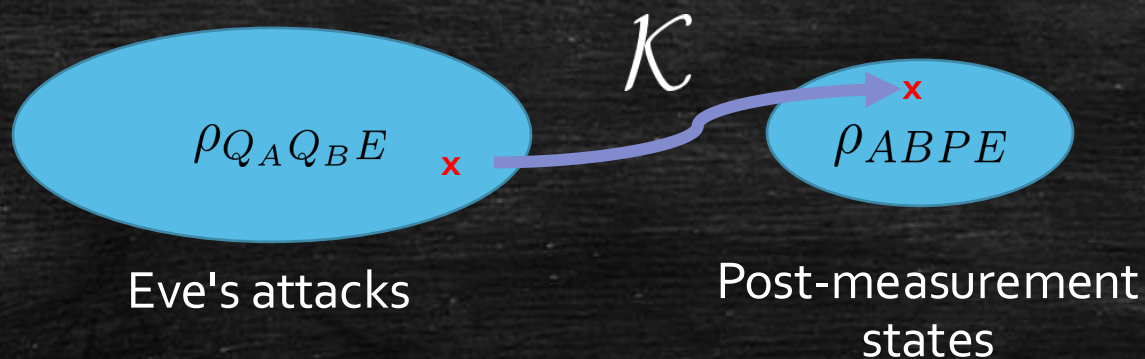
Eve's attacks

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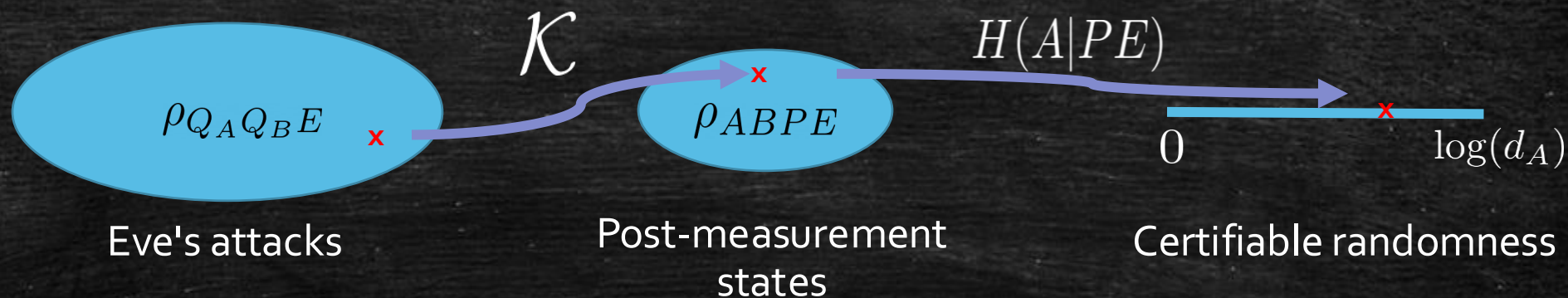
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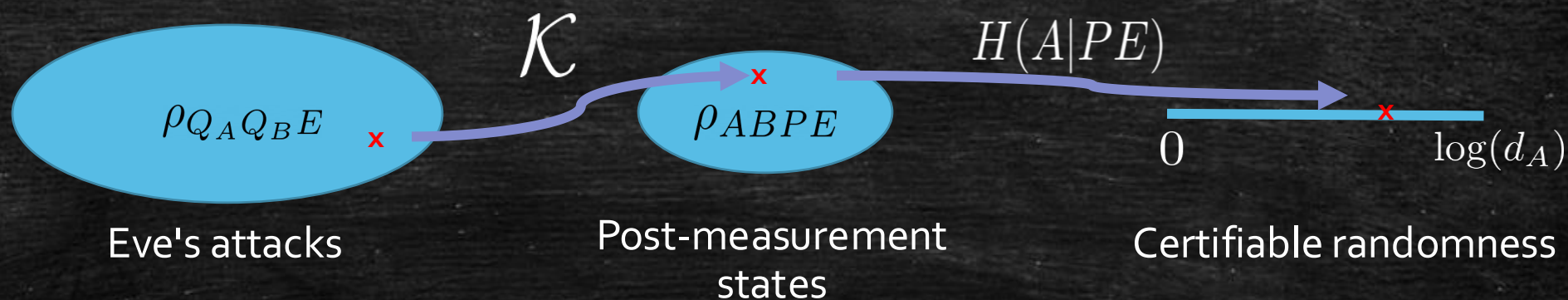
How much certifiable randomness does Alice generate in one-round? $\min_{\text{Attacks}} H(A|PE)$



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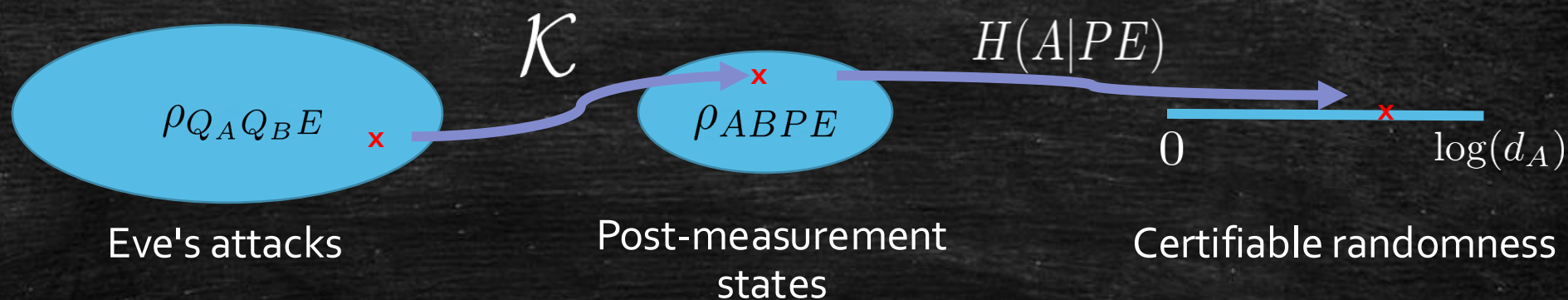
Post-measurement state

Valid quantum state

DD-QKD key rate problem



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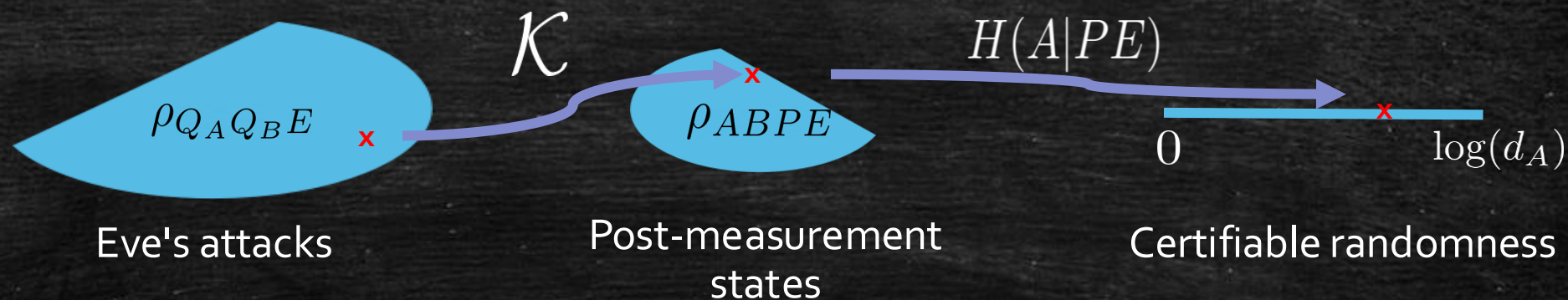
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We have more constraints on Eve's attacks!

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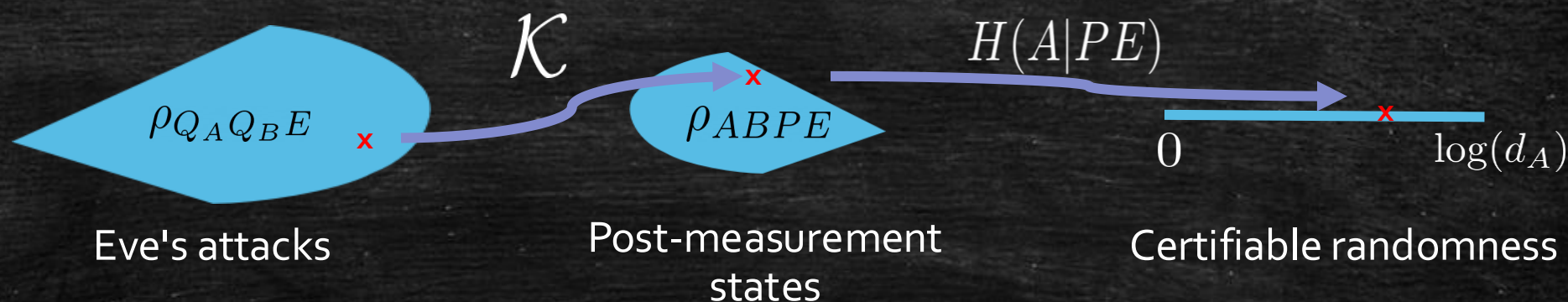
Valid quantum state

