Accuracy and robustness of learning and inference in Bayesian networks
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Probabilistic reasoning is an important aspect of many AI applications, in the context of for example sensor fusion or forecasting. Discrete Bayesian networks facilitate such reasoning, and are popular in applications that have to deal with a high degree of uncertainty. Their modular nature and intuitive parameters make them relatively easy to construct by human domain experts.

Inevitably, small mistakes will be made during construction. Human experts can be biased, or have difficulty expressing their knowledge directly into probabilities. Example data used for learning can be incomplete. This begs the question what influence these mistakes have on the reliability of the outcome of probabilistic reasoning. Small errors in the value of a parameter might be admissible in some cases, but not always. This thesis investigates what characterizes networks that are robust against small parameter errors, and how much parameters are allowed to change without harming the accuracy of the network.

In Chapter 3 we show how we can view probabilistic inference as a voting process, with votes coming from separate network fragments. If a small parameter error does not change the votes, then the outcome is likely not to change. This sets limits on the amount of admissible change.

Also in Chapter 3, we present an algorithm for inference with Bayesian networks, based on the voting view. This voting algorithm is very fast, and achieves a good accuracy for several classes of networks.

In Chapter 4, we focus on learning the parameters of a Bayesian network from incomplete example data. We present a learning algorithm that uses the voting view, in the sense that it first attempts to learn a network that gives correct votes, before fine-tuning the parameters. The algorithm turns out to converge fast, and perform better than other algorithms when learning from small data sets. This is an indication that our algorithm is more resistant against local maxima in the search space.

Chapter 5 deals with the issue of ‘adequate’ parameters; parameters that make a network inherently robust. We identify relations between parameters that
should be satisfied, and argue that the correct relations are easy to find. If the parameters in a network are adequate, the votes (mentioned above) are most likely to be correct.

We present two algorithms that are based on this observation. The first uses the number of votes in favor of an outcome as a measure of the confidence in that outcome. The second algorithm compares the votes of different network fragments to locate parameters that are not adequate. Both algorithms are shown to be effective at identifying inaccurate inference outcomes and locating their causes. They can be used to monitor a Bayesian network for errors.