

# Correlation and Causation – the logic of co-habitation

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## Abstract

Recent advances in graphical models and the logic of causation have given rise to new ways in which scientists analyze cause-effect relationships. Today, we understand precisely the conditions under which causal relationships can be inferred from data, the assumptions and measurements needed for predicting the effect of interventions (e.g., treatments on recovery) and how retrospective counterfactuals (e.g., “I should have done it differently”) can be reasoned about algorithmically or derived from data. The paper provides a brief account of these developments.

## Introduction

James Lee paper, Correlation and Causation, would probably raise a few eye brows among readers of the *European Journal of Personality*. “Again?” Some will ask, “Haven’t we heard enough about this subject? and isn’t it an established fact that even seasoned experts cannot agree on the definition of cause and effect or on how one should estimate such relationships from observational studies?”

Things have changed in the past two decades. Today, experts agree (some unwittingly) on almost every aspect of causal analysis; controversies have given way to theorems, paradoxes have been resolved, and estimation problems have been algorithmitized.

James Lee is right in starting the discussion by introducing new notation. Most controversies of the past have originated with notational confusion and most mistakes today stem from the belief that probability calculus is sufficient for handling causal relations. The insufficiency of probability (and statistics) is traumatic to most researchers in the field of data analysis because our schooling has given us the illusion that, first, a joint density function of all observed variables is the ultimate source of all knowledge and, second, everything that can be inferred from data can be inferred using the mathematical machinery of probability and statistics.

While the *do*-operator and expressions of the type  $P(mud | do(rain))$  may appear to be an unnecessary, if not offensive infringement on probability theory, the causal diagrams

associated with such expressions convey their meaning vividly and unambiguously, especially to researchers familiar with path analysis and Structural Equation Models (SEM). I strongly recommend therefore that researchers invest the time in acquiring the few fundamental graphical tools necessary for causal analysis. *D*-separation is one such tool, without which one is at a loss as to what the testable implications are of a given model, whether a variable  $Z$  qualifies to serve as an Instrumental Variable, or whether two proposed models are statistically indistinguishable. The back-door criterion is another, with the help of which one can tell immediately whether a causal effect can be estimated by adjustment on observed covariates.

However, the theory of causal diagrams differs in two fundamental aspects from conventional SEM. First, no commitment is made to linearity or to any parametric representation of the equations – these remain strictly qualitative. Second, the causal assumptions that go into the diagram are precisely defined and, contrary to conventional practice, are not conflated with their statistical surrogates.

In the sequel I will summarize the tools that the new theory of causation offers to researchers: For details, please see (Pearl, 2009, 2010, 2012a).

## Summary of Capabilities

1. Tools for reading and explicating the causal assumptions embodied in SEM models as well as the set of assumptions that support each individual causal claim.
2. Methods of identifying the testable implications (if any) of the assumptions in (1), and ways of testing, not the model in its entirety, but the testable implications of the assumptions behind each causal claim.
3. Methods of deciding, prior to taking any data, what measurements ought to be taken, whether one set of measurements is as good as to another, and which measurements tend to bias our estimates of the target quantities.
4. Methods for devising critical statistical tests by which two competing theories can be distinguished.
5. Methods of deciding mathematically if the causal relationships of interest are estimable from non-experimental data and, if not, what additional assumptions, measurements or experiments would render them estimable,
6. Methods of recognizing and generating equivalent models.
7. Generalization of SEM to categorical data and non-linear interactions.
8. A formal solution to the problem of “external validity” (Campbell and Stanley, 1963), that is, under what conditions can results from an empirical study be transported to another environment, differing from the first, how the results should be calibrated to account for the differences, and what measurements need be taken in each of the two environments to license the transport (Pearl and Bareinboim, 2011).

9. A simple, causally-based solution to the so called “Mediation Problem,” taking the form of estimable formulas for direct and indirect effects that are applicable to both continuous and categorical variables, linear as well as nonlinear interactions.

## The Mediation Formula

This last result deserves further discussion because the problem of mediation is extremely important in personality research for it unveils the mechanisms that mediate between causes and effects.

The analysis of mediation has long been a thorny issue in the social and behavioral sciences (Baron and Kenny, 1986; MacKinnon, 2008) primarily because the distinction between causal parameters and their regressional surrogates were too often conflated (Pearl, 2012b). The difficulties were amplified in nonlinear models, were interactions between pathways further obscures their distinction.

The nonparametric analysis now permits us to define the target quantity in a way that reflects its actual usage in decision making applications. For example, if our interest lies in the fraction of cases for which mediation was *sufficient* for the response, we can pose that very fraction as our target question, whereas if our interest lies in the fraction of responses for which mediation was *necessary*, we would pose this fraction as our target question (Pearl, 2001, 2012b).

In both cases we can dispose of parametric analysis altogether and ask under what conditions can the target question be identified/estimated from observational or experimental data. One can further show that, if certain conditions of “no unmeasured confounders” hold, a simple Mediation Formula can be derived that captures the effects of interest. The Mediation Formulas are applicable to both continuous and categorical variables, and can consistently be estimated from the data.

I commend James Lee for illustrating so vividly the power of causal diagrams in a language familiar to personality researchers. I am hopeful that readers will appreciate both the transparency of the model and the power of the approach.

## References

- BARON, R. and KENNY, D. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology* **51** 1173–1182.
- CAMPBELL, D. and STANLEY, J. (1963). *Experimental and Quasi-Experimental Designs for Research*. Wadsworth Publishing, Chicago.
- MACKINNON, D. (2008). *An Introduction to Statistical Mediation Analysis*. Lawrence Erlbaum Associates, New York.
- PEARL, J. (2001). Direct and indirect effects. In *Proceedings of the Seventeenth Conference on Uncertainty in Artificial Intelligence*. Morgan Kaufmann, San Francisco, CA, 411–420.

- PEARL, J. (2009). *Causality: Models, Reasoning, and Inference*. 2nd ed. Cambridge University Press, New York.
- PEARL, J. (2010). The foundations of causal inference. *Sociological Methodology* **40** 75–149.
- PEARL, J. (2012a). The causal foundations of structural equation modeling. In *Handbook of Structural Equation Modeling* (R. Hoyle, ed.). Guilford Press, New York, 68–91.
- PEARL, J. (2012b). The causal mediation formula – a guide to the assessment of pathways and mechanisms. *Prevention Science* DOI: 10.1007/s11121-011-0270-1, Online, March 2012. <[http://ftp.cs.ucla.edu/pub/stat\\_ser/r379.pdf](http://ftp.cs.ucla.edu/pub/stat_ser/r379.pdf)>.
- PEARL, J. and BAREINBOIM, E. (2011). Transportability across studies: A formal approach. In *Proceedings of the Twenty-Fifth AAAI Conference on Artificial Intelligence*. Menlo Park, CA, 247–254.