Information-Theoretic Scoring Rules to Learn Additive Bayesian Network Applied to Epidemiology

Gilles Kratzer[1], Reinhard Furrer[1,2]

[1]Department of Mathematics, [2]Department of Computational Science; University of Zurich (Switzerland)

Contact: gilles.kratzer@math.uzh.ch

Motivation

- ABN[1] methodology extends the classical generalized linear model (GLM) framework to **multiple dependent variables**
- The key perspective of ABN is to extract the conditional independence information from an **observational dataset**
- ABN is a suitable methodology to mastermind **complex and messy data** in an exploratory analysis

Summary

- ABN is a mixture between **machine learning** and **statistical** approach
- **abn** is distributed as an R package **https://CRAN.R-project.org/package=abn**
- Several implemented information theory scores: **AIC**, **BIC**, **MDL**
- **Bayesian** scoring function
- **Exact** and **Heuristic** search algorithm

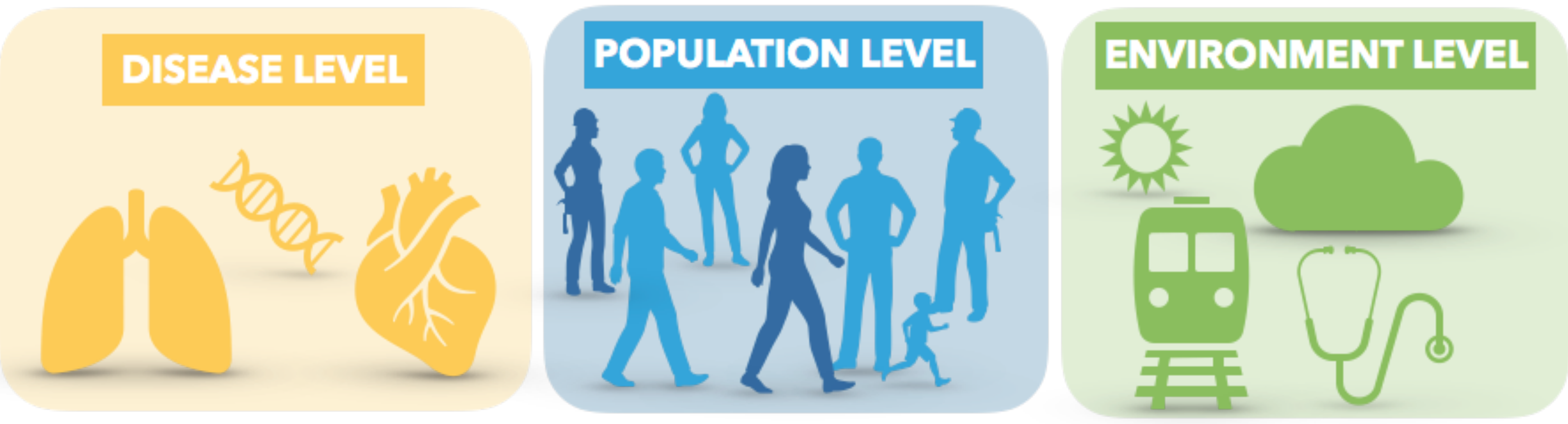
Results

- Perform **structure discovery**
- ABN modelling empirically identifies associations in complex and high dimensional data as a **machine learning technique**

