Title: Can Quantum Correlations be Explained Causally?

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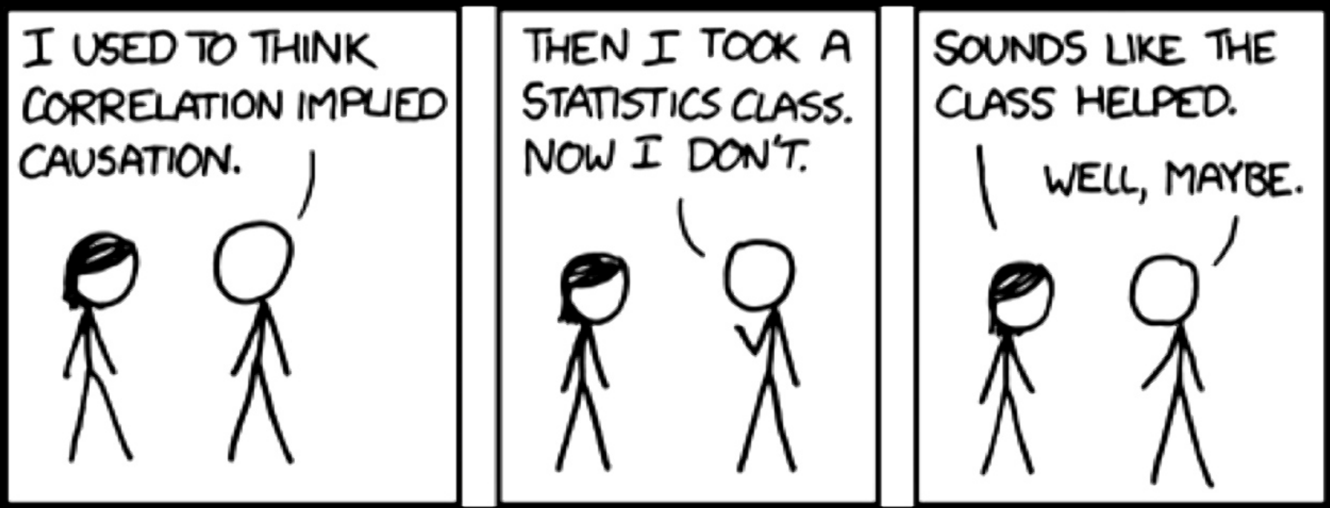
Abstract: <p>Abstract: There is a strong correlation between the sun rising and the rooster crowing, but to say that the one causes the other is to say more. In particular, it says that making the rooster crow early will not precipitate an early dawn, whereas making the sun rise early (for instance, by moving the rooster eastward) can lead to some early crowing. Intervening upon the natural course of events in this manner is a good way of discovering causal relations. Sometimes, however, we can't intervene, or we'd prefer not to. For instance, in trying to determine whether smoking causes lung cancer, we'd prefer not to force any would-be nonsmokers to smoke. Fortunately, there are some clever tricks that allow us to extract information about what causes what entirely from features of the observed correlations. One of these tricks was discovered by the physicist John Bell in 1964. In a groundbreaking paper, he used it to demonstrate the seeming impossibility of providing a causal explanation of certain quantum correlations. This revealed a fundamental tension between quantum theory and Einstein's theory of relativity --the two central pillars of modern physics. It is a tension that is still with us today.</p>

Can Quantum Correlations Be Explained Causally?

Robert Spekkens
Perimeter Institute



From XKCD comics

ISSYP 2018

Simpson's Paradox

P(recovery | drug) > P(recovery | no drug)

Simpson's Paradox

P(recovery | drug) > P(recovery | no drug)

P(recovery | drug, male) < P(recovery | no drug, male)

P(recovery | drug, female) < P(recovery | no drug, female)

Simpson's Paradox

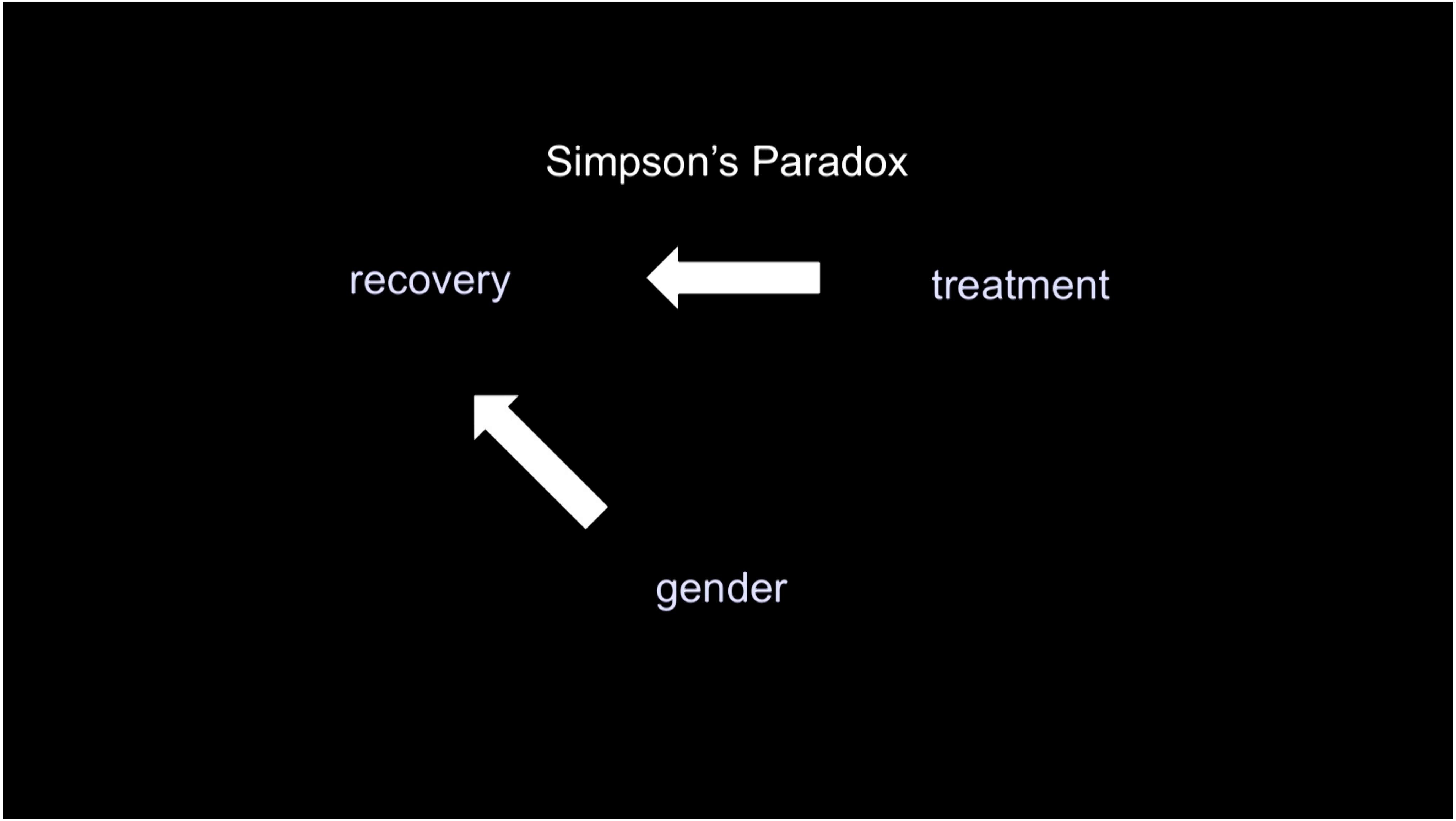
P(recovery | drug) > P(recovery | no drug)

