

Certifying Local-Realism Violation

Manny

NIST

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Overview

Test Configurations and Models

Bell Functions

Anti-Local-Realism Certificates

Applications to Experiments

Recommendations

Parties, Settings and Measurements

- (2,2,2) (parties, settings choices, measurement outcomes):

	A	00	01	10	11	B	
A							B
	n					n	

Parties, Settings and Measurements

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A		<table><thead><tr><th data-bbox="426 228 499 280">A</th><th data-bbox="499 228 572 280">00</th><th data-bbox="572 228 644 280">01</th><th data-bbox="644 228 717 280">10</th><th data-bbox="717 228 790 280">11</th><th data-bbox="790 228 862 280">B</th></tr></thead><tbody><tr><td data-bbox="426 280 499 335">n</td><td data-bbox="499 280 572 335">0</td><td data-bbox="572 280 644 335">1</td><td data-bbox="644 280 717 335">0</td><td data-bbox="717 280 790 335">0</td><td data-bbox="790 280 862 335">n</td></tr><tr><td data-bbox="426 335 499 390">n</td><td data-bbox="499 335 572 390">1</td><td data-bbox="572 335 644 390">0</td><td data-bbox="644 335 717 390">0</td><td data-bbox="717 335 790 390">0</td><td data-bbox="790 335 862 390">e</td></tr><tr><td data-bbox="426 390 499 445">e</td><td data-bbox="499 390 572 445">0</td><td data-bbox="572 390 644 445">0</td><td data-bbox="644 390 717 445">0</td><td data-bbox="717 390 790 445">1</td><td data-bbox="790 390 862 445">n</td></tr></tbody></table>	A	00	01	10	11	B	n	0	1	0	0	n	n	1	0	0	0	e	e	0	0	0	1	n		B
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Parties, Settings and Measurements

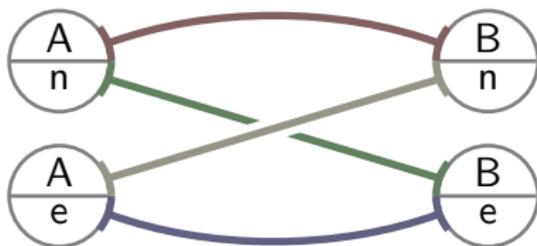
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- Compatibility graph:



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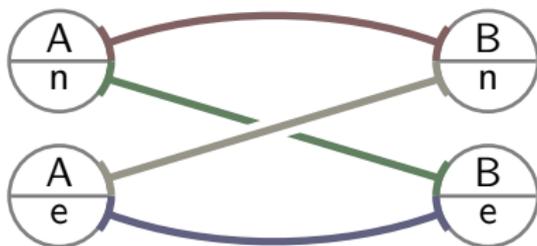
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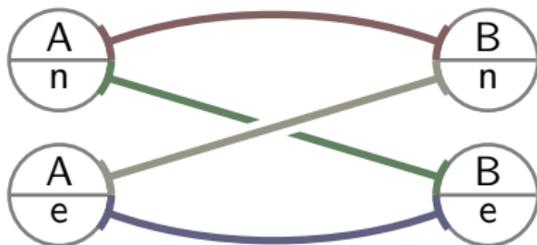
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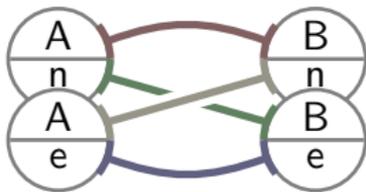


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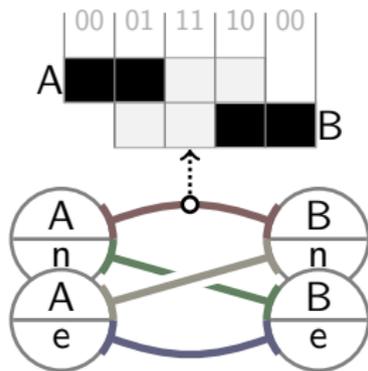


- Trial* record: Outcomes and settings (o_A, o_B, s_A, s_B).
- Trial* model: $\text{Prob}(O_A = o_A, O_B = o_B, S_A = s_A, S_B = s_B | \text{past})$.

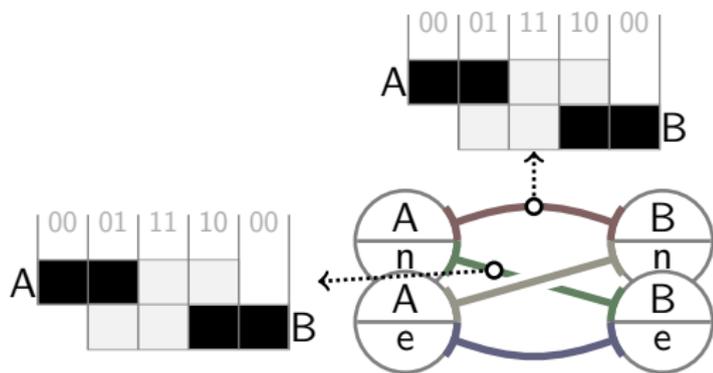
Example I



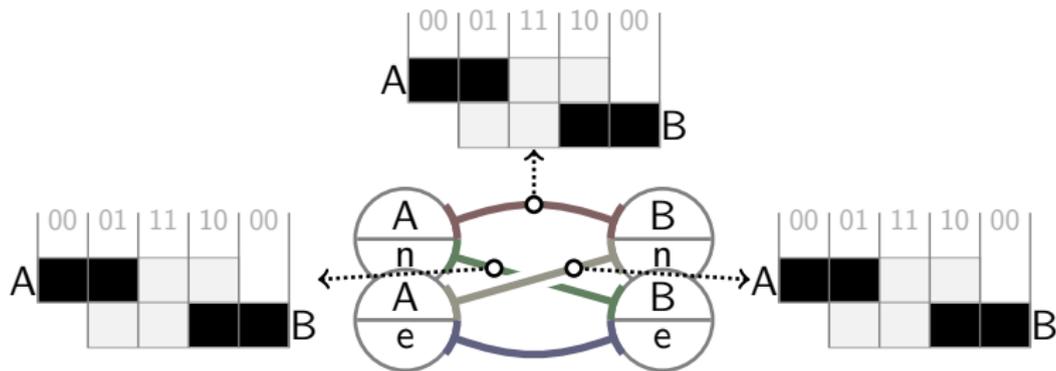
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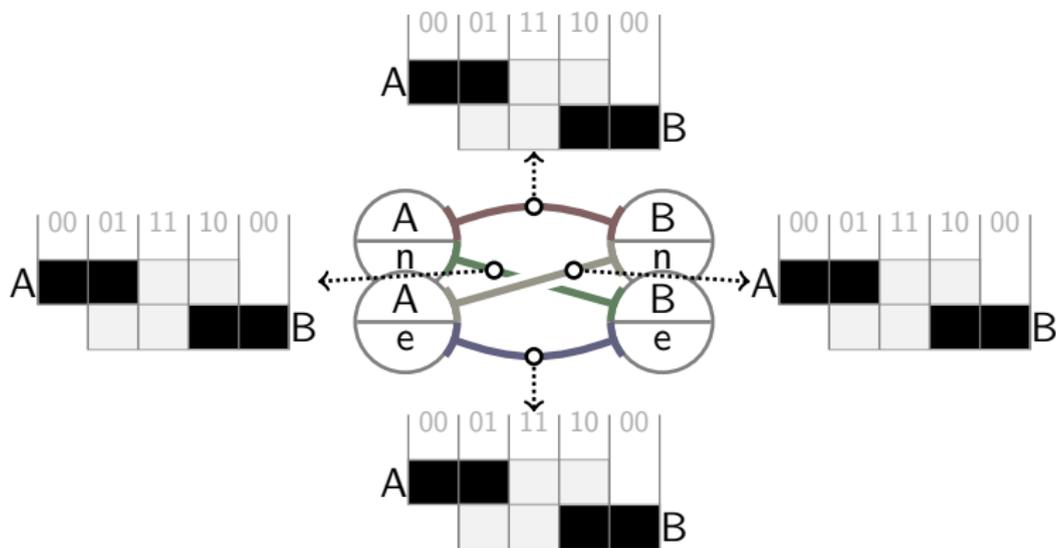
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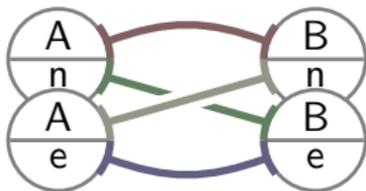
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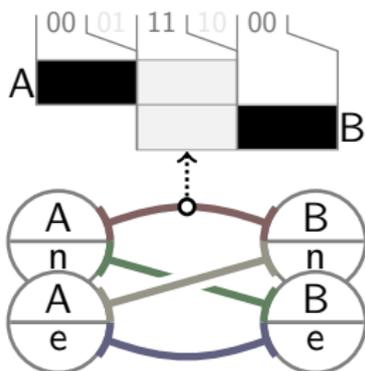
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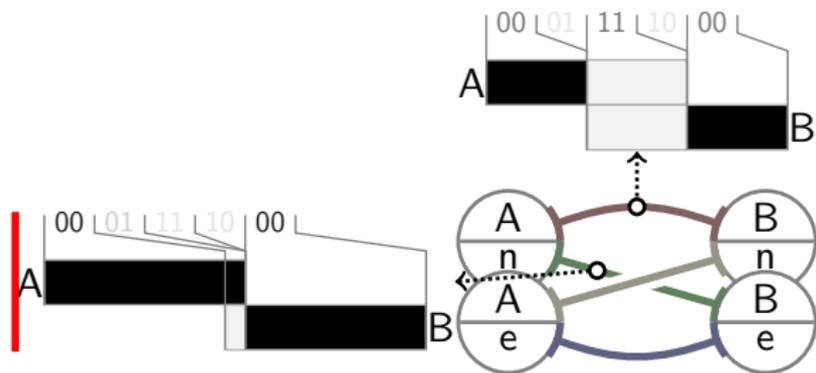
Examples II,III



