Title: A quantum tale of causes and effects

Speakers: Rafael Chaves

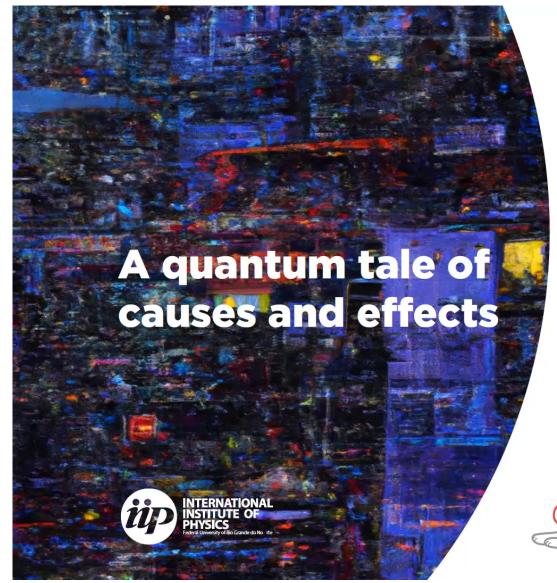
Collection: Causal Inference & Quantum Foundations Workshop

Date: April 19, 2023 - 2:00 PM

URL: https://pirsa.org/23040117

Abstract: Explaining the natural world through cause-and-effect relations is the fundamental principle of science. Although a classical theory of causality has been recently introduced, enabling us to model causation across diverse research fields, it is crucial to examine which aspects of it require modification or abandonment to also comprehend causality in the quantum world. To address this question, we will investigate paradigmatic scenarios, including the double slit, Bell's theorem and generalizations to quantum networks, also exploring recent experimental advancements.

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#### **Rafael Chaves**

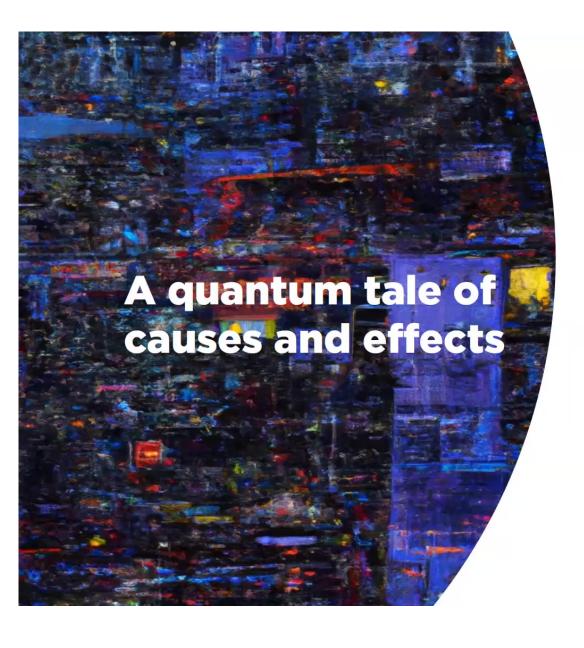
Causal Inference & Quantum Foundations Workshop 2023



Quantum Information and Quantum Matter Group

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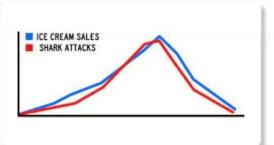


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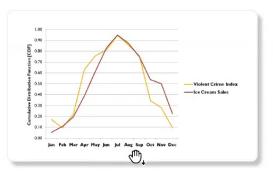


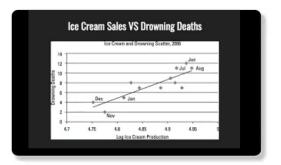


Don't blame the ice cream



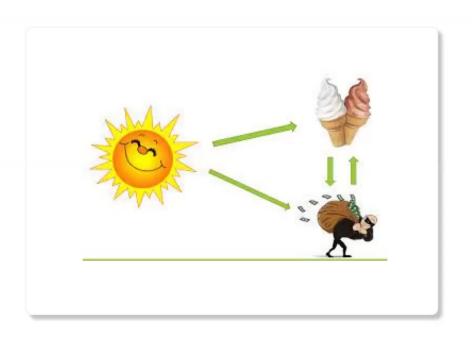






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Correlation does not imply causation!



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"Correlation supersedes causation, and science can advance even without coherent models, unified theories, or really any mechanistic explanation at all.

...

Correlation is enough. We can stop looking for models. We can analyze the data without hypotheses about what it might show. We can throw the numbers into the biggest computing clusters the world has ever seen and let statistical algorithms find patterns where **science cannot**.



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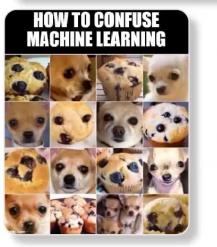
# Correlation does not imply causality but...

"Very large databases have to contain **arbitrary correlations**. These correlations appear only due to the size, not the nature, of data... **most correlations are spurious**. **Too much information** tends to behave like **very little information**. The scientific method can be enriched by computer mining in immense databases, but not replaced by it."

