erties that will terminate as a result of F_i from those that will persist despite of acting F_i. Such a model of persistence was invoked in (Pearl, 1993b); there, it was assumed that only those properties should persist that are not under any causal influence to terminate. This assumption yields formulas for the effect of *conditional interventions* (conditioned on the observation C) which, again, given Γ, can be estimated from nonexperimental data.

A more ambitious task has been explored by Spirtes, Glymour and Scheines, (1993) – estimation of the effect of intervention when the structure of Γ is not available and must also be inferred from the data. Recent developments in graphical models (Pearl and Verma, 1991; Spirtes, Glymour and Scheines, 1993) have produced methods that, under certain conditions, permit us to infer plausible causal structures from nonexperimental data, albeit with a weaker set of guarantees than those obtained through controlled randomized experiments. These guarantees fall into two categories: minimality and stability (Pearl and Verma, 1991). Minimality guarantees that any other structure compatible with the data is necessarily more redundant, and hence less trustworthy, than the one(s) inferred. Stability ensures that any alternative structure compatible with the data must be less stable than the one(s) inferred; namely, slight fluctuations in the distributions of the disturbances ε_i (2) will render that structure no longer compatible with the data.

When the structure of Γ is to be inferred under these guarantees, the formulas governing the effects of interventions and the conditions required for estimating these effects become rather complex (Spirtes, Glymour and Scheines, 1993). Alternatively, one can produce bounds on the effect of interventions by taking representative samples of inferred structures and estimating $P_{\check{x}_i}(x_j)$ according to (10) for each such sample.

In summary, I hope my comments convince the reader that DAGs can be used not only for specifying assumptions of conditional independence but also as a formal language for organizing claims about external interventions and their interactions. I hope to have demonstrated as well that DAGs can serve as an analytical tool for predicting, from nonexperimental data, the effect of actions (given substantive causal knowledge), for specifying and testing conditions under which randomized experiments are not necessary and for aiding experimental design and model selection.

Comment

Michael E. Sobel

It is a pleasure to discuss these excellent papers. Spiegelhalter, Dawid, Lauritzen and Cowell nicely put together a number of themes, demonstrating, in a Bayesian context, the utility of graphical modelling in the construction of probabilistic expert systems. The authors show how graphs can be used heuristically to solicit expert opinion, and in Section 6, how the theory of conditional independence graphs can be used to make tractable (while maintaining reasonable substantive assumptions) the calculation of probabilistic features of the system (monitors). For example, the authors want to apply to the directed independence graph of their Figure 2 the decomposability theorem for undirected conditional independence graphs, which permits a full factorization of the probability distribution. To do so, they associate the graph of Figure 2 with its moral graph (an undirected conditional independence graph) and use the fact that the separation properties of the moral graph apply to the directed independence graph. They then embed the moral graph into a triangulated graph, enabling use of the desired theorem; further simplications come from organizing the cliques of the triangulated graph into junction trees.

My vantage point is that of a social statistician: as such, there is more for me to say about the paper by Cox and Wermuth. In particular, I want to expand on and further tie several themes in this paper to research in the social and behavioral sciences. Thus, discussion focuses primarily on this paper; I shall often freely borrow notation from there.

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TYPES OF INDEPENDENCE GRAPHS

Cox and Wermuth nicely characterize various types of dependencies among random variables. Prior work has focused attention on two types of independence graphs. If no ordering is imposed on the variables, undirected graphs are used; here, the absence of an edge between two vertices denotes conditional independence of the variables associated with the vertices,