BAYESIAN NETWORKS MEET OBSERVATIONAL DATA

University of Zurich UZH

NATIONAL VETERINARY INSTITUTE SVA

http://r-bayesian-networks.org/

gilles.kratzer@math.uzh.ch

arianna.comin@sva.se

GILLES KRATZER, APPLIED STATISTICS GROUP, UZH

ARIANNA COMIN, DEP. OF DISEASE CONTROL AND EPIDEMIOLOGY, SVA

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Credit Card Fraud Detection Using Bayesian and Neural Networks

Sam Maes Karl Tuyls Bram Vanschoenwinkel
Bernard Manderick
Vrije Universiteit Brussel - Department of Computer Science
Computational Modeling Lab (COMO)
Pleinlaan 2
B-1050 Brussel, Belgium
{sammaes@,ktuyls@,bvschoen@,bernard@arti.}vub.ac.be

Abstract

This paper discusses automated credit card fraud detection by means of machine learning. In an era of digitalization, credit card fraud detection is of great importance to financial institutions. We apply two machine learning techniques suited for reasoning under uncertainty: artificial neural networks and

do the fraud detection. After a process of learning, the program is supposed to be able to correctly classify a transaction it has never seen before as fraudulent or not fraudulent, given some features of that transaction.

The structure of this paper is as follows: first we introduce the reader to the domain of credit card fraud detection. In Sections 3 and 4 we briefly ex-

MOTIVATIONAL EXAMPLE: CREDIT CARD FRAUD DETECTION PREDICTION

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experiment	±10% false pos	±15% false pos
ANN-fig 2(a)	60% true pos	70% true pos
ANN-fig 2(a)	47% true pos	58% true pos
ANN-fig 2(c)	60% true pos	70% true pos
BBN-fig 2(e)	68% true pos	74% true pos
BBN-fig 2(g)	68% true pos	74% true pos

Table 1: This table compares the results achieved with ANN and BBN, for a false positive rate of respectively 10% and 15%.

Abstract

This paper discusses ... tection by means of ... of digitalization, cre... great importance to ... two machine learning techniques suited for reasoning under uncertainty: artificial neural networks and

...rocess of learning, ...e to correctly clas- ...n before as fraud- ...ne features of that ...s follows: first we introduce the reader to the domain of credit card fraud detection. In Sections 3 and 4 we briefly ex-

MOTIVATIONAL EXAMPLE: VETERINARY EPIDEMIOLOGY DATA VISUALISATION

Contents lists available at SciVerse ScienceDirect

Preventive Veterinary Medicine

journal homepage: www.elsevier.com/locate/prevetmed

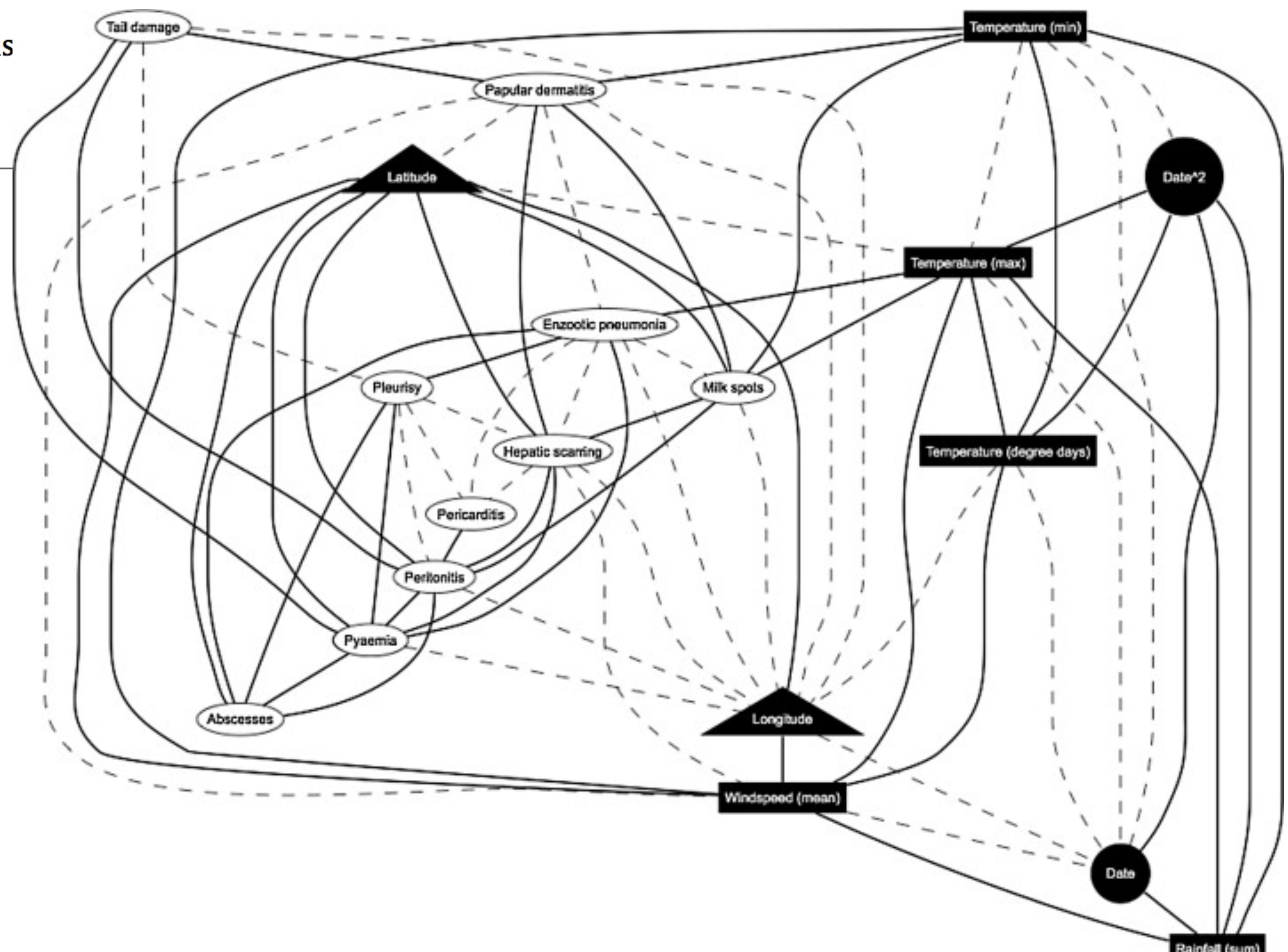
ELSEVIER

Using Bayesian networks to explore the role of weather as a potential determinant of disease in pigs