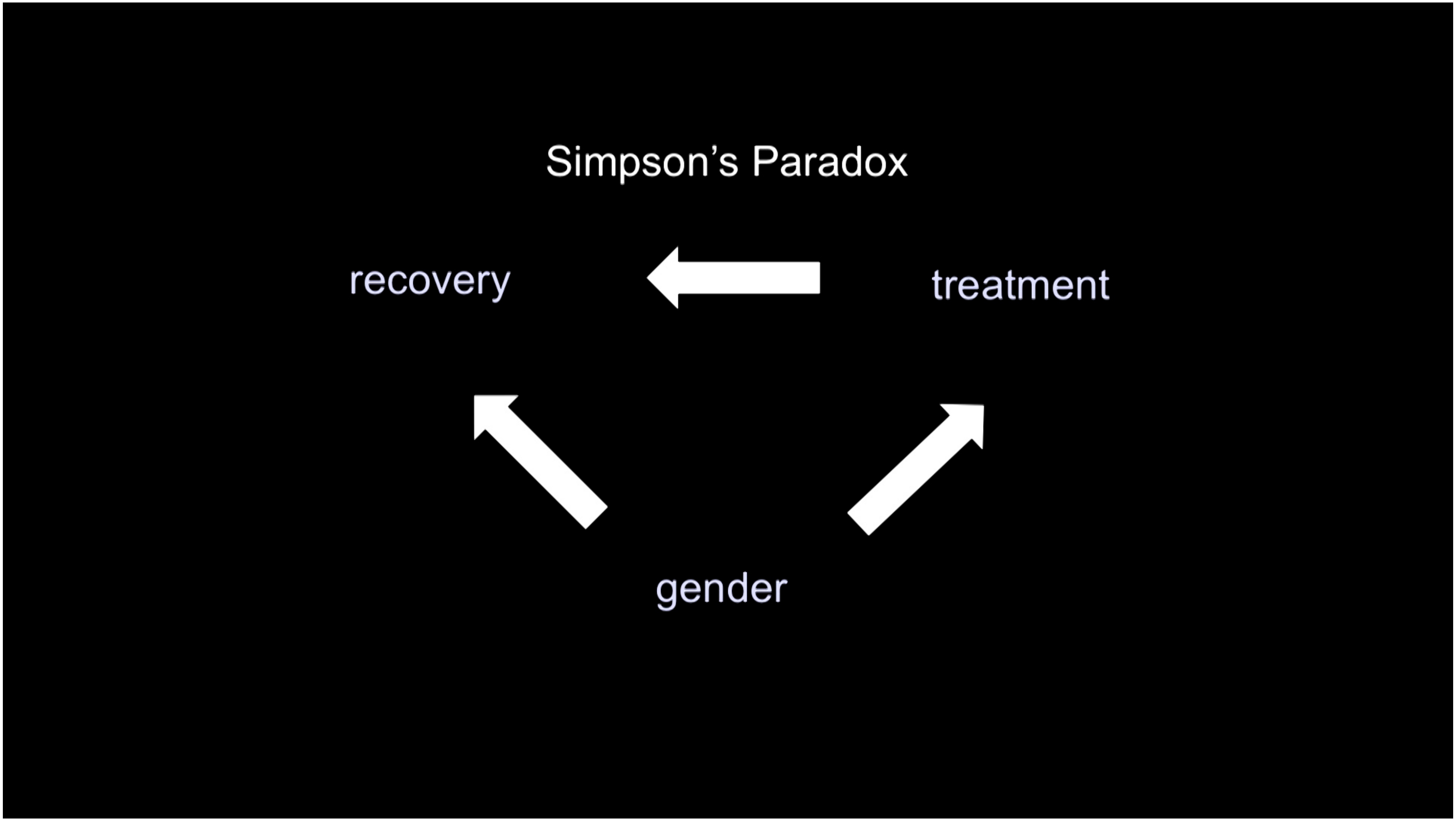
P(recovery | drug, male) < P(recovery | no drug, male)

P(recovery | drug, female) < P(recovery | no drug, female)

Recovery probability

	drug	no drug
male	180/300 = 60%	70/100 = 70%
female	20/100 = 20%	90/300 = 30%
combined	200/400 = 50%	160/400 = 40%


Simpson’s Paradox
recovery
treatment
gender


Simpson's Paradox
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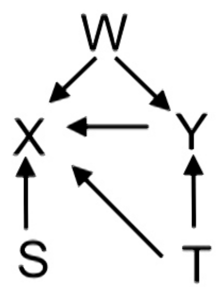
Causal Model

Causal Structure



Causal-Statistical Parameters

$P(W)$

$P(S)$

$P(T)$

$P(X|S,T,W,Y)$

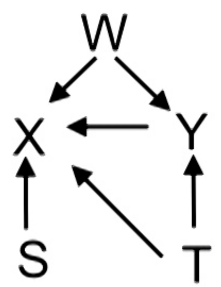
$P(Y|T,W)$

$$P(X,Y,W,S,T) = P(X|S,T,W,Y)P(Y|T,W)P(W)P(S)P(T)$$

Causal Model

Causal Structure

Causal-Statistical Parameters



$P(W)$

$P(S)$

$P(T)$

$P(X|S,T,W,Y)$

$P(Y|T,W)$

$$P(X,Y,W,S,T) = P(X|S,T,W,Y)P(Y|T,W)P(W)P(S)P(T)$$

Causal inference algorithms seek to solve the inverse problem

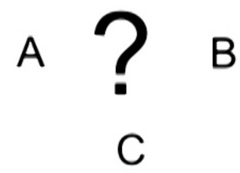
Principle #1
Statistical dependences need to be explained causally

