

Title: Can Quantum Correlations be Explained Causally?

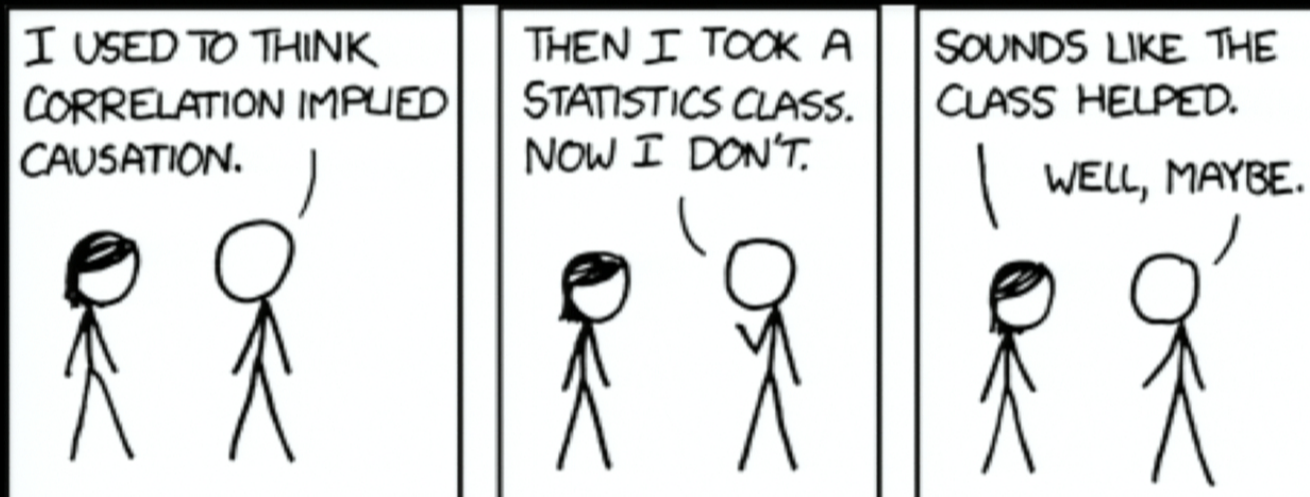
Date: Jul 21, 2014 10:30 AM

URL: <http://pirsa.org/14070026>

Abstract: <span>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. </span>

# Can Quantum Correlations Be Explained Causally?

Rob Spekkens  
Perimeter Institute



From XKCD comics

ISSYP 2014





# Simpson's Paradox

$$P(\text{recovery} \mid \text{drug}) > P(\text{recovery} \mid \text{no drug})$$



## Simpson's Paradox

$$P(\text{recovery} \mid \text{drug}) > P(\text{recovery} \mid \text{no drug})$$

$$P(\text{recovery} \mid \text{drug, male}) < P(\text{recovery} \mid \text{no drug, male})$$

# Simpson's Paradox

$$P(\text{recovery} \mid \text{drug}) > P(\text{recovery} \mid \text{no drug})$$

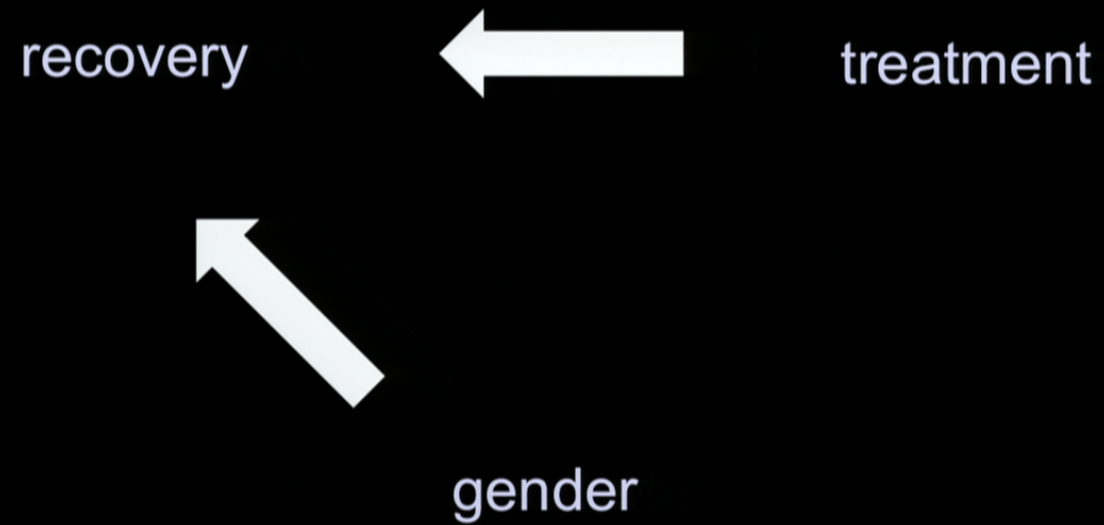
$$P(\text{recovery} \mid \text{drug, male}) < P(\text{recovery} \mid \text{no drug, male})$$