CrossMark

B.J.J. McCormick[a], M.J. Sanchez-Vazquez[b], F.I. Lewis

[a] *Fogarty International Center, National Institutes of Health, Bethesda, MD 20892, USA*
[b] *OIE Organisation Mondiale de la Santé Animale, 12, rue de Prony, 75017 Paris, France*
[c] *Section of Epidemiology, University of Zurich, Zurich, Switzerland*



MOTIVATIONAL EXAMPLE: SOCIAL SCIENCES DATA INTERPRETATION

Discovering complex interrelationships between socioeconomic status and health in Europe: A case study applying Bayesian Networks

Javier Alvarez-Galvez [a, b, *]

[a] Loyola University Andalusia, Department of International Studies, Campus de Palmas Altas, Faculty of Political Sciences and Law, Seville 41014, Spain
[b] Complutense University of Madrid, Department of Sociology IV (Research Methodology and Communication Theory), Campus de Somosaguas, Faculty of Political

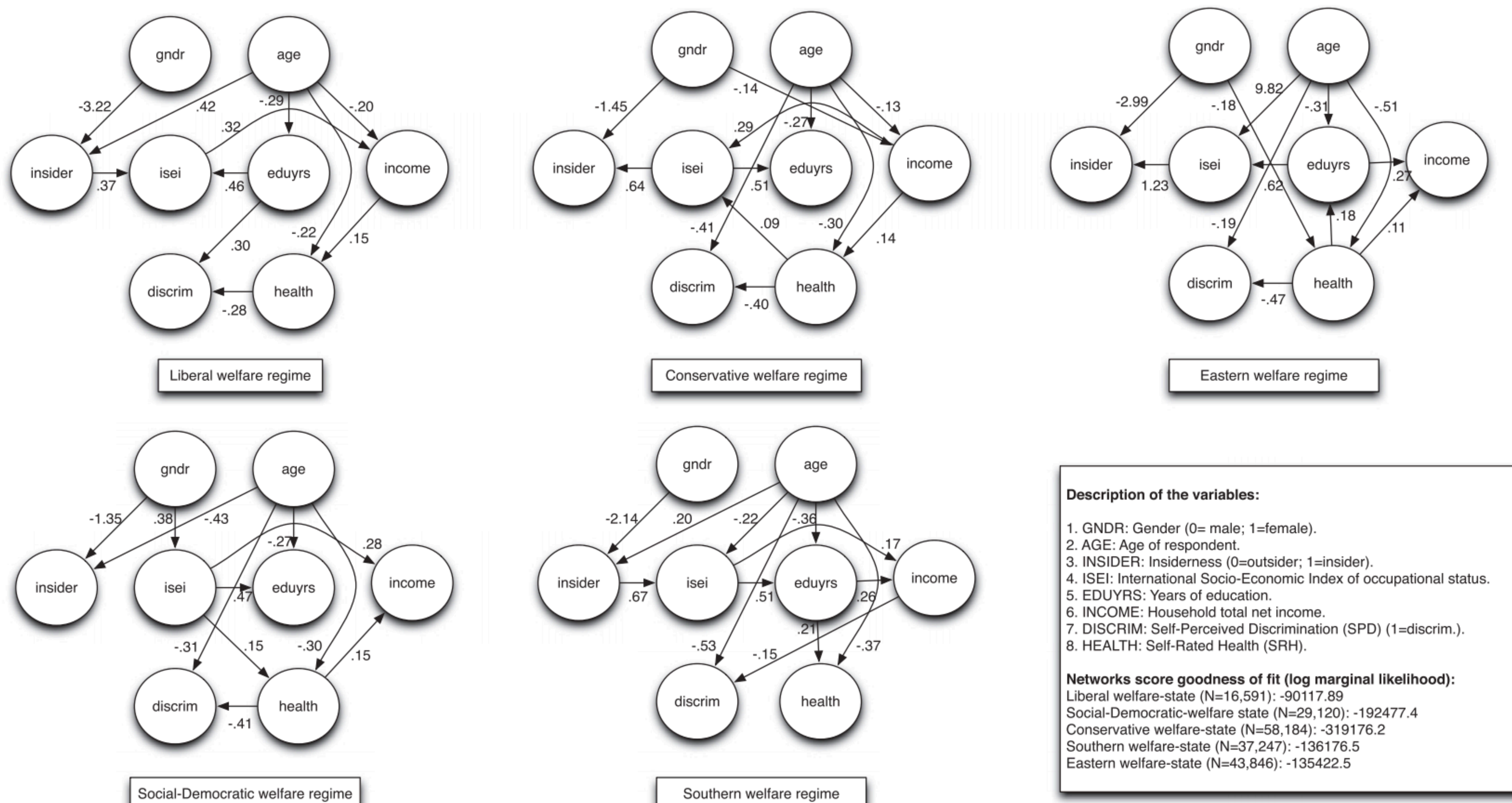


Fig. 1. Bayesian networks describing interrelationships between SES and health in five European welfare states.