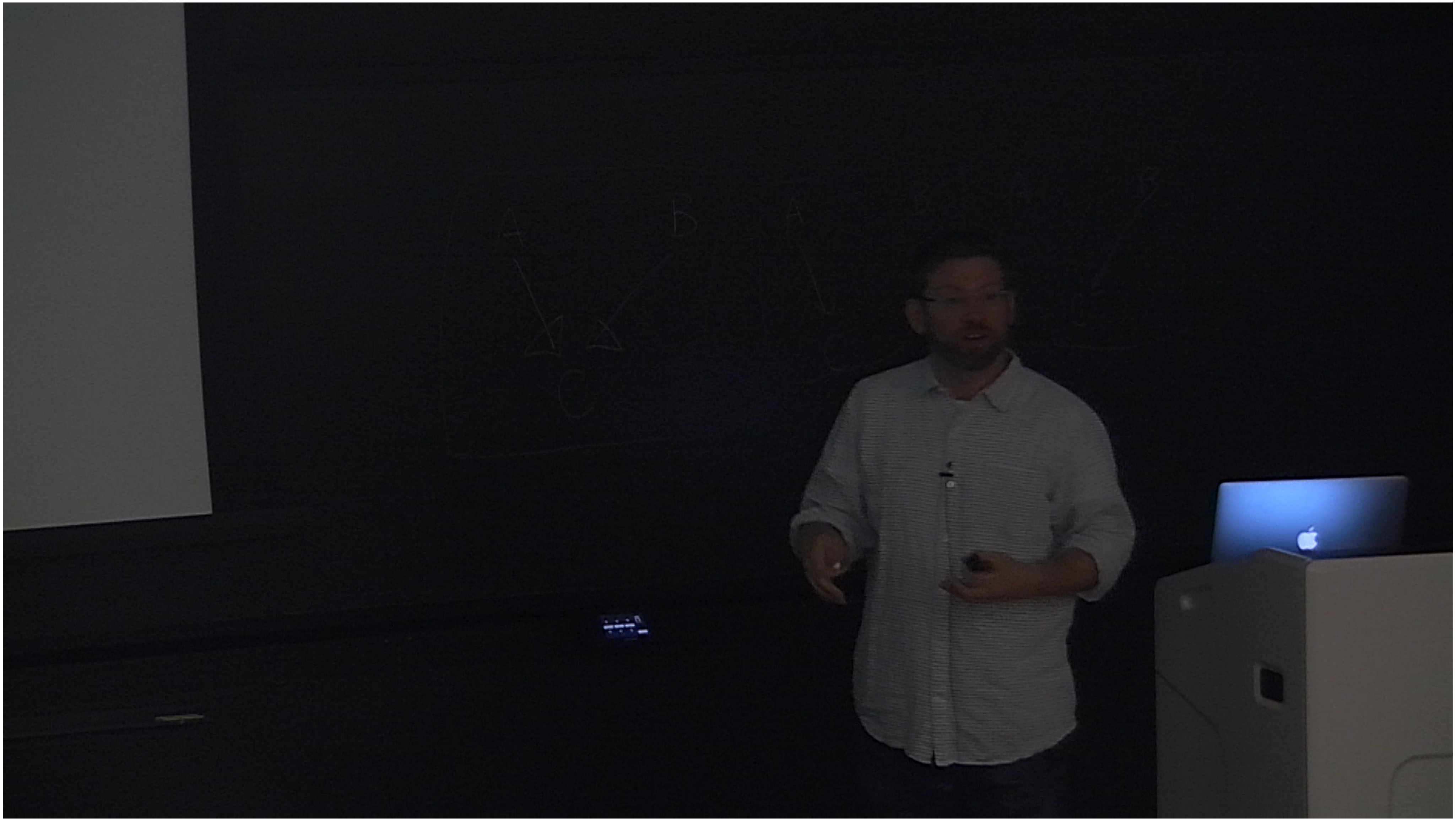
$$P(A, B, C)$$

A is independent of B

$$P(A, B) = P(A)P(B)$$

no other independence relations





$$P(A, B, C)$$

A is independent of B

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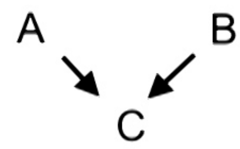
no other independence relations