#### The Deluge of Spurious Correlations in Big Data

Cristian S. Calude & Giuseppe Longo

Foundations of Science 22 (3):595-612 (2016) <sup>(2)</sup> Copy <sup>(2)</sup> BBT<sub>E</sub>X







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If we look enough, we will always find patterns where there is only noise...

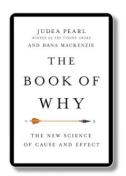


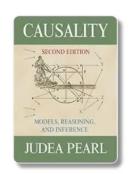
Data cannot be interpreted in a theoretical vacuum!
We should start with an hyphotesis and only then generate the date to confirm or falsify it!

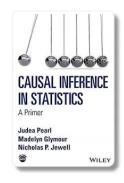
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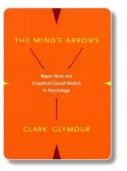


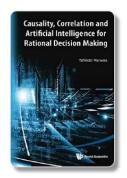
# Causality Theory

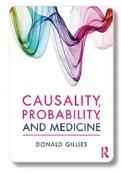




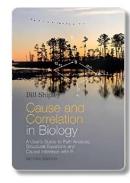


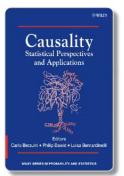












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## • DAGs and the Language of Causality

- Double slit experiment
- Quantifying quantum causality
- Quantum networks

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"If an improbable coincidence has ocurred, there must exist direct influence and/or a common cause."





# Reichenbach's principle:

no correlation without causation.

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"If an improbable coincidence has ocurred, there must exist direct influence and/or a common cause."





# Reichenbach's principle:

no correlation without causation.

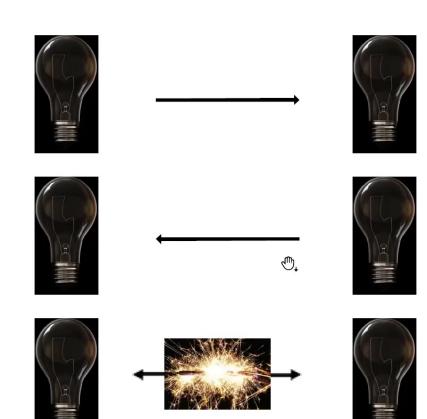
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"If an improbable coincidence has ocurred, there must exist direct influence and/or a common cause."

# Reichenbach's principle:

no correlation without causation.



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"If an improbable coincidence has ocurred, there must exist direct influence and/or a common cause."









no correlation without causation.













Task: Infer causal relationships from observational (statistical) data.

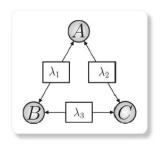


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DAGs: Representing causal relations For n variables  $X_n$ , ...,  $X_n$ , the causal relationships are encoded in a causal structure, represented by a **directed acyclic graph** (DAG), with ith variable being a deterministic

$$x_i = f_i(pa_i, u_i)$$

of its parents  $\mathbf{pa_i}$  and jointly independent noise variables  $\mathbf{u_i}$ 

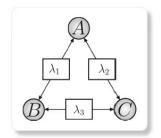


## DAGs: Representing causal relations

For n variables  $X_{1}$ , ...,  $X_{n}$ , the causal relationships are encoded in a **causal structure**, represented by a **directed acyclic graph** (DAG), with ith variable being a deterministic

$$x_i = f_i(pa_i, u_i)$$

of its parents  $\mathbf{pa_i}$  and jointly independent noise variables  $\mathbf{u_i}$ 



- Causal relationships are encoded in the conditional
- independencies (CIs) implied by the DAG

$$p(\lambda_1, \lambda_2) = p(\lambda_1)p(\lambda_2)$$

$$p(A, B|\lambda_1) = p(A|\lambda_1)p(B|\lambda_1)$$
...



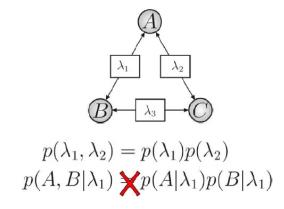
Conditional independencies hold information about causation!

[See J. Pearl, Causality]

## Conditional independencies: Uncovering causal relations Part 1

## Is a given probability distribution compatible with a presumed *causal structure*?

Example: Is a given  $p(\lambda_1, \lambda_2, \lambda_3, A, B, C)$  compatible with



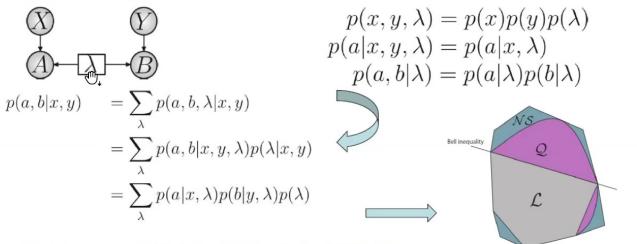
➤ If the the full probability distribution (of all nodes in a DAG) is available, CIs hold all information required to solve the compatibility problem

However...