BAYESIAN NETWORKS IN THE MACHINE LEARNING WORLD

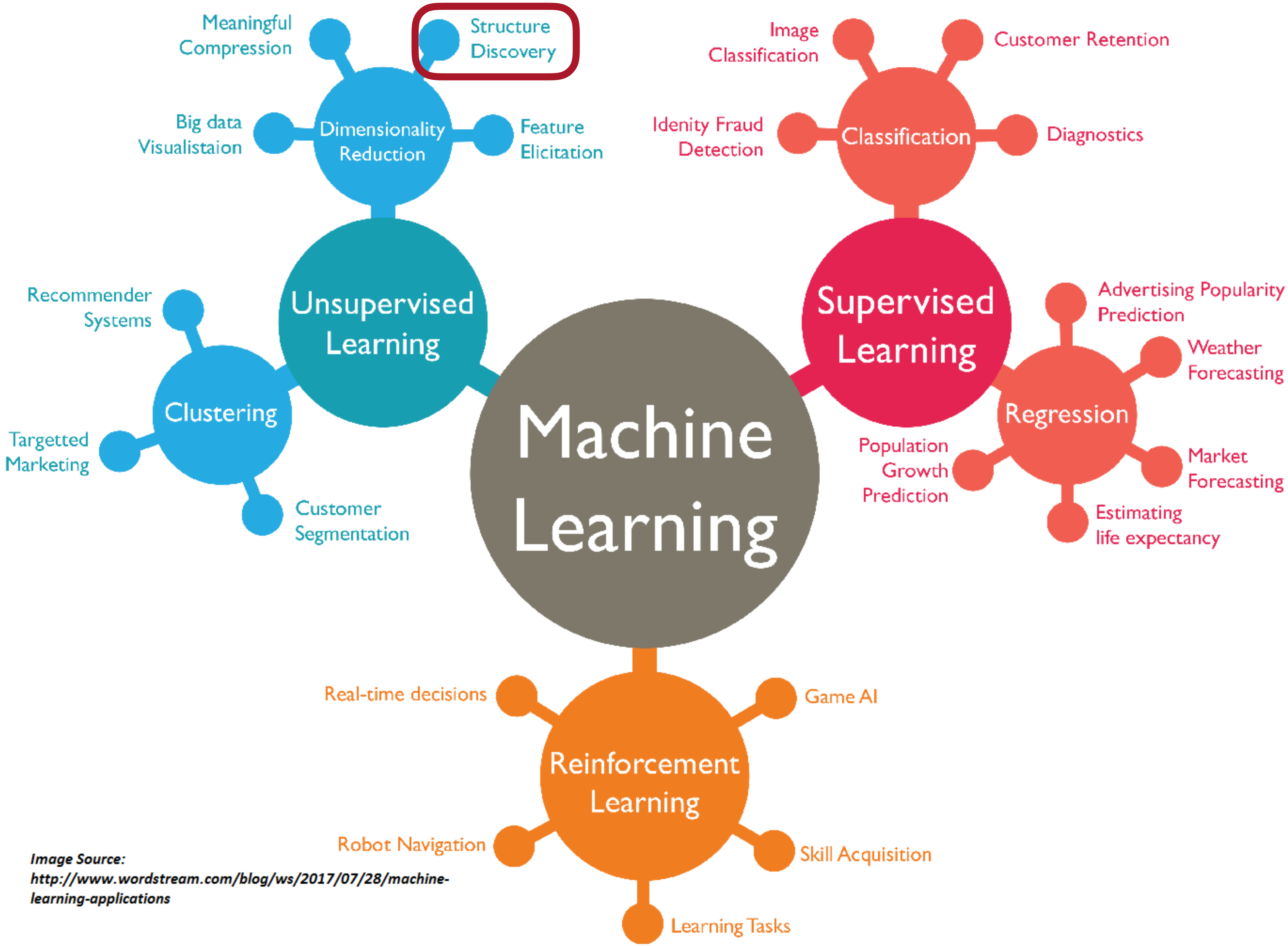


Image Source: http://www.wordstream.com/blog/ws/2017/07/28/machine-learning-applications

Objectif of the workshop:

How to learn Bayesian networks from observational data?

Objectif of the workshop:

select

How to ~~learn~~ Bayesian networks from observational data?

Bayesian Networks are defined by two elements:

Network structure:

Directed Acyclic Graph (DAG): G = (V, A)

in which each node $v_i \in V$ corresponds to a random variable X_i

Probability distribution:

Probability distribution X with parameters Θ, which can be factorised into smaller local probability distributions according to the arcs $a_{ij} \in A$ present in the graph.

A BN encodes the factorisation of the joint distribution

$$P(\mathbf{X}) = \prod_{j=1}^{n} P(X_j \mid \mathbf{Pa}_j, \Theta_j), \text{ where } \mathbf{Pa}_j \text{ is the set of parents of } X_j$$

PLAN

1. From observationnal dataset deduce probabilistic model
    - Usually discrete BN or jointly Gaussian
    - Epidemiological constrain: mixture of distributions
2. From probabilistic model deduce structure

EXPONENTIAL FAMILY

Observational dataset

X1	X2	X3	...
12	23	53	...
32	31	23	...
10	16	45	...
...	...	...	...

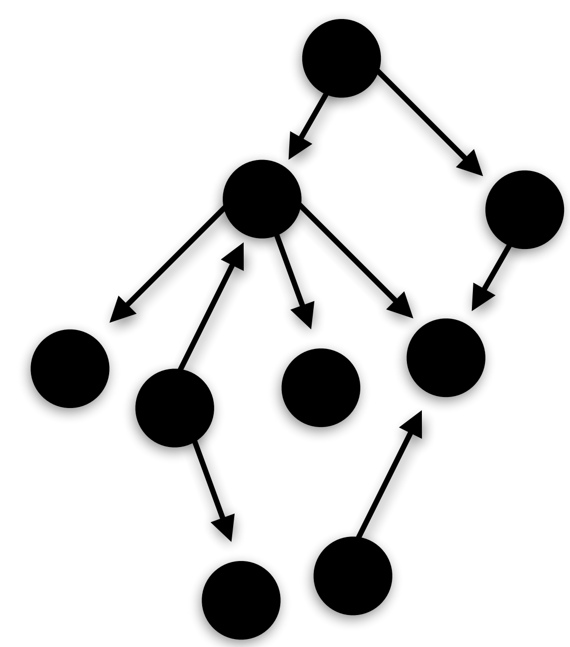
$\xrightarrow{1}$

Probabilistic model

$$P(X_1, \dots, X_n) = P(X_i | X_j, \dots) \dots$$

$\xrightarrow{2}$

Network structure



COMBINATORIAL WALL

# Nodes	# DAGs	Inference
1 - 15 Nodes	< 10^{41} DAGs	Exact inference
16 - 25 Nodes	< 10^{100} DAGs	Exact inference possible
26 - 50 Nodes	< 10^{400} DAGs	Approximate inference
51 - 100 Nodes	< 10^{1700} DAGs	Approximate inference
101 - 1000 Nodes	< 10^{100000} DAGs	(very) approximative inference

Typical domain of interest

Approximations:

- limiting number of parents per node
- Decomposable scores/efficient algorithm
- Score equivalence