Linear constraints on $P(a, b, x, y)$

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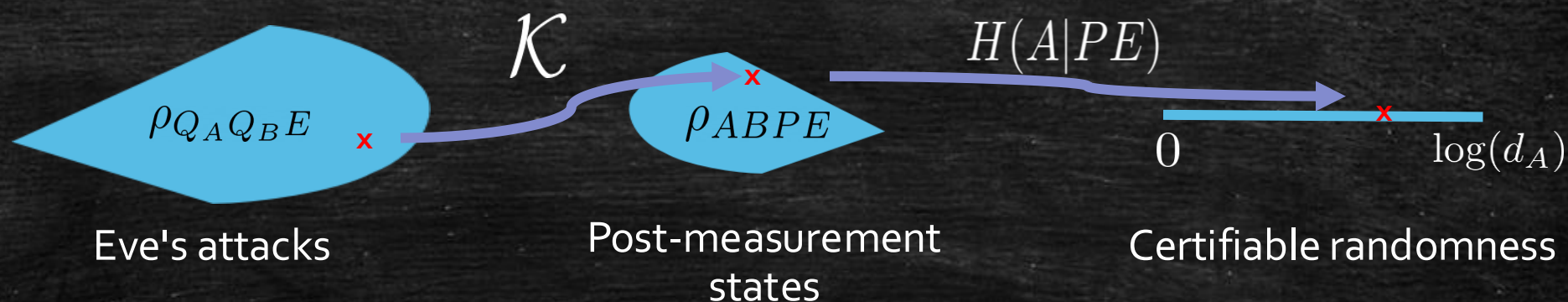
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Attacks



Post-measurement state

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E dimension a priori
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Simplification 1:

Eve can always purify!

$$\rho_{Q_A Q_B E} \mapsto |\psi\rangle_{Q_A Q_B E F}$$

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(strong subadditivity)

$$H(A|PEF) \leq H(A|PE)$$

Simplifying the problem

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Minimizing a concave
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Tool: Isometric equivalence of purifications

If $|\psi\rangle_{QE}$ and $|\phi\rangle_{QF}$ are both purifications of ρ_Q . Then there exists an isometry $V: E \rightarrow F$ or $V: F \rightarrow E$ such that

$$(I_Q \otimes V)|\psi\rangle = |\phi\rangle \quad \text{or} \quad (I_Q \otimes V)|\phi\rangle = |\psi\rangle$$

Simplifying the problem

$$\min H(A|PE)$$

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Isometric invariance
of entropy

$$H(A|PE) = H(A|PF)$$

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$$\text{s.t. } \rho_{ABPE} = \mathcal{K}(|\psi\rangle\langle\psi|_{Q_A Q_B E})$$

$$\text{Tr}[(M_{ax} \otimes N_{by})\rho_{Q_A Q_B}] = p(a, b, x, y)$$

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$$\text{Tr}[|\psi\rangle\langle\psi|_{Q_A Q_B E}] = 1$$

E dimension a priori
unbounded

Minimizing a concave
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Simplification 2: All purifications are equivalent!

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The simpler problem



The simpler problem



Theorem:

The device-dependent rate problem is
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Current approaches

Computing DD key-rates is easy...

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...because some nice people have done the hard work for us.

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Ref.	Method	Language	Code
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[LPCA24]	Conic optimization	Julia	github.com/araujoms/ConicQKD.jl
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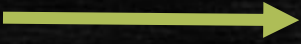
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Specify protocol  Construct key channel

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Specify protocol → Construct key channel → Pass to a package

Example code (QICS – BB84)

```
import numpy as np

import picos

qx = 0.25
qz = 0.75

X0 = np.array([[.5, .5], [.5, .5]])
X1 = np.array([[.5, -.5], [-.5, .5]])
Z0 = np.array([[1., 0.], [0., 0.]])
Z1 = np.array([[0., 0.], [0., 1.]])

Ax = np.kron(X0, X1) + np.kron(X1, X0)
Az = np.kron(Z0, Z1) + np.kron(Z1, Z0)

# Define problem
P = picos.Problem()
X = picos.SymmetricVariable("X", 4)

P.set_objective("min", picos.quantkeydist(X))
P.add_constraint(picos.trace(X) == 1)
P.add_constraint((X | Ax) == qx)
P.add_constraint((X | Az) == qz)

# Solve problem
P.solve(solver="qics")

analytic_rate = np.log(2) + (qx*np.log(qx) + qz*np.log(qz))
numerical_rate = P.value

print("Analytic key rate: ", analytic_rate)
print("Numerical key rate:", numerical_rate)
```

Device-independent rates

Making convexity

Device-independent QKD – Eve's attacks



Device-independent QKD – Eve's attacks



Eve can manipulate the transmitted state and measurements

$$\rho_{Q_A Q_B E} \quad \{M_{a|x}\}_a \quad \{N_{b|y}\}_b$$

Device-independent QKD – Eve's attacks



Eve can manipulate the transmitted state and measurements

$$\rho_{Q_A Q_B E} \quad \{M_{a|x}\}_a \quad \{N_{b|y}\}_b$$

State at end of round

$$\rho_{ABXYE} = \sum_{abxy} p(xy) |abxy\rangle \langle abxy| \otimes \text{Tr}_{Q_A Q_B} [(M_{a|x} \otimes N_{b|y} \otimes \mathbb{I}) \rho_{Q_A Q_B E}]$$

Device-independent QKD – Eve's attacks



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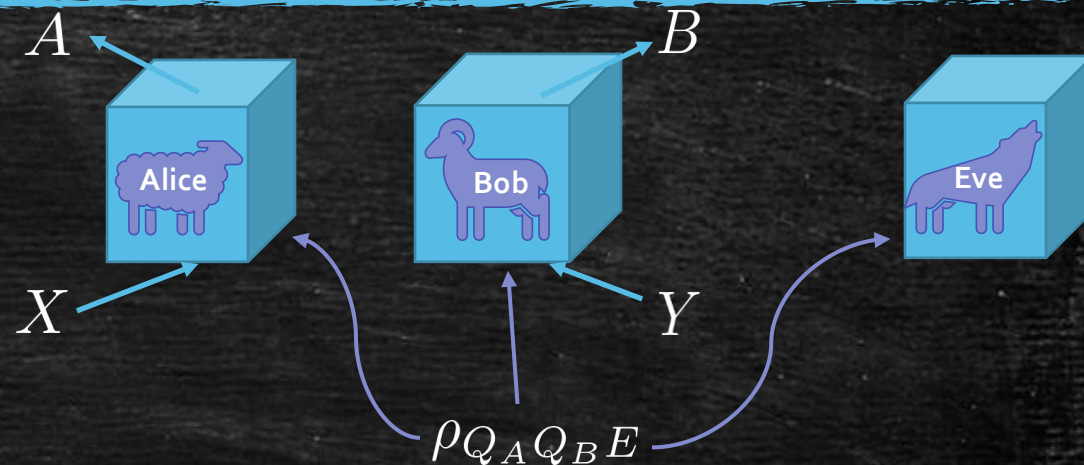
Statistical (e.g. Bell-inequality violation)

$$\text{Tr}[(M_{a|x} \otimes N_{b|y} \otimes I_E) \rho_{Q_A Q_B E}] = p(a, b|x, y)$$

The DI randomness problem

$$\min_{\text{Attacks}} H(A|X=0, E)$$

How much randomness is generated from Alice's device when $x=0$?



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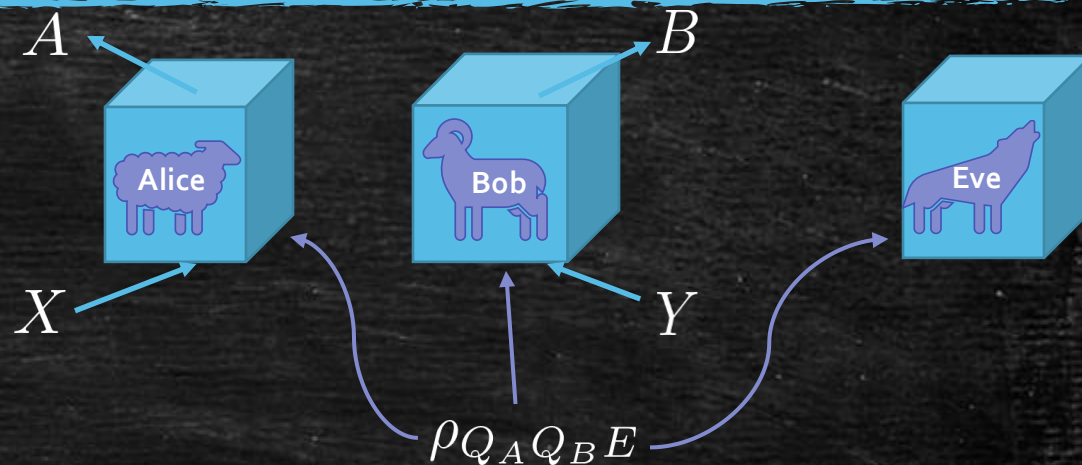
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Eve is more powerful

