CHAPTER 10

RELATED WORK

In this chapter, we discuss work related to this thesis. We begin with other work on modeling time with Bayesian networks. We continue with work on event history analysis and Markov process models.

10.1 BAYESIAN NETWORKS AND TIME

The approach is based on time intervals — where events can only happen in one of small number intervals. Inference is done by instantiating known events within known time intervals (where the timing of a trigger event gives a basis for determining the actual times for the relative intervals) and propagating the evidence to generate a posterior distribution. Tawfik and Neufeld (1994) present Temporal Bayesian Networks which allow time to be modeled as discrete or continuous. Probabilities are represented as functions of time. However, this framework only allows the calculation of distributions over the state at a given time — not distributions over time. Also, the problem of learning probabilities as functions over time is not addressed.
Finally, Tawfik and Neufeld (2000) provide an overview of techniques used for modeling time with Bayesian networks. Significantly, they include mention of continuous time survival analysis as a method of modeling the time to occurrence of significant events in causal models. However, temporal distributions generated by these survival functions are not used for modeling state durations of local variables. The resulting models are analogous to standard event history analysis.

10.2 Event History Analysis and Markov Process Models

There are many different methodologies used for continuous time modeling. We have discussed (finite state) continuous time Markov processes extensively as the basis of the CTBN framework. Note that phase type duration distributions have been used extensively with these methods (Aalen, 1995). In counting process models (Aalen, 1975; Andersen et al., 1993), the distinguished event is repeatable and we are interested in the distribution over how many times it has occurred. Queues are often characterized by the distribution over the occurrence of arrival events and the distribution over the service time.
10.3 CTBNs

Gopalratnam et al. (2005) extend the basic CTBN representation by allowing durations to be modeled as Erlang-Coxian distributions, which is a limited subclass of general phase distributions. Since our general method from Chapter 9 is based on the EM algorithm, it allows the use of general phase-type distributions in CTBNs without restriction.

More generally, semi-Markov models (Lévy, 1954; Howard, 1971; Blossfeld et al., 1988) can include arbitrary distributions over the time until some variable changes state. If we are only interested in modeling one variable, choosing an arbitrary distribution over when it will transition is less of a problem. The difficulty is how to define a globally coherent probabilistic semantics over a process where we have different variables transitioning with arbitrary distributions. Ng et al. (2005) extend the CTBN representation to allow for a hybrid state model — i.e., one that includes nodes with finite state spaces and nodes with continuous state spaces. Finally, El-Hay et al. (2006) develop a new framework of continuous time Markov nets (CTMNs) based on CTBNs. The CTMN framework factors a continuous time Markov process over an undirected graph.
CHAPTER 11

CONCLUSION

This thesis has introduced CTBNs, a new framework for modeling continuous time over a factored state. It allows us to model processes without needing to choose an arbitrary temporal granularity. We have developed principled learning algorithms that learn CTBN models from both fully and partially observed data. We also have a polynomial time structure search algorithm (when limited to some fixed maximum number of parents per node). We have shown how to model state durations for individual CTBN variables as phase-type distributions — an extraordinarily expressive class. That includes more work examining the impact of phase distributions on learning and inference. In the current CTBN model, every event is simply the transition of a state variable from one value to another. Here the local intensity might be expressed as functions of time instead of constant. A clearer theory of evaluation might allow us to develop a single framework which would allow the use of continuous time nodes, discrete time nodes (of varying granularities), periodic nodes, one time event nodes, and static nodes — any of which with discrete or continuous state.