SOME ELEMENTS OF PROBABILITY THEORY

The conditional probability of A given B is: $P(A \mid B) = \frac{P(A,B)}{P(B)}$

Bayes theorem: $$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}$$

Let A, B and C non intersecting subsets of nodes in a DAG G

A is conditionally independent of B given C if: $A \perp\!\!\!\perp_P B | C$

$$P(A, B \mid C) = P(A \mid C)P(B \mid C)$$

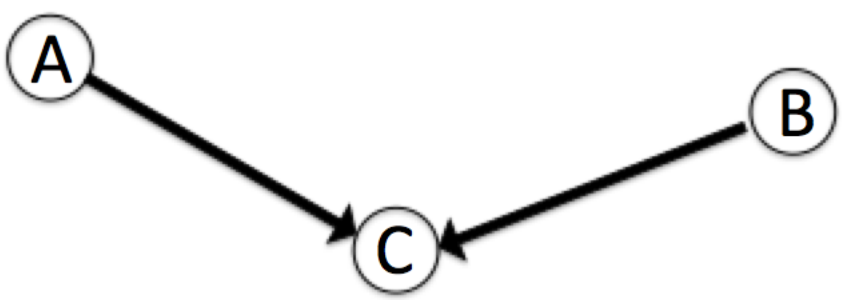
ELEMENT OF GRAPH THEORY

Let A, B and C non intersecting subsets of nodes in a DAG G

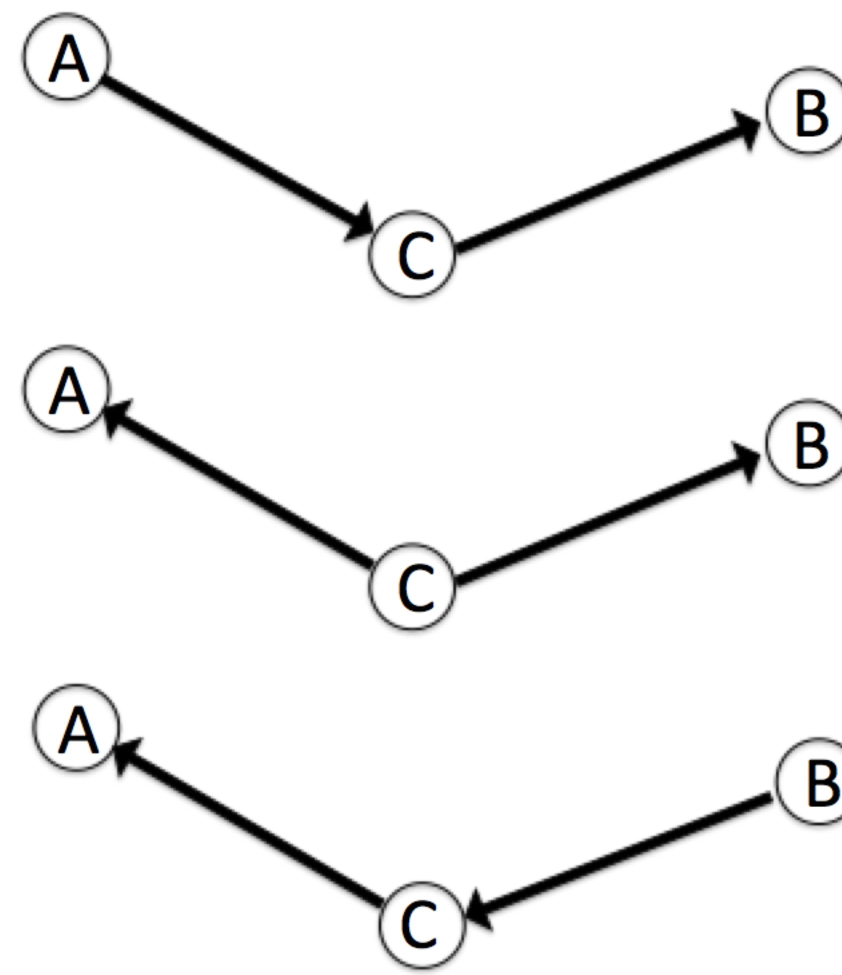
A is conditionally independent of B given C if: $A \perp\!\!\!\perp_P B|C$