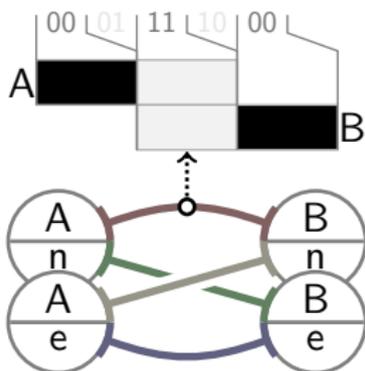
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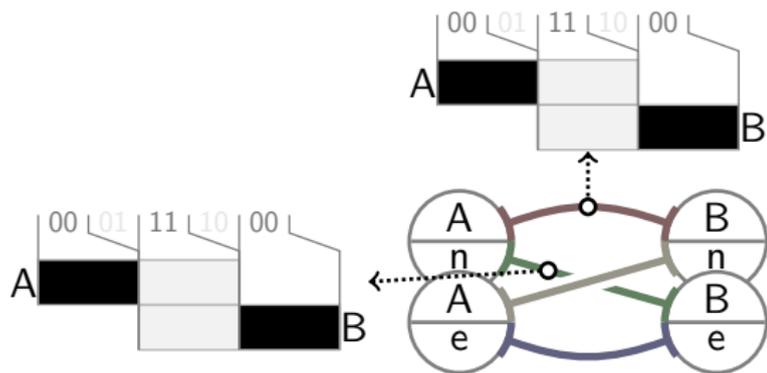
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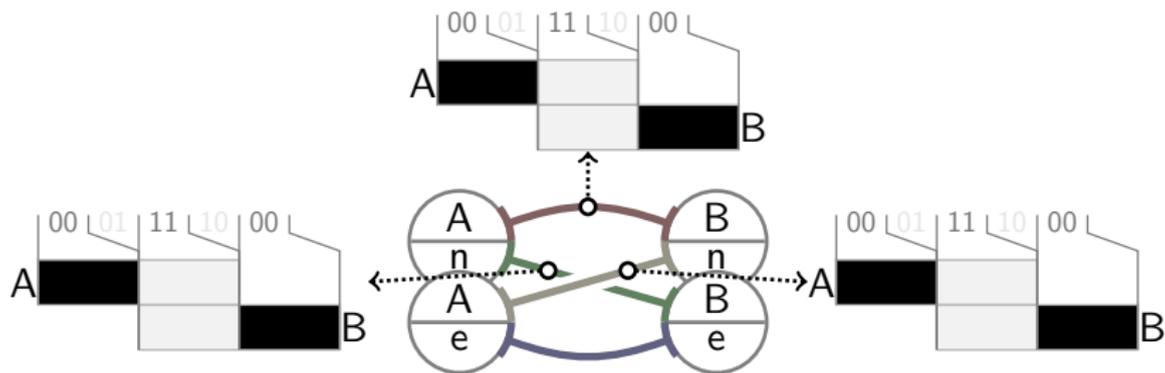
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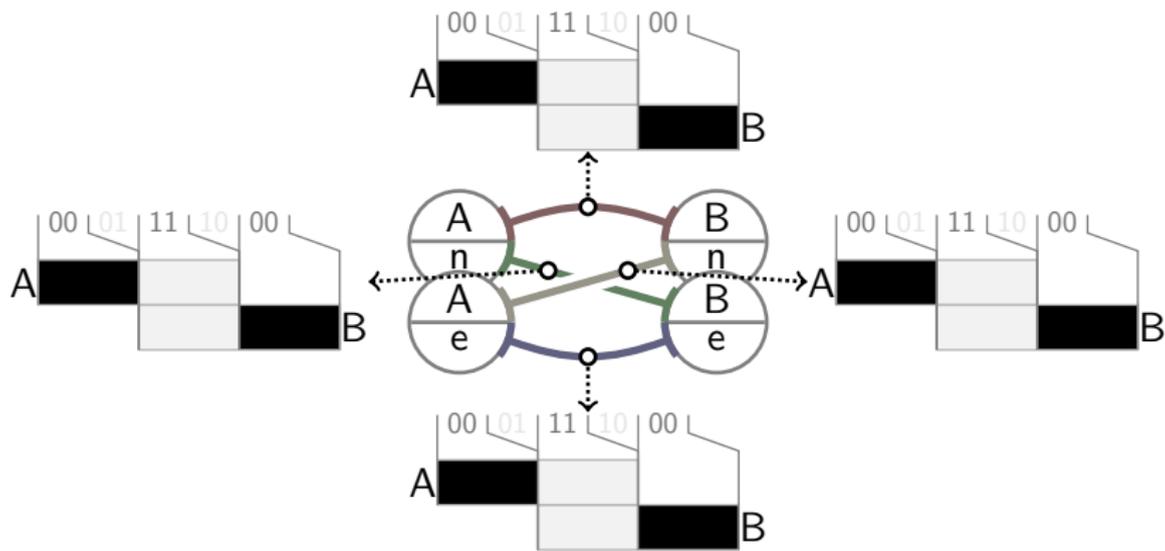
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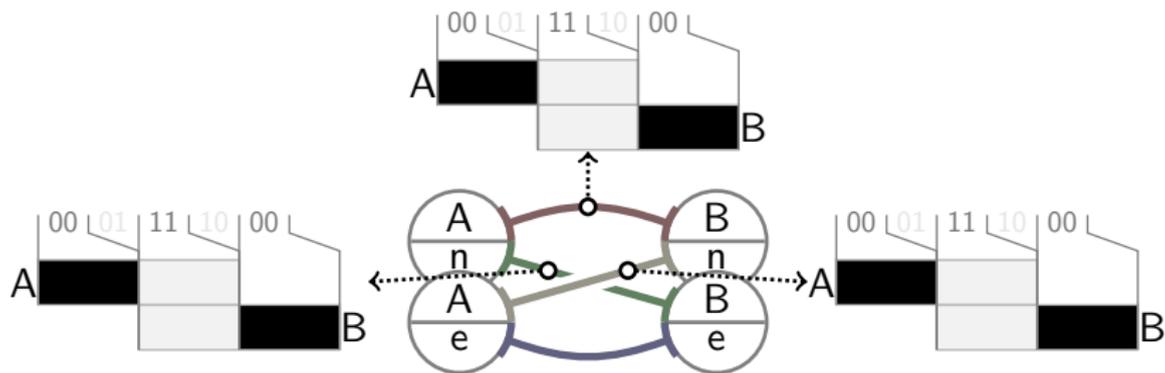
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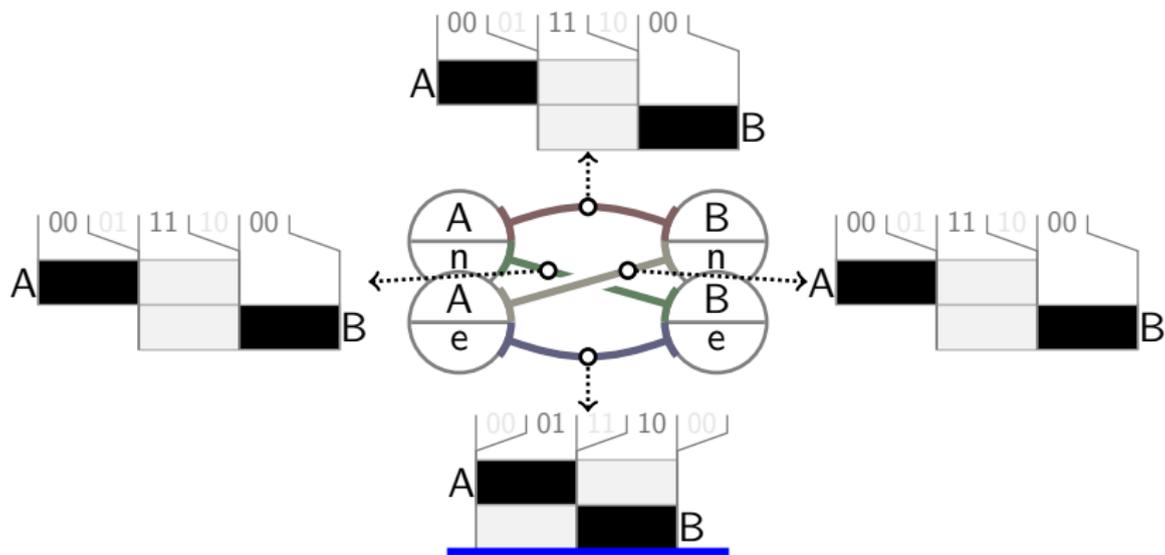
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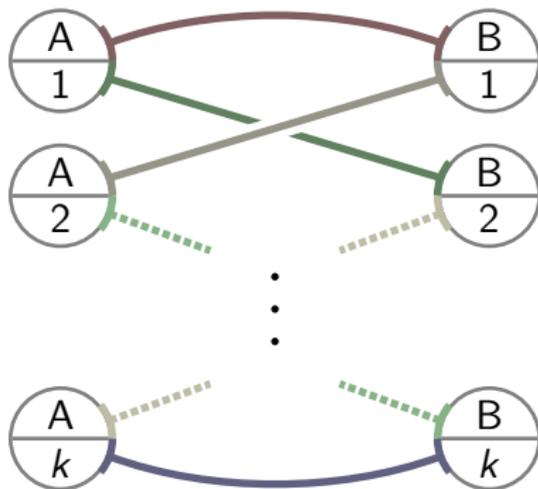
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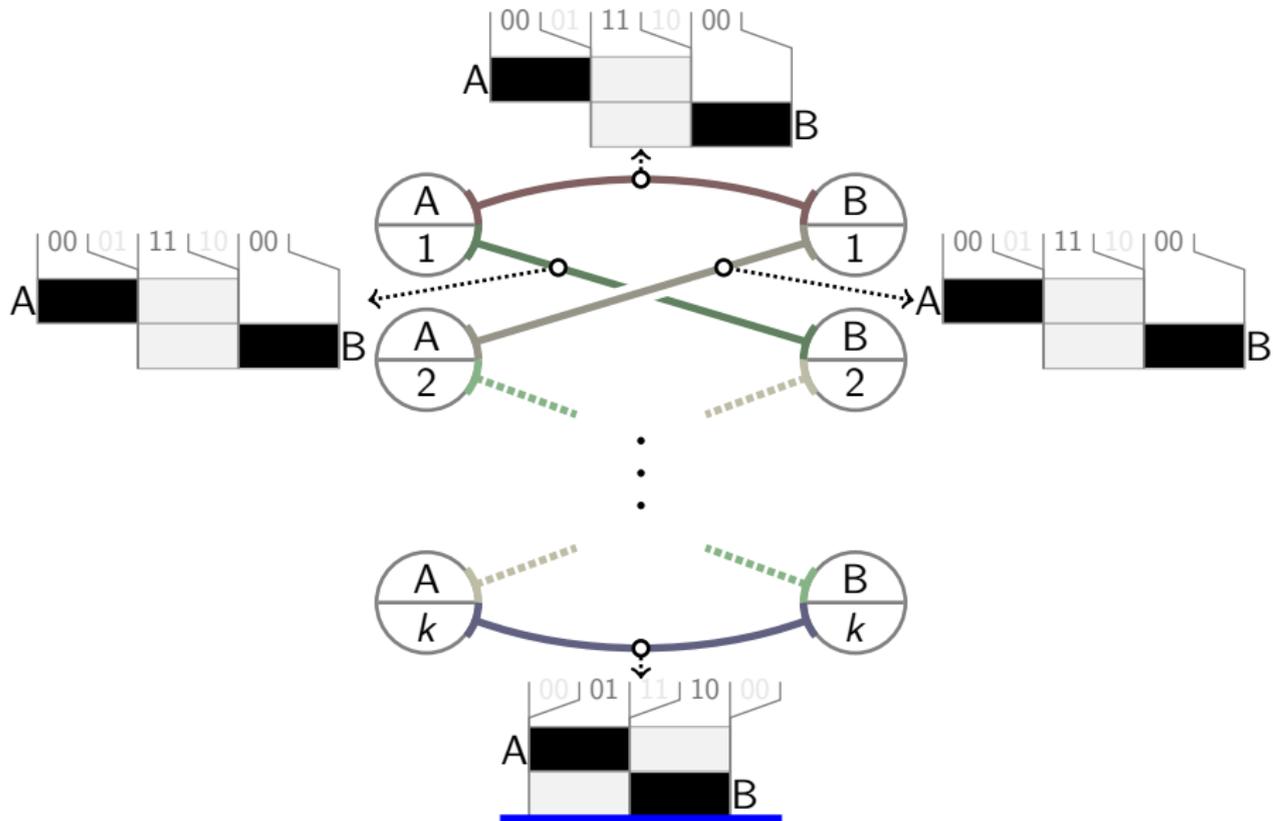
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The $2k$ -cycle