$$P(\text{recovery} \mid \text{drug, female}) < P(\text{recovery} \mid \text{no drug, female})$$

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







# Simpson's Paradox

$$\begin{array}{ccc} P(\text{recovery} \mid \text{do}(\text{drug})) & \neq & P(\text{recovery} \mid \text{observe}(\text{drug})) \\ \text{causation} & & \text{correlation} \end{array}$$



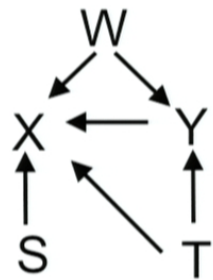
# How can we infer causal relations from correlations?

J. Pearl, Causality: Models, Reasoning and Inference  
P. Spirtes, C. Glymour, R. Scheines, Causation, Prediction  
and Search



## Causal Model

Causal  
Structure



Causal-Statistical  
Parameters

$$P(W)$$

$$P(S)$$

$$P(T)$$

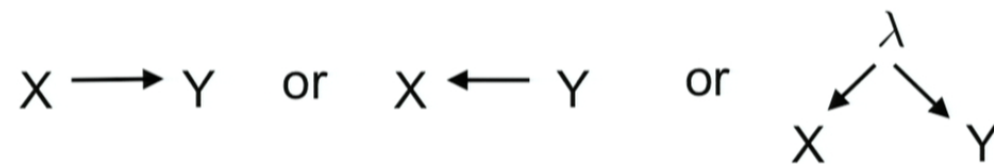
$$P(X|S, T, W, Y)$$

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

## Reichenbach's principle

Statistical correlations must be explained causally

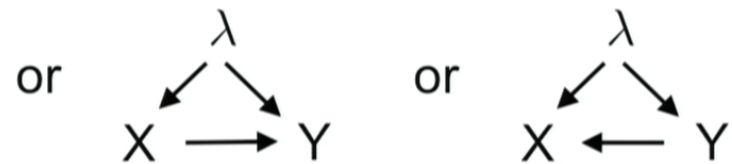
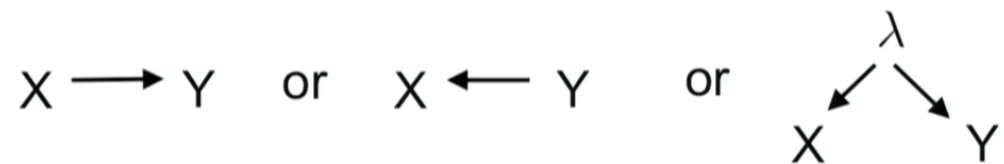
If X and Y are correlated, then