$$\rho_{Q_A Q_B E}$$

$$\{M_{a|x}\}$$

$$\{N_{b|y}\}$$

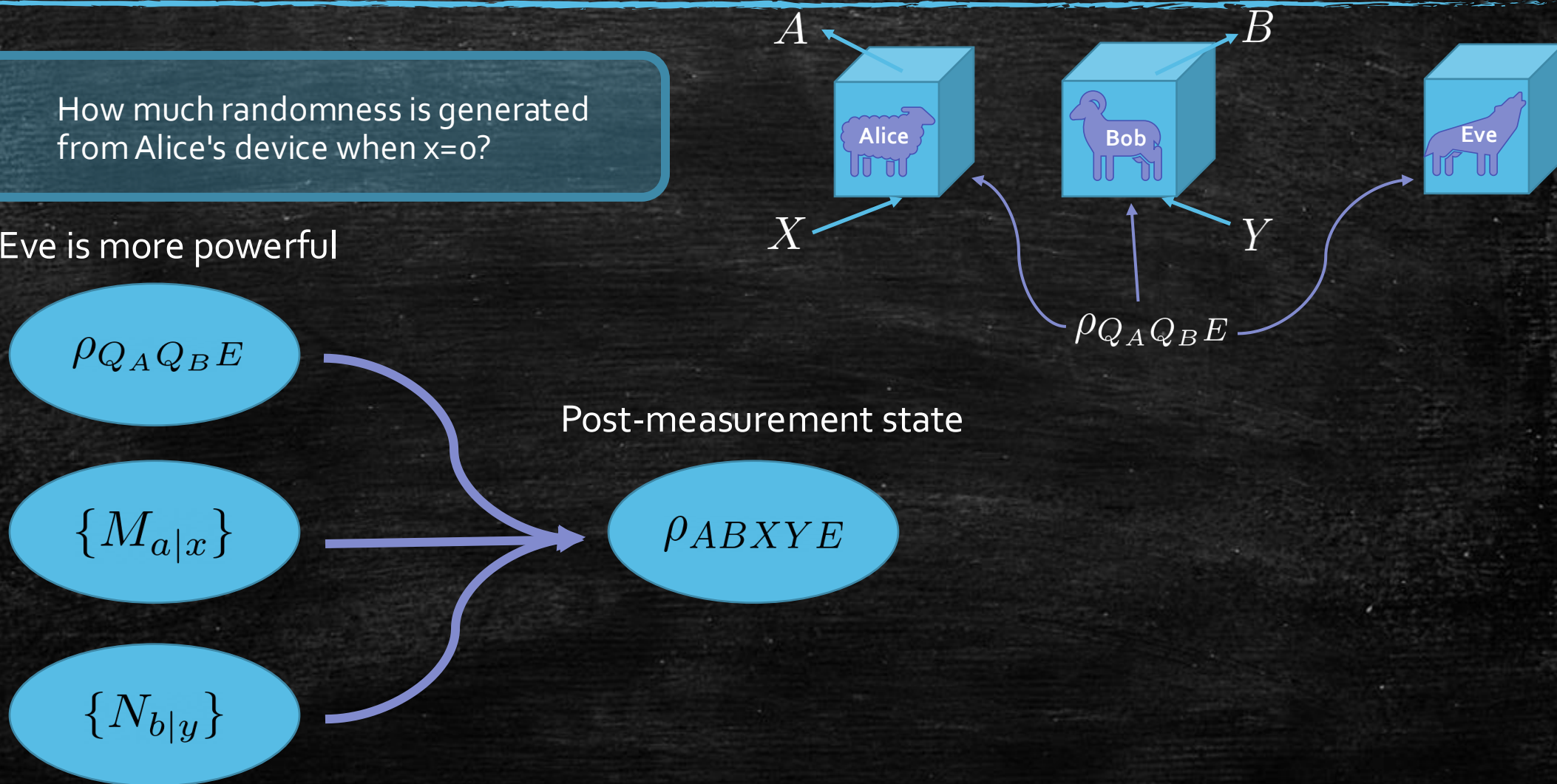


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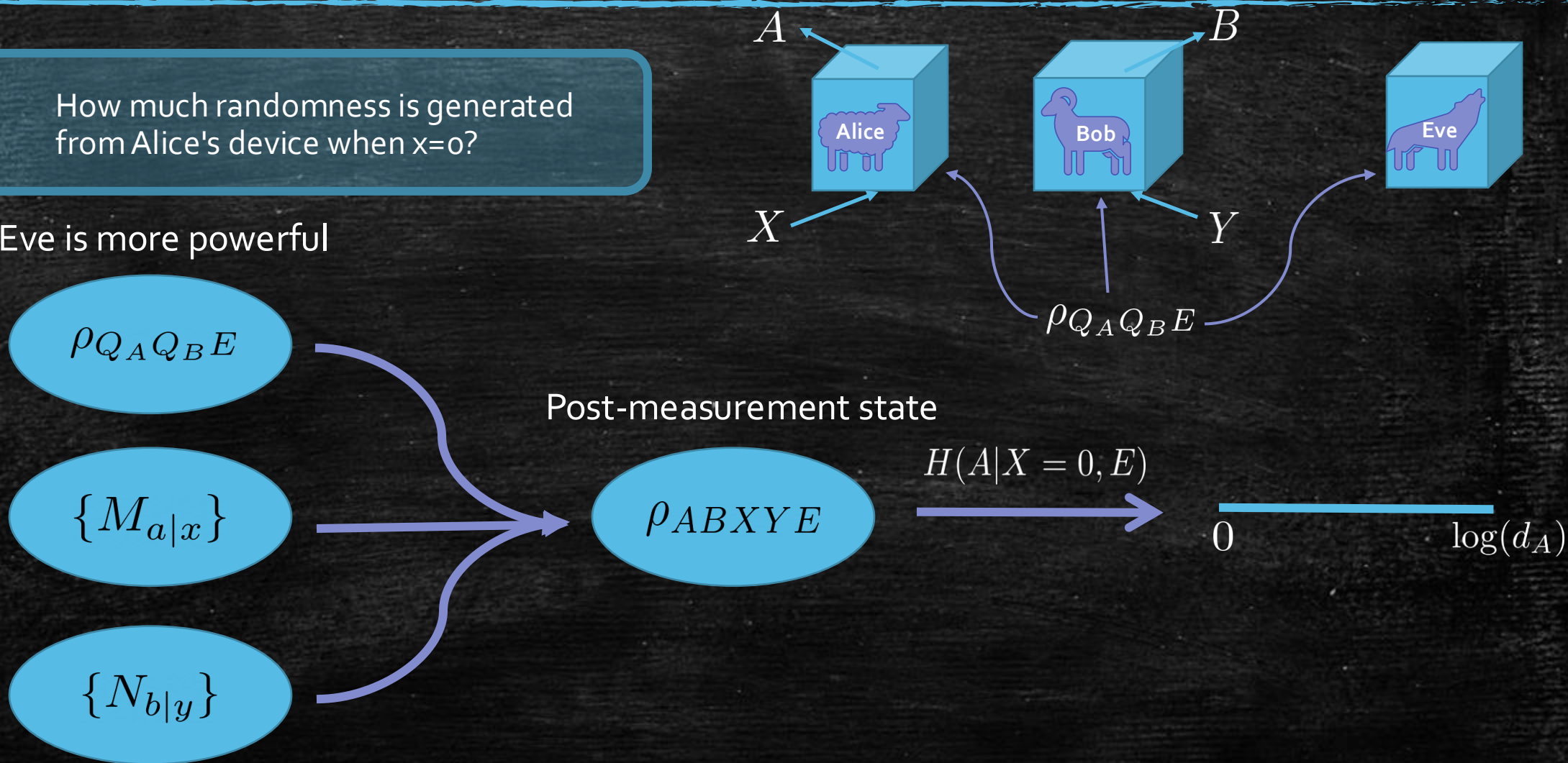


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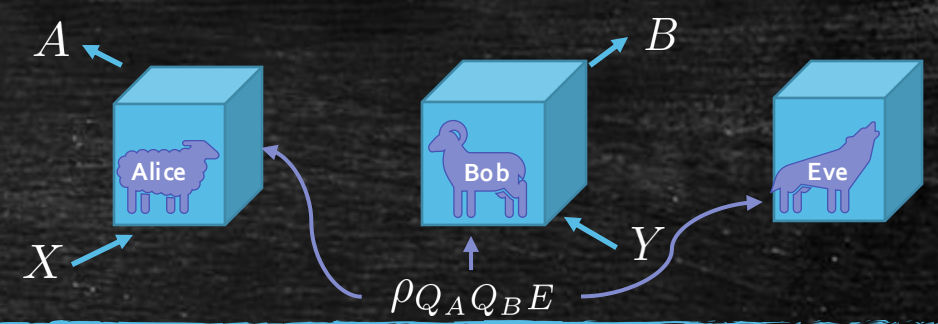
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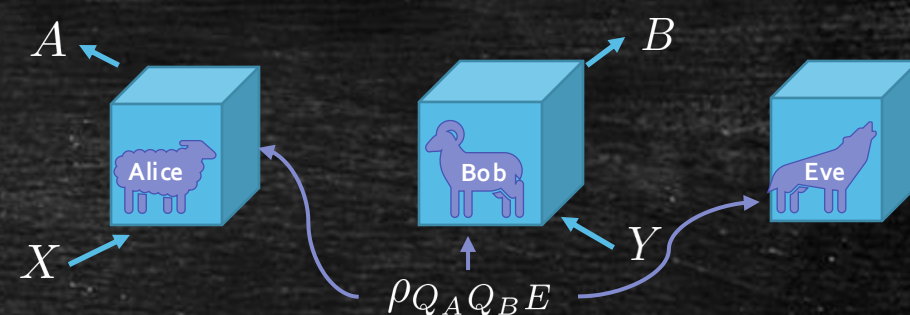
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The DI randomness problem