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## Bell Inequalities: Uncovering causal relations Part 2

➤ Usually and for a variety of reasons not all variables in a DAG are observable, i.e., not all CIs are available from empirical data

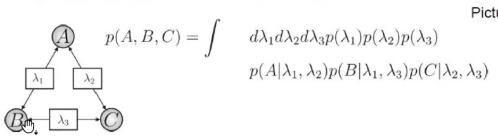


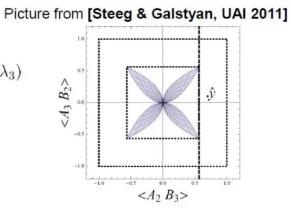
- Cls impose non-trivial constraints on the level of the observable variables, for example, Bell inequalities.
- > In quantum mechanics non commuting observables cannot be jointly observed

Marginal scenario: subset of variables that are (jointly) observable

## The challenge: Uncovering causal relations Part 3

- Describe marginals compatible with DAGs
- The observable probability dist. contains the full information required for that...
- ...very difficult, non-convex sets (algebraic geometry methods required, see for instance [Geiger & Meek, UAI 1999])





[Chaves et al, Uncertainty in Artificial Intelligence (UAI 2014)]
[Chaves, Phys. Rev. Lett. 116, 010402 (2016)]
[Lee, Spekkens, Journal of Causal Inference 5 (2017)]
[Wolfe, Spekkens, Fritz, J. Causal Inference 7 (2019)]
[Kela et al, IEEE Transactions on Information Theory 66, 339 (2019)]



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## **Outline**

- DAGs and the Language of Causality
- Double slit experiment
- Quantifying quantum causality
- Quantum networks

#### PHYSICAL REVIEW LETTERS 120, 190401 (2018)

#### Causal Modeling the Delayed-Choice Experiment

Rafael Chaves, Gabriela Barreto Lemos, and Jacques Pienaar International Institute of Physics, Universidade Federal do Rio Grande do Norte, Campus Universitario, Lagoa Nova, Natal, Rio Grande do Norte 59078-970, Brazil

#### PHYSICAL REVIEW A 100, 022111 (2019)

#### Device-independent test of a delayed choice experiment

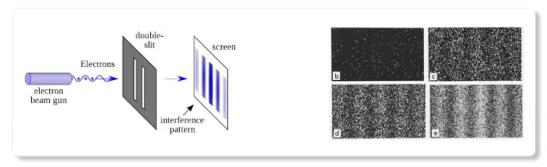
Emanuele Polino, <sup>1</sup> Iris Agresti, <sup>1</sup> Davide Poderini, <sup>1</sup> Gonzalo Carvacho, <sup>1</sup> Giorgio Milani, <sup>1</sup> Gabriela Barreto Lemos, <sup>2,3</sup> Rafael Chaves, <sup>2,4,\*</sup> and Fabio Sciarrino <sup>1,5,†</sup>

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# The double slit experiment

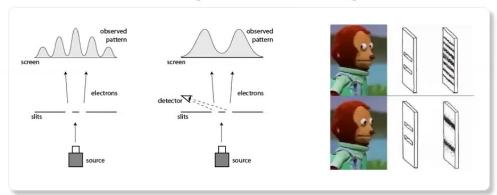
I will take just this one experiment, which has been designed to contain all of the mystery of quantum mechanics... Any other situation in quantum mechanics, it turns out, can always be explained by saying, 'You remember the case of the experiment with the two holes? It's the same thing'.

#### **Richard Feynman**



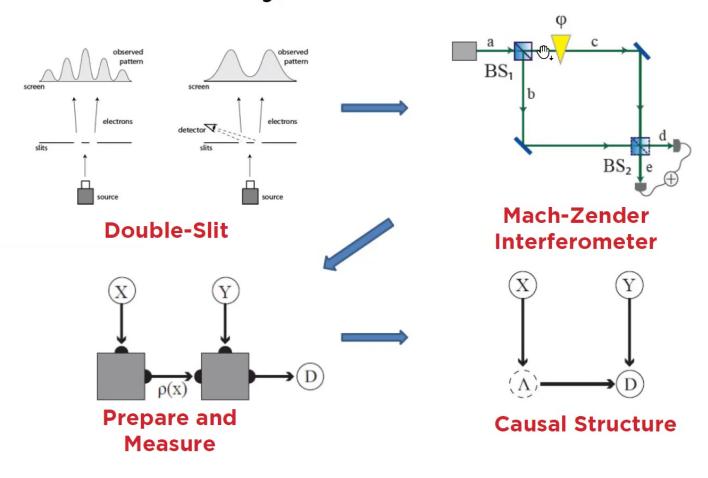
#### Wave-particle duality?