## Reichenbach's principle

Statistical correlations must be explained causally

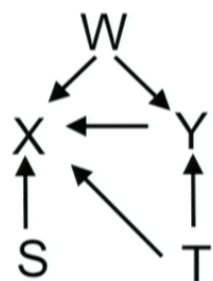
If X and Y are correlated, then





## Causal Model

Causal  
Structure



Causal-Statistical  
Parameters

$$P(W)$$

$$P(S)$$

$$P(T)$$

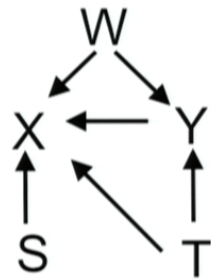
$$P(X|S, T, W, Y)$$

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

- Parentless variables are independently distributed

## Causal Model

Causal  
Structure



Causal-Statistical  
Parameters

$$P(W)$$

$$P(S)$$

$$P(T)$$

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

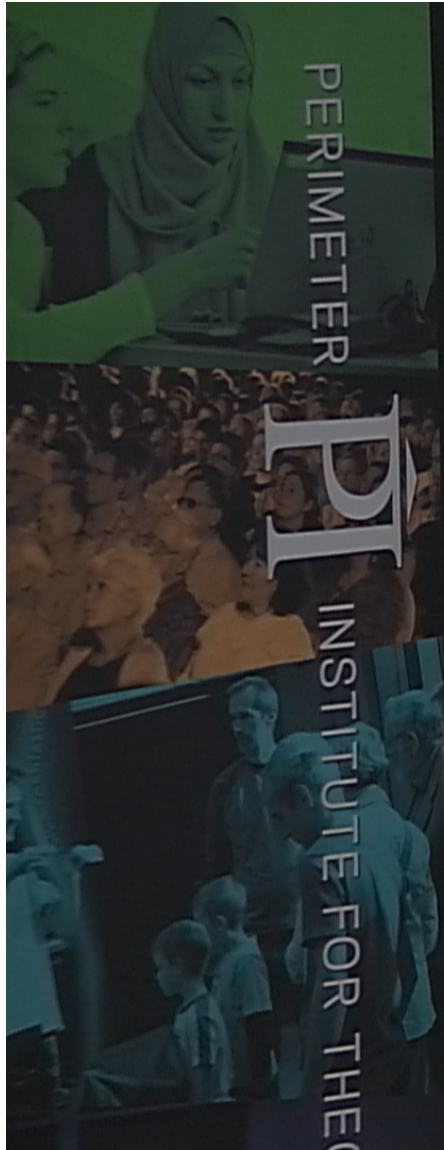
$$P(Y|T, W)$$

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

Causal inference algorithms seek to solve the inverse problem

Inferring facts about the causal structure from  
statistical independences





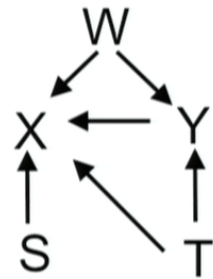
$A$  and  $B$  are independent

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

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

$$P(A \cap B) = P(A)P(B)$$

## Causal Model



$$P(W)$$

$$P(S)$$

$$P(T)$$

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

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

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

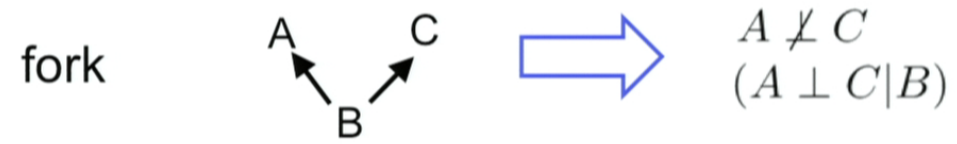
**Def'n: A and B are conditionally independent given C**

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

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

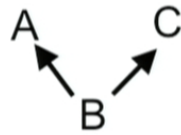
$$P(A, B|C) = P(A|C)P(B|C)$$

Denote this  
 $(A \perp B|C)$



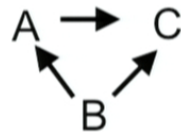


fork



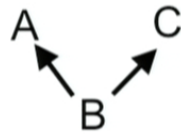
$$A \not\perp C \\ (A \perp C | B)$$

confounded  
cause



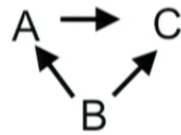
$$A \not\perp C \\ (A \not\perp C | B)$$