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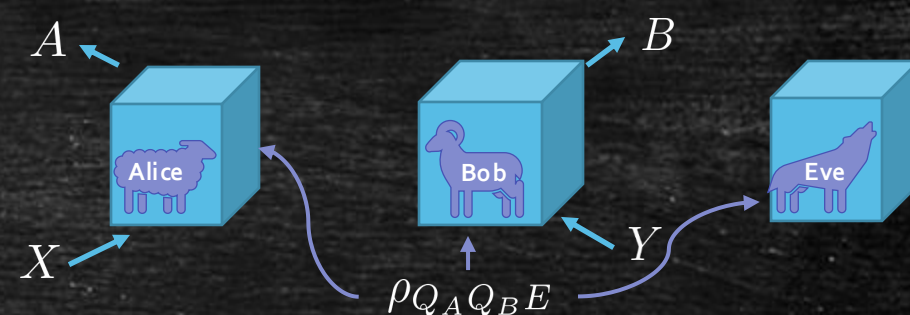
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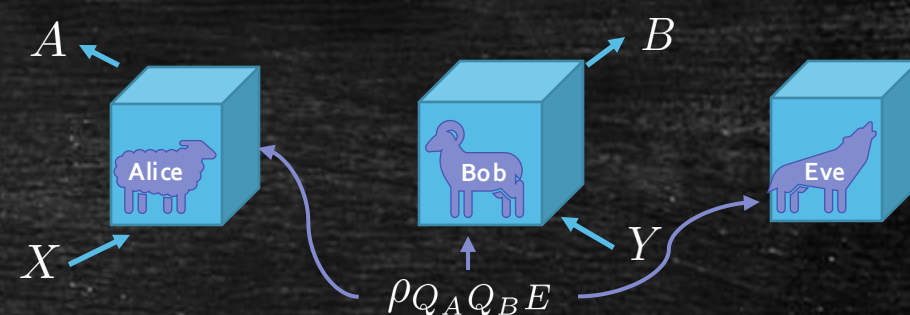
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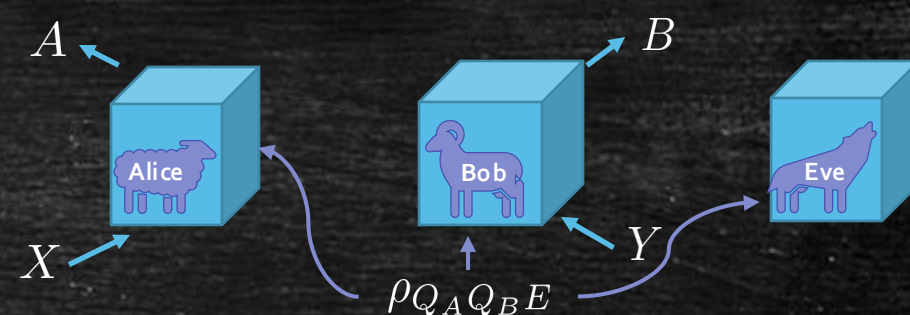
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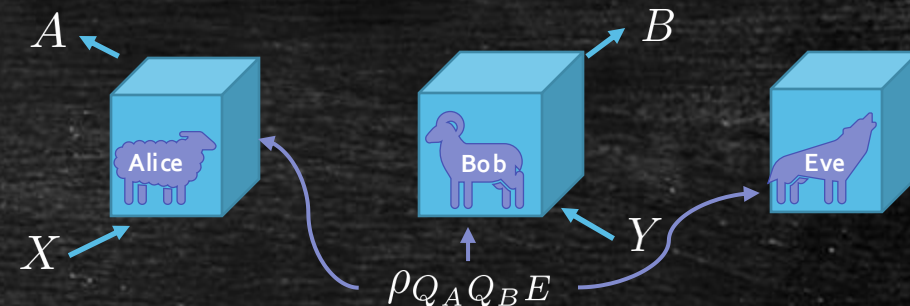
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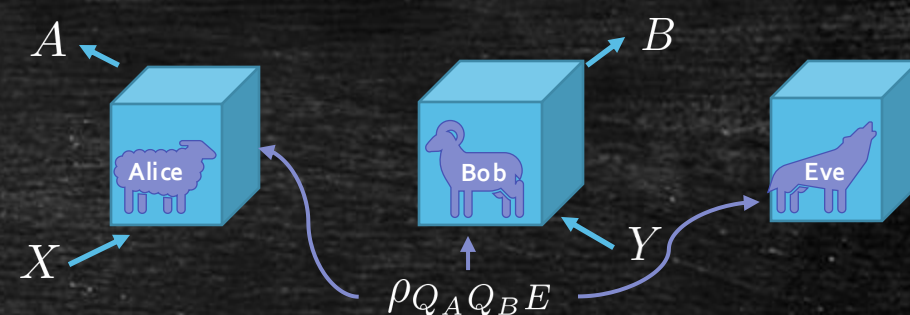
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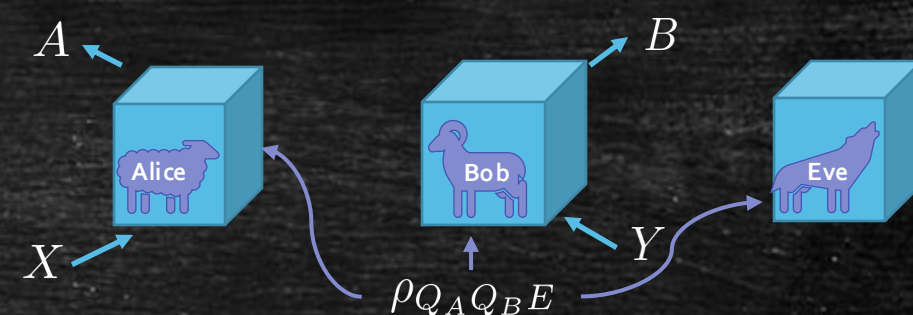
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Dimension of all quantum systems is unbounded...

...need a new perspective

Toolbox: Polynomial optimization [NPA07, PNA10]

Let's look at a simpler problem:

$$\begin{aligned} \max \quad & \text{Tr}[\rho(X_1 X_2 + X_2 X_1)] \\ \text{s.t.} \quad & X_1^2 = I, \quad X_2^2 = I \\ & \text{Tr}[\rho X_1] = \alpha, \quad \text{Tr}[\rho X_2] = 0 \\ & \text{Tr}[\rho] = 1, \quad \rho \succeq 0 \end{aligned}$$

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Dimension still unbounded

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Need a dimension-free compressed representation of a system...

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Need a dimension-free compressed representation of a system...

... re-express everything in terms of moments! $\text{Tr}[\rho X^m]$

Toolbox: Polynomial optimization

Building a moment matrix:

1. Gather the operators of your problem

$$\{I, X_1, X_2\}$$

$$\begin{array}{ll} \max & \text{Tr}[\rho(X_1X_2 + X_2X_1)] \\ \text{s.t.} & X_1^2 = I, \quad X_2^2 = I \\ & \text{Tr}[\rho X_1] = \alpha, \quad \text{Tr}[\rho X_2] = 0 \\ & \text{Tr}[\rho] = 1, \quad \rho \succeq 0 \end{array}$$

Toolbox: Polynomial optimization

Building a moment matrix:

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Compressed representation
of the system
Infinite dimensions $\rightarrow$ 3x3

$$\begin{array}{c} I \\ X_1 \\ X_2 \end{array} \begin{array}{ccc} I & X_1 & X_2 \\ \left(\begin{array}{ccc} \text{Tr}[\rho] & \text{Tr}[\rho X_1] & \text{Tr}[\rho X_2] \\ \text{Tr}[\rho X_1^\dagger] & \text{Tr}[\rho X_1^\dagger X_1] & \text{Tr}[\rho X_1^\dagger X_2] \\ \text{Tr}[\rho X_2^\dagger] & \text{Tr}[\rho X_2^\dagger X_1] & \text{Tr}[\rho X_2^\dagger X_2] \end{array} \right) \end{array}$$

Toolbox: Polynomial optimization

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Compressed representation
of the system
Infinite dimensions $\rightarrow 3 \times 3$

$$\begin{array}{c} I \\ X_1 \\ X_2 \end{array} \begin{array}{ccc} I & X_1 & X_2 \\ \left(\begin{array}{ccc} \text{Tr}[\rho] & \text{Tr}[\rho X_1] & \text{Tr}[\rho X_2] \\ \text{Tr}[\rho X_1] & \text{Tr}[\rho X_1^2] & \text{Tr}[\rho X_1 X_2] \\ \text{Tr}[\rho X_2] & \text{Tr}[\rho X_2 X_1] & \text{Tr}[\rho X_2^2] \end{array} \right) \end{array}$$

We can simplify!

- **Hermitian X**

Toolbox: Polynomial optimization

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Any **feasible** quantum system has a moment matrix of the form

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Not tight
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Semidefinite program (SDP)

- Efficient algorithms
- Guaranteed optima

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Achievable!

$$\begin{aligned} \rho = |0\rangle\langle 0| \quad & X_1 = \alpha \sigma_Z + \sqrt{1 - \alpha^2} \sigma_X \\ & X_2 = \sigma_X \end{aligned}$$

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Toolbox: Polynomial optimization

- Moment matrix method gives SDP relaxations.

