Analysis of Three Bayesian Network Inference Algorithms: Variable Elimination, Likelihood Weighting, and Gibbs Sampling

Bayesian networks are a type of probabilistic graphical models lie at the intersection between statistics and machine learning. They have been shown to be powerful tools to encode dependence relationships among the variables of a domain under uncertainty. Thanks to their generality, Bayesian networks can accommodate continuous and discrete variables, as well as temporal processes. In this paper authors review Bayesian networks and how they can be learned automatically from data by means of structure learning algorithms. Also, authors examine how a user can take advantage of these networks for reasoning by exact or approximate inference algorithms that propagate the given evidence through the graphical structure. Despite their applicability in many fields, they have been little used in neuroscience, where they have focused on specific problems, like functional connectivity analysis from neuroimaging data. Here we survey key research in neuroscience where Bayesian networks have been used with different aims: discover associations between variables, perform probabilistic reasoning over the model, and classify new observations with and without supervision. The networks are learned from data of any kind-morphological, electrophysiological, -omics and neuroimaging-, thereby broadening the scope-molecular, cellular, structural, functional, cognitive and medical- of the brain aspects to be studied. Authors also draw conclusions on which algorithm is more appropriate for the different bayesian networks

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