fork



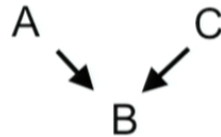
$$A \not\perp C \\ (A \perp C | B)$$

confounded  
cause



$$A \not\perp C \\ (A \not\perp C | B)$$

collider



$$A \perp C \\ (A \not\perp C | B)$$

$A \perp B$   
and no other  
independence  
relations



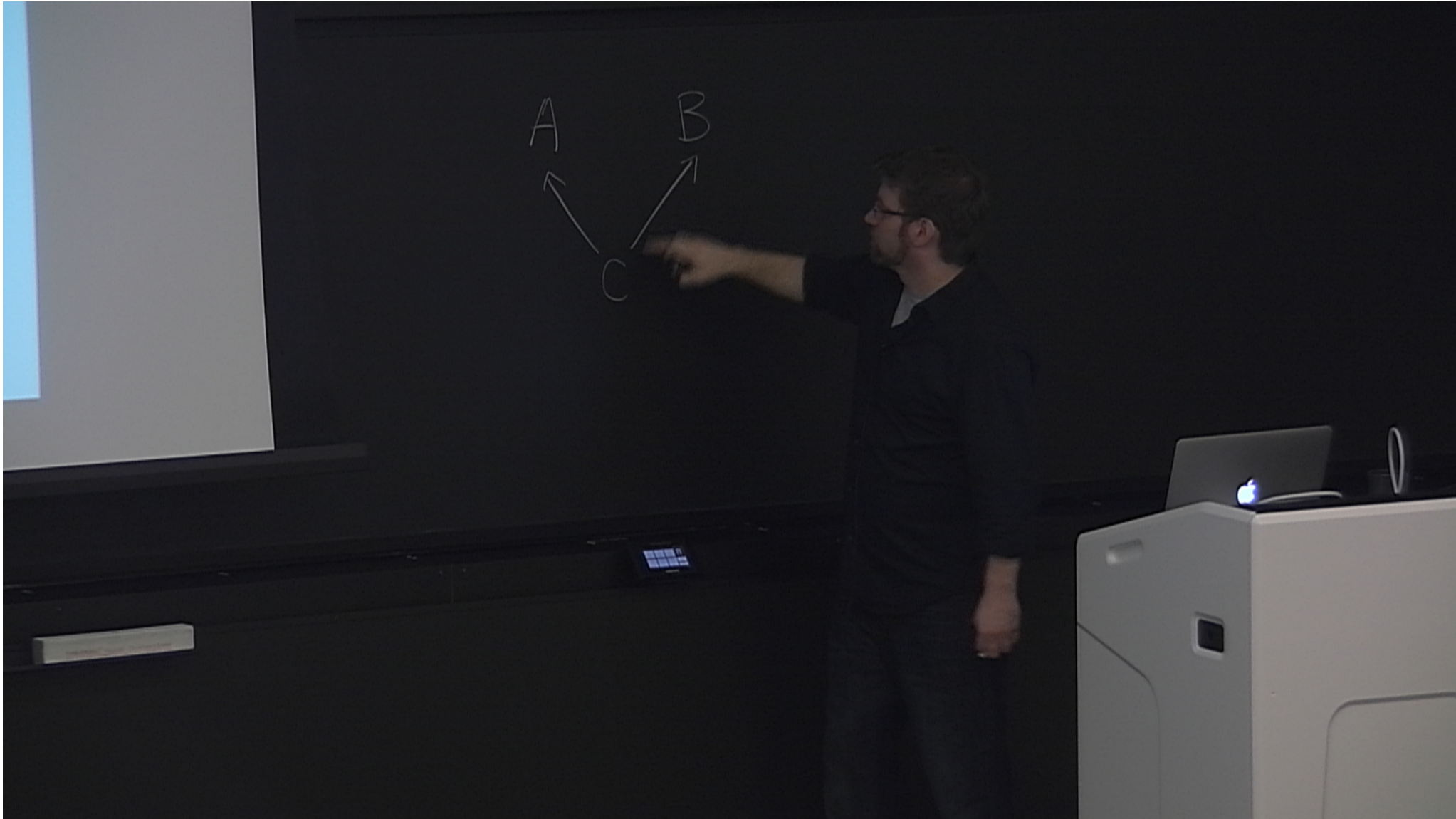
A ? B  
C