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- Better relaxations possible with larger indexing sets

$$\{I, X_1, X_2, X_1^2, X_1X_2, X_2X_1, X_2^2\}$$

"Level 2" relaxation

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"Level 2" relaxation

- Relaxations converge to actual optima under mild conditions

Bounded operators
sufficient

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$$\begin{aligned} \max / \min \quad & \text{Tr}[\rho P(X_1, \dots, X_n)] \\ & \text{Tr}[\rho Q_i(X_1, \dots, X_n)] \leq q_i \\ & R_j(X_1, \dots, X_n) \succeq 0 \\ & \rho \succeq 0 \end{aligned}$$

Expectation of polynomial

Equalities and inequalities

Operator constraints

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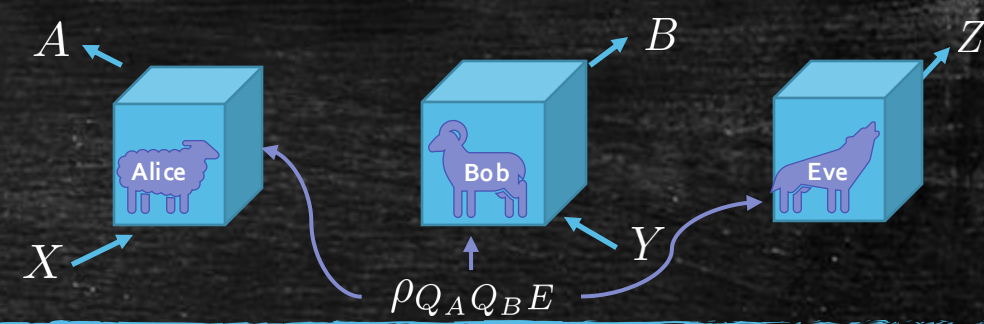
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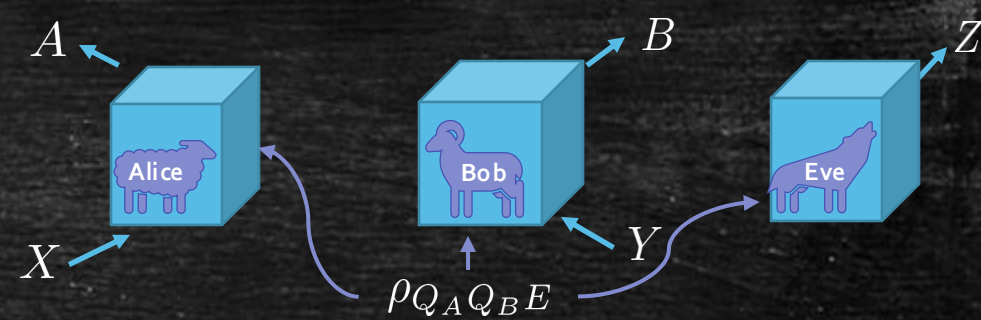
Lots of applications
beyond DI cryptography
Review [TPBA24]

Simple DI key-rate bounds



The von Neumann entropy is complicated, so let's make things easier

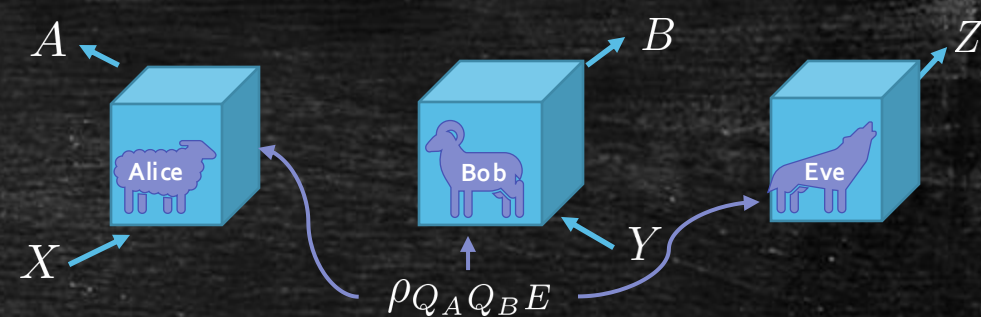
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$$\min_{\text{Attacks}} H(A|X=0, E) \geq \min_{\text{attacks}} H_{\min}(A|X=0, E)$$

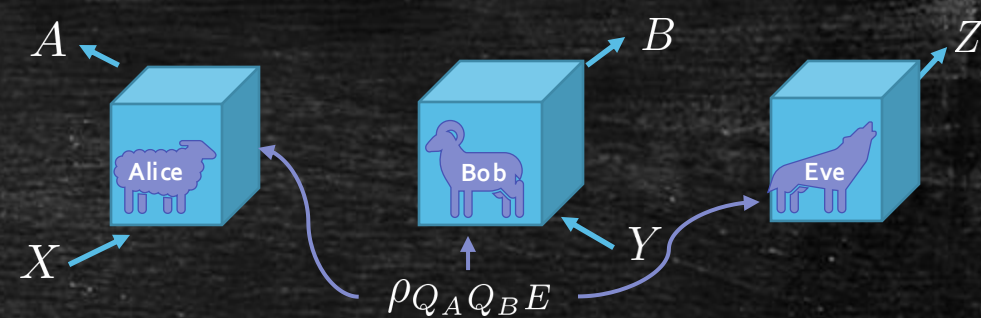
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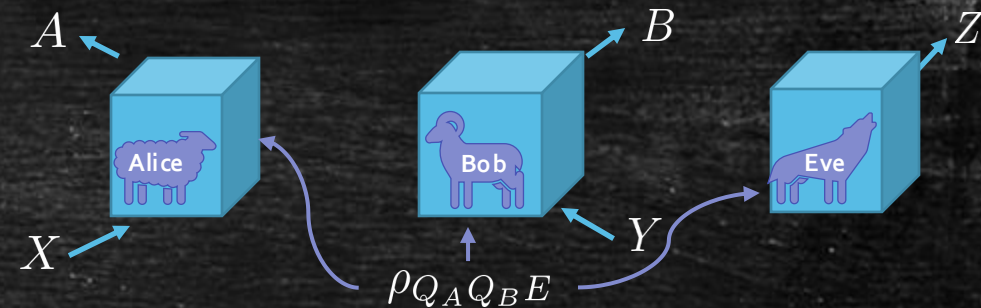
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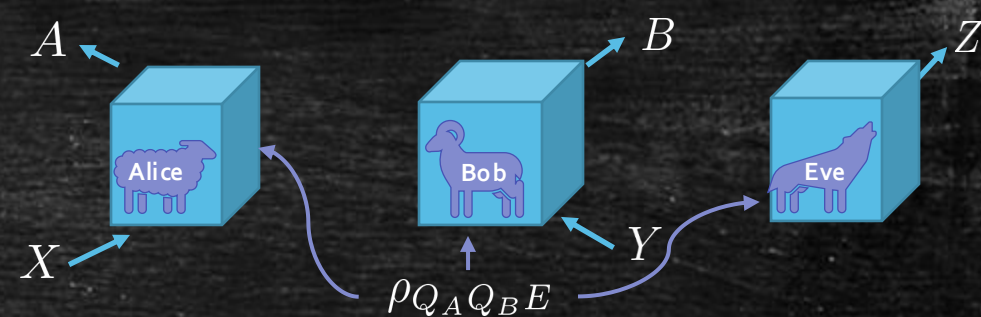
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So we will try to solve

$$\max_{\text{attacks}} P_{\text{guess}}(A|X=0, E)$$

CHSH example



Guessing probability problem

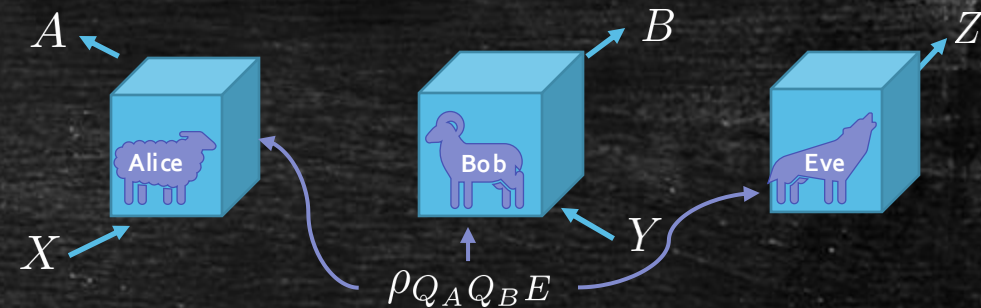
$$g(\omega) := \max \sum_a \text{Tr}[(M_{a|0} \otimes I_B \otimes Z_a) \rho_{Q_A Q_B E}]$$

$$\text{s.t. } \frac{1}{4} \sum_{a \oplus b = xy} \text{Tr}[(M_{a|x} \otimes N_{b|y} \otimes I_E) \rho_{Q_A Q_B E}] = \omega$$

$$\rho_{Q_A Q_B E} \succeq 0, \quad M_{a|x} \succeq 0, \quad N_{b|y} \succeq 0, \quad Z_c \succeq 0$$

$$\text{Tr}[\rho_{Q_A Q_B E}] = 1, \quad \sum_a M_{a|x} = I_A, \quad \sum_b N_{b|y} = I_B, \quad \sum_c Z_c = I_E$$

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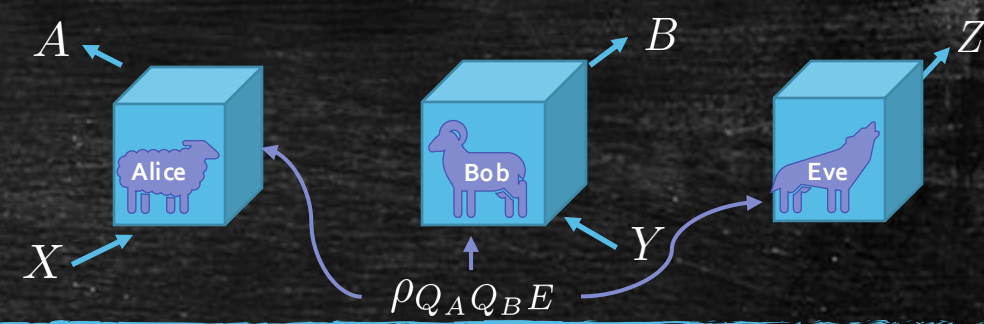
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Not quite a
polynomial
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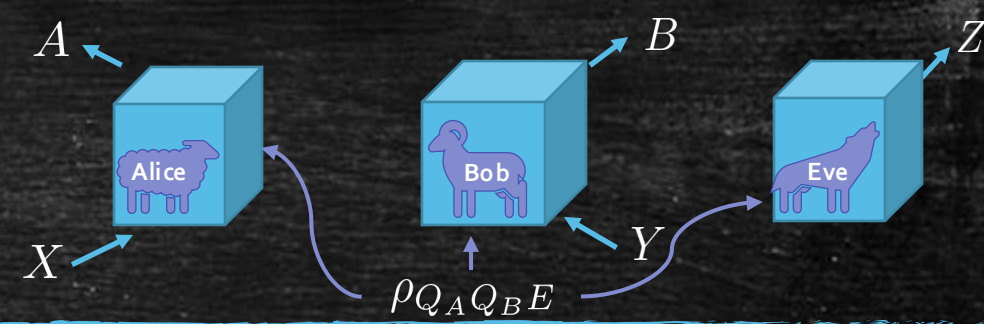
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Need to "forget" the tensor product

$$\widehat{M}_{a|x} = M_{a|x} \otimes I_{Q_B} \otimes I_E \quad \widehat{N}_{b|y} = I_{Q_A} \otimes N_{b|y} \otimes I_E \quad \widehat{Z}_c = I_{Q_A} \otimes I_{Q_B} \otimes Z_c$$

