

REVIEWS

Edited by **Darren Glass**

Department of Mathematics, Gettysburg College, Gettysburg, PA 17325

The Book of Why: The New Science of Cause and Effect. By Judea Pearl and Dana Mackenzie, Basic Books, New York, NY, 2018. 432 pp., Print ISBN: 978-0141982410, \$19.99.

Reviewed by **Jeff Witmer**

Judea Pearl has a big idea and he wants the world to know it: statistical inference is possible with observational data. Pearl and others have known this and have been saying it, in various ways, for many years. Pearl has been a leader in spreading the gospel of causality in writings such as [4–6], and even creating the Causality in Statistics Education award in 2013. However, we in the statistics community have largely ignored the message, much to our detriment. Not only is inference possible with observational data, but there are good ways to approach the issue and we can learn a lot about the world by using the tools that Pearl and others have created.

The scientific community would benefit greatly from a better understanding of causal inference—and “better” is quite a low bar, given how little the tools of causal reasoning have been used over the years. But statisticians have stood in the way, insisting that cause-and-effect conclusions can only be drawn from randomized experiments and delighting in telling stories about confounded effects that arise when analyzing observational data, all while repeating the mantra that correlation is not causation. In so doing, we statisticians congratulate ourselves too much, while turning students away from asking and answering questions of genuine interest. At the same time, we hamper the advancement of scientific and societal progress. It is high time that we listen to what Pearl has been trying to say for a couple of decades now.

I wrote “trying to say” because it would be easier to follow Pearl’s leadership if he communicated more clearly. Unfortunately, most of what Pearl has written in the past has been rather dense and technical, making it difficult to read if you are not an expert in the area (and I am not). *The Book of Why* is a laudable attempt to bridge the gap between specialists in the field and a more general audience, and to make accessible and understandable the best thinking in the area of causal inference. This goal is supported by the book’s conversational style, which results in a presentation of causal inference that is easier to read than other work by Pearl; a good deal of credit must surely go to his co-author Dana Mackenzie, a mathematician-turned-science writer, and one of the people responsible for the *What’s Happening in the Mathematical Sciences* series of books published by the American Mathematical Society.

Simplifying Pearl’s message for *The Book of Why* was partly, but not entirely, successful. The organization of the book is sensible. Pearl starts with a discussion of the three levels of causation: association, intervention, and counterfactuals—in other words, seeing (“I noticed that students with a background in algebra do better in statistics classes than students without one”), doing (“Let’s require students to take college algebra before they take statistics”), and imagining (“Does math skill make students successful in stats, or is it general intelligence that is at work here?”). He moves on to describe path diagrams that can be used to illustrate causal relationships and then he

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discusses Bayes's rule and Bayesian networks. He then discusses the confounding and lurking variables that complicate our understanding of causation before presenting a chapter on paradoxes. Along the way, he introduces his "do-operator," which allows one to formalize these notions and express interventions in a way that one can analyze mathematically. He follows with chapters on counterfactuals and on mediation, finally ending the book with a chapter on big data and artificial intelligence. All of these chapters include examples and stories about the history and development of ideas.

Prominent here is the tale of Jerome Cornfield taking on R. A. Fisher in a notorious debate in the 1950s over whether smoking causes cancer. This led to what are known as the Cornfield conditions, which show how strong a confounder has to be in order to explain away an observed relative risk. Fisher, a smoker and the world's most prominent statistician, argued that the link between smoking and lung cancer might be caused by genetics, the potential confounder. Cornfield rebutted this argument in [2] by showing that the effect of genetics is not strong enough to fully explain the link between smoking and cancer, based on the prevalence of certain genetic conditions in the general population. Cornfield's mathematics laid the groundwork for future understanding of risk sensitivity and causation. Sadly, the statistics community was very slow to pick up on this. Indeed, even today many statisticians are not familiar with the Cornfield conditions. We refer readers interested in learning more about this work to [3].