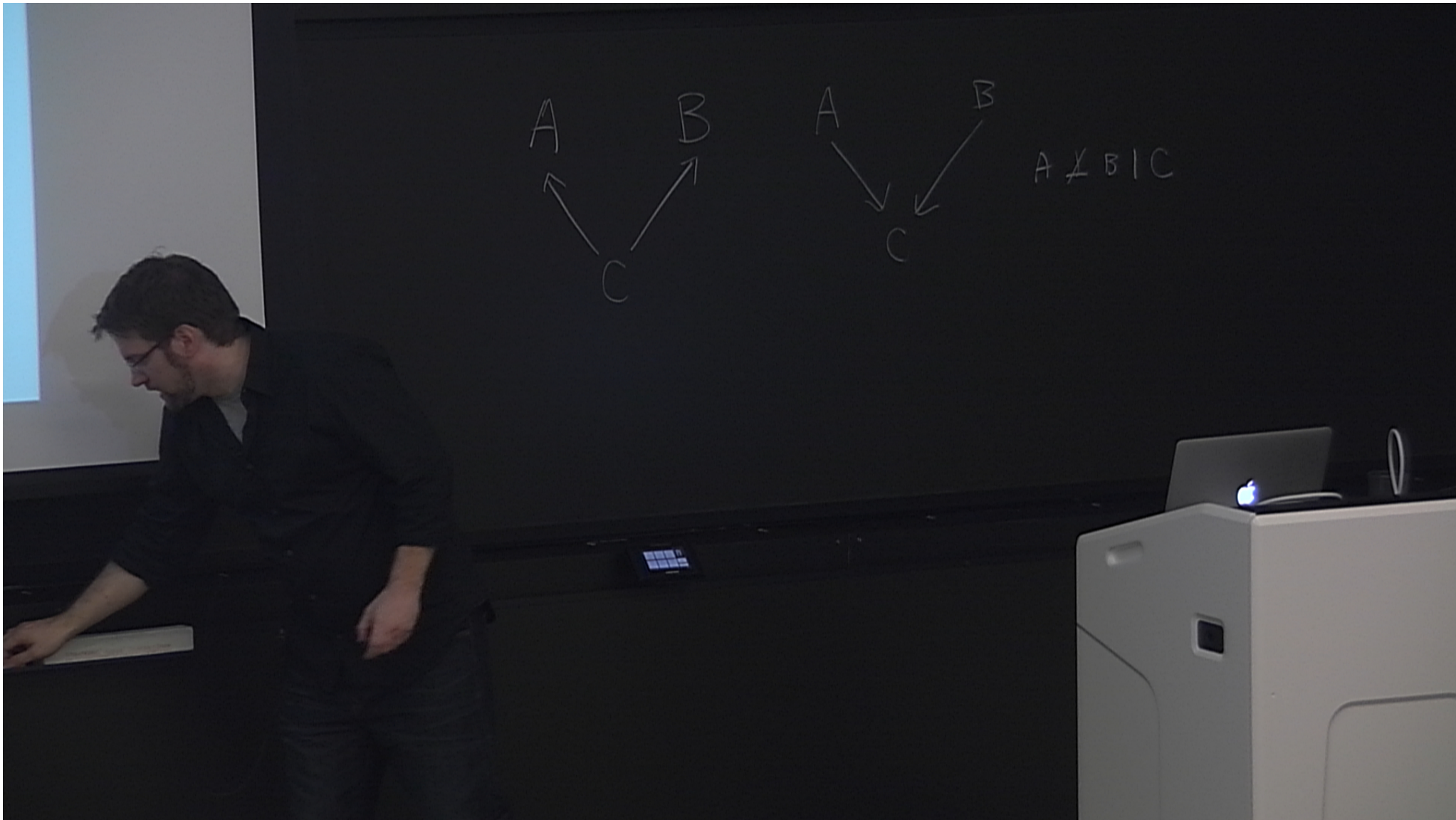
$A \perp B$   
and no other  
independence  
relations



A ? B  
C

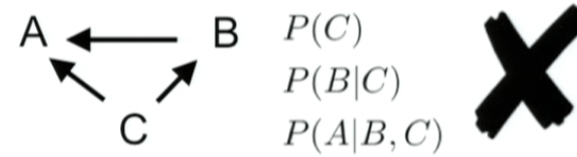
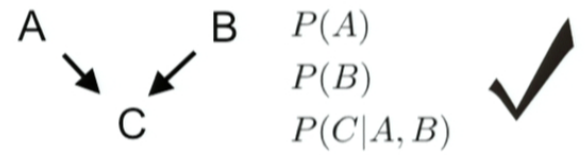








$A \perp B$   
and no other  
independence  
relations



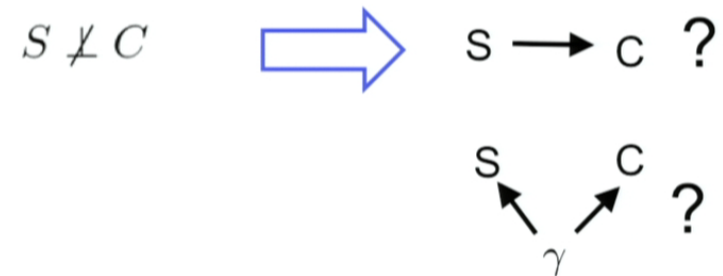
No Fine-tuning!