$$P(A, B \mid C) = P(A \mid C)P(B \mid C)$$

$$A \not\perp\!\!\!\perp_P B|C$$



$$A \perp\!\!\!\perp_P B|C$$



LEARNING BAYESIAN NETWORKS

$$\mathcal{M} = (\mathcal{S}, \Theta_{\mathcal{M}})$$

Model selection

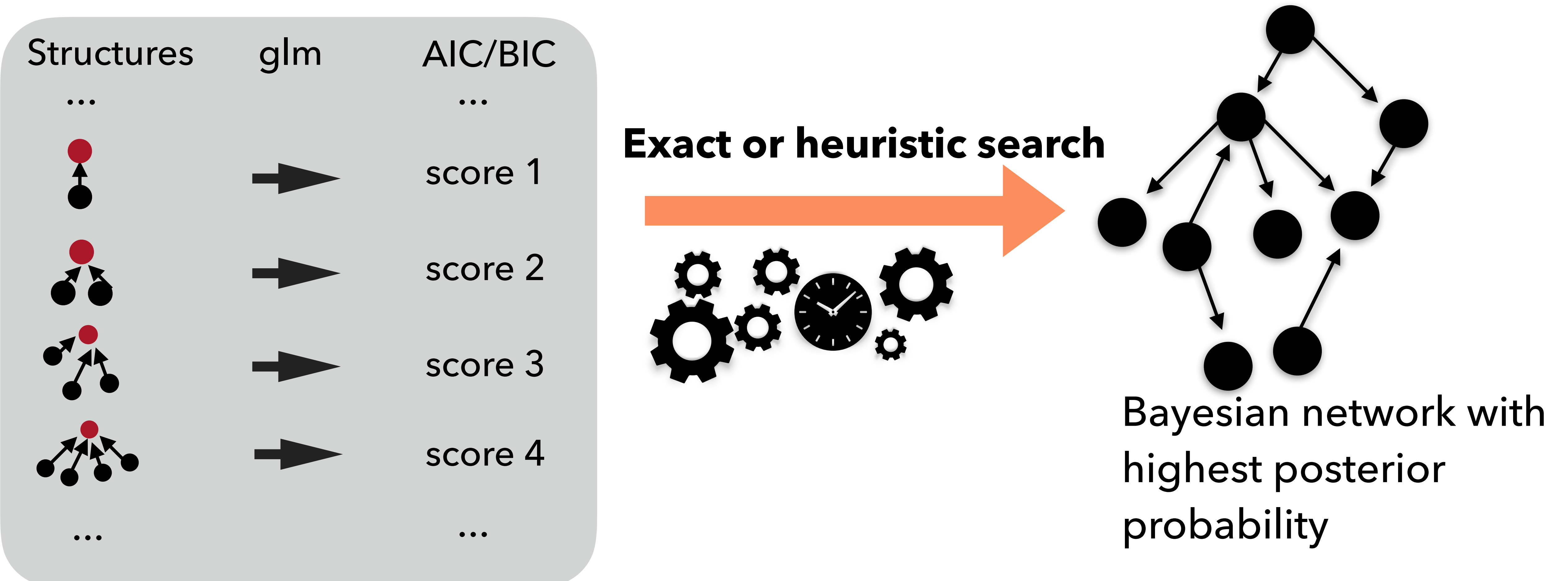
Structure learning

Parameter estimation

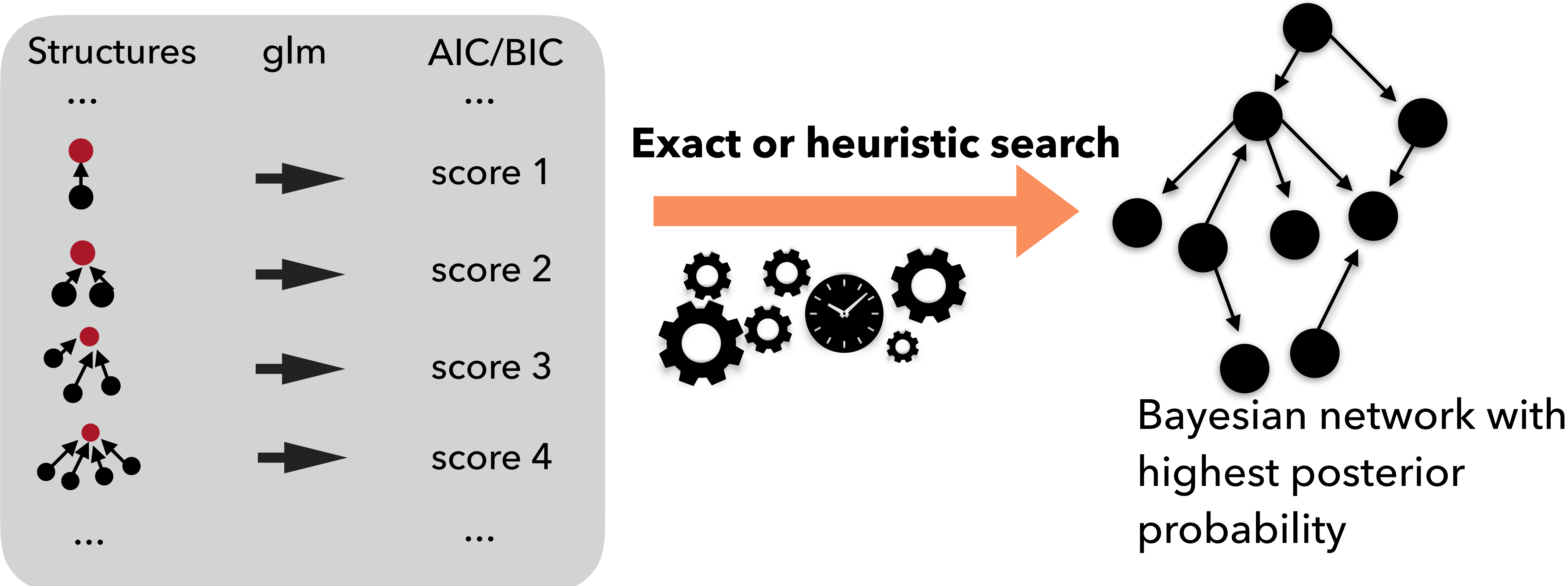
Parameter learning

$$P(\mathcal{M}|\mathcal{D}) = \underbrace{P(\Theta_{\mathcal{M}}, \mathcal{S}|\mathcal{D})}_{\text{model learning}} = \underbrace{P(\Theta_{\mathcal{M}}|\mathcal{S}, \mathcal{D})}_{\text{parameter learning}} \cdot \underbrace{P(\mathcal{S}|\mathcal{D})}_{\text{structure learning}}$$