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“chained Bell inequalities”, Braunstein(1990) [1], application in Colbeck&Pironio(2011) [3]

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- Universal pre-trial model.
 - $S = (S_A, S_B, \dots)$: settings random variables,
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- Possible constraints:
 - Remote context independence/no-signaling/consistent marginals.
 - Remote outcome independence.
 - Definiteness given the “complete state”.

Model Constraints to Consider



CI. Remote context independence.

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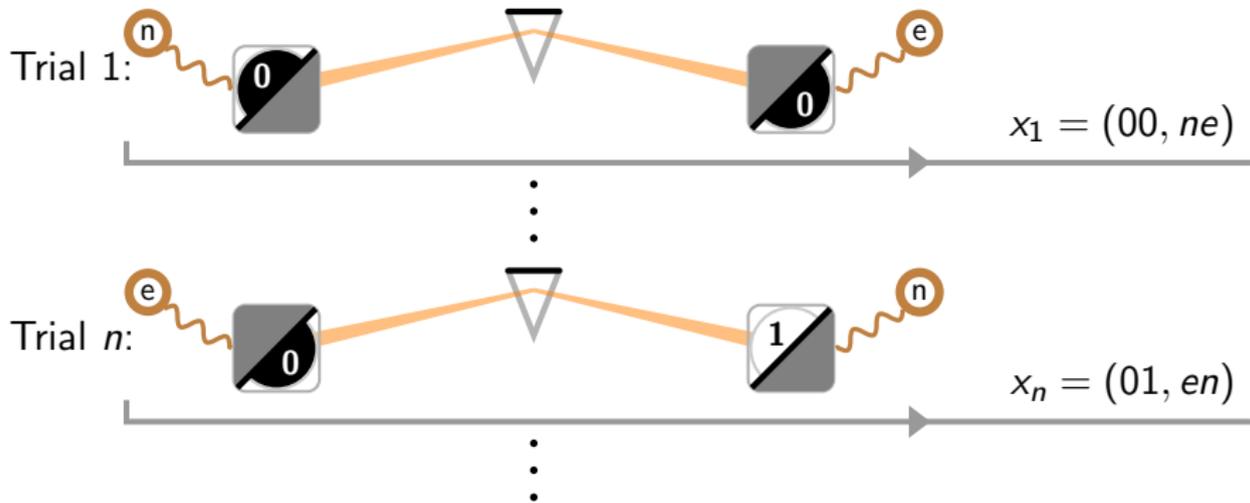
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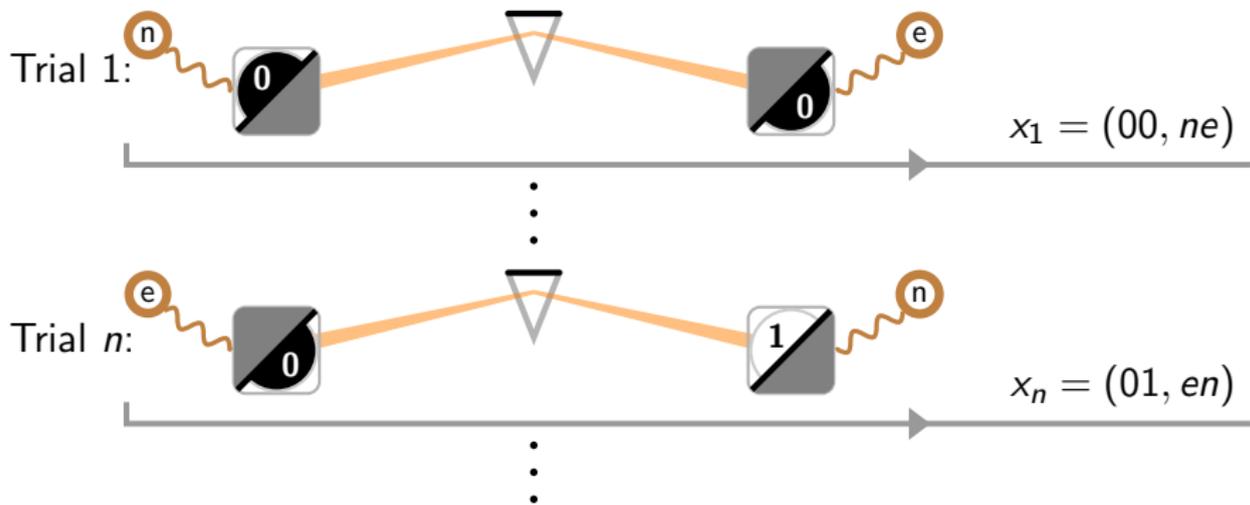
LR. Local realism, $CI \wedge (OI \vee D) \wedge \mu(\lambda)$.