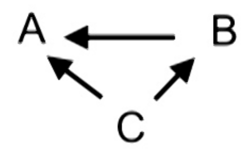


$P(A)$

$P(B)$

$P(C|A, B)$

$$P(A, B, C) = P(C|A, B)P(A)P(B)$$



$P(C)$

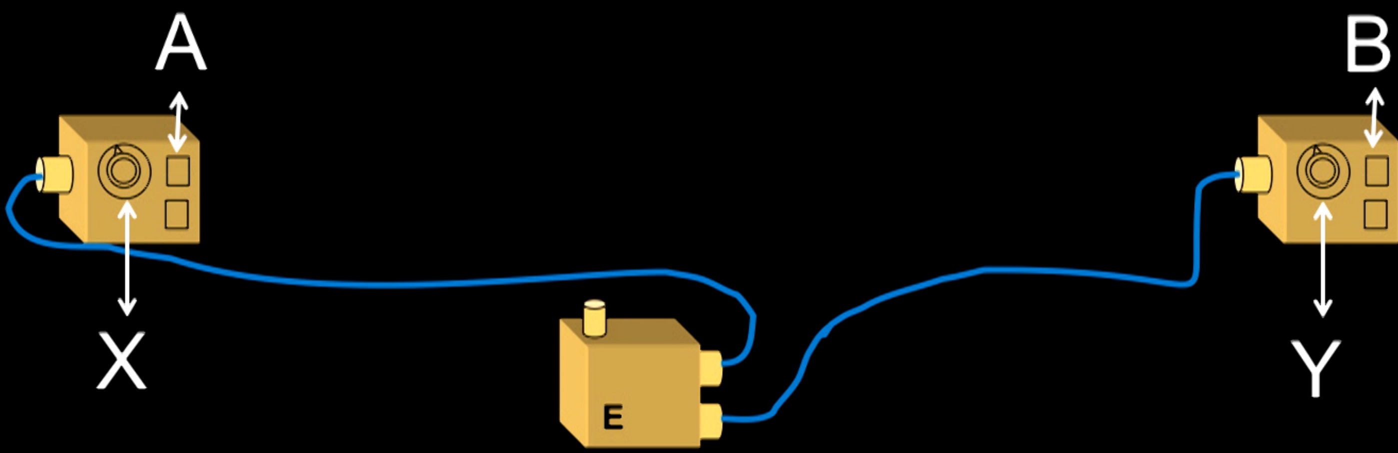
$P(B|C)$

$P(A|B, C)$

$$P(A, B, C) = P(A|B, C)P(B|C)P(C)$$

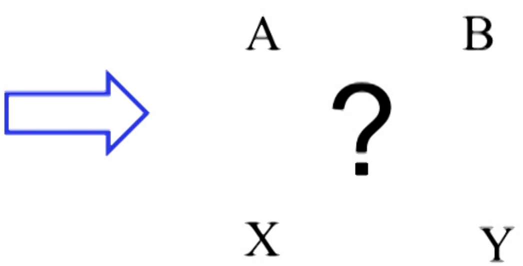
This model is fine-tuned

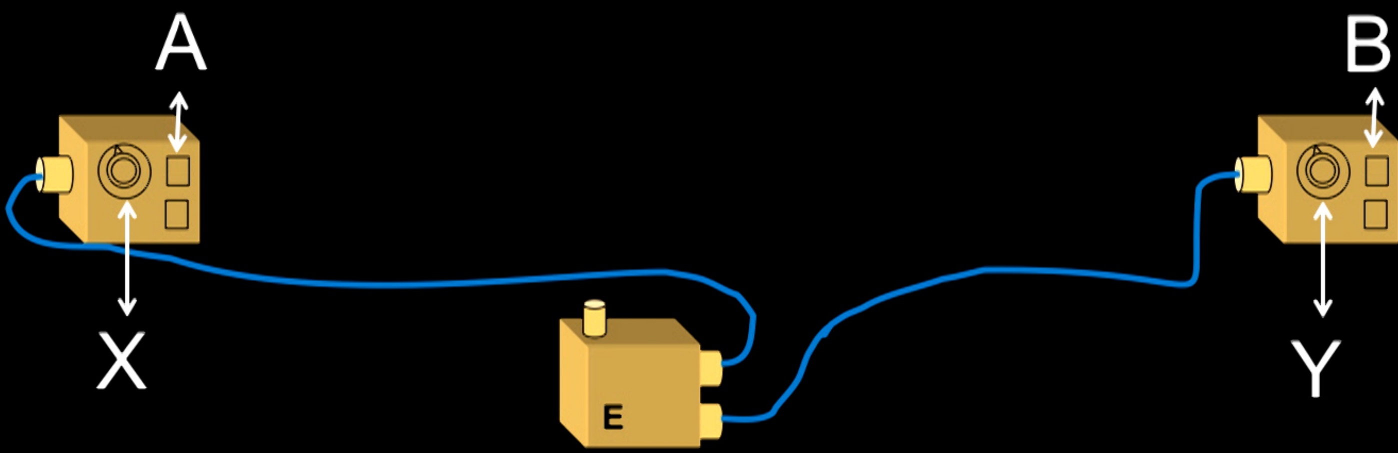
Principle #2
No fine-tuning



P(A,B|X,Y)

	A=0, B=0	A=0, B=1	A=1, B=0	A=1, B=1
X=0, Y=0	0.427	0.073	0.073	0.427
X=0, Y=1	0.427	0.073	0.073	0.427
X=1, Y=0	0.427	0.073	0.073	0.427
X=1, Y=1	0.073	0.427	0.427	0.073





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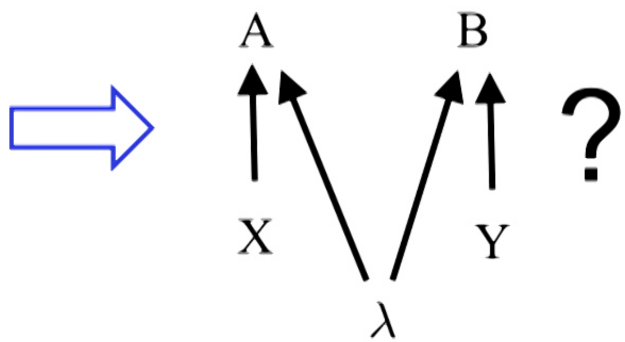
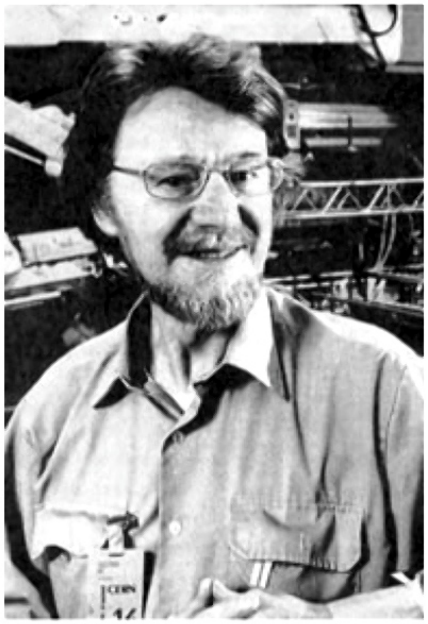
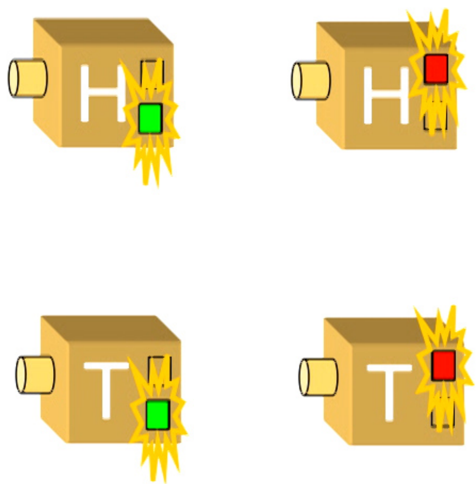


Bell's theorem



John S. Bell
(1928-1990)

A pair of two-outcome measurements



There are two possible measurements, H and T, with two outcomes each: green or red

Suppose which of H or T occurs at each wing is chosen at random

Scenario 1

1. Whenever the same measurement is made on A and B, the outcomes always agree	H and H or T and T
2. Whenever different measurements are made on A and B, the outcomes always disagree	H and T or T and H


H
H
outcomes agree
outcomes disagree
outcomes disagree
T
T
outcomes agree

There are two possible measurements, H and T, with two outcomes each: green or red

Suppose which of H or T occurs at each wing is chosen at random

Scenario 2

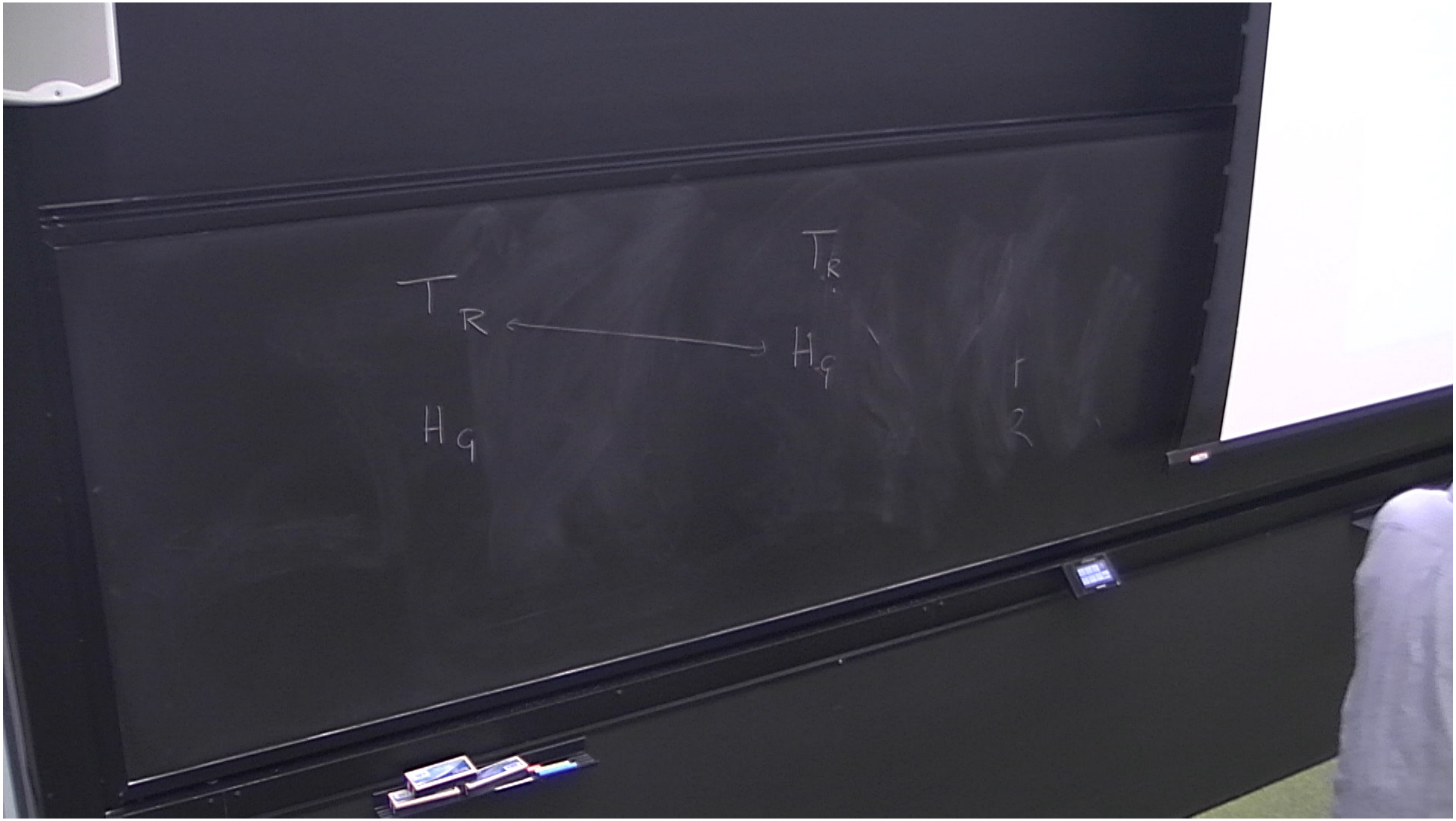
1. Whenever the same measurement is made on A and B, the outcomes always disagree	H and H or T and T
2. Whenever different measurements are made on A and B, the outcomes always agree	H and T or T and H