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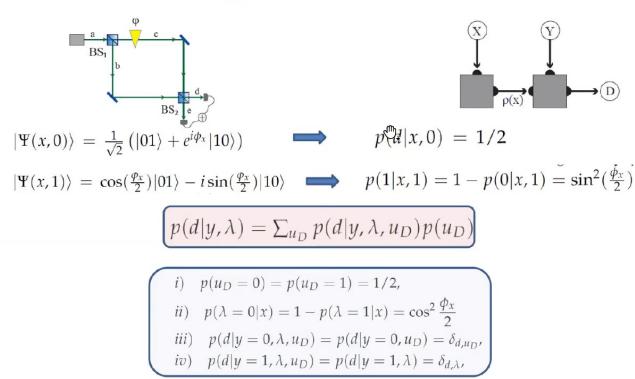
## The delayed choice version



Can this causal model explain the observed statistics?

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## The delayed choice version



Can this causal model explain the observed statistics?

#### YES!!!

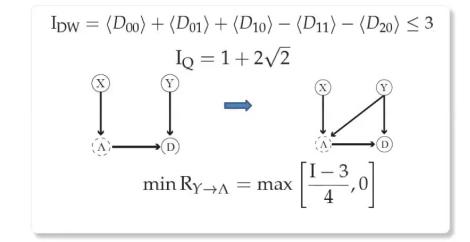
If we give up on wave-particle concepts, the double-slit experiment does have a classical explanation.

## The delayed choice version



If we slightly change the experiment, a classical model with the same dimension constraints cannot explain the data.

## Non-classicality!

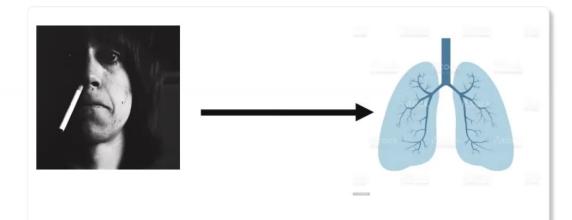




- DAGs and the Language of Causality
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- Quantum networks

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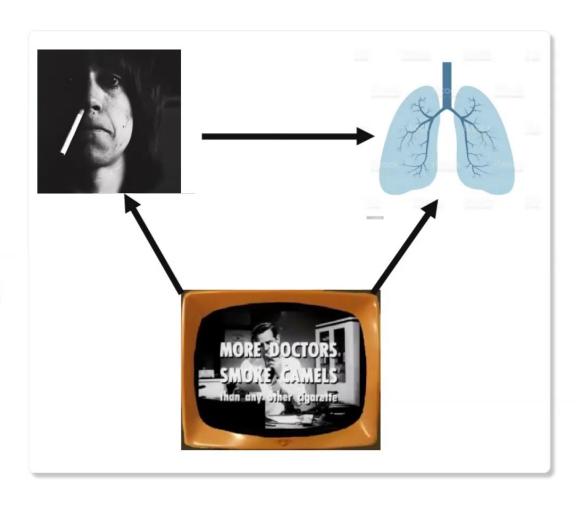
# Common causes X Causal Influences



Does smoking cause cancer?

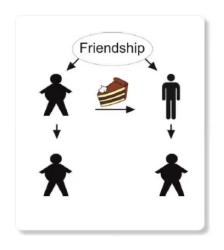
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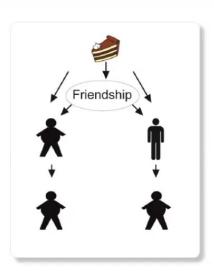
Common causes X Causal Influences



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Common causes Causal Influences





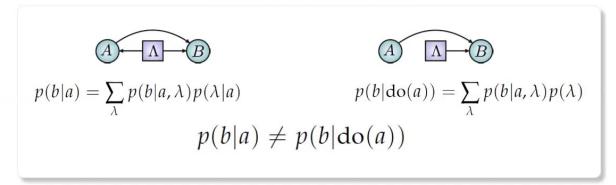
Is obesity contagious?

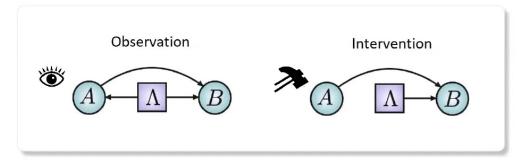
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## What about quantum causality/interventions?

Does A have some causal influence over B, or all the correlations between A and B are mediated via the common ancestor?

## Intervention



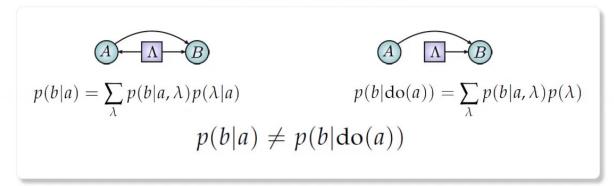




## What about quantum causality/interventions?

Does A have some causal influence over B, or all the correlations between A and B are mediated via the common ancestor?