## A key assumption of causal discovery algorithms

### **No fine-tuning**

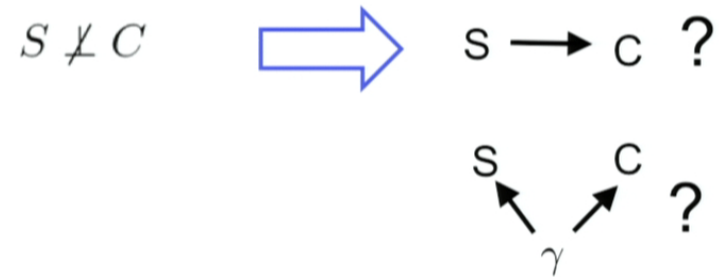
A causal model of an observed distribution is fine-tuned if the conditional independences in the distribution only hold for a **set of measure zero** of the values of the causal-statistical parameters in the model

Does smoking cause lung cancer?





Does smoking cause lung cancer?



Suppose you also observe

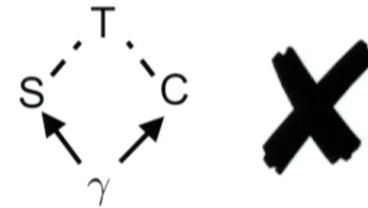
$$S \perp C \mid T$$

and no other independences

