quires the graph to be chordal for there to be equivalence, whereas Theorem 1+ puts no requirements on it. Theorem 2* requires the hypergraph to be acyclic for there to be equivalence, whereas Theorem 2+ requires only that it be conformal. Theorem 3* requires the set of conditional independencies to have a conflict-free cover for there to be equivalence, whereas Theorem 3+ puts no requirements on it (actually, the closure with respect to strictly positive distributions of a set of conditional independencies is always graph-generated).

As far as I know, Theorems 1*, 2* and 3* are new, although, by now, they are probably not unexpected.

Parallel developments in the two fields have occurred in the past, with neither aware of the other, apparently. For example, Vorob'ev's (1962) results on extending consistent marginal distributions parallel similar results for the extension of consistent databases (Beeri et al., 1983). And Beeri and Kifer's (1986a, 1986b, 1987) work on fixing sets of multivalued dependencies that have intersection anomalies parallels Dawid's (1979b) method for fixing up sets of conditional independencies.

3. MODELS AND DATA

Two simple but important points, each mentioned in both papers and neither having to do directly with graph theory, deserve to be emphasized. First, both papers take the position that a model represents the substantive knowledge that an expert brings to the problem prior to seeing specifically relevant data. One practical consequence of such a position is that statisticians cannot work in a vacuum; rather, they must interact and communicate effectively with domain specialists. And, on a more philosophical note, this position highlights the fact that a scientifically meaningful model for the data is as much a subjective prior assessment of the relative likelihood of possible values as is a scientifically meaningful model for the parameters of such a model. Second, SDLC stress and CW mention that observed data allow us not only to estimate parameters in the model but also to monitor and, if need be, to critique the model. It is refreshing to see frequentists concerned about representing expert knowledge and Bayesians worried about model criticism.

4. SOME QUESTIONS FOR THE AUTHORS

Can you have discrete variables in chain graphs with dashed edges? Can you explain why the diagnostic ability of the Bayesian network was not as good as that of the CART-like algorithm? From Table 6, it appears that for 110 cases (of 168) the Bayesian network assigned the correct diagnosis the highest probability; what were the ranks of the correct diagnoses for the other 58 cases? Has anyone created Bayesian networks with both discrete and continuous variables? Of course, with mixed models the number of parameters in each distribution will not stay fixed after updating. Has anyone considered creating a "Bayesian chip" that could be used to create truly parallel "Bayesian machines"?

Reading and thinking about these papers has been a real pleasure.

Comment: What's Next?

David Madigan

These papers represent two of the many different graphical modeling camps that have emerged from a flurry of activity in the past decade. The paper by Cox and Wermuth falls within the statistical graphical modeling camp and provides a useful generalization of that body of work. There is, of course, a price to be paid for this generality, namely that the interpretation of the graphs is more complex. I cannot resist complementing the authors on the remarkable feat of finding an example for each of the different graphical models they propose.

The paper by Spiegelhalter, Dawid, Lauritzen and Cowell falls within the probabilistic expert system camp. This is a tour de force by researchers responsible for much of the astonishing progress in this area. Ten years ago, probabilistic models were shunned by the artificial intelligence community. That they are now widely accepted and used is due in large measure to the insights and efforts of the authors, along with other pioneers such as Judea Pearl and Peter Cheeseman.

I will confine my remaining comments to the Spiegelhalter et al. paper and explore some open questions that I believe will rapidly become important, now that

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