## Intervention

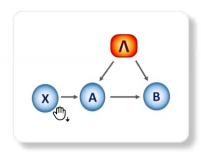


## Measure of causality

$$ACE_{A\to B} = \sup_{a,a',b} |p(b|do(a)) - p(b|do(a'))|$$



Can we do it with observational data only, i.e., without interventions? Yep, use an instrumental variable X.



Empirical data is encoded in the distribution p(a,b|x)

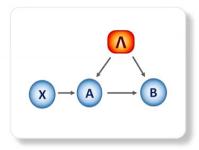
Instrumental variables

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Instrumental

variables

Can we do it with observational data only, i.e., without interventions? Yep, use an instrumental variable X.

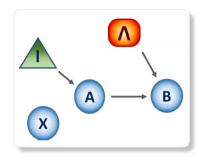


Empirical data is encoded in the distribution p(a,b|x)

Can estimate causal influence in a device independent way, e.g, the average causal effect (ACE).

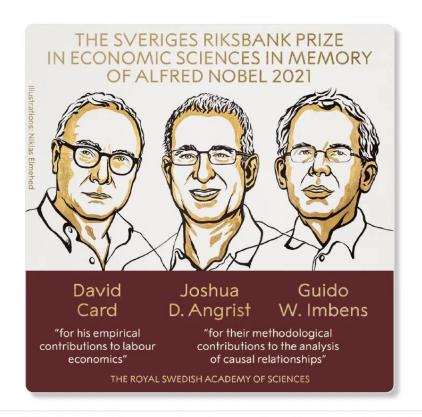
Balke & Pearl JASA 1997

$$ACE_{A\to B} \equiv \sup_{a,a',b} |p(b|do(a)) - p(b|do(a'))|$$



$$ACE_{A \to B} \ge 2p(a = 0, b = 0 | x = 0) - 2$$
  
  $+p(a = 1, b = 1 | x = 0) + p(b = 1 | x = 1)$ 





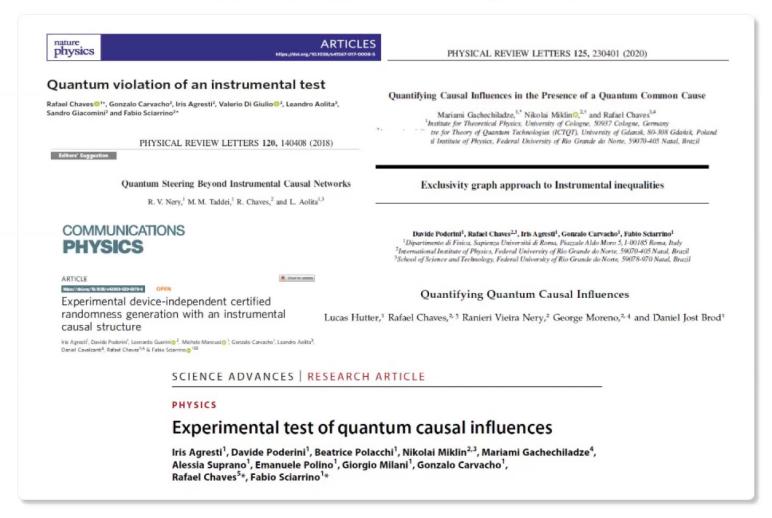
#### Identification of causal effects using instrumental variables

<u>JD Angrist</u>, <u>GW Imbens</u>, <u>DB Rubin</u> - Journal of the American ..., 1996 - Taylor & Francis We outline a framework for causal inference in settings where assignment to a binary treatment is ignorable, but compliance with the assignment is not perfect so that the receipt of treatment is nonignorable. To address the problems associated with comparing subjects ...

☆ ワワ Citado por 6370 Artigos relacionados Todas as 26 versões

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## What about quantum causality/interventions?

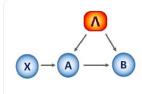


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Quantum causal

influences



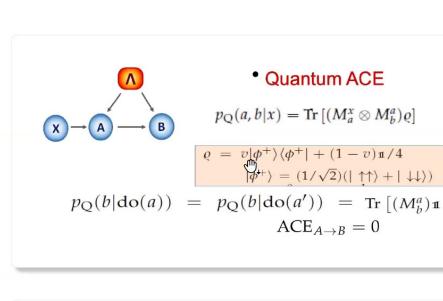
 In the <u>simplest scenario</u> all <u>correlations</u> are <u>classical</u> [Henson,Lal,Pusey NJP 2014]

$$p(a,b|x) = \sum_{\lambda} p(a|x,\lambda) p(b|a,\lambda) p(\lambda)$$
$$p(a,b|x) = \text{tr}[(M_a^x \otimes N_b^a) \rho_{AB}]$$

But what about interventional data?

$$p(b|do(a)) = \sum_{\lambda} p(b|a,\lambda) p(\lambda)$$
$$p(b|do(a)) = \operatorname{tr} \left[ (\mathbb{1} \otimes N_b^a) \rho_{AB} \right] = \operatorname{tr} \left[ N_b^a \rho_B \right]$$