$$\mu(o, s) = \sum_{f: \text{for all } X f_X(s_X) = o_X} \mu(f) \mu(s).$$

Ideal Test

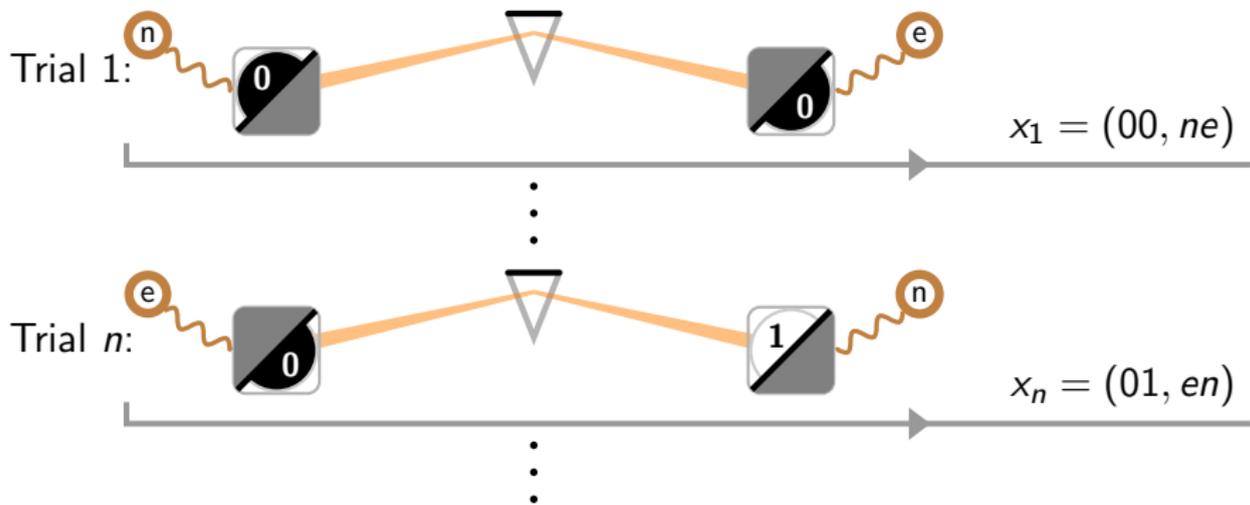


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From $\mathbf{x} = (x_1, \dots, x_n, \dots)$ compute $C_{\neg\mathcal{P}}(\mathbf{x})$, a certificate for $\neg\mathcal{P}$.
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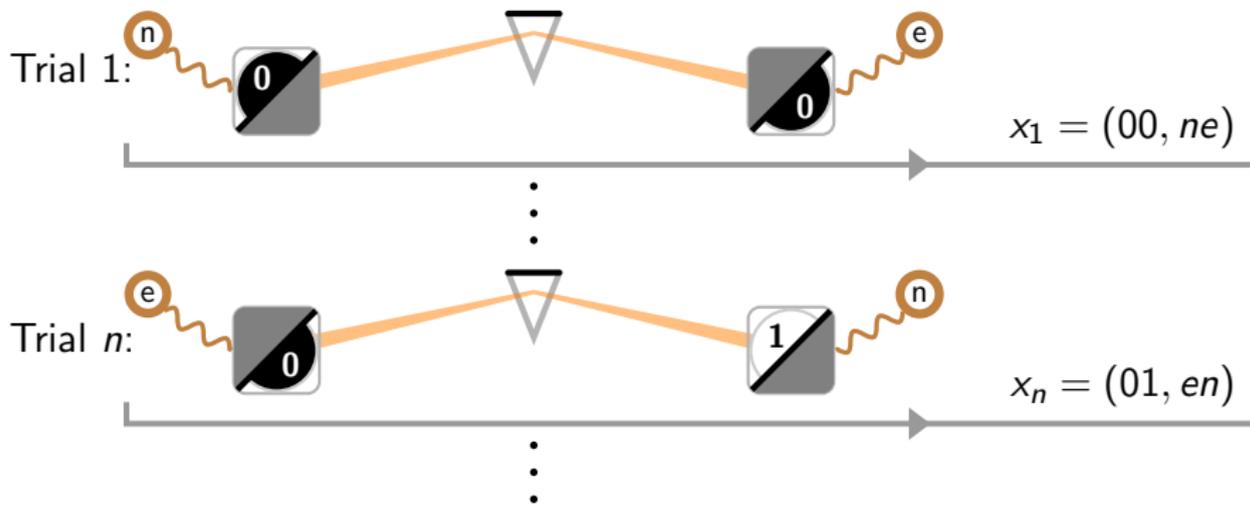
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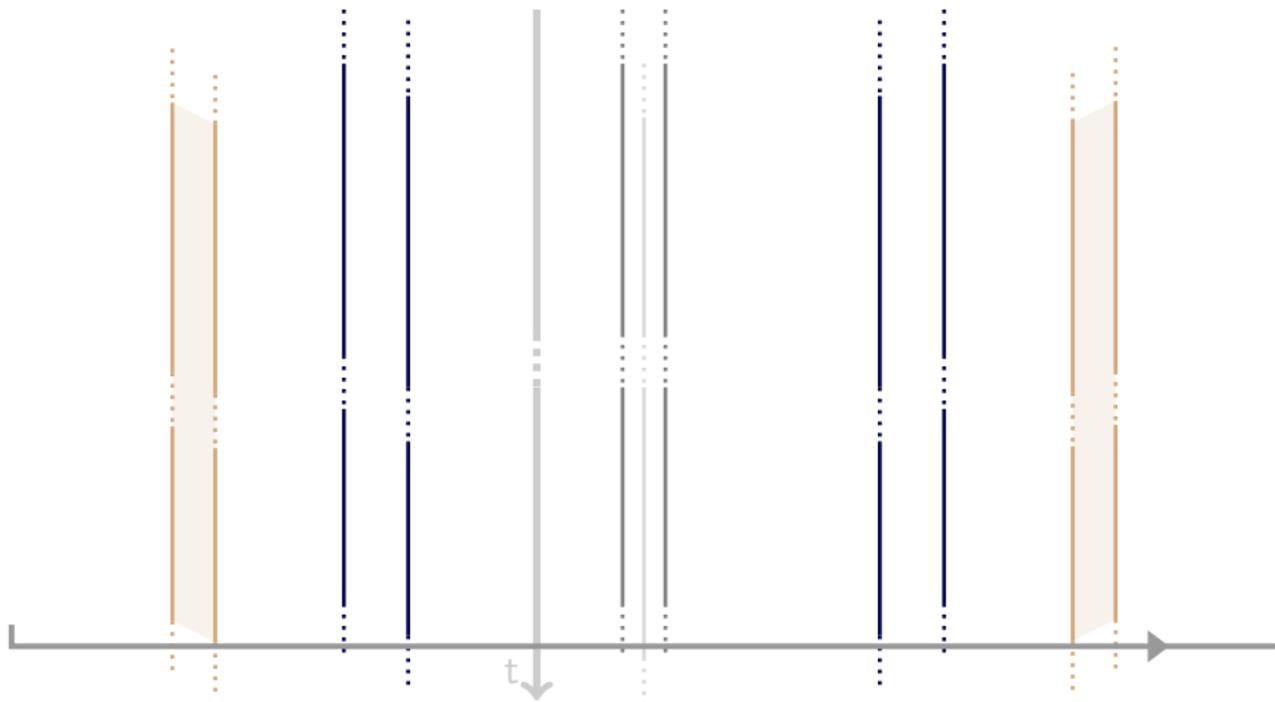
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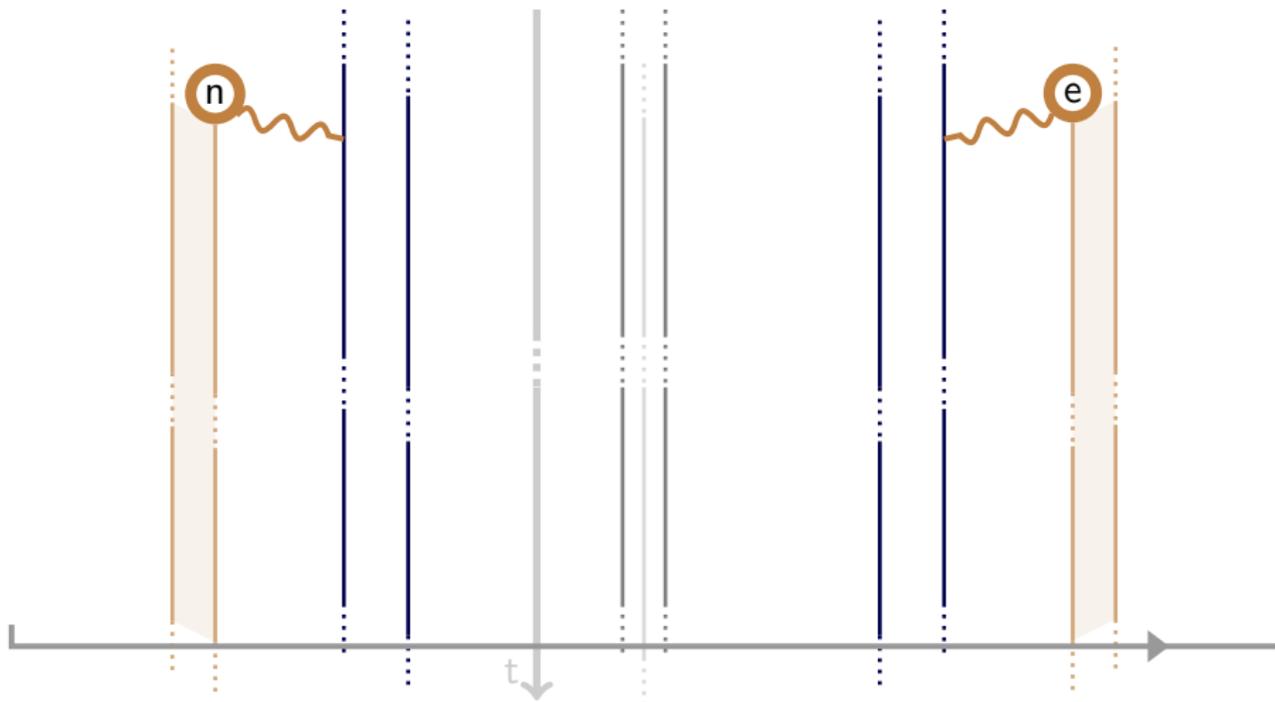
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- Protocols: Constrain hacker’s access.