Despite the interesting stories and examples, the writing in *The Book of Why* is at times somewhat opaque. For example, Pearl presents the "do-calculus," which is a set of rules based on his "do-operator" that show how doing something (giving someone aspirin) rather than merely observing something (some people take aspirin but some don't) can lead to understanding causal associations. He gives examples as well as some rules for assessing whether a particular argument holds, and with enough work the reader can follow the logic, but I would have benefitted from seeing the steps spelled out, one by one, in a more simple manner.

For me, the most valuable lesson about the usefulness of causal diagrams concerns Simpson's paradox where, for example, two variables X and Y have a positive association at every level of a third variable Z , but X and Y have a negative association when collapsing over all levels of Z . For example, there is a famous Berkeley graduate school admissions example in which X represents the sex of the applicant, Y represents the admissions decision, and Z is the department to which the person applied. It turns out that women have lower acceptance rates than men in the aggregate, but higher within individual departments, making this an example of Simpson's paradox (see [1] for more details).

For years I taught students about this paradox and simply said that sometimes it makes sense to use the conditional association and sometimes to use the aggregated association, hoping that the diligent could figure out which level of association was correct to use on a case-by-case basis. The causal diagrams developed by Pearl cast a new, and much appreciated, light on the problem. The thing one should do is to make a diagram with arrows pointing among X , Y , and Z showing what causes what. This helps clarify the question of whether Z causes X and Y ; see Figure 1.

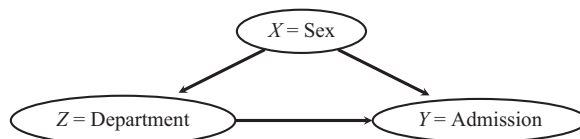


Figure 1. Causal diagram showing the case of possible gender discrimination in Berkeley graduate admissions.

If Z causes X , then use the aggregated association; so if applying to a certain department caused one's sex to change, then we should use the association between sex and admission and we would conclude that Berkeley was biased against women. If Z does not cause X , then use the conditional association. The act of applying to the English department ($Z = \text{English}$) versus the Chemistry department ($Z = \text{Chemistry}$) does not cause one's sex (X) to change, so we should use the conditional associations between sex and admission and conclude that Berkeley did not discriminate against women.

Berkson's paradox is much less well known, but is also important. It might be that two variables X and Y are independent, but they might both be related to a third variable Z , which is called a collider. Pearl describes this situation with a causal diagram $X \rightarrow Z \leftarrow Y$. If we condition on Z we might think that X and Y are related. This paradox originated from examining medical studies, but is perhaps more easily understood in the context of baseball. Suppose X is baseball hitting ability and Y is pitching ability and let Z indicate that a player is in the major leagues. If we only look at data for major league players, then X and Y appear to be negatively correlated (i.e., we see that MLB pitchers have low batting averages). Although the negative association would vanish if we looked at all baseball players, by limiting our analysis to MLB players we are excluding players who are low on both X and Y (since you can't make it to the major leagues unless you can either hit well or pitch well). Many of my students don't follow baseball, so I discuss dating: let X be intelligence, let Y be attractiveness, and let Z be that you have dated the person. Assuming you only date people who you think are smart or good looking (or both), you might think that intelligence and attractiveness are inversely related; but you would be wrong. A negative association might exist among the set of people you have dated, but that is because your dating pool excludes part of the general population.

The Book of Why is an admirable but flawed attempt to do something very important. And this review of it is flawed but you are reading it anyway. Such is life. You should also read the book. Seriously, everyone should read *The Book of Why*. The writing is dense in many places and it doesn't flow as smoothly as one might have hoped, but the content is important. Students are going to apply causal reasoning to situations they encounter, whether or not they are trained in how to do that properly. They need to understand how to think about causal relationships and we educators should be helping them. But what should we tell them? At what level of detail? In what course? I won't prescribe answers to those questions, but if you read *The Book of Why* you'll have a good start on constructing your own answers.

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Department of Mathematics, Oberlin College, Oberlin, OH 44074
jeff.witmer@oberlin.edu