in contemporary statistics is not the only way to achieve simplicity. The main lesson that I took away from Wermuth's doctoral research (cf. Dempster, Schatzoff and Wermuth, 1977) is that smooth systems of declining parameter values are usually a more efficient way to simplify statistical complexity than sharp cutoffs that set most parameter values to zero. Computational strategies of choice then become radically different. Classical estimation techniques that are adequate with relatively few parameters must be replaced with Bayesian or similar methods that reflect prior assessments of patterns of smooth decline. Donoho et al. (1992) illustrate a notable non-Bayesian approach. My own preference is for Bayesian models with many more hidden variables and many more dependence parameters than SDLC allow, to have a reasonable possibility of capturing actual mechanisms. I believe that rapidly developing computing power and algorithms that sample posteriors should be used to implement and test more complex Bayesian models.

Beyond the elicitation of priors and beyond the problem of simplifying the complex structures of highly multivariate and selectively filtered populations encountered in real practice, there remains a gray area that SDLC address briefly in two sentences as situations where "the number of assessments made is insufficient to specify a joint distribution uniquely." The use of maximum entropy or other arbitrary prior generation principles typically leads to exactly the unrealistic procedures that the smoothing of large parameter sets is designed to avoid. SDLC fail to mention the belief function approach (Shafer, 1976) that Dempster

and Kong (1988) show fits naturally into network modelling built on decompositions of evidence into independent sources similar in spirit to the "graphical modelling" approach of SDLC. It is my view as a coinventor of the BEL theory that it is a near cousin of the Bayesian strategy that descends directly from classical subjective probability and is not a foreign interloper from distant tribes of semicoherent formal systems. Unlike the naive upper and lower probability models that have been studied by Good, Walley and others, the BEL system constructs models from judgmentally independent assessments on knowledge spaces and combines the components by a simple precise rule that reduces to the Bayesian rule for combining likelihood and prior in the special Bayesian case. The chief hindrance to developing and testing BEL models for probabilistic expert systems has been computational difficulties. Shafer, Kong and others showed in the mid-1980s how to decompose BEL computations coincidentally with the parallel demonstrations of Lauritzen and Spiegelhalter (1988) that SDLC feature. But these clever algorithms only stave off computational complexity temporarily. The future of both Bayesian and BEL approaches depends on the revolution that has been gathering speed for the past five years on Monte Carlo posterior sampling.

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## Comment: Conditional Independence and Causal Inference

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Fourteen years ago, in an essay on conditional independence as a unifying theme in statistics, Philip Dawid wrote that "Causal inference is one of the most important, most subtle, and most neglected of all the

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problems of Statistics" (Dawid, 1979a). Only shortly later, several statisticians (Wermuth and Lauritzen, 1983; Kiiveri and Speed, 1982) introduced frameworks that connect conditional independence, directed acyclic graphs (hereafter DAGs) and causal hypotheses. In these models the vertices of a DAG G represent variables, and a directed edge  $X \rightarrow Y$  expresses the proposition that some change in variable X will produce a change in Y even if all other variables represented in G are prevented from changing. The power and generality of DAG models derive from their dual role in representing both causal or structural claims and