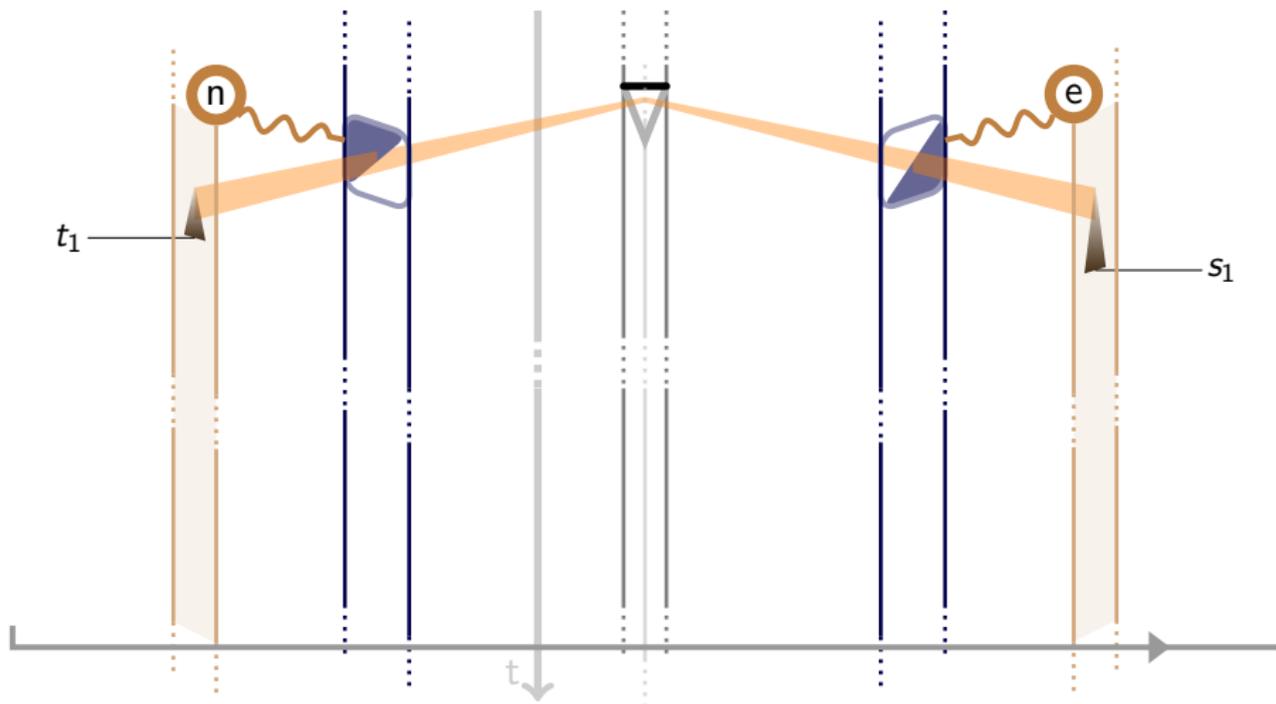
Common Photon-Based Trials



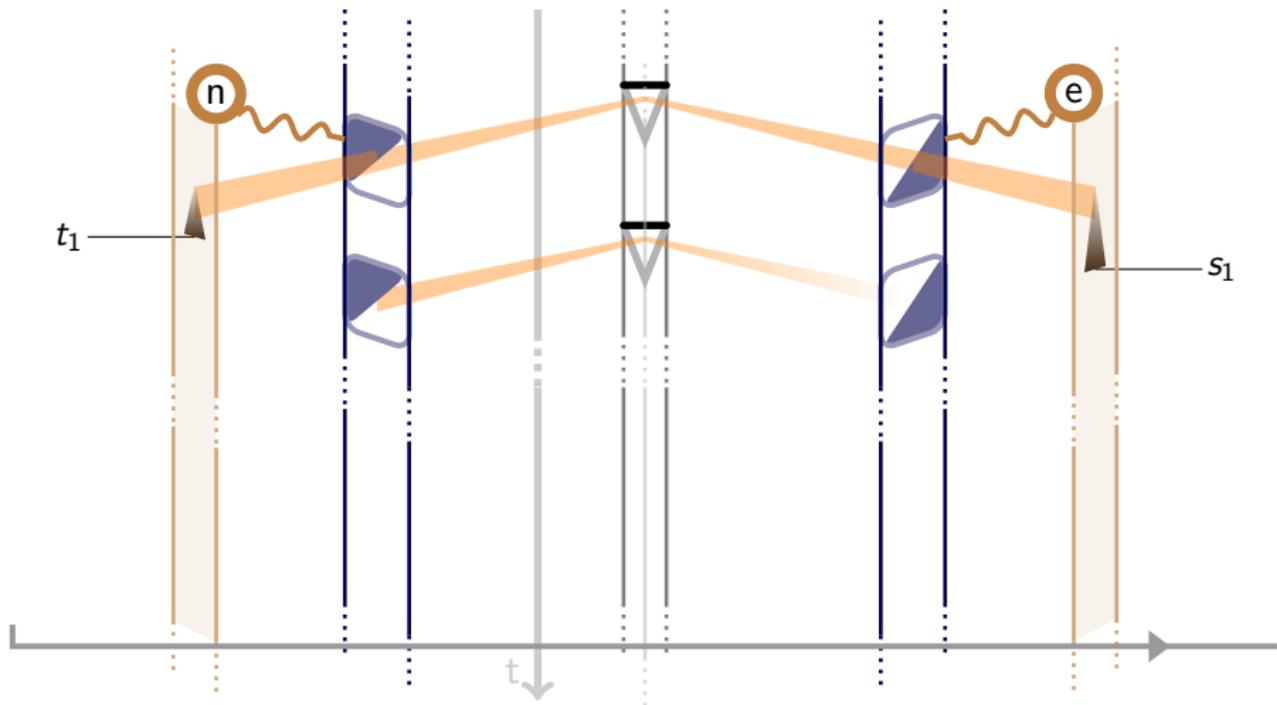
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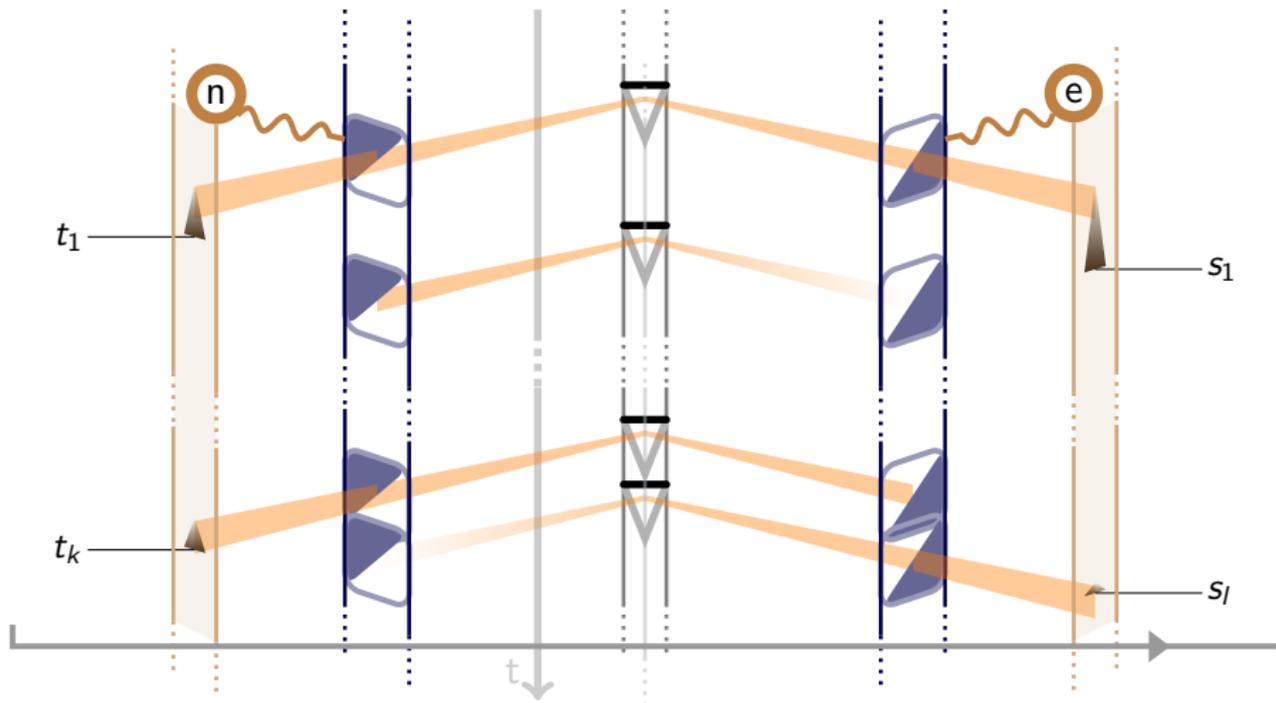
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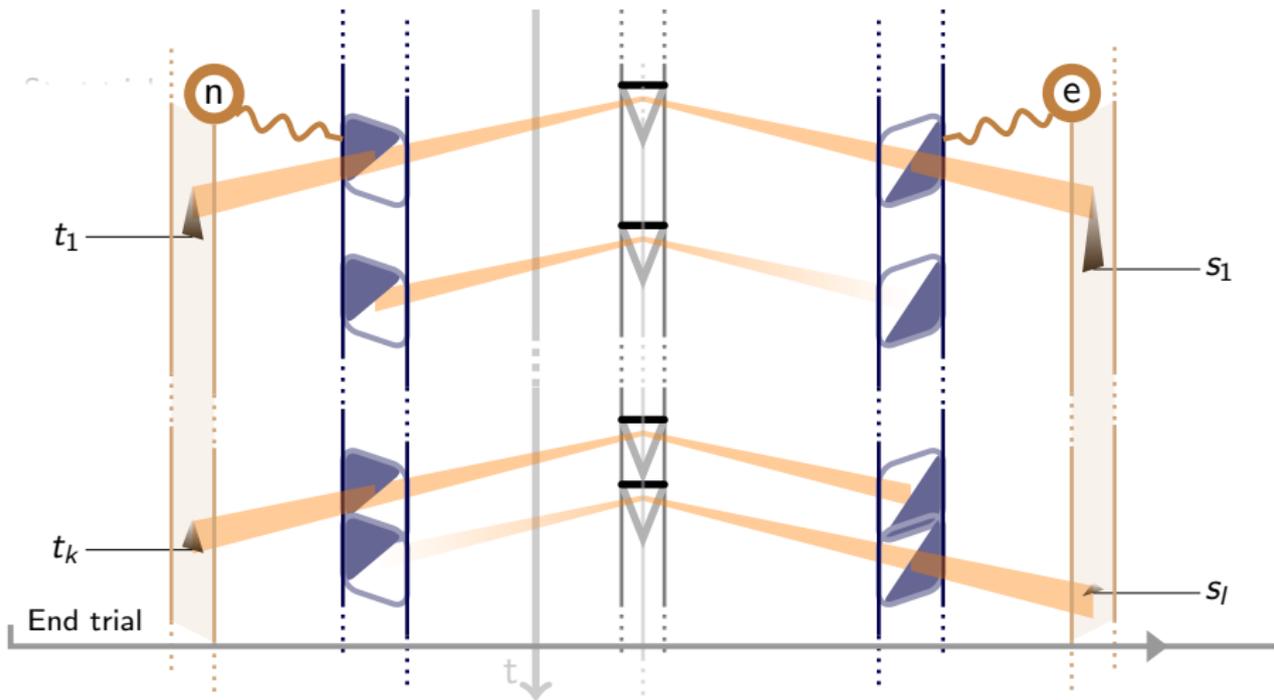
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...this can be considered as *one* trial.

