Center for Philosophy, Science, and Politics

# The Statistical Nature of Causation

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## Introduction

Let's assume we know the correlations between some variables.

("Correlation" means (i) *any* probabilistic *dependency*, not specifically linear or Gaussian, (ii) *population-level* distributions (we're not worried about issues of statistical inference), (iii) that holds within some (often implicitly assumed) kind of context.)

Can we draw any causal conclusions?

**Linkage** (cf "Reichenbach's Principle")

If **X corr Y**, then X and Y must be *causally linked* by one or more *causal paths* (in which either X causes Y, or vice versa, or they have a common cause).

In such cases, if we *control* for some element Z in all such paths, then **X ⊥ Y | {Z}**.

**Unlinkage**

If **X ⊥ Y**, then X and Y are *not causally linked.*

If **X ⊥ Y | {Z}**, then X and Y are *not causally linked* by paths that do not involve any of {Z}.

## Bayesian Networks

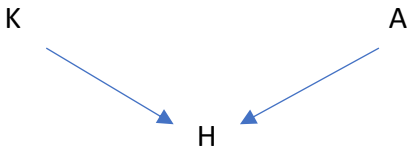
Now, if we assume that our set of variables is *causally complete* (it contains all *common causes* of variables it does contain), then these assumptions imply the "*Causal Markov*" and "*Faithfulness*" Conditions, and these will often suffice, given enough correlations, to determine a unique causal ordering of the variables.

Imagine kidney disease (K) and alcohol drinking (A) are both correlated with hypertension (H), though neither is correlated with the other.

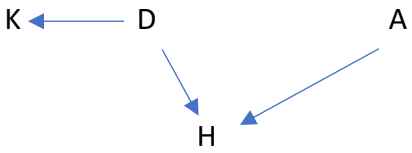
So there must be paths linking K and A with H, but there can't be a path linking K and A.

But if H caused either K or A or both, then K and A would be correlated, which they aren't.

So the only possible causal structure is:




Note how causal completeness is needed here. Without it we can't rule out the correlations being due to:




Note here that it's specifically the *common* causes of included variables we need to include, not *all* such causes. Omitting causes that aren't common causes might leave us ignorant about the precise causal route by which one quantity X causes another Y, but this won't mean we're wrong if we conclude that X does cause Y.

(Can we ever be confident that we've attended to all possible confounders? My impression is that on this economists are far less optimistic than epidemiologists and data scientists.)

**Probabilistic Theories**

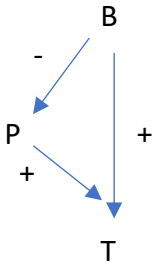
Anyway, my concerns are metaphysical, not methodological. *Why* is it possible to infer causes from correlations (given causal completeness)? Amazingly, most philosophical theories of causation offer no answer. For all they say, "causal inference" is a mystery.

A few philosophers have tried simple "*probabilistic*" reductive theories of causation: causation *just is* the kind of asymmetric structure implied by the Causal Markov and Faithfulness Conditions. In support, we might observe that these structures are just what we need as guides to action.

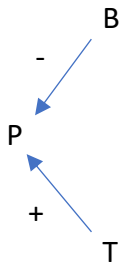
But there are two good reasons for thinking that causation itself lies metaphysically deeper, and that the correlational patterns are merely fallible evidence of it: (1) Failures of Faithfulness; (2) single-case counterfactuals.

*Faithfulness Failures*

Hesslow's famous example with **B**irth control pills, **P**regnancy and **T**hromboses.



If the two paths cancelled out precisely, then there'd be no correlation between B and T, and the structure implied by the correlations alone would be as below, which by hypothesis is wrong.




*Counterfactuals*

Suppose the correlations show that "smoking causes cancer". Jim smokes and gets cancer. Did *his cancer* depend causally on *his smoking?* Not necessarily. Again it looks as if the metaphysical substance of causation lies deeper than the correlational patterns that evidence them.

**<u>Causation as Structural Dependencies</u>**

A better idea is that causation consists of the kind of detailed deterministic dependencies represented by "structural equations" like:

$X = e_x$
$Y = aX + e_y$
$Z = bX + cY + e_z$

Can't we reorder the equations so that X, say, depends on Y and Z rather than vice versa? But then the exogenous terms $e_i$ won't be probabilistically independent.

So I suggest:

*Structure*: X causes Y if and only if it is an ancestor of Y in a recursive structure of deterministic dependencies $X_i = F(X_1, \ldots X_{i-1}, e_i)$ with independent exogenous terms.

Note that we don't have to assume linearity, nor real-valued variables.

If we assume *Structure*, then it is trivial to derive the Causal Markov Condition. For variables to be correlated, they need to be linked in the equations.

But the Faithfulness Condition isn't guaranteed. That's just what we want. As a rule of thumb, independency indicates unlinkage. But nothing in principle excludes misleading independencies due to freaky cancelling out.

Descending to the full set of structural dependencies also allows a natural account of single-case counterfactuals like *If Jim hadn't smoked, he wouldn't have got cancer*.