# Quantum causal influences



#### Quantum ACE

$$p_{\mathbb{Q}}(a,b|x) = \operatorname{Tr}\left[ (M_a^x \otimes M_b^a) \varrho \right]$$

$$p_{Q}(b|do(a)) = p_{Q}(b|do(a')) = Tr[(M_{b}^{a})_{1}/2] = 1/2.$$

$$ACE_{A \to B} = 0$$

#### Classical ACE

$$ACE_{A\to B} \ge 2p(a = 0, b = 0|x = 0) - 2$$
  
  $+p(a = 1, b = 1|x = 0) + p(b = 1|x = 1)$ 



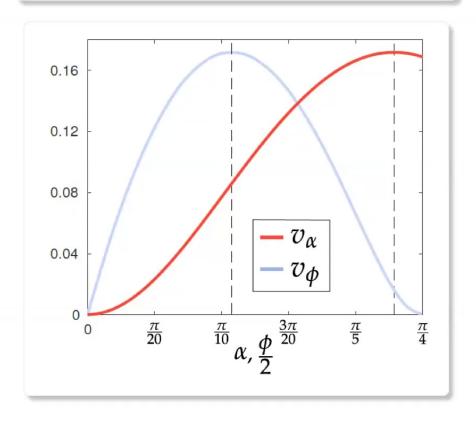
$$ACE_{A \rightarrow B} \gtrsim 0.91v - 0.75$$

Quantum effects can lead to an overestimation of causal influences!

## Quantifying causal influences

- Even though **no Bell inequality** can be violated, we still can witness the **non-classicality** of the correlations.
- A quantum common source leads to na overestimation of causal influences if the classical bounds are used.

**Result 1.** Every pure entangled state can generate correlations that violate the classical bound on ACE. Moreover, entanglement is necessary but not sufficient for such violations.



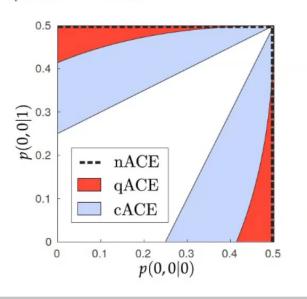
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# Quantifying quantum causal influences

**Result 3.** *In the instrumental scenario with dichotomic measurements* qACE *is lower bounded as* 

$$qACE_{A\to B} \ge \sum_{x=0.1} (p(0,0|x) + p(1,1|x)) + \zeta - 1, (11)$$

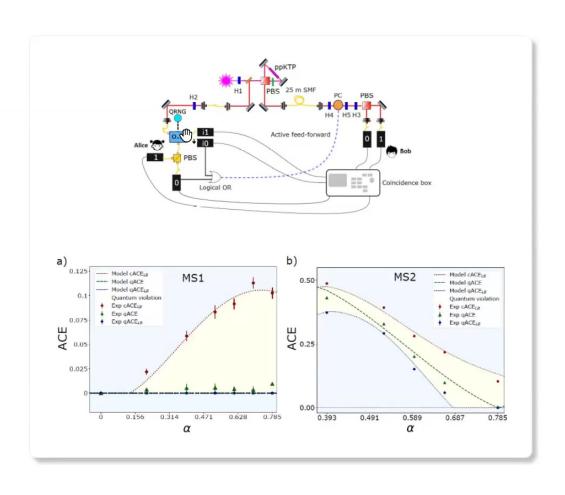
$$\zeta = \max_{\pm} \sqrt{\prod_{a=0,1} (1 \pm \sum_{x=0,1} (-1)^x (p(a,0|x) - p(a,1|x)))}.$$



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Experimental test of quantum causal influences



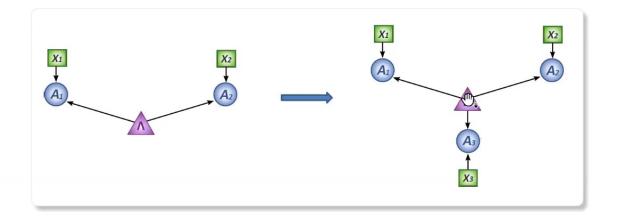
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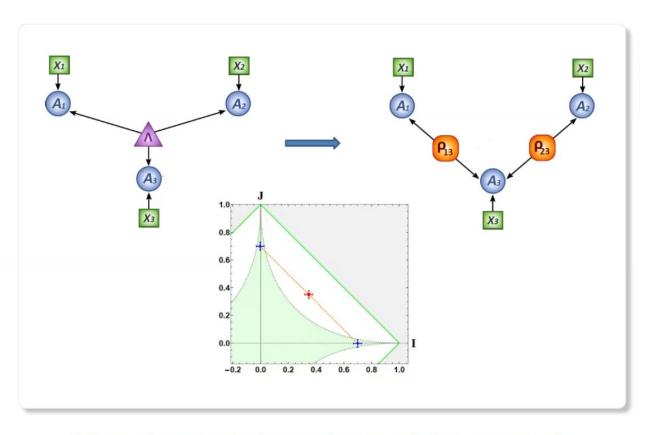
### Beyond Bell



Quantum networks can have much more interesting topologies than the "single source connects all" scenario!