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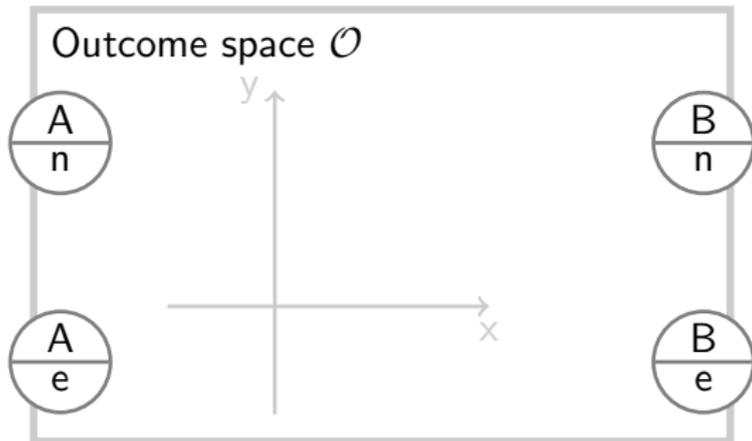
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- Blind the trials: Automated settings choices, no tweaking when settings are “visible”.
- Plan for generation of training data and confirmatory experiments.
- Compute certificates and gain rate per setting bit.
- Report: Certificate values, gain rates *and* model assumptions.