# Does smoking cause lung cancer?

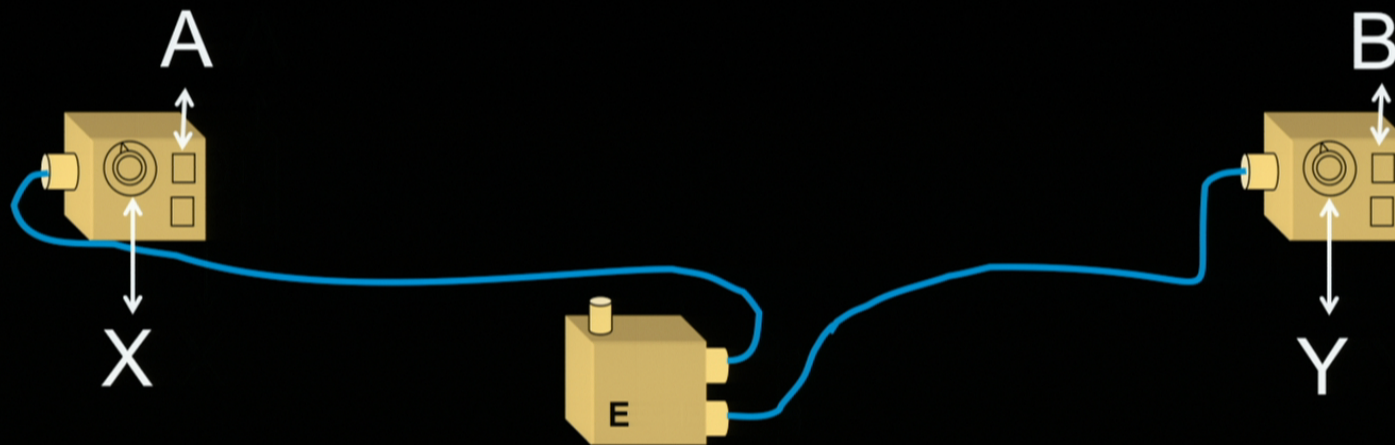
$$S \perp C \mid T$$

and no other  
independence  
relations



Inferring facts about the causal structure from  
the strength of correlations





Quantum predictions for  
 $P(A, B, X, Y)$



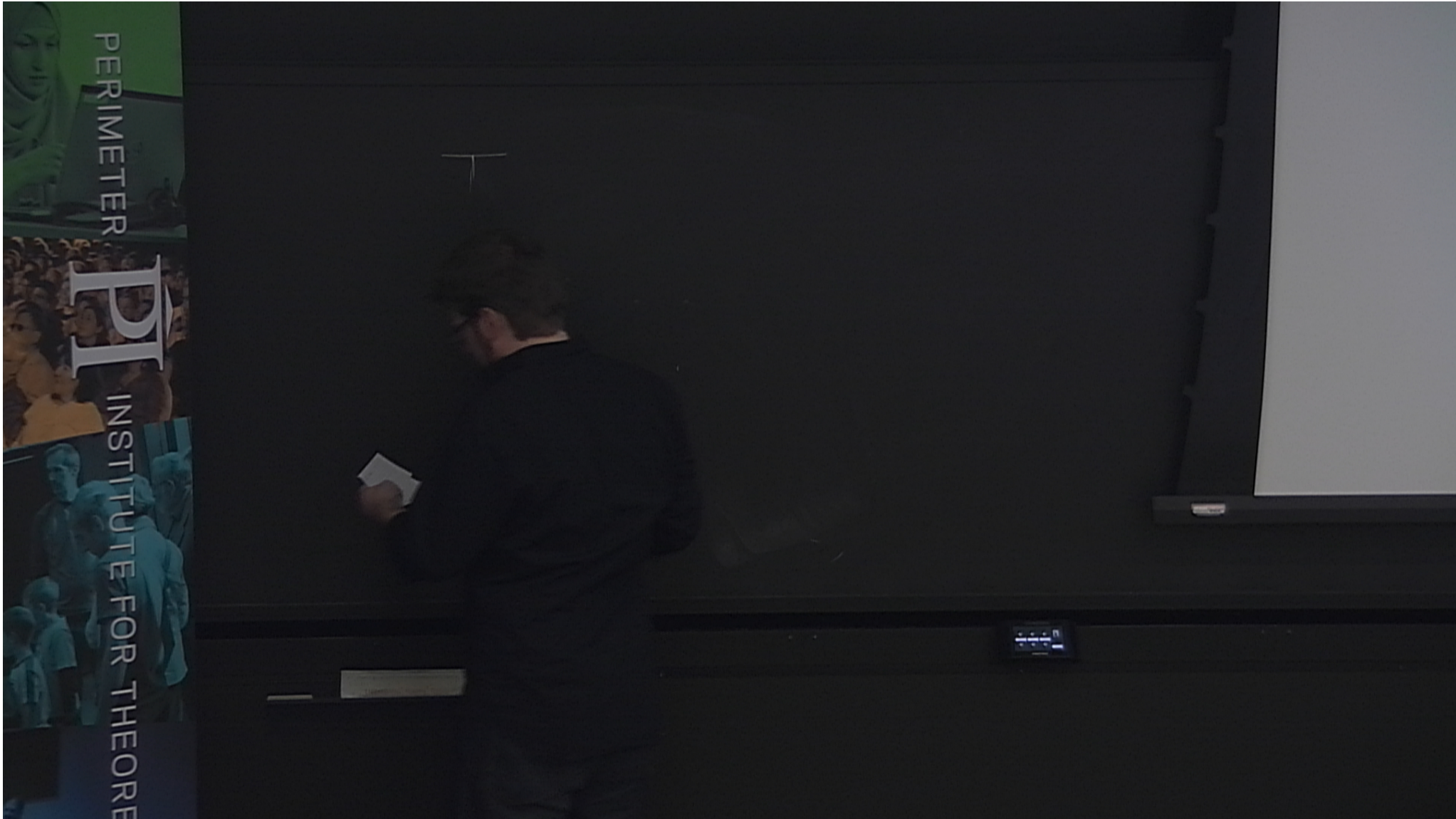
A	B
?	
X	Y

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





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

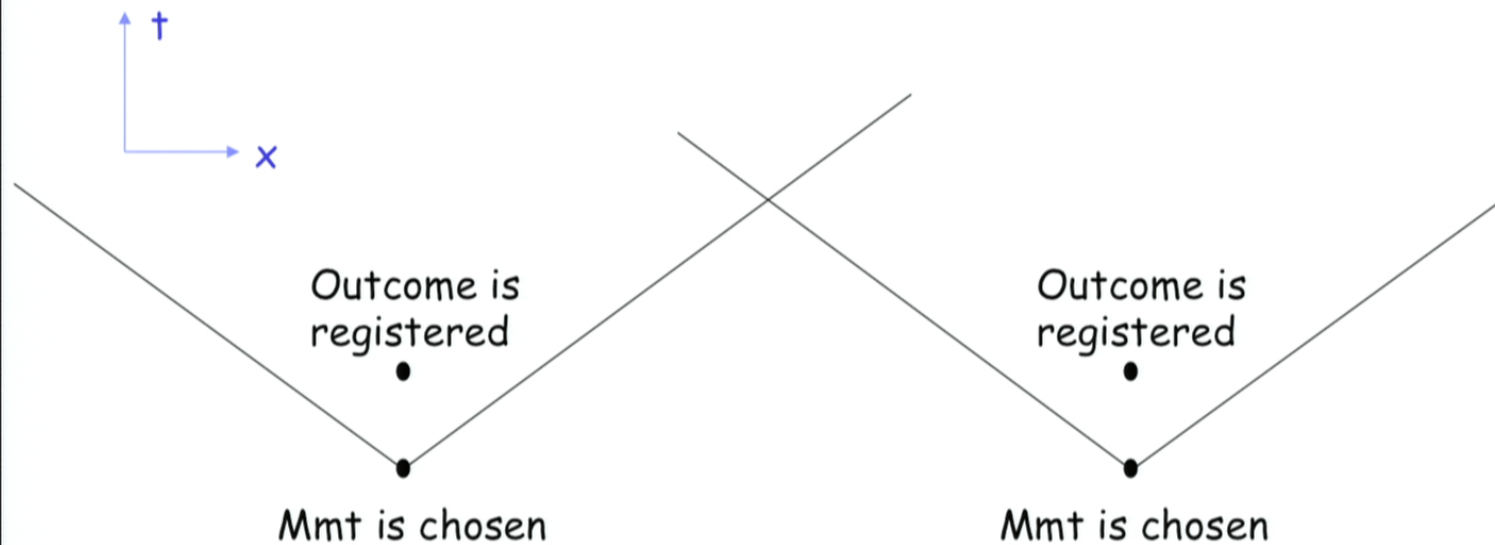


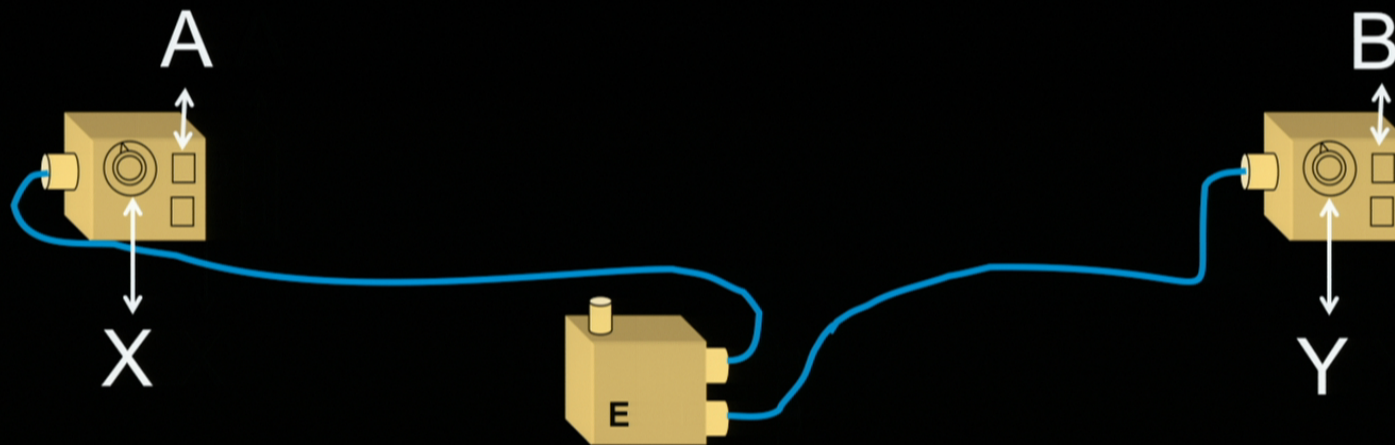
A: Rig the game so that the choices of settings are not random but instead are correlated with the local strategies

But surely nature isn't so conspiratorial...



## Tension with the theory of relativity





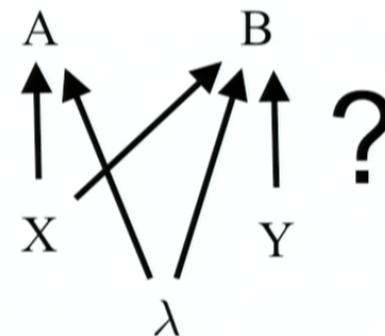
$$P(X, Y)$$

$$= (\tfrac{1}{2}[0] + \tfrac{1}{2}[1])(\tfrac{1}{2}[0] + \tfrac{1}{2}[1])$$

$$P(A, B|X, Y)$$

$$= \tfrac{1}{2}[00] + \tfrac{1}{2}[11] \quad \text{if } XY = 0$$

$$= \tfrac{1}{2}[01] + \tfrac{1}{2}[10] \quad \text{if } XY = 1$$



- Reichenbach's principle
  - No fine-tuning



Contradiction with quantum theory and  
experiment