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Beyond Bell

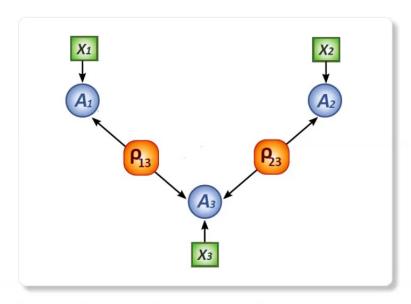


### Bilocality: the independence of the sources is explicility taken into account

[Branciard, Gisin, Pironio, PRL 104, 170401 (2010)]

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Unlocking new features with quantum networks



### Non-localitity activation of measurements [Pozas et al, PRL 123, 140503 (2019)

### Self-testing quantum theory [Weilenmann, Colbeck, PRL 125, 060406 (2020)]

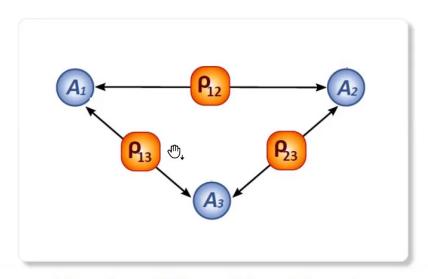
### Proving the need of complex numbers [Renou et al, Nature 600, 625-629 (2021)

### Full network nonlocality

[Pozas, Gisin, Tavakoli , PRL 128, 010403 (2022)

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Unlocking new features with quantum networks



### Non-localitity without inputs [Fritz, NJP 14, 103001 (2012)] [Renou et al, PRL 123, 140401 (2019)]

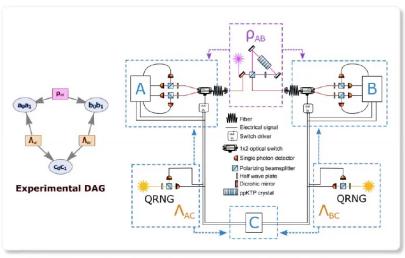
### Genuine Multipartite non-locality in a network [Suprano et al, PRX Quantum 3, 030342 (2022)]

### Quantifying measurement dependence in Bell's theorem

[Chaves et al, PRX Quantum 3, 040323 (2021)]

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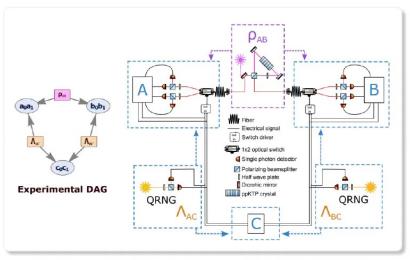
Experimental realization of the "Fritz" distribution



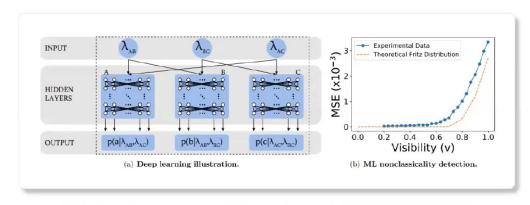
[Polino et al, Nat Comm14, 909 (2023)

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Experimental realization of the "Fritz" distribution

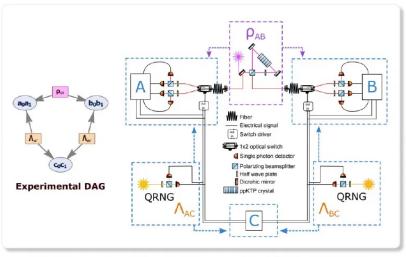


[Polino et al, Nat Comm14, 909 (2023)

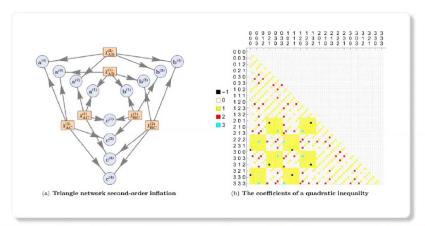


[Krivachy et al, npj Quantum Inf 6, 70 (2020)]

Experimental realization of the "Fritz" distribution

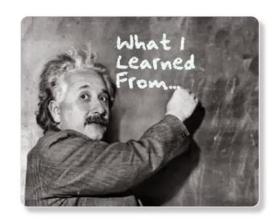


[Polino et al, Nat Comm14, 909 (2023)



[Wolfe, Spekkens Fritz, J. Causal Inference 7, 2019]

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Take-Home Messages

Causality theory provides a fairly unexplored framework

Causal analysis of the double slit experiment shows its classicality

Interventions and the quantification of causal influences allow for new method to detect non-classicality

