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REVIEW

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Judea Pearl. *Causality: Models, reasoning, and inference*. Cambridge: Cambridge University Press. 384 pp., 2000, ISBN 0521773628.

Readers of this journal will need no reminder that structural equation modeling (SEM) has taken its place as a widely accepted and applied technology for investigating relations in nonexperimental multivariate data. The seminal work of Jöreskog on the LISREL model introduced this technology to psychometrics, and this was followed by variant but equivalent models developed by Muthén, Bentler, McDonald and others. We have computer packages for the fitting and testing of extremely complex composite hypotheses, and a general, settled, conventional wisdom for their application. This is not to deny that there are many unsettled questions about SEM, but there seems little disagreement over procedures for determining the identifiability of the model globally, fitting it globally, and testing fit globally, by general asymptotic criteria.

To those who may feel that a little unsettling of this settled wisdom may be desirable, the publication of Judea Pearl's account of causality is timely. Over the last decade or so, Pearl and his co-workers have been engaging with problems of central concern in SEM (and, indeed, of central concern in many areas of social/behavioral science method) from a refreshingly distinct perspective. The basis of this work is a generally nonparametric, nonlinear structural equation model. The central feature of this model is that it is structured by a Directed Acyclic Graph (DAG). By interrogating a picture of the graph that structures a model, we obtain qualitative information about its important features. We can fairly easily list the testable constraints on data, check the identifiability of specified causal effects, and generate a class of further equivalent models.

A strong case is made for (a) DAG-based specific identifiability conditions, (b) the replacement of global goodness of fit of a complex composite hypothesis by DAG-based small-sample tests on individual constraints (commonly in the classic path-analytic form of vanishing partial covariances), and (c) the DAG-based treatment of observationally equivalent models. These are the main practical benefits of Pearl's refreshingly different approach.

The account of causality has a larger purpose than the achievement of the practical objectives just listed. A case is made for "the primacy of causal over associational knowledge". This is a clear challenge to researchers trained to hold positivist positions about causal claims based on nonexperimental data. Pearl makes a distinction between conditioning on observations of independent variables—regression relations—and conditioning on conjectural (or actual) controlled values of independent variables—structural relations. Graphical criteria determine conditions under which these will or will not coincide. He is consequently able to give a rigorous account of the conclusions that can be drawn about causal effects, and appropriate statistical control, in a correctly specified causal model.

Readers of this journal can, of course, be assumed competent in linear algebra and in statistical theory associated with structural models. Yet it is necessary to warn that such competence may not necessarily make this book easy reading. In conventional SEM, drawing a path diagram is just an easy way to invent an impressively complex, but possibly arbitrary and inappropriate model for a set of multivariate observations, and the graphical properties of the diagram are not usually exploited in any serious way. We are assured by Pearl that on mastering the central concept of d-separation—the graphical condition in which a pair of nodes (representing variables) is said to be directionally separated by a set of further nodes—we can arrive quickly and easily, by inspection, at conclusions about identified effects, implied constraints, equivalent models, and other applications, in quite complex causal networks. The DAG theory needed takes this reviewer

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at least into unfamiliar territory. Other readers might join me in hoping that in due course Judea Pearl or one of his students will write a more elementary introduction to this important topic, with a gentler treatment of the central concepts, and many more examples. Given the relative unfamiliarity of the material, it is a matter of some regret that proofs of a number of basic theorems are omitted, and must be sought after in technical reports, conference proceedings, and journals not regularly accessed by psychometricians or statisticians.

A few remarks are needed about what the book does **not** try to do. Although it is based on a general nonparametric, nonlinear SEM, no attempt is made to develop nonlinear models or parametric models more general than those currently in use. We may hope that the next generation of workers on SEM methodology can use this framework for just such developments, but it is not an objective intended by Pearl, who has more urgent concerns, as indicated. By strict definition, *directed, acyclic* graphs do not cover models with correlated disturbances or nonrecursive models. Theory is extended to such models, but the range of application of some of the theorems could have been made a little clearer, and the account of such cases looks incomplete. More explicit connections between general nonparametric results and results (chapter 5) for linear models are needed. (Some models with the same graph are identified in the linear model and underidentified more generally.) This book is a timely account of work in progress. It stands as a challenge and an invitation to workers in a number of fields to undertake further developments of this important new research program.

According to the preface "the sequence of discussion follows more or less the chronological order by which our team at UCLA have tackled these topics" (p. xv). The preface supplies a sequence of sections that can be read as an introduction to the nonmathematical aspects of causation, and an alternative sequence for "more formally driven readers" (p. xv). Both these sequences require a certain amount of guesswork and backtracking. My own recommendation is that specialist readers go straight to the topic that will motivate them to master the rest of the material needed. For psychometricians this will be chapter 5. (For most statisticians it will be chapter 6, and for philosophers of science, chapter 7.) They will then decide to work through the book in sequence or to find the minimally necessary foundations for their interests by backtracking. And every reader should go first to the epilogue—a public lecture that sets out the topic in a way that is both nontechnical and very enjoyable reading.

While this book could be used by students in a number of fields, as a basis for a specialist graduate course on causality, it is more likely to serve as supplementary reading in the context of an existing course. I recommend it as essential reading for all researchers for whom the question of causality arises. Does that leave anyone out?

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