CHSH example



Guessing probability problem

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$$g(\omega) \leq \max \sum_a \text{Tr}[\widehat{M}_{a|0} \widehat{Z}_a \rho]$$

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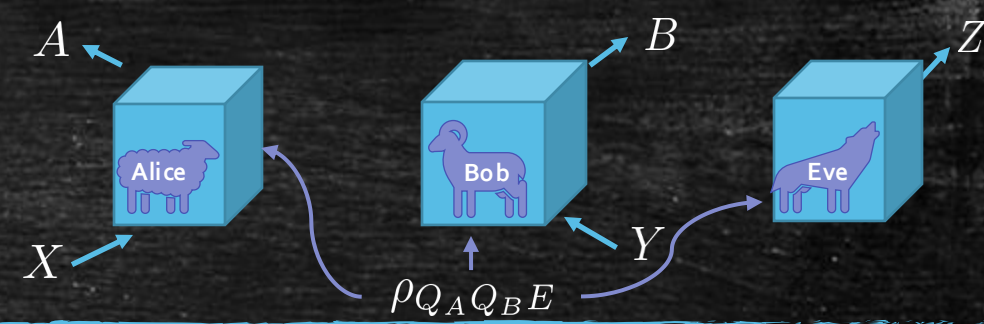
$$\text{Tr}[\rho] = 1, \quad \sum_a \widehat{M}_{a|x} = I, \quad \sum_b \widehat{N}_{b|y} = I, \quad \sum_c \widehat{Z}_c = I$$

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$$\text{Tr}[\rho] = 1, \quad \sum_a \widehat{M}_{a|x} = I, \quad \sum_b \widehat{N}_{b|y} = I, \quad \sum_c \widehat{Z}_c = I$$

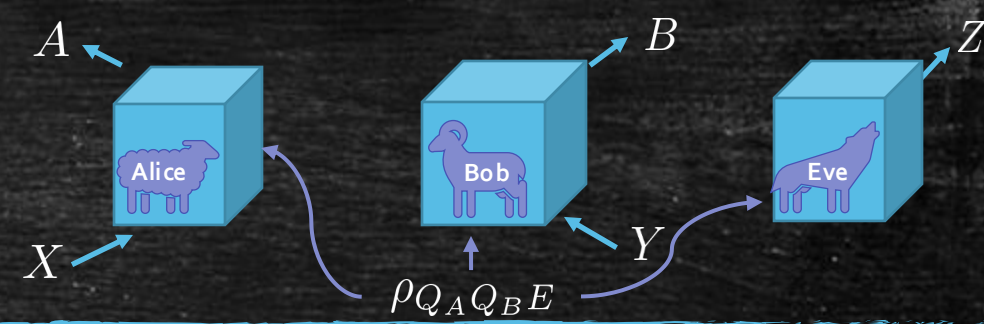
$$[\widehat{M}_{a|x}, \widehat{N}_{b|y}] = 0, \quad [\widehat{M}_{a|x}, \widehat{Z}_c] = 0, \quad [\widehat{N}_{b|y}, \widehat{Z}_c] = 0$$

Relaxes the tensor
product constraint.

Need to "forget" the tensor product

$$\widehat{M}_{a|x} = M_{a|x} \otimes I_{Q_B} \otimes I_E \quad \widehat{N}_{b|y} = I_{Q_A} \otimes N_{b|y} \otimes I_E \quad \widehat{Z}_c = I_{Q_A} \otimes I_{Q_B} \otimes Z_c$$

CHSH example



Guessing probability problem

$$g(\omega) \leq \max \sum_a \text{Tr}[\widehat{M}_{a|0} \widehat{Z}_a \rho]$$

$$\text{s.t.} \quad \frac{1}{4} \sum_{a \oplus b = xy} \text{Tr}[\widehat{M}_{a|x} \widehat{N}_{b|y} \rho] = \omega$$

Not quite a
polynomial
problem yet

Now we have a
polynomial
problem!

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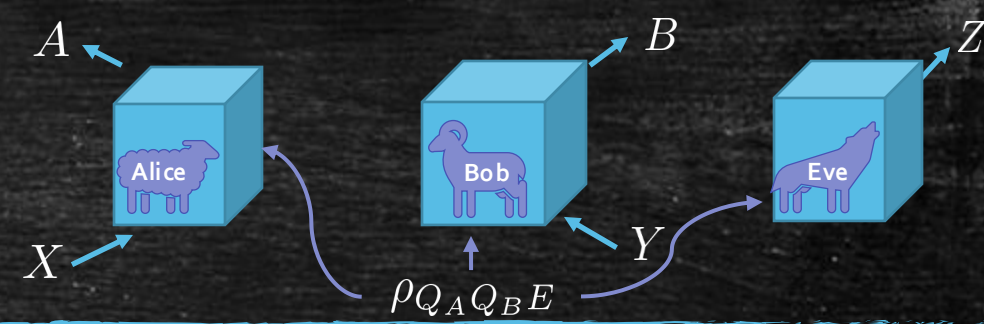
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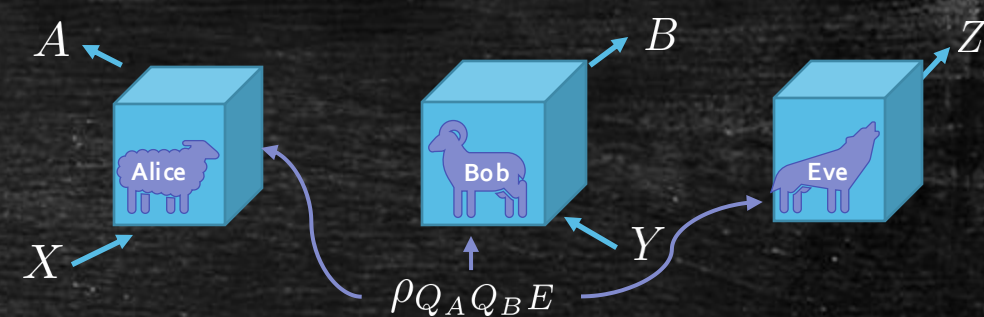
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CHSH example



DI rates are also easy to compute

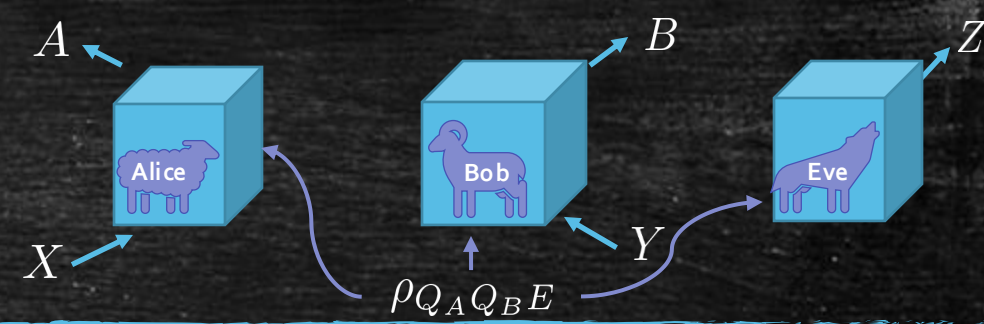
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Name	Language	Code
PCPOP.jl	Julia	https://abh1mishra.github.io/PCPOP.jl/dev/
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CHSH example



