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Introductory Chapter: Timeliness of Advantages of Bayesian Networks

Douglas S. McNair

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1. The timeliness of Bayesian networks in an era of problematized truth-claims

As a child, I was raised as a Lutheran, with an earnest interest and concern for scripture. I became notorious for asking my Sunday school teachers imponderable and impolitic questions. Upon encountering Genesis 3:11–13 around age 6, I noticed that God confronts Adam in the Garden of Eden and asks, "Have you eaten from the tree?" Adam prevaricates: "The woman whom you gave to be with me, she gave me fruit from the tree." God inquires of Eve about this. She answers, "The serpent tricked me." My youngster mind recognized this pattern of dialog as very much akin to my own defensive dissembling with my parents when I had been the cause of some accident or had done something wrong. I very much wanted to know why Adam's and Eve's reasoning was insufficient.

God asks "what," but humans typically answer with proposals as to "why" (see [1], p. 24). We humans crave reasons and often we value causal explanations far more than facts. Adam and Eve believed that identifying causes outside themselves would exculpate them. This notion can be wrong, but the tendency in our species is strong and is an important aspect of computational ("artificial") intelligence, particularly in the present era in which AI is being widely deployed and operationalized and bestowed with progressively greater autonomy and influence over our lives. The present volume is motivated in part in recognition of this trend and the fact that social acceptance of AI strongly depends upon transparency and face-valid explanations that justify or satisfactorily legitimate authority that is exerted over us.

Bayesian networks (BNs) have come a long way since Rev. Bayes' original paper [2], and the applications in which they excel are by now very diverse. For example, Kass and Raftery [3] set forth a summation of dozens of uses for, interpretations of, and advantages and

disadvantages of Bayes factors in hypothesis testing. Bayesian networks represent graphically uncertainties and decisions that expressly represent the relationships and the strengths of probabilistic dependences among the variables and the associated information flows. A chief advantage of BNs is that they allow to address uncertainties and evidence from disparate sources, such as expert judgment [4–6] and observable experience, being able to take into account common causes and influences of social and logistical aspects [7]. In BNs, variables and their interdependencies are encoded as nodes and directed arcs with conditional probability tables (CPTs) linked with the nodes. Under the assumption of conditional independence, a BN represents the joint probability distribution of variables [8]. Bayesian networks, besides this natural transparency, revealing joint dependencies graphically in directed acyclic graphs (DAGs) whose nodes denote elements or factors associated with concepts that we can name and understand, have the notable advantage of modeling causality (more conveniently than by other methods, e.g., transfer entropy, Granger asymmetric/noncommutative correlation, etc.), in a manner that yields empirically credible transmission of evidence or influence. This capability in turn produces stochastic classifiers that can be combined with utility functions to automate optimal decision-making that emulates the decision-making embodied in the data from which the BN was learned.

2. Bayesian networks in use-cases involving epistemological or perceptual complexity

Other attributes of BNs that are timely and valuable for contemporary use-cases and applications include:

- facilitate incorporating causal knowledge resulting in probabilities that are easy to explain;

- enable consistent combining of information from various sources (including expert elicitation and crowd-sourcing) and mixed data types;

- batch or continuous updating that can be responsive to newly acquired or incoming data;

- amenable to processes aimed at measuring and accounting for model structural uncertainty;

- amenable to modeling partially observed and unlabeled data; and

- can estimate certainties for the values of variables that are not observable (or whose cost or rate of change limits the extent or frequency of direct observation).

Bayesian networks function most effectively when the arcs that are learned or induced for the BN accurately represent the direction of causality. Events or states that share a common cause are likely to be conditionally independent given the cause; arrows in the causal direction capture this independence. Adam's and Eve's (and our) human nature and mortal susceptibility to temptation were (are) common causes in just such a way, in a manner that even a child could grasp [9–11]. In a naïve Bayes network, the arcs are often not in the right causal

direction (e.g., diabetes does not cause aging). But in non-naïve and other BN types, the arcs are mostly accurate regarding causality (e.g., diabetes does cause insulin to be low or insulin sensitivity to be low), and this feature is sufficient to make such BNs not only useful but humanly understandable and socially endorsable, even in highly complex contexts [12–23].

Contributions in other chapters in the present volume explore a variety of novel ways in which BNs are becoming ever more relevant and impactful within the broader armamentarium of AI methods for real-world applications. My own recent engagement with Bayesian networks has been primarily directed to pharmacogenomics-related systems biology and physiologically based pharmacokinetics (PBPK) modeling for efficient drug development and personalized medicine. However, the aspect of credible (Bayesian) accounts of causation that were timely and salient to me at age 6 remain so now 60 years later and are exemplified by contemporary BNs. I anticipate that readers will likely find them so as well.

"A model is a simplification or approximation of reality and hence will not reflect all of reality. ... [George E. P. Box] noted that 'All models are wrong, but some are useful.' While a model can never be [full, immutable, ground] 'Truth,' a model might be ranked from very useful, to useful, to somewhat useful to, finally, essentially useless." —Kenneth Burnham and David Anderson (2002).

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