Future Work

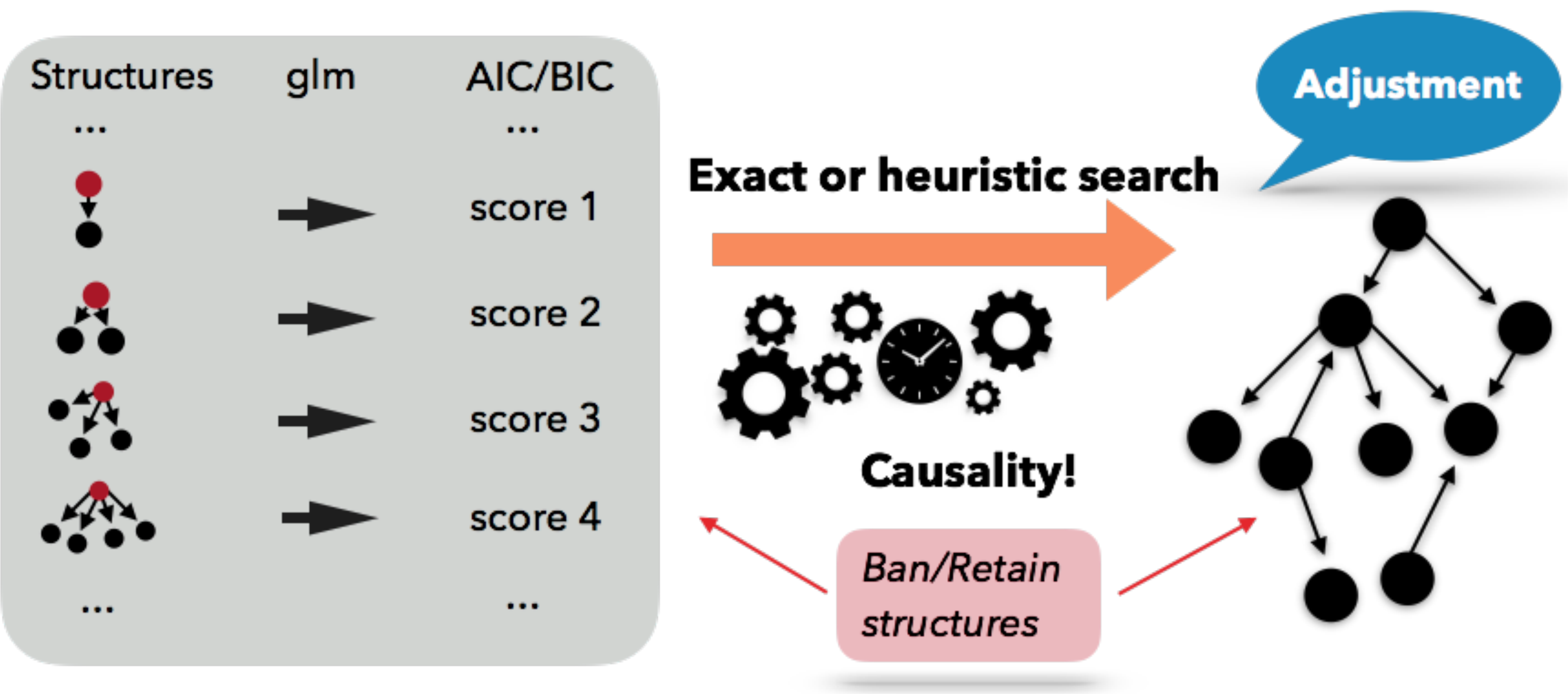
- Implementation of wider classes of **distributions**
- Implementation of **boosted information theoretic scores**

Why systemic thinking?



- Systems epidemiology implies contributions at different levels
- Confounding factors
- Complex dependance structure
- Multicollinearity

How to learn Bayesian Networks from data using search and score method[2]?



Why information-theoretic scores?

Data separation and sparsity

No optimal solution for Bayesian regression in the ABN context

Multinomial distribution

Actually no implementation of multinomial Bayesian estimation with suitable prior