Search and score algorithm

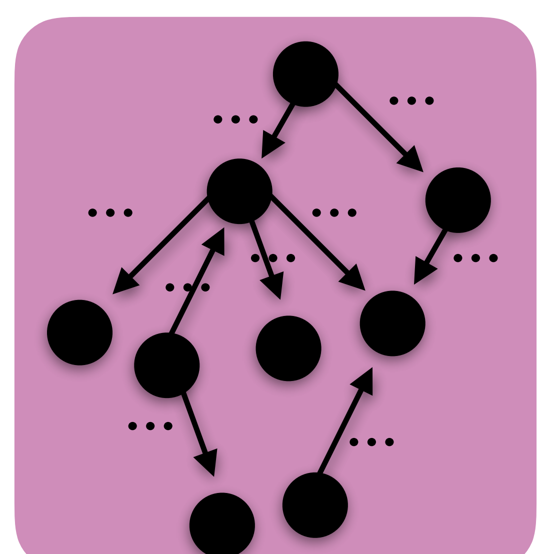


Search and score algorithm

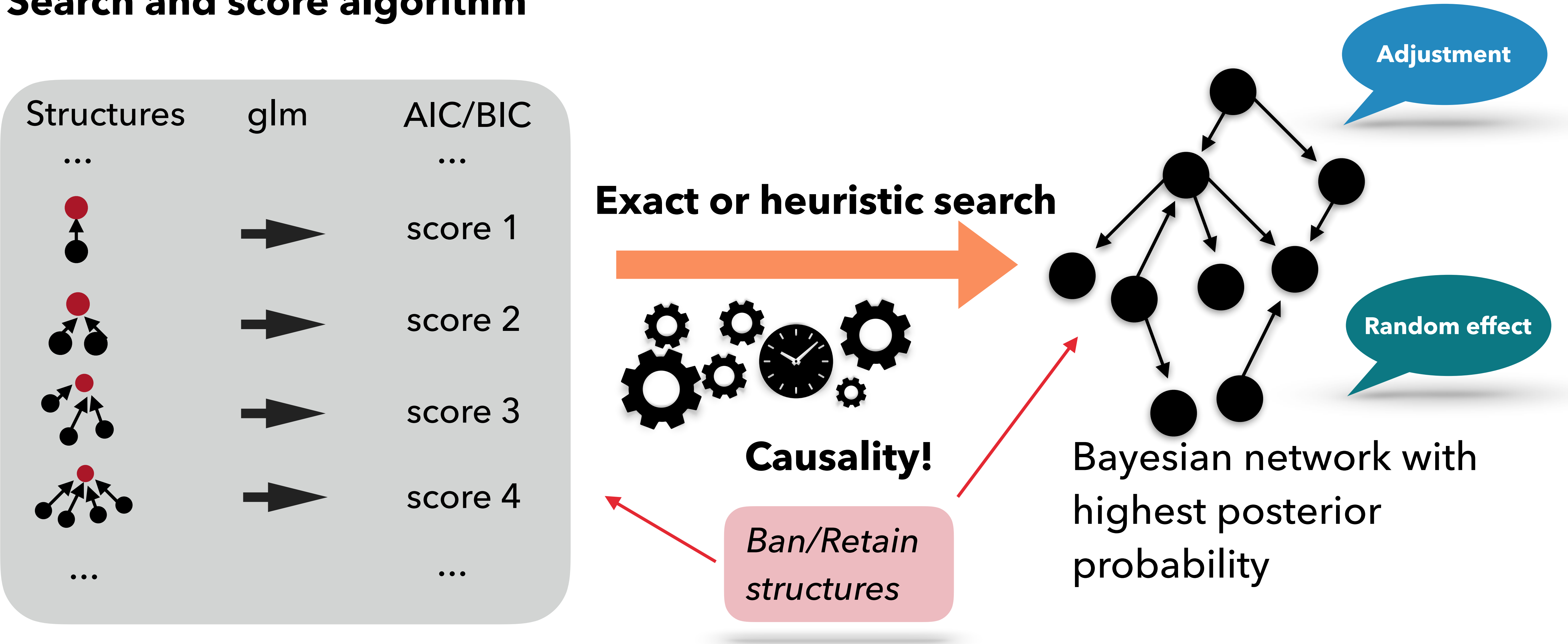


Parameter estimation

- compute marginal posterior density
- regression estimate



Search and score algorithm



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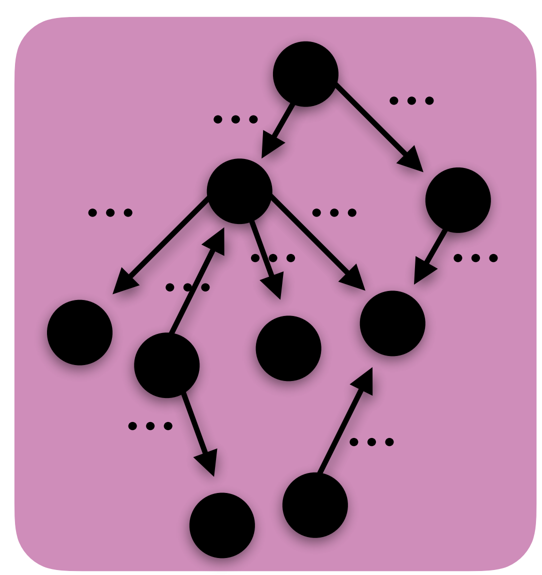
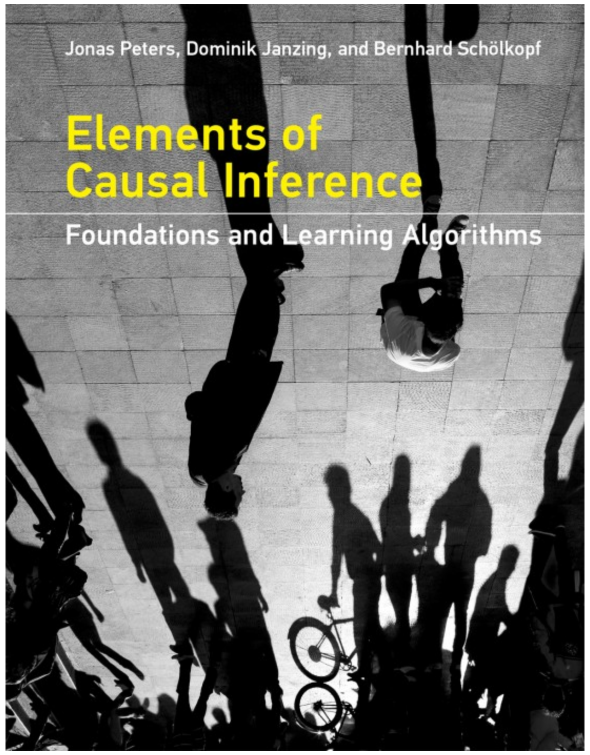
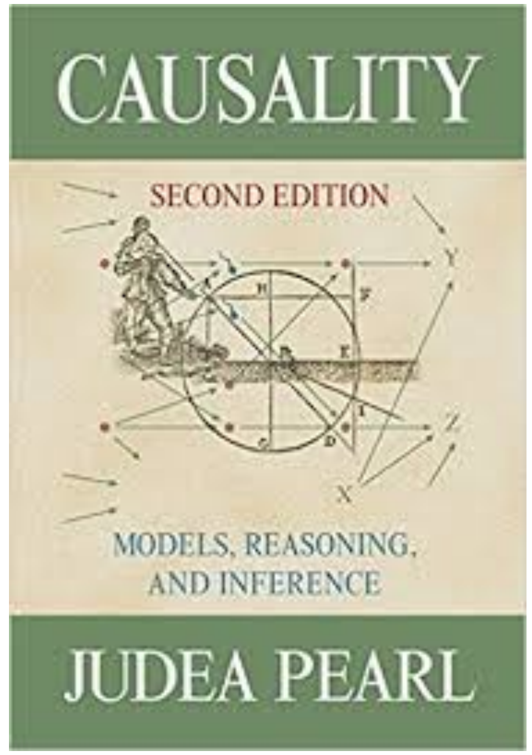