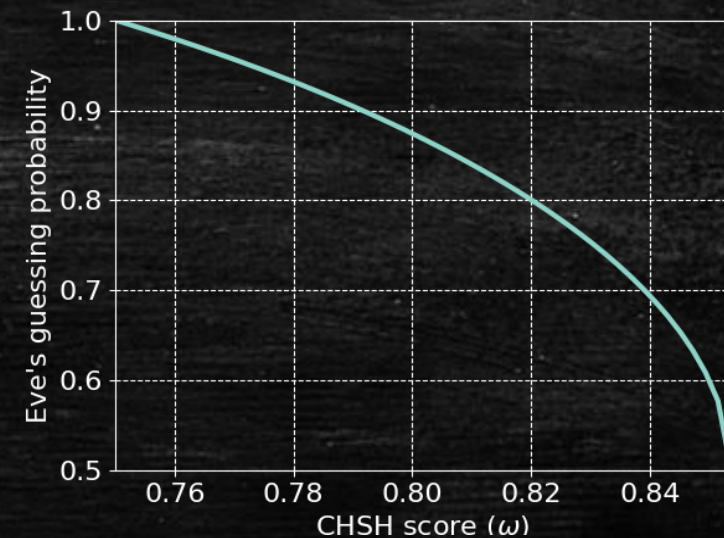
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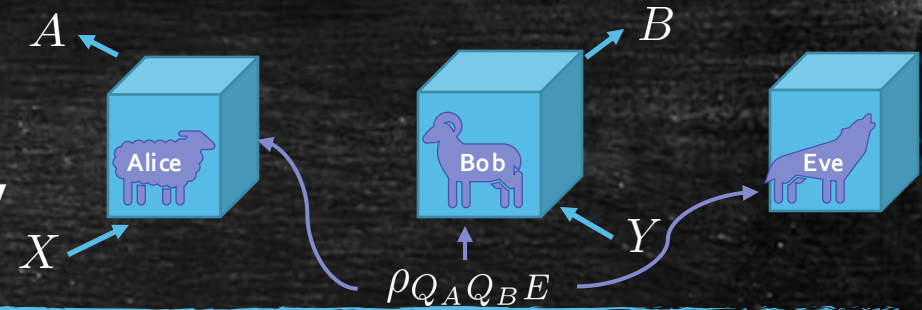
Running the numerics we find:

- Level 1 is not sufficient
- Level 2 gives optimal bound [MPA11]

$$g(\omega) = \frac{1 + \sqrt{2 - (8\omega - 4)^2/4}}{2}$$



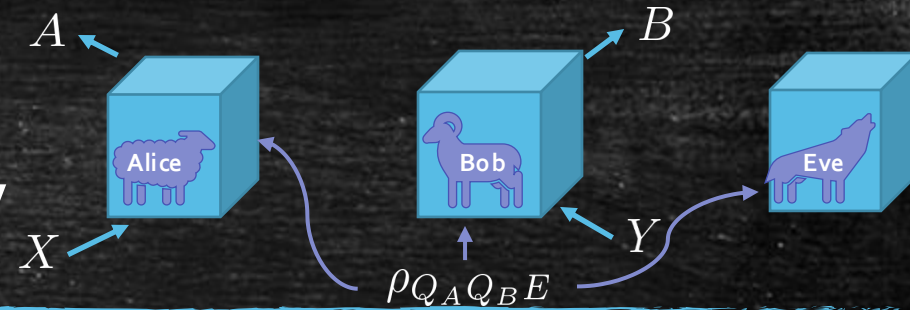
Min vs. von Neumann entropy



Guessing probability gives us a min-entropy bound

$$\min_{\text{Attacks}} H_{\min}(A|X=0, E) \geq -\log g(\omega)$$

Min vs. von Neumann entropy



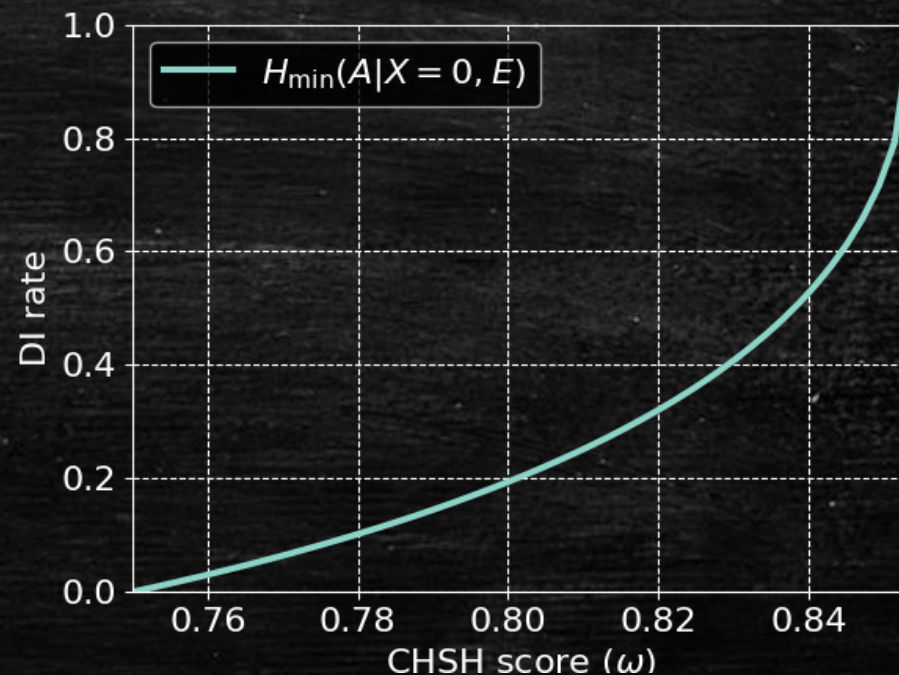
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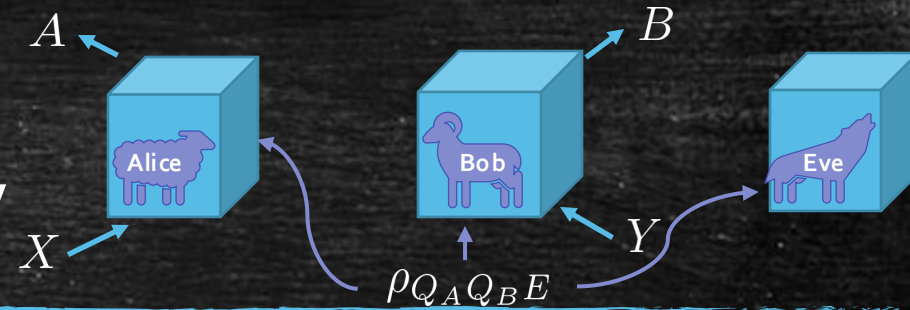
This lower bounds the von Neumann entropy

$$H_{\min}(A|X=0, E) \leq H(A|X=0, E)$$

**Valid lower bound on our
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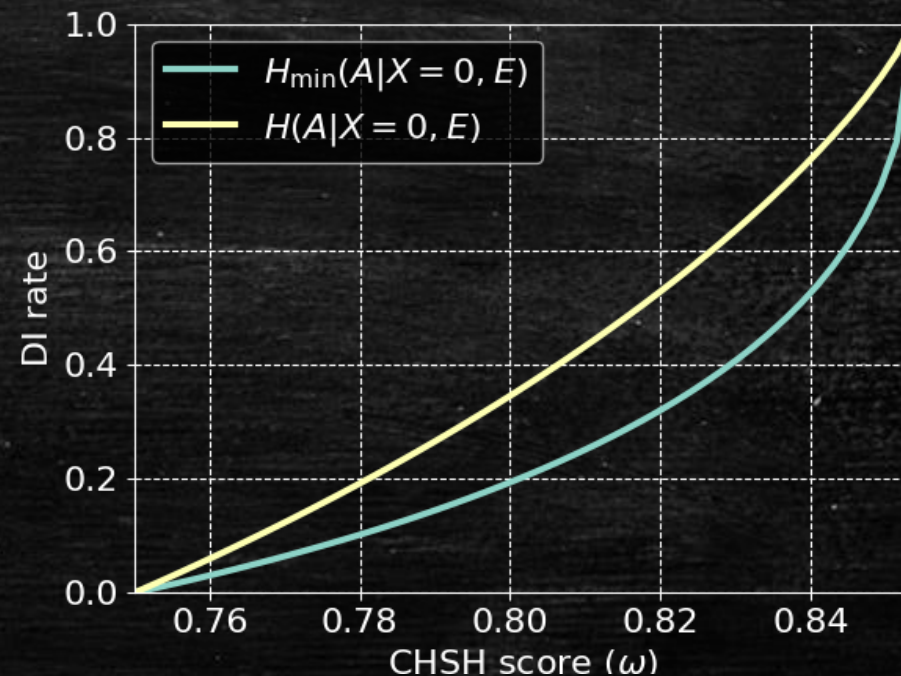
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Valid lower bound on our randomness rates

Far from optimal...

$$\min_{\text{Attacks}} H(A|X=0, E) = 1 - h\left(\frac{1}{2} + \frac{1}{4}\sqrt{(8\omega - 4)^2 - 4}\right)$$

[PABGMS09]



Better bounds on $H(A|E)$?

