Belief Network Inference in Dynamic Environments

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Belief networks (BNs) are an essential knowledge representation technique in AI (Pearl 1988). Substantial progress has been made over the last ten years in all areas of BN research. However, at AAAI-96, Horvitz called for more research related to handling time, synchronicity, and streams of events (Selman et el. 1996):

> We [...] need to develop better means of synchronizing an agent's perceptions, inference, and actions with important events in the world.

In this abstract, I consider how to achieve efficient and synchronized inference by approximate BN inference and BN approximation. For *approximate BN inference* I investigate genetic algorithms (GAs). GAs are robust function optimizers that employ stochastic, instance-based (or population-based) search (Goldberg 1989). Since a BN represents a function, it is natural to consider using GAs to search in the space of instantiated BNs, and to combine GA search with existing algorithms for BN inference.

I assume that the GA fitness function is a joint probability density function (pdf), and in particular a joint pdf represented as a BN. The constraints on such pdfs therefore transfer to the GA fitness function. This is a restriction on the fitness function, but probability theory in general and BNs in particular have proven sufficiently rich to make this an interesting restriction. The joint pdf assumption allows us to bound the error made by the GA, which for instance can be used as a stopping criterion for GA search. On the other hand, the search provided by a GA should give robust inference across a spectrum of BNs. In addition there might be BNs where the GA is superior to other inference algorithms, in particular for efficient and synchronized inference in dynamic environments.

The simple GA needs to be extended with niching to be useful for BN inference. Niching is an extension of the two-armed bandit problem, which models the simple GA, to multiple players and shared payoff (Goldberg 1989). Instead of one individual, there are multiple individuals that receive payoff from the two-armed bandit. In addition, the payoff is shared between all the individuals that line up in front of an arm. In current research I consider different niching schemes in the context of BN inference.

In the area of *BN approximation* I investigate how arbitrary BNs can be aggregated and decomposed, and how this affects inference speed. Model-based and BN inference have been integrated by means of abstraction and aggregation; in particular by translating a hierarchical functional schematic into a hierarchical BN (Srinivas 1995). The idea of compilation in order to gain inference is recurring in AI, for example in explanation-based learning, case-based reasoning, and chunking. The hierarchical BN model needs to be generalized to allow for such models. First, there are BNs that do not have a strong hierarchical structure. Second, in the hierarchical BN model, sensing is well-defined and certain, while in the general case sensing is uncertain. I investigate how to generalize the hierarchical BN model and related research in these two directions.

Acknowledgments. Thanks to my advisor David C. Wilkins as well as ONR Grant N00014-95-1-0749 and ARL Grant DAAL01-96-2-0003 for supporting this research.

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