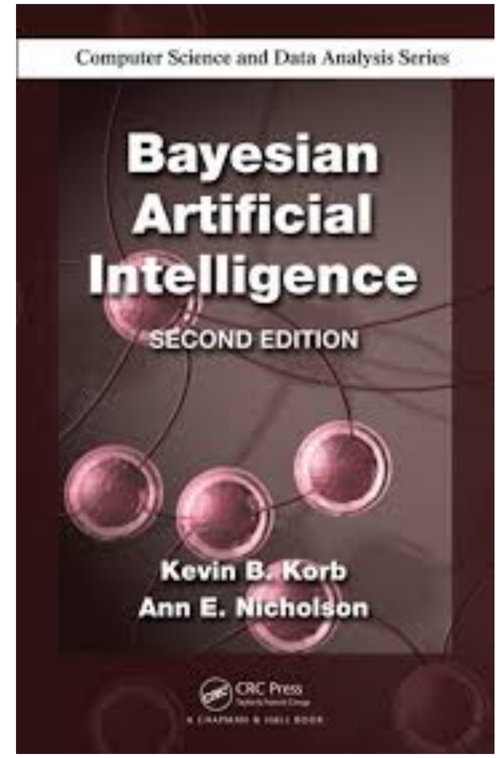
Using R

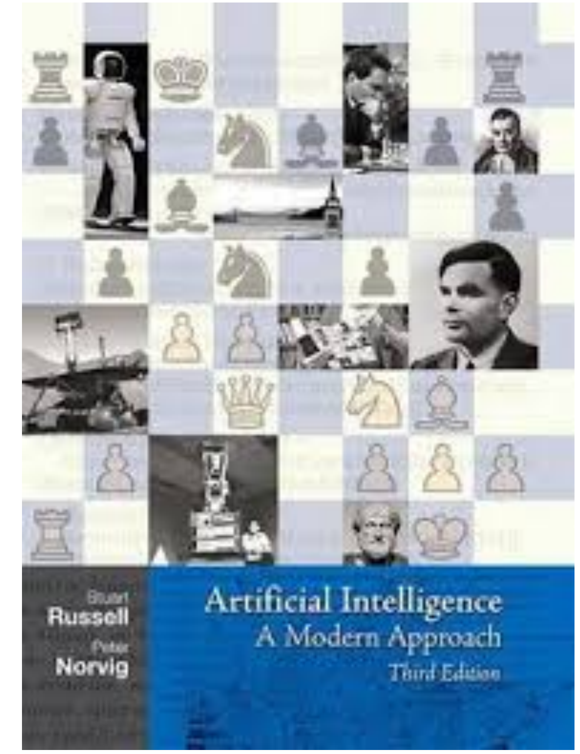
- *buildscorecache()*
- *mostprobable()*
- *fitabn()*