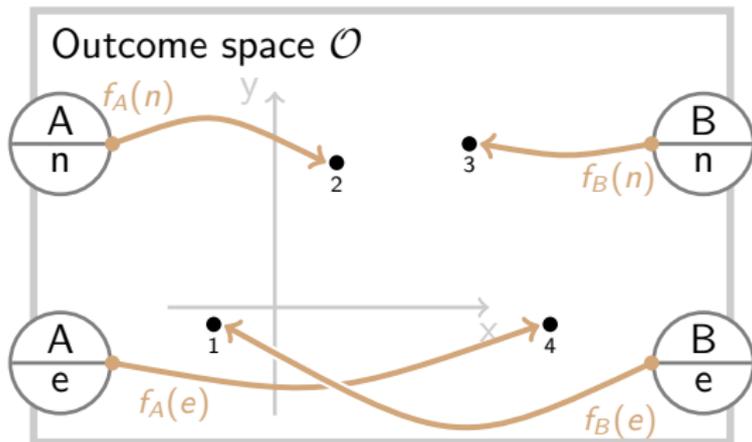
$(2, 2, \mathcal{O})$ -Bell inequalities

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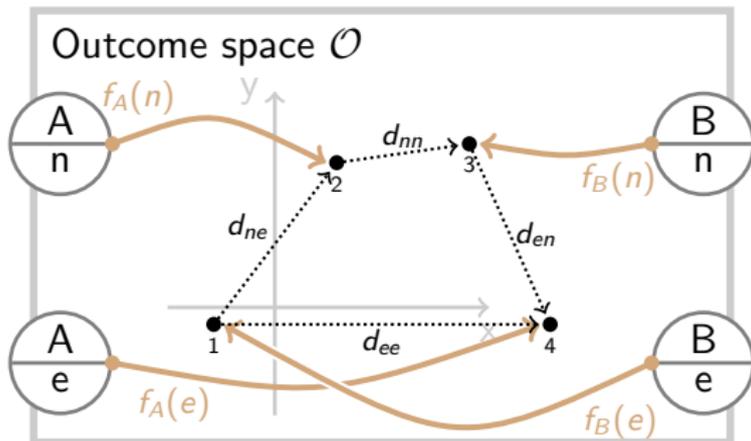
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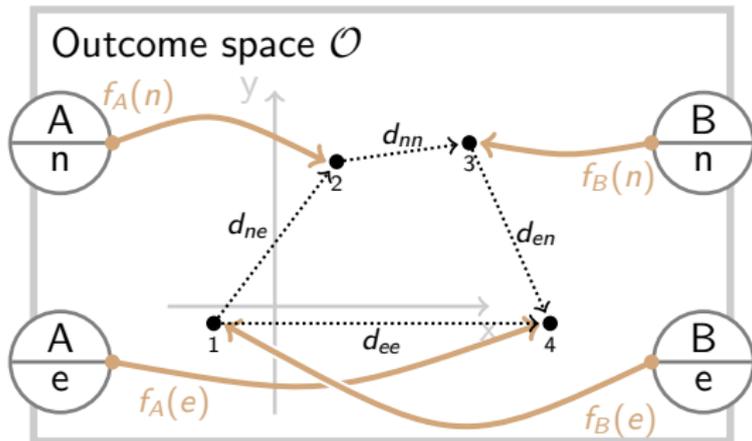
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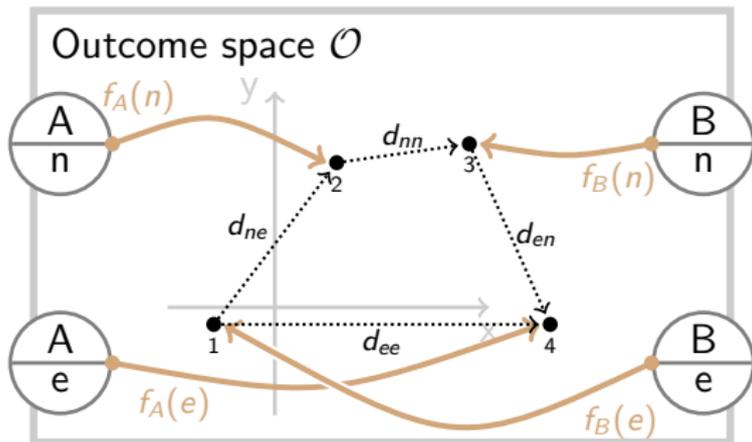


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$$\text{Example. } \mathcal{O} = \{0, 1\}: \begin{cases} d(a, b) = |b - a| & \rightarrow \text{CHSH variant,} \\ d(a, b) = \max(0, b - a) & \rightarrow \text{CH variant.} \end{cases}$$

Bell Functions

Assumptions and context:

- RCI must hold for each trial. RCI:

Remote context independence with control over settings dist. $p(s)$.

$$\mu(o_X|s) = \mu(o_X|s_X), \quad \mu(o, s) = \mu(o|s)p(s).$$

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Bell function: A function $B : (o, s) \mapsto B(o, s) \in \mathbb{R}$ satisfying

$$b_{B,p} \doteq \sup_{\mu \in \text{LRI}(p)} \langle B(O, S) \rangle_{\mu} < \sup_{\mu \in \text{RCI}(p)} \langle B(O, S) \rangle_{\mu}$$

Measuring Bell-Functions

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1. Compute the sample mean $\bar{b} = \sum_i B(o_i, s_i)/N$.
2. Compute the sample variance s^2 .
3. Report $B = \bar{b} \pm s$ and *nominal SNR* $s/(\bar{b} - b_{B,p})$.

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Interpretation:

Average Bell-values of trial states with confidence intervals.

Interpreting Bell Values

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⋮

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Not addressed:

- Fair comparison of experiments w. different configurations, Bell functions, assumptions.
- Fair comparison of implemented trials.
- Quantify ability of LRI to yield observed effects.

Anti-LRI Certificates

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Comparative:

- Certificate: Comparable overall strength.
- Gain rate: Comparable device/configuration strength.
- Independent of experimental details or Bell function, given model assumptions.

Recent Experiments

- Pironio et al. (2010) [7]:
 - Entangled atoms in two iontraps at 1 m.
 - Aim: Certified random number expansion.
 - Average CHSH value: $2 < 2.41(6)$ per trial for 3016 trials.
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- Christensen et al. (2013) [2]:
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 - PBR certificate (\log_2 -p): TBD

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- Plan for generation of training data and confirmatory experiments.
- Compute certificates and gain rate per setting bit.
- Report: Certificate values, gain rates *and* model assumptions.

PBRs: Optimizing Certificate Algorithms

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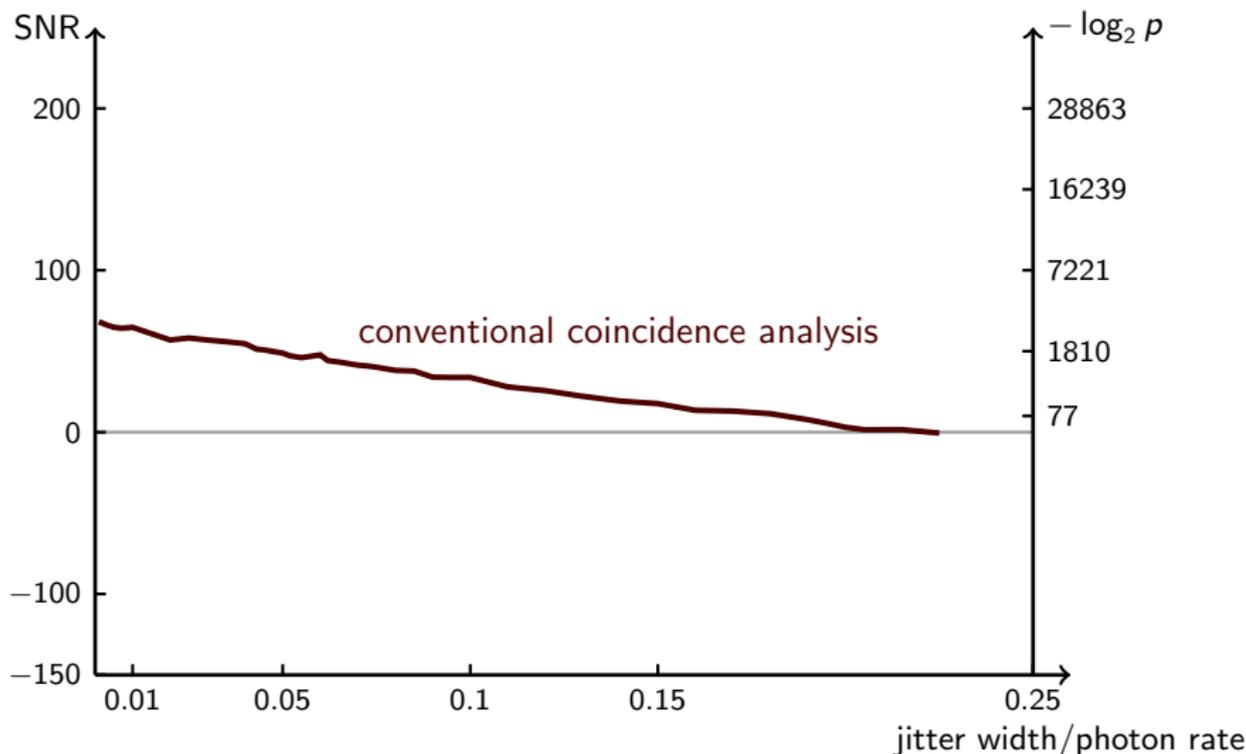
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Features:

- Adapts to changing states, experimental drifts; stop anytime.
- Matches or improves other approaches (e.g. Hoeffding bounds).
- Asymptotically optimal when trials are i.i.d.
- Can automatically optimize equivalent Gaussian SNR.
- Adaptable to unbounded triangle-inequality Bell functions.

