Efficient Modeling of Temporally Variable User Properties With Dynamic Bayesian Networks

Boris Brandherm
Department of Computer Science, Saarland University
P.O. Box 15 11 50, D-66041 Saarbrücken, Germany
brandherm@cs.uni-sb.de, http://w5.cs.uni-sb.de/∼borisbra

The overall goal of the project that I am working within is the automatic adaptation of the behavior of a mobile assistance system to a user's *resource limitations* in order to realize a situationally appropriate presentation of instructions and information. Specifically, our assistance system models the temporally variable user properties of cognitive load, time pressure, and affective states. Because these properties are not directly observable, they have to be estimated on the basis of indirect evidence. Such evidence can be found, for example, in the user's speech and motor behavior, in data from physiological sensors, and in knowledge about possible causes of resource limitations, such as the system's own behavior or the user's activities. The system needs to track the user's state from moment to moment, taking into account previous states as well as new evidence.

Dynamic Bayesian networks (DBNs) are a suitable computational framework for this problem, but they raise serious problems of computational complexity. Rollup methods must be applied that cut off older time slices but incorporate their impact on the remaining time slices of the DBN.

There are two lines of research that I will first pursue in parallel and then bring together. One of these lines is to investigate relevant ways of increasing efficiency and the other one is to construct and test DBNs using relevant data.

Increasing Efficiency

I have designed transformations that make DBN structures specified by a human designer computationally more tractable. For example, in a DBN in which not all time slices have the same structure, it can be natural to specify static nodes, which do not lie inside any one time slice; or to specify an edge between the nth and the $n + 2$nd time slice. The above-mentioned transformations embed time-slice-skipping edges in the skipped time slice and convert static nodes into dynamic ones so that the rollup methods mentioned above can be applied directly.

I have extended the polynomial-based framework suggested by Darwiche (2000) to handle DBNs, in particular with regard to forward and backward propagation over time slices (see Kjærulff, 1995). I plan to develop new approximation techniques within the polynomial-based framework, which I will then compare and combine with other existing approximation techniques to achieve greater efficiency in the processing of DBNs.

Constructing DBNs for Modeling Temporally Variable User Properties

I have combined two already existing Bayesian networks, one to handle speech symptoms and another to handle manual input behavior, to yield an overall network which enables the interpretation of speech and motor symptoms in multimodal input.

I have compiled causal relationships between diverse physiological variables (e.g., heart rate and muscle activity) and environmental variables (e.g., speed of movement) on the basis of a literature study, which also resulted in plausible structures for a DBN that processes this type of evidence.

The next step is to acquire suitable example data for testing (speech symptom data is already available) through cooperation with other institutions. For example, from the Evaluation Center of the German Research Center for Artificial Intelligence (DFKI), we will obtain eye tracker data showing the pupil dilations of subjects working at a computer, which can be used as an index of their cognitive load.

To make these data suitable as input to DBNs, I will have to develop appropriate methods for preprocessing the input data. One possibility, for example, is to average pupil dilations over certain windows (time-directed instantiation) instead of instantiating whenever new evidence arrives (event-directed instantiation). But because not everything can be meaningfully averaged over time (e.g., infrequently occurring but significant speech symptoms), both time-directed and event-directed instantiation have to be supported. I have worked out theoretical considerations as to how these types of instantiation can be combined.

References

Darwiche, A. 2000. A differential approach to inference in Bayesian networks. In Boutilier, C., and Goldszmidt, M., eds., *Uncertainty in Artificial Intelligence: Proceedings of the Sixteenth Conference*. San Francisco: Morgan Kaufmann.

Kjærulff, U. 1995. dHugin: A computational system for dynamic time-sliced Bayesian networks. *International Journal of Forecasting* 11:89–111.