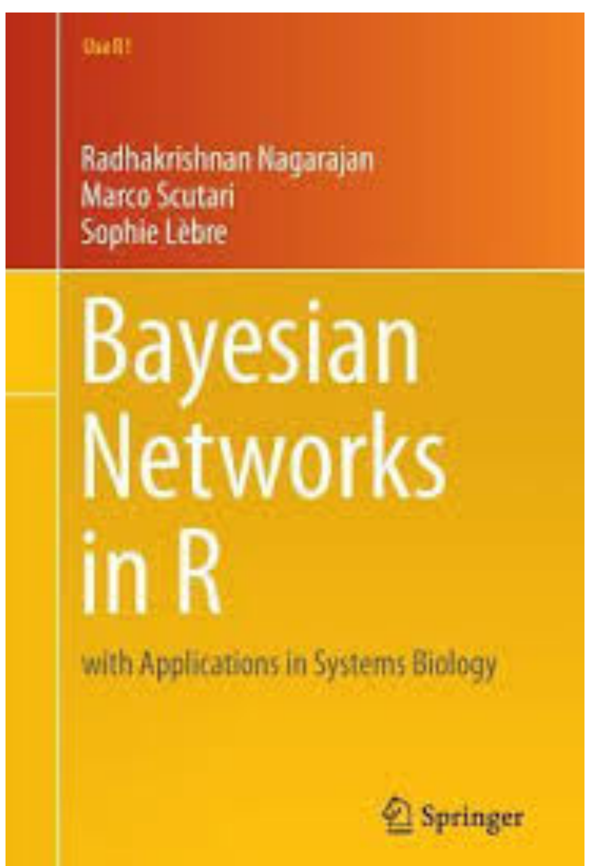
SELECTED BIBLIOGRAPHY

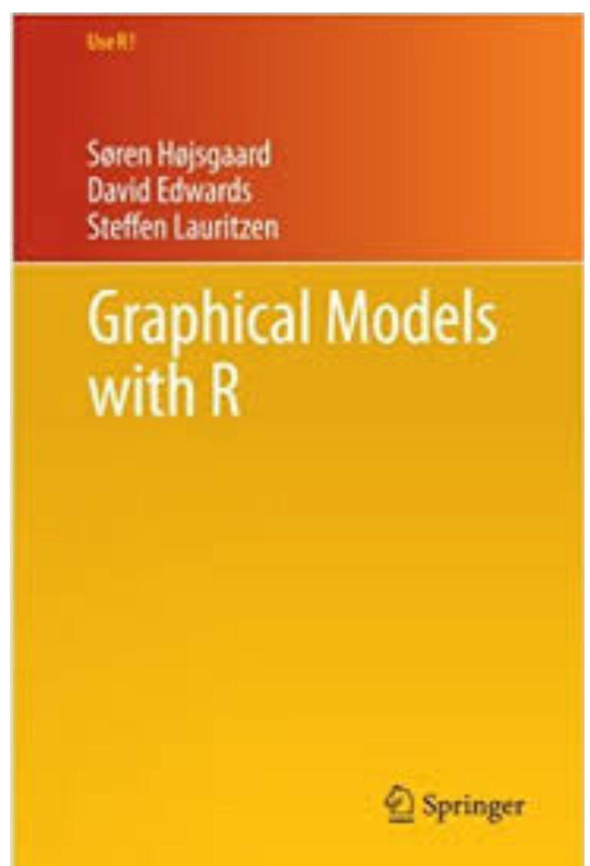


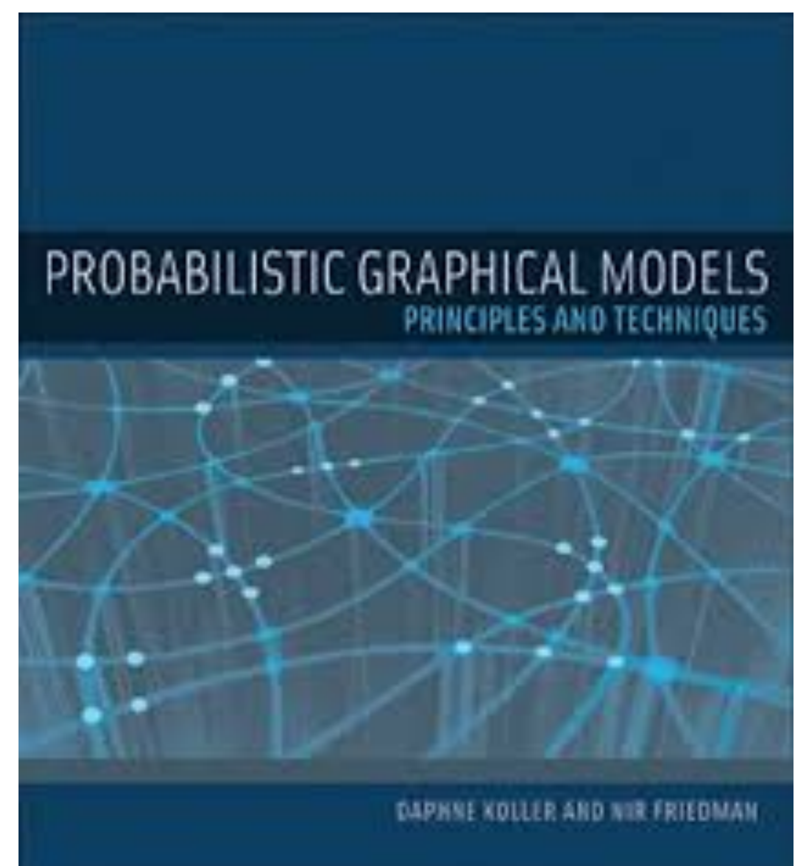






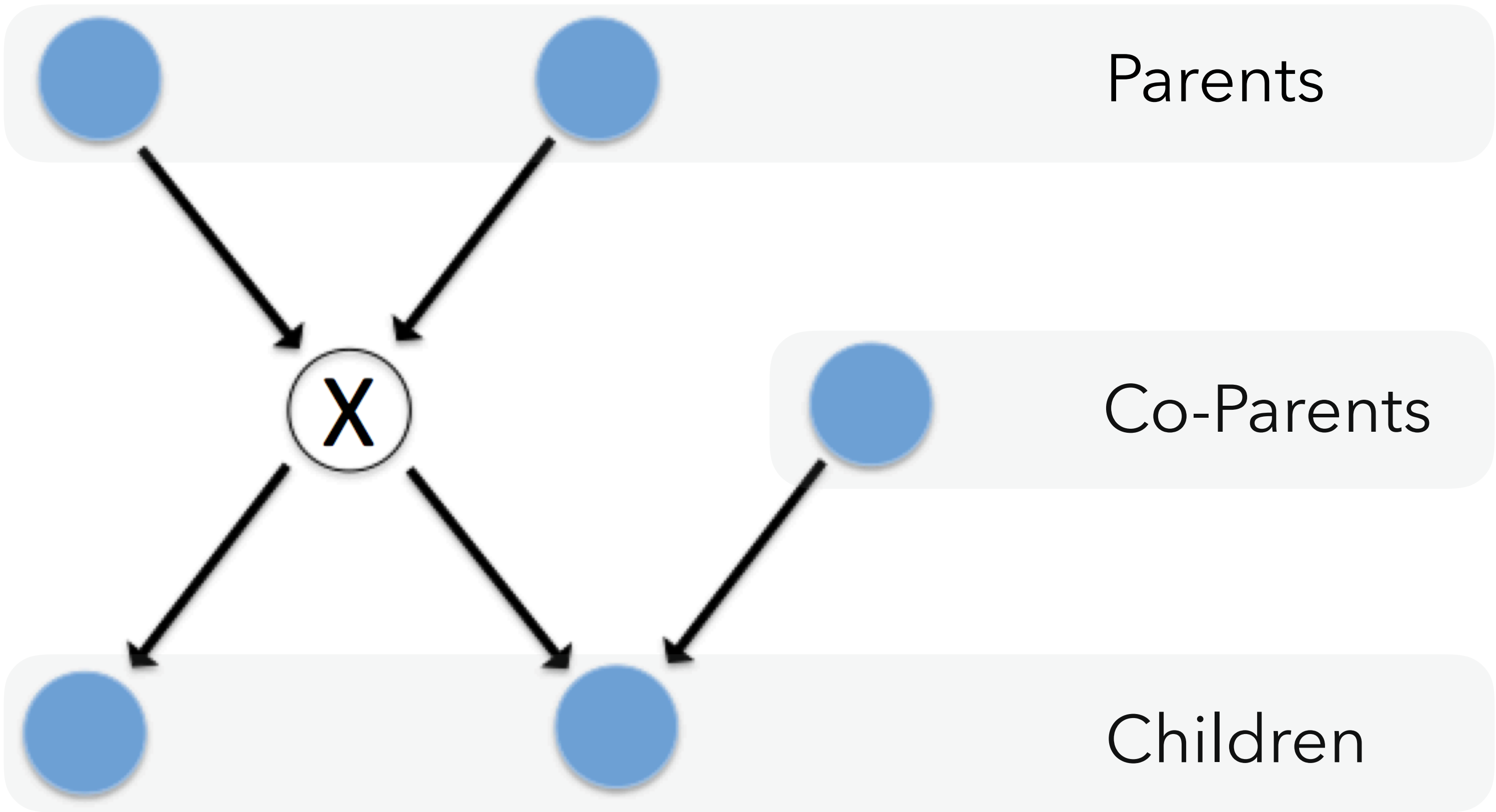






ELEMENT OF GRAPH THEORY: MARKOV BLANKET

The Markov Blanket of a node is the set of parents, co-parents and children.



$$P(X_k \mid X_n, k \neq n) = P(X_k \mid X_{\mathrm{MB}(k)}), \forall k$$

The Markov Blanket of a node is the set of nodes that shields the index node from the rest of the network

Local Markov property:

$$X \perp \text{ Non-Descendants(X) } | Pa(X)$$

- In a practical perspective, for observational data, if learning algorithms rely on probabilistic learning algorithm. Then one can learn up to the Markov equivalence class.
- Markov equivalence class are the set of DAGs that have the same skeleton and v-structure.