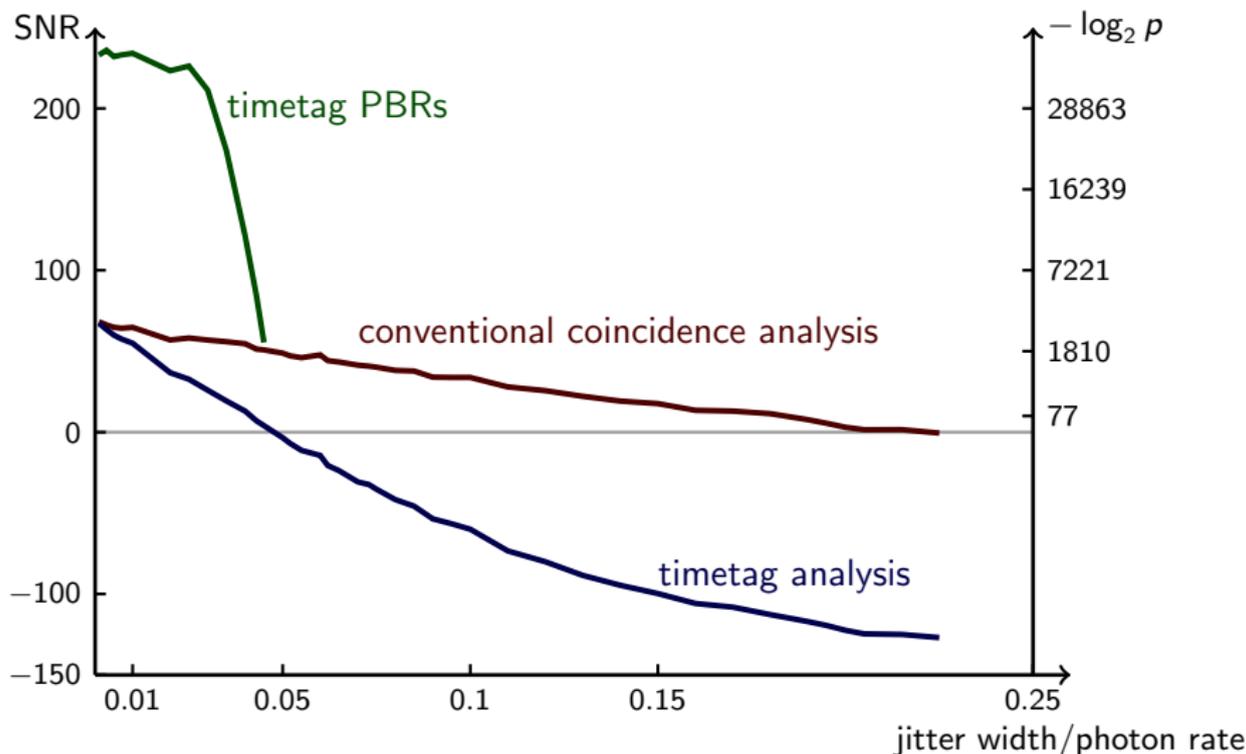
Simulation: Quantum Timetag Trials

Specs: Poisson pairs, efficiency 80%, square jitter.
1 detector/party, CHSH optimized.



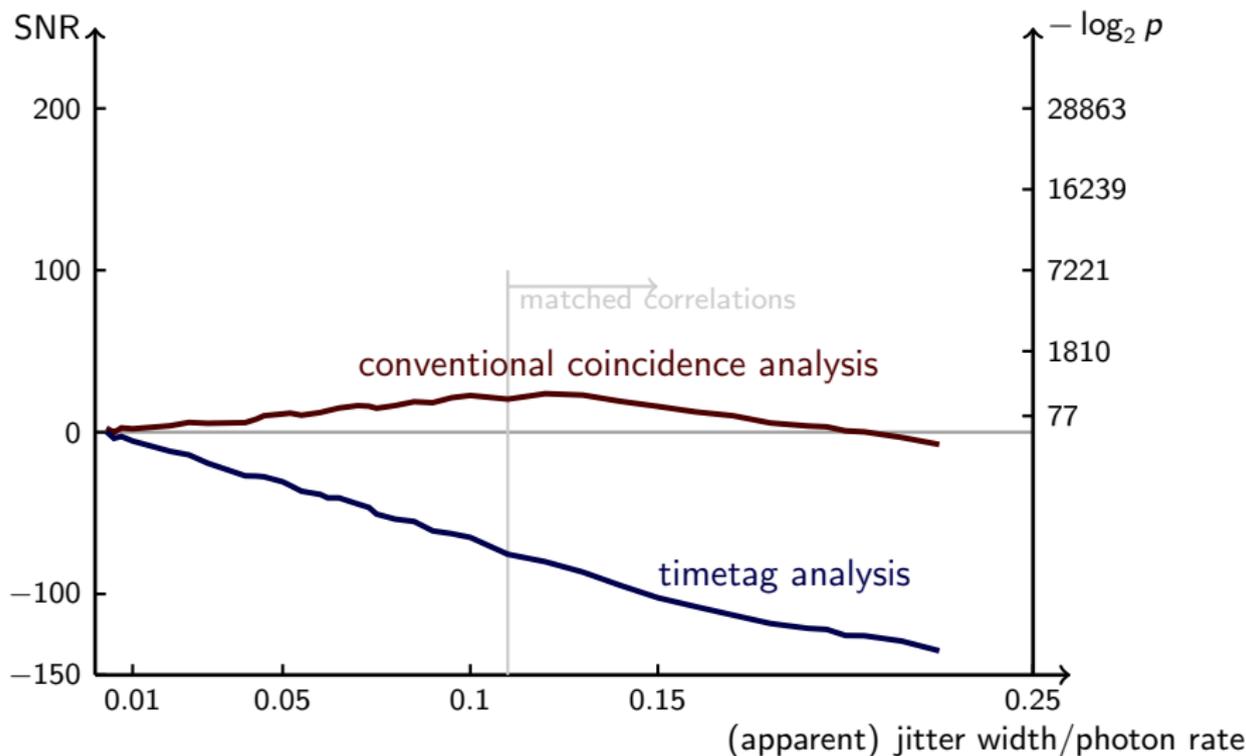
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Simulation: LRI Timetag Trials

Specs: Match 1st and 2nd-order q. counting statistics at high apparent jitter.



TOC I

0.0.1. Title Page

0.0.2. Overview

1.1.1. Parties, Settings and Measurements

1.1.2. Example I

1.1.3. Examples II,III

1.1.4. The $2k$ -cycle

1.1.5. General Measurement-Outcome Model

1.1.6. Model Constraints to Consider

1.1.7. Ideal Test

1.1.8. Common Photon-Based Trials

1.2.1. Recommendations

2.1.1. $(2, 2, \mathcal{O})$ -Bell inequalities

2.1.2. Bell Functions

2.1.3. Measuring Bell-Functions

2.1.4. Interpreting Bell Values

3.1.1. Anti-LRI Certificates

3.1.2. Interpretation of Anti-LRI Certificates

4.1.1. Recent Experiments

5.1.1. Recommendations

5.1.2. PBRs: Optimizing Certificate Algorithms

5.1.3. Simulation: Quantum Timetag Trials

5.1.4. Simulation: LRI Timetag Trials

5.1.5. TOC

5.1.6. References

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