Effective computation

Iterative reweighting least square method is fast and highly reliable

Adjustment for confounders

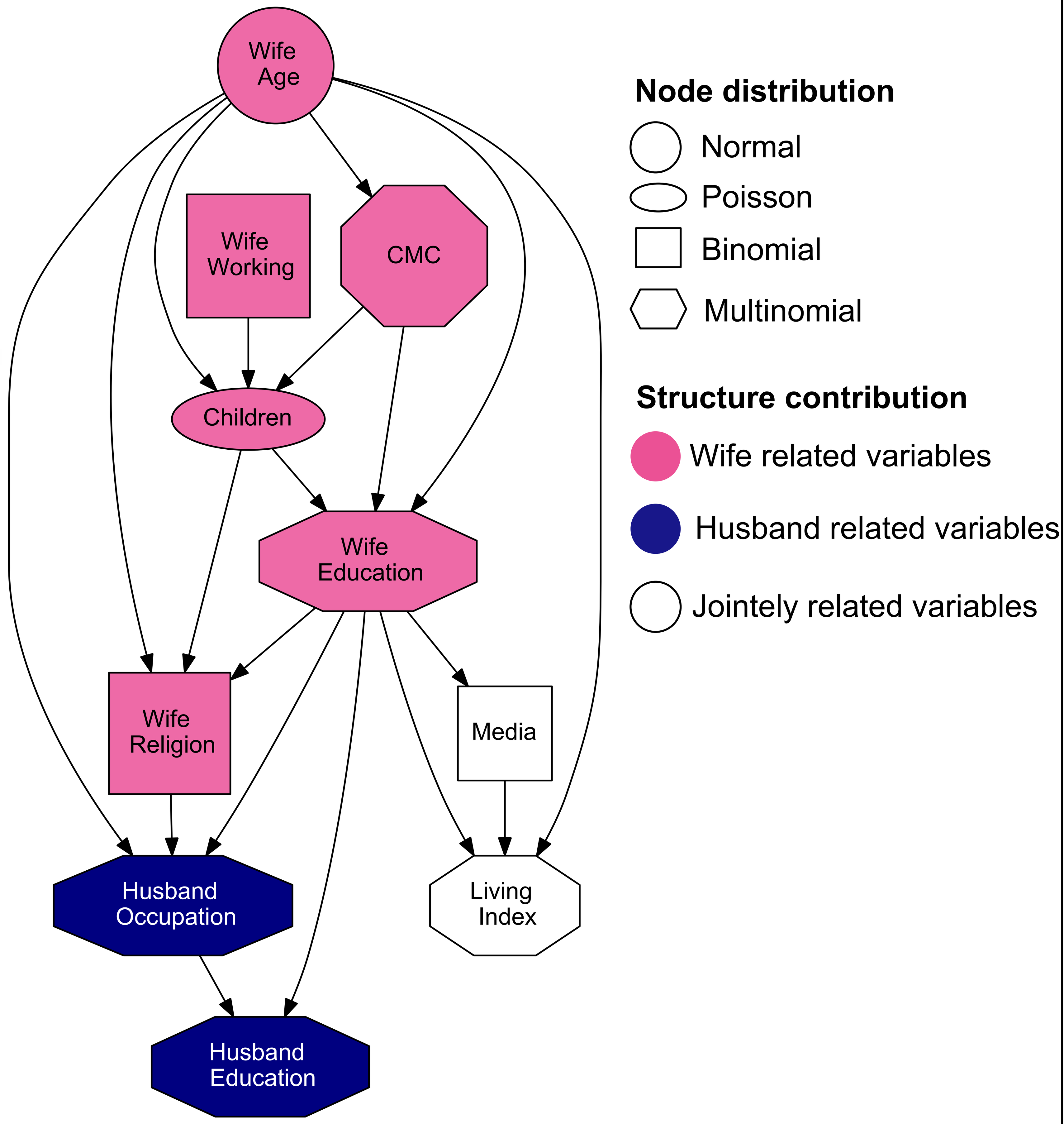
Possibility to compute an adjusted DAG with classical epidemiological confounders

Illustrative example

Subset of the 1987 National Indonesia Contraceptive Prevalence Survey[3]. Selection criteria: no pregnant and married womans.

10 variables, n = 1473 observations (no missing data)

- Wife's age (normal)
- Husband's education (multinomial, 4 levels)
- Number of children (Poisson)
- Wife's religion (binomial)
- Wife is currentely working (binomial)
- Husband's occupation (multinomial, 4 levels)
- Standard-of-living index (multinomial, 4 levels)
- Media exposure (binomial)
- Contraceptive method choice (multinomial, 3 levels)



References

1. Lewis, F. I. et al. "*Structure discovery in Bayesian networks: An analytical tool for analysing complex animal health data*", Preventive Veterinary Medicine 100.2 (2011): 109-115.
2. Koivisto, M. et al."*Exact Bayesian structure discovery in Bayesian networks*". Journal of Machine Learning Research, 549-573. (2004)
3. Lim, T.-S. et al. "*A Comparison of Prediction Accuracy, Complexity, and Training Time of Thirty-three Old and New Classification Algorithms*", Machine Learning, pp 203 (1999).