There are two possible measurements, H and T, with two outcomes each: green or red

Suppose which of H or T occurs at each wing is chosen at random

Scenario 3

1. Whenever the measurement T is made on both A and B, the outcomes always disagree	T and T
2. Otherwise, the outcomes always agree	H and H or H and T or T and H


T R
H g
T R
H g


H
H
outcomes agree
outcomes agree
outcomes agree
T
T
outcomes disagree

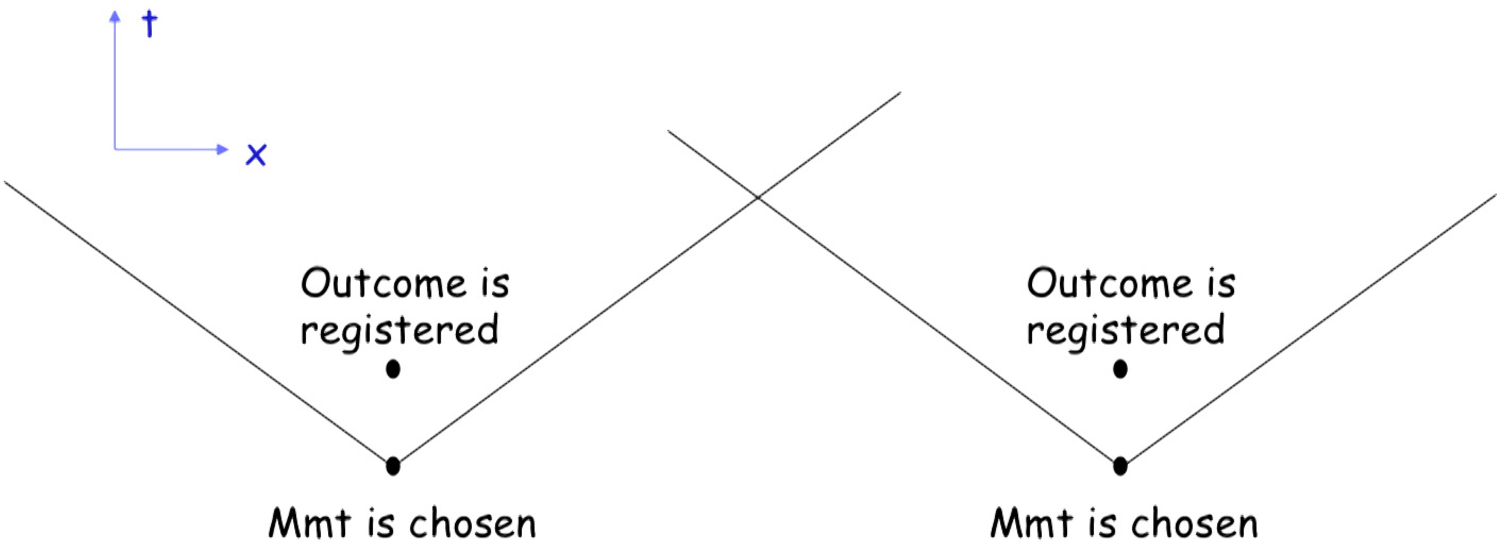
The game can be won at most 75% of the time by local strategies

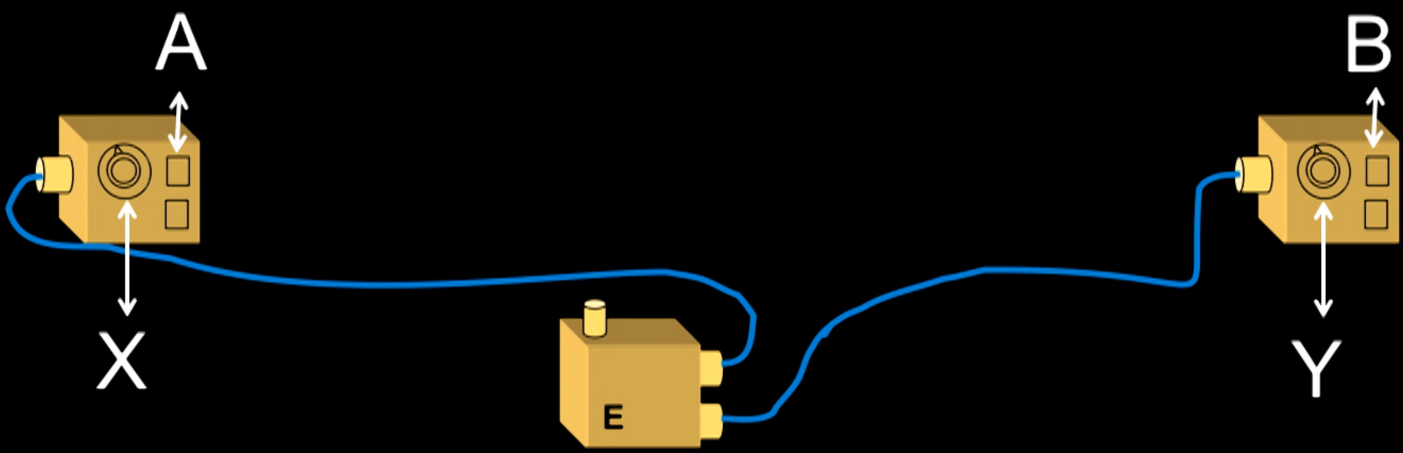
The game can be won at most 75% of the time by local strategies

Using quantum theory, it can be won 85% of the time!