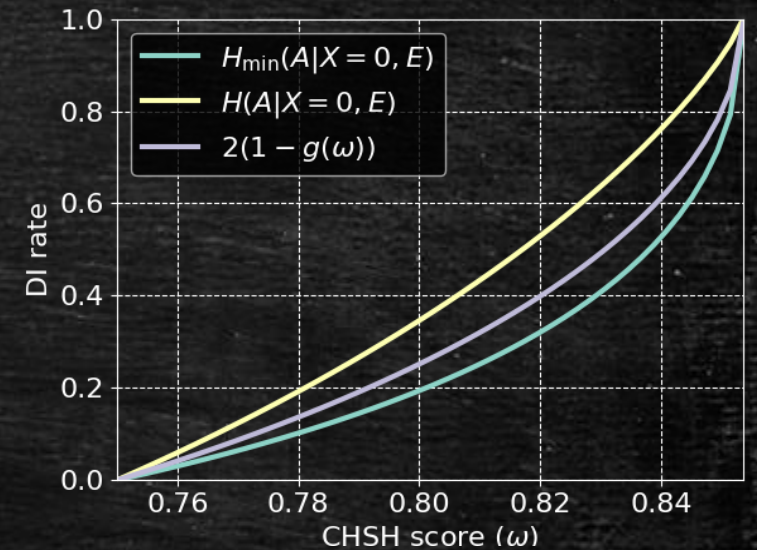
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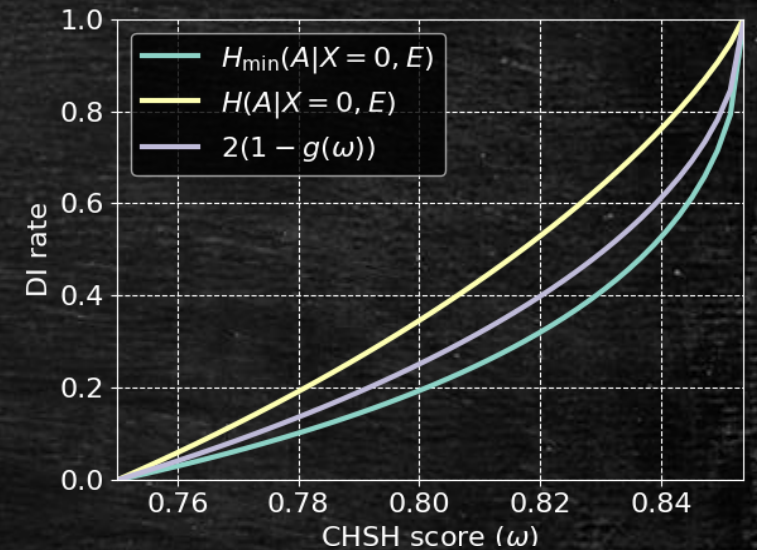
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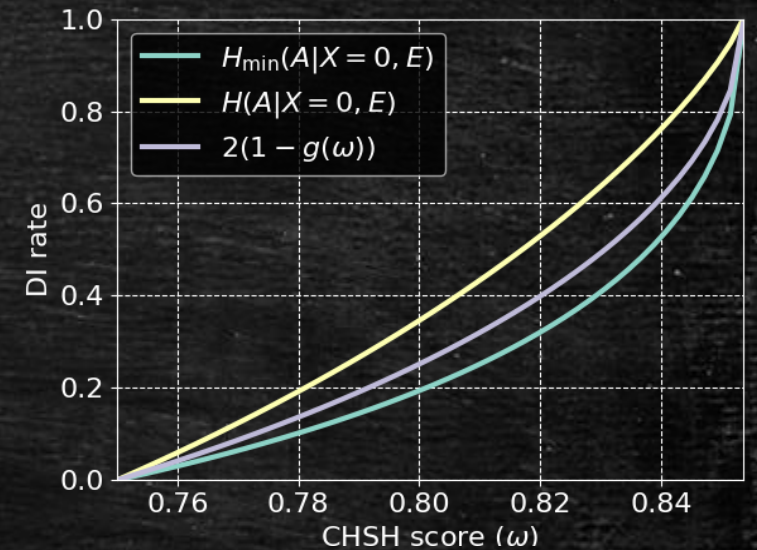
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Better polynomial bounds: Bounds of the form

$$H(A|E) \geq \min \quad \text{Tr}[\rho P(M, N, Z)] \quad [\text{TSGPL21, BFF21, BFF24, KS25}]$$

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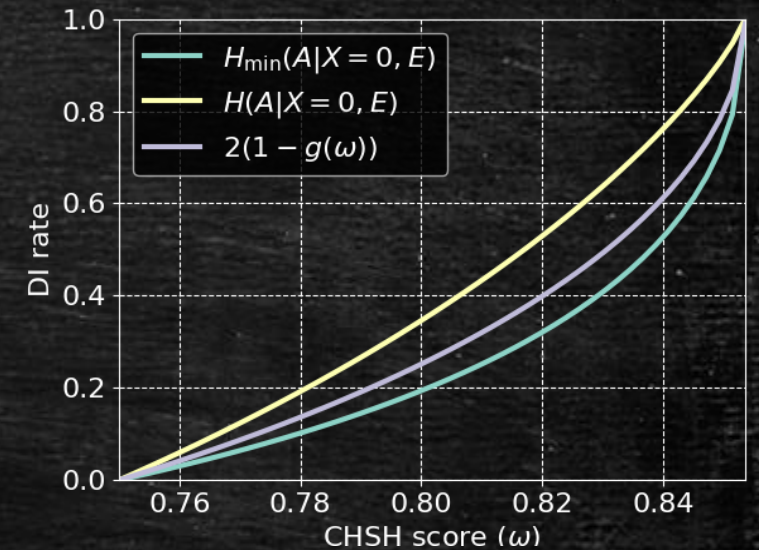
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General and tight*
Quickly too expensive

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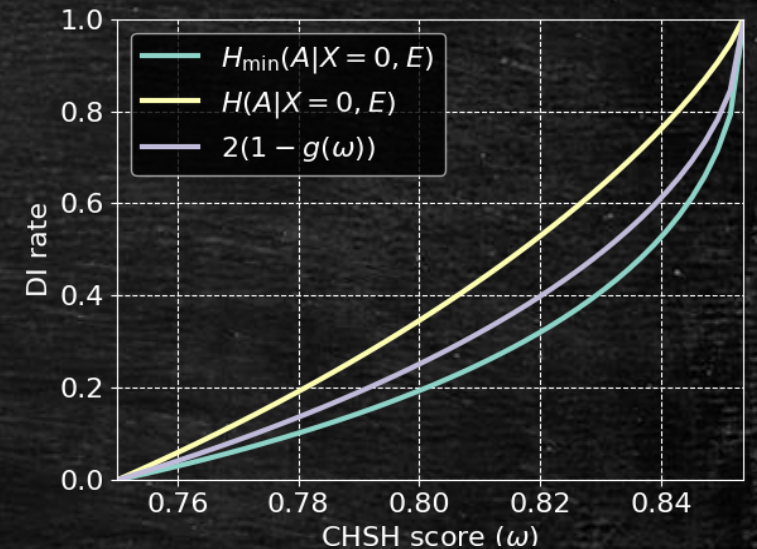
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$$\min_{\text{Attacks}} H(A|E) \longmapsto \min_{\text{Qubit attacks}} H(A|E)$$

[MPW22]

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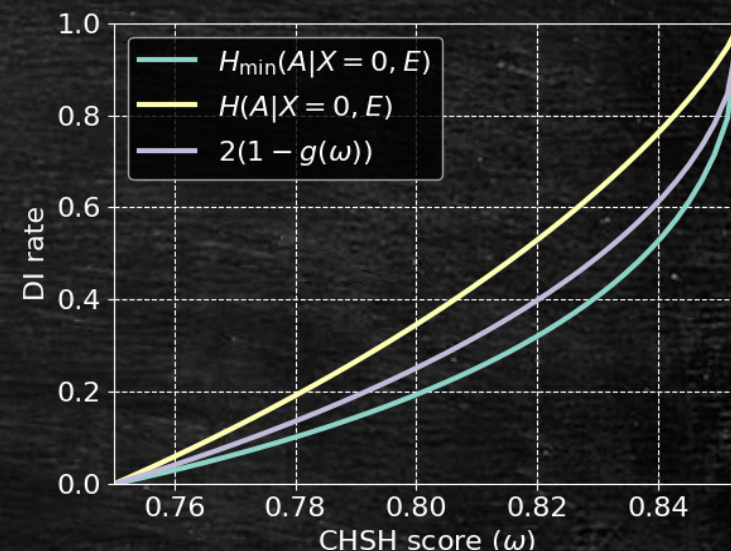
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Hybrid bounds: Analytical reductions + numerics

Fast and tight

Limited scope

$$\min_{\text{Attacks}} H(A|E) \longmapsto \min_{\text{Qubit attacks}} H(A|E)$$

[MPW22]

What's next?

Further topics

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- Different assumptions / attacks
- New convex relaxations (see posters)

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References

- **[PABGMS09]** Pironio, Stefano, et al. "Device-independent quantum key distribution secure against collective attacks." *New Journal of Physics* 11.4 (2009): 045021.
- **[NPA07]** Navascués, Miguel, Stefano Pironio, and Antonio Acín. "A convergent hierarchy of semidefinite programs characterizing the set of quantum correlations." *New Journal of Physics* 10.7 (2008): 073013.
- **[PNA10]** Pironio, Stefano, Miguel Navascués, and Antonio Acín. "Convergent relaxations of polynomial optimization problems with noncommuting variables." *SIAM Journal on Optimization* 20.5 (2010): 2157-2180.
- **[TPBA24]** Tavakoli, Armin, et al. "Semidefinite programming relaxations for quantum correlations." Accepted in *Rev. Mod. Phys.* arXiv:2307.02551 (2023).
- **[BFF21]** Brown, Peter, Hamza Fawzi, and Omar Fawzi. "Computing conditional entropies for quantum correlations." *Nature communications* 12.1 (2021): 575.
- **[BFF24]** Brown, Peter, Hamza Fawzi, and Omar Fawzi. "Device-independent lower bounds on the conditional von Neumann entropy" *Quantum* 8 (2024): 1445.
- **[TSGPL21]** Tan, Ernest Y-Z., et al. "Computing secure key rates for quantum cryptography with untrusted devices." *npj Quantum Information* 7.1 (2021): 158.
- **[KS25]** Koßmann, Gereon and Schwonnek, René. "Reliable Entropy Estimation from Observed Statistics for Device-Independent Quantum Cryptography" arXiv:2411.04858
- **[MPW22]** Masini, Michele, Stefano Pironio, and Erik Woodhead. "Simple and practical DIQKD security analysis via BB84-type uncertainty relations and Pauli correlation constraints." *Quantum* 6 (2022): 843.
- **[BH09]** Briët, Jop, and Peter Harremoës. "Properties of classical and quantum Jensen-Shannon divergence." *Physical Review A—Atomic, Molecular, and Optical Physics* 79.5 (2009): 052311.