Learning optimal independence tests for Bayesian Networks

Anonymous Author(s)
Affiliation
Address
email

Abstract

1 Introduction

Learning Bayesian networks for general distributions is intractable task Chickering [1996]. However, in practise for distributions appearing in real data, still we are able to recover Bayesian network structure. This implies that real data distribution has some special properties, which simplify process of structure recovery. This process is almost always based on computation local statistics, and then reasoning about global structure Jaakkola et al. [2010]; Tsamardinos et al. [2006]. Local statistics describe complexity (e.g. number of parents in case of BIC), and level of independence between nodes (e.g. mutual information tests, conditional independence tests). We focus in this work on improvement of independence tests by learning it for CPDs present in data.

2 Related work

LL (Log-likelihood) (1912-22) MDL/BIC (Minimum description length/Bayesian Information Criterion) (1978) AIC (Akaike Information Criterion) (1974) NML (Normalized Minimum Likelihood) (2008) MIT (Mutual Information Tests) (2006)

Margaritis [2003]

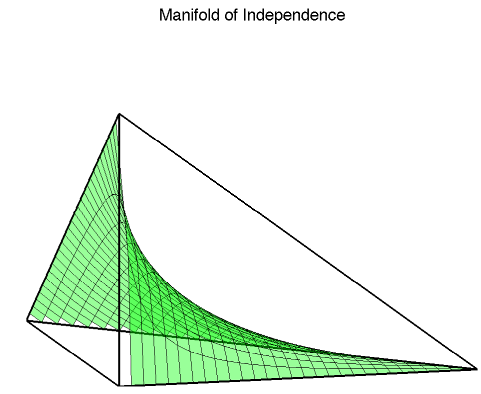

Figure 1: A

3 Independence testing

3.1 Discrete variables formulation

3.2 Continuous variables formulation

4 Experiments

4.1 Classification of Synthetic CPDs

4.2 Classification of CPDs from Gene Expression

4.3 Synthetic Bayesian networks

4.4 Gene expression data

5 Discussion

References

D. M. Chickering. Learning bayesian networks is np-complete. In *Learning from data*, pages 121–130. Springer, 1996.

T. Jaakkola, D. Sontag, A. Globerson, and M. Meila. Learning bayesian network structure using lp relaxations. In *International Conference on Artificial Intelligence and Statistics*, pages 358–365, 2010.

D. Margaritis. *Learning Bayesian network model structure from data*. PhD thesis, University of Pittsburgh, 2003.

I. Tsamardinos, L. E. Brown, and C. F. Aliferis. The max-min hill-climbing bayesian network structure learning algorithm. *Machine learning*, 65(1):31–78, 2006.