A: Communication of the choice of measurement in one wing to the system in the opposite wing

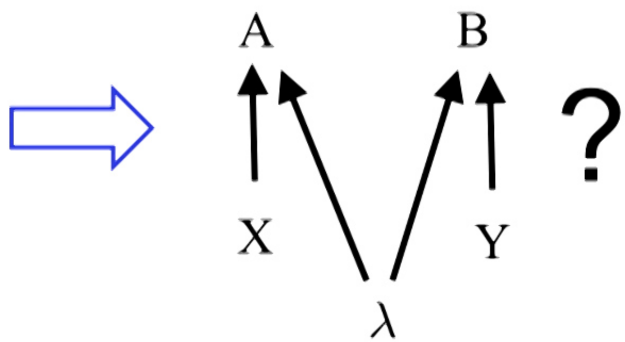
Tension with the theory of relativity

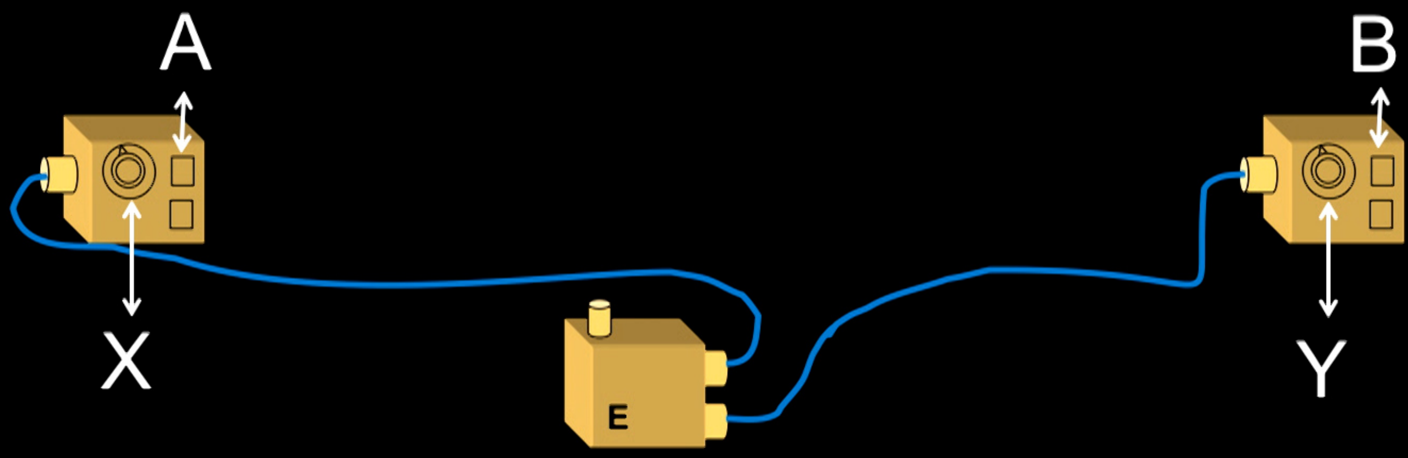




P(A,B|X,Y)

	A=0, B=0	A=0, B=1	A=1, B=0	A=1, B=1
X=0, Y=0	1/2	0	0	1/2
X=0, Y=1	1/2	0	0	1/2
X=1, Y=0	1/2	0	0	1/2
X=1, Y=1	0	1/2	1/2	0





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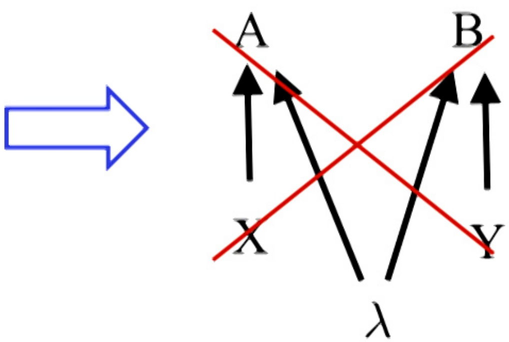
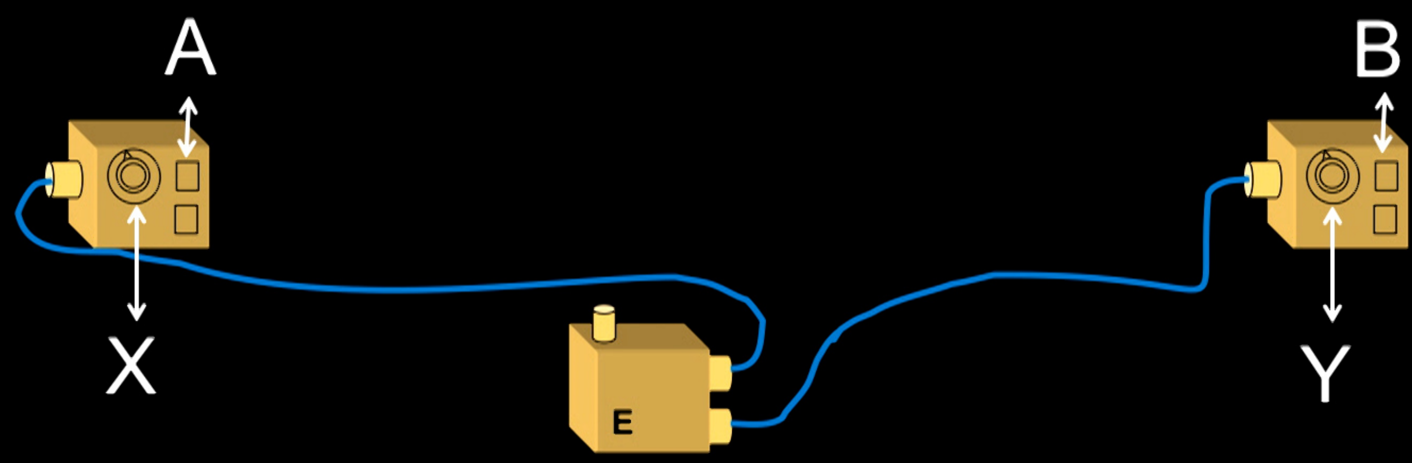
X=1, Y=0	1/2	0	0	1/2
X=1, Y=1	0	1/2	1/2	0





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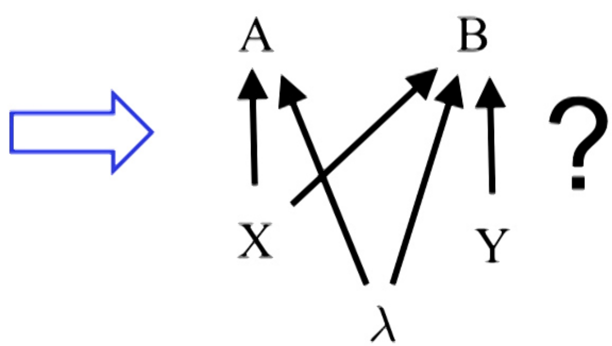

