# Controlling State-Space Abstraction in Bayesian Networks* (Abstract)

Chao-Lin Liu

Artificial Intelligence Laboratory, University of Michigan
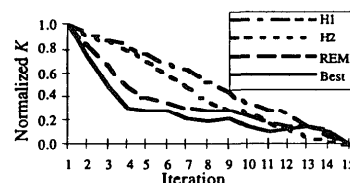1101 Beal Avenue
Ann Arbor, Michigan 48105
chaolin@umich.edu

Many applications require computational systems to respond to queries by a particular deadline. Failure to meet the deadlines may render the returned solution useless. Moreover, the deadlines of such time-critical applications are often uncertain at system design time. *Anytime algorithms* have been suggested to cope with these challenges by trading the quality of the solutions for the reactiveness of the systems at run time [1]. We have introduced an anytime evaluation algorithm [2] for a formalism commonly used in uncertain reasoning: Bayesian networks. Empirical results indicate that approximations of good quality can be obtained within a much shorter time than would be required to directly evaluate the networks by exact algorithms. Also the quality of the approximation improves with the allocated computational time on average.

Approximations of the desired solutions may be acquired by evaluating abstract versions of the given Bayesian networks, where the abstract networks ignore some of the distinctions between states of the variables, called *abstracted variables*. Reduction of the state spaces can dramatically cut down the computational time, at the expense of the quality of the solutions. When there is time for more computation, the evaluation algorithm recovers some of the ignored distinctions, and gets another approximation by evaluating the refined network. The algorithm iteratively evaluates refined abstract networks until stopped.
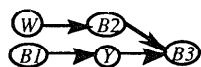
The structure of the Bayesian network has a special bearing on the quality of approximations K, defined based on the divergence between the true and the approximated distributions. Notice that larger K means worse quality. Specifically, we have shown that the quality of the approximated distribution of a set of variables that d-separates another set of variables from the abstracted variables is not better than that of the d-separated set. D-separation is a graphical property that implies conditional independence. Namely when variables in set X d-separate variables in set Y from the abstracted variables A given the instantiated variables, Y is conditionally independent of A. Consider the Bayesian network shown above. If we instantiate variable $B3$ and abstract $B1$, then the qualities of the approximated marginal distributions of other variables have the relationship: $K_Y \geq K_{B2} \geq K_W$.

We are searching for the control methods of the state-space abstraction, aiming at improving performance profiles of the algorithm. In particular, we are exploring score functions for selecting the aggregated states to refine. The score functions compute the goodness of the aggregated states based on factors that are local to the aggregated states. It is hoped that the scores be highly correlated with the actual improvement of the approximation. Among the functions being investigated, the REMB function based on the relative entropy of the Markov boundary of the abstracted variable has demonstrated the best average performance in experiments. This is illustrated by the closeness of the REMB curve to the "Best" curve in the chart shown above. The "Best" curve is achieved by an ideal function that *always* lead to correct selection of the aggregated state to refine. Such a perfect capability is achieved in part by the evaluating the original network, and is *not* a practically achievable feature.

We have established a theorem that addresses the relationship between state-space abstraction and the quality of approximations. We also have limited, empirical results regarding control of state-space abstraction using a variety of heuristics. Future work will consider the usage of *value of information* in score functions. The goal is to establish strategies for controlling the state-space abstraction such that the algorithm provides the best performance possible.

References

[1] Boddy, M., and T. L. Dean. 1994. Deliberation scheduling for problem solving in time-constrained environments. *Artificial Intelligence* 67: 245-285.

[2] Wellman, M. P., and C.-L. Liu. 1994. State-space abstraction for anytime evaluation of probabilistic networks. *Proceedings of the Tenth Conference on Uncertainty in Artificial Intelligence*, pp. 567-574.