Causal networks reveal new quantum features

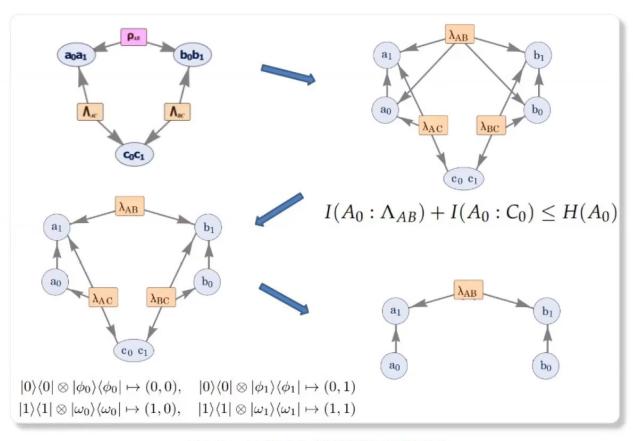
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### Come to Paraty! Registration is open!



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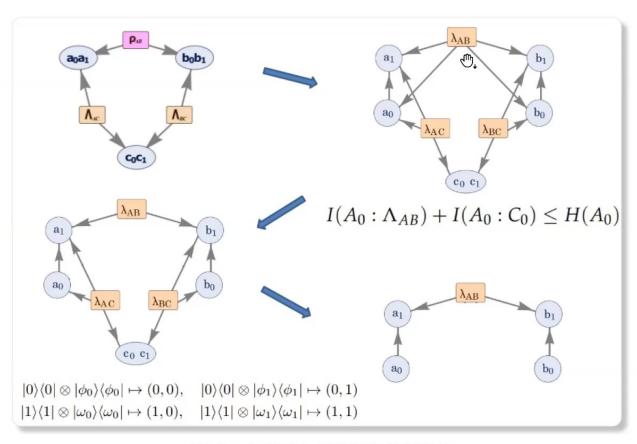
Embedding Bell in a Triangle



[Fritz, NJP 14, 103001 (2012)]

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Embedding Bell in a Triangle



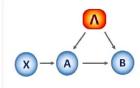
[Fritz, NJP 14, 103001 (2012)]

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Quantum causal

influences



 In the <u>simplest scenario</u> all <u>correlations</u> are <u>classical</u> [Henson,Lal,Pusey NJP 2014]

$$p(a, b|x) = \sum_{\lambda} p(a|x, \lambda) p(b|a, \lambda) p(\lambda)$$
$$p(a, b|x) = \text{tr}[(M_a^x \otimes N_b^a) \rho_{AB}]$$

But what about interventional data?

$$p(b|do(a)) = \sum_{\lambda} p(b|a,\lambda) p(\lambda)$$
$$p(b|do(a)) = \operatorname{tr} [(\mathbb{1} \otimes N_b^a) \rho_{AB}] = \operatorname{tr} [N_b^a \rho_B]$$

Do the classical bounds on ACE still apply?

$$ACE_{A\to B} = \max_{a,a',b} \left( p(b|do(a)) - p(b|do(a')) \right)$$

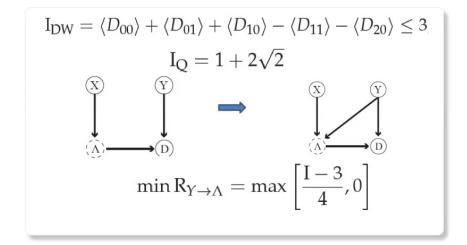
$$ACE_{A\to B} \ge 2p(a = 0, b = 0|x = 0) - 2$$
  
  $+p(a = 1, b = 1|x = 0) + p(b = 1|x = 1)$ 

### The delayed choice version

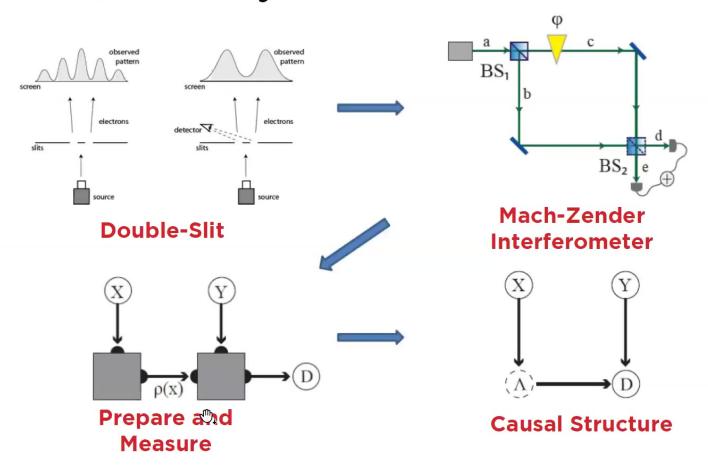


If we slightly change the experiment, a classical model with the same dimension constraints cannot explain the data.

### Non-classicality!



### The delayed choice version



Can this causal model explain the observed statistics?

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