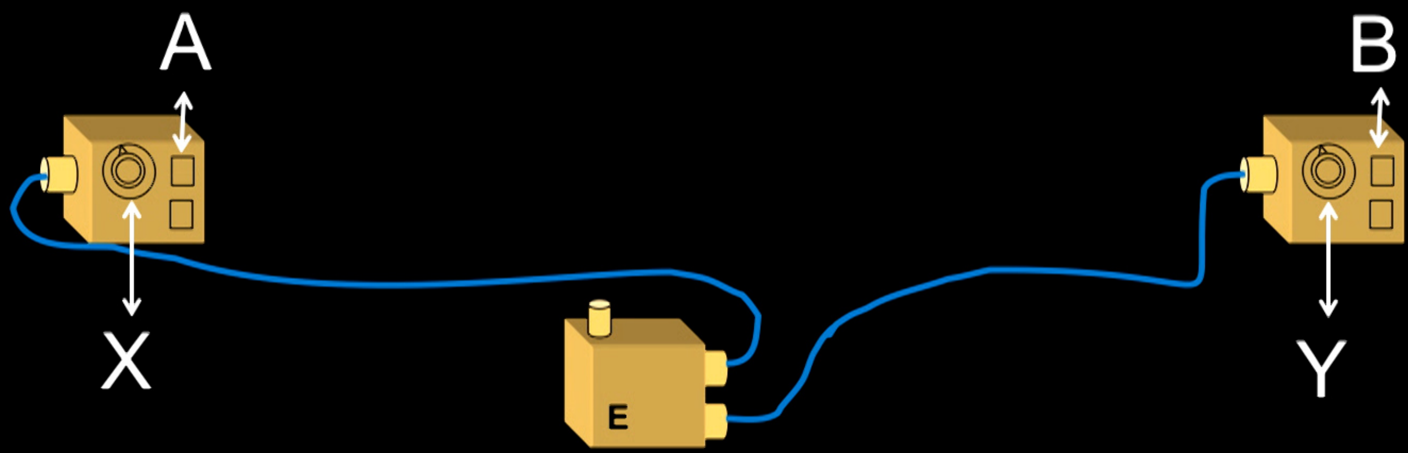

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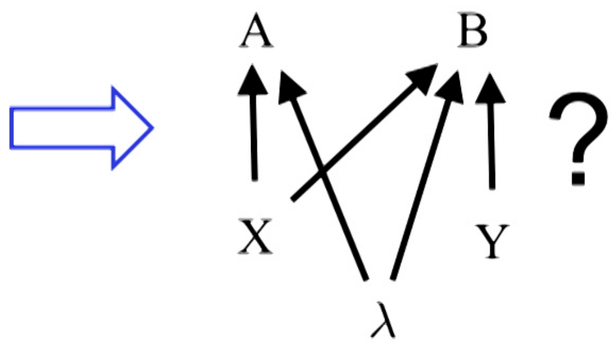
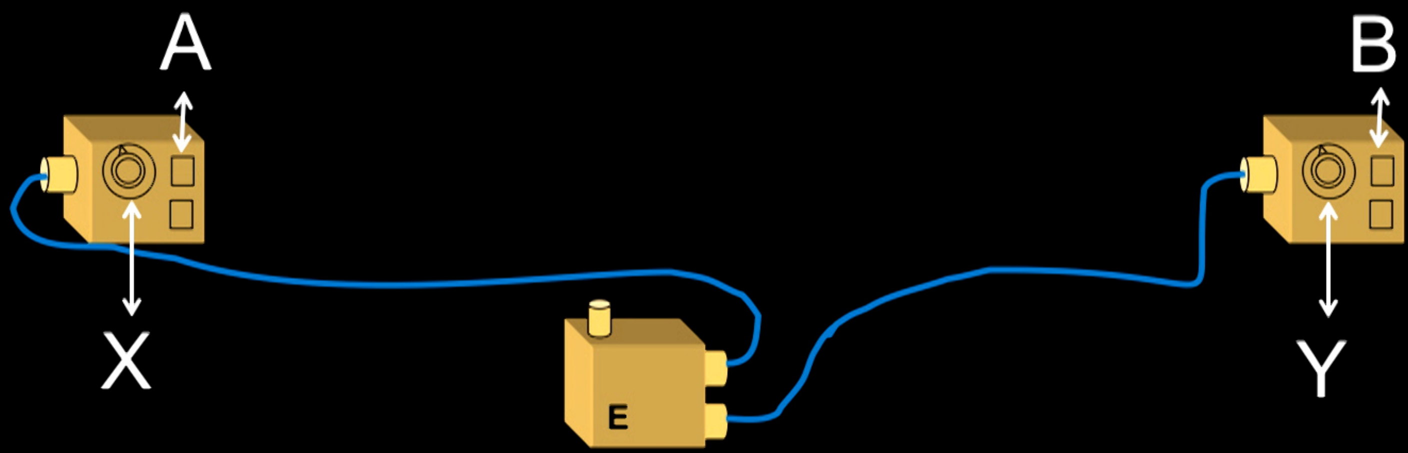



X
E
Y
P(A,B|X,Y)
A=0, B=0
A=0, B=1
A=1, B=0
A=1, B=1
X=0, Y=0
X=0, Y=1
X=1, Y=0
X=1, Y=1
0.427 0.073 0.073 0.427
0.427 0.073 0.073 0.427
0.427 0.073 0.073 0.427
0.073 0.427 0.427 0.073
A
B
X
Y
μ
λ



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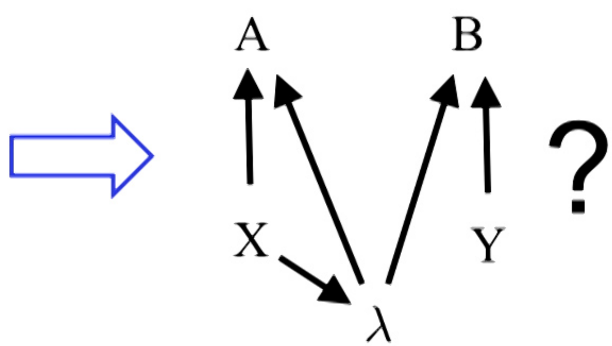

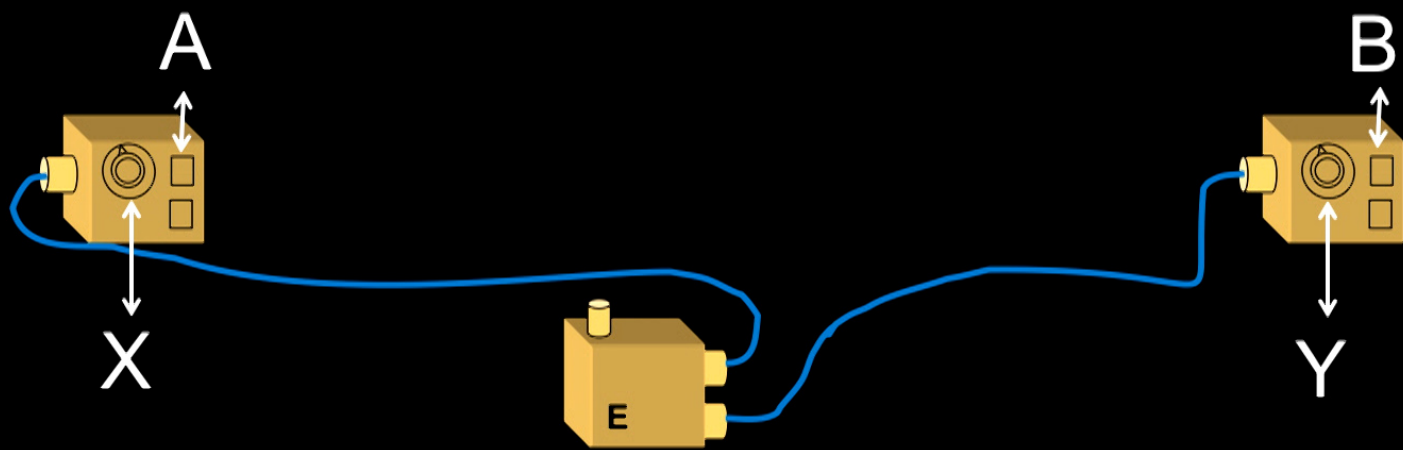

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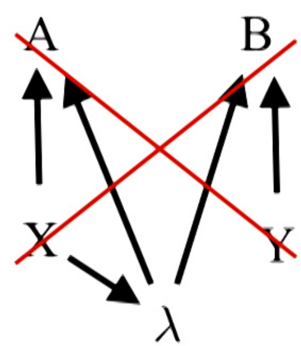

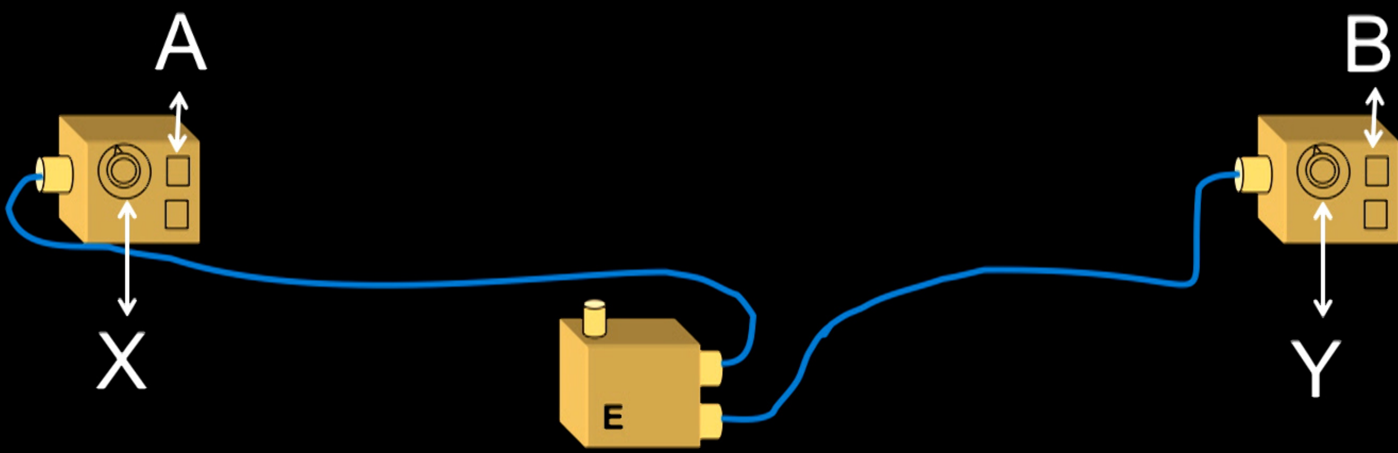

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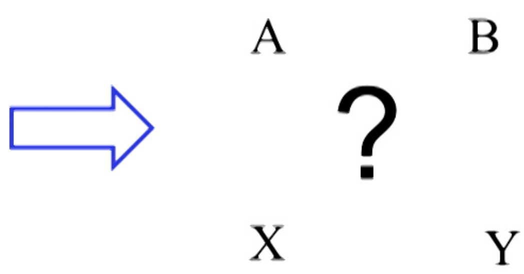
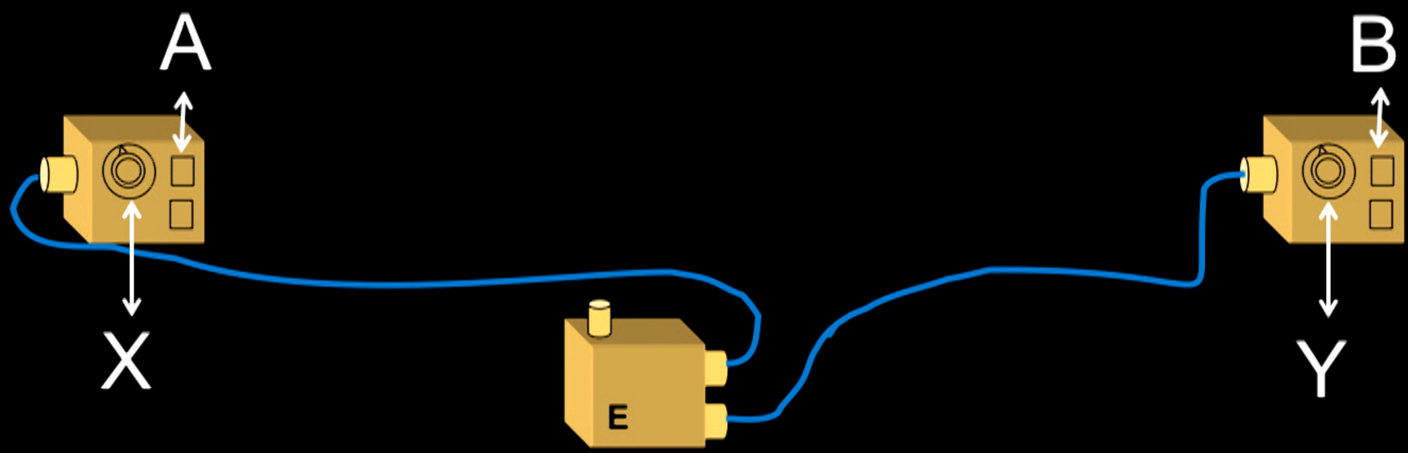
X=0, Y=1	0.427	0.073	0.073	0.427
X=1, Y=0	0.427	0.073	0.073	0.427
X=1, Y=1	0.073	0.427	0.427	0.073





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X=0, Y=1	0.427	0.073	0.073	0.427
X=1, Y=0	0.427	0.073	0.073	0.427
X=1, Y=1	0.073	0.427	0.427	0.073

⇨ Nothing works!

- Statistical dependences need to be explained causally
  - No fine-tuning

⇩

Contradiction with

	A=0, B=0	A=0, B=1	A=1, B=0	A=1, B=1
X=0, Y=0	0.427	0.073	0.073	0.427
X=0, Y=1	0.427	0.073	0.073	0.427
X=1, Y=0	0.427	0.073	0.073	0.427
X=1, Y=1	0.073	0.427	0.427	0.073