Learning Bayesian Network Structure by Self-Generating Prior Information: The Two-Step Clustering-Based Strategy

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Outline

Bayesian Networks

- Probabilistic graphical models
- Annotated directed acyclic graphes
- Address uncertainty and causal relationships

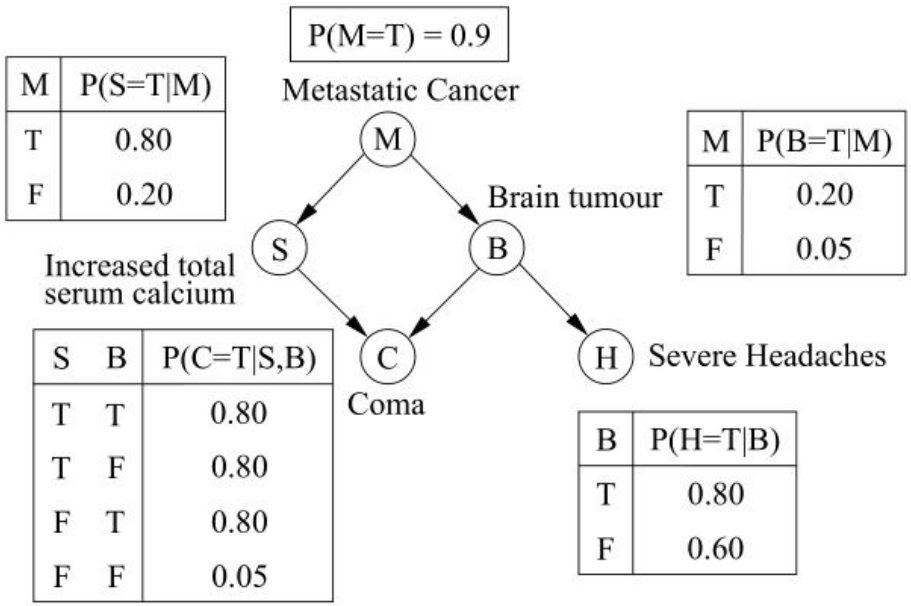

Figure: A simple Bayesian network model for the metastatic cancer problem: structure and CPTs (Twardy et al., 2006)

Bayesian Networks and Health Intelligence

- Meningitis epidemic outbreaks modeling (Beresniak et al., 2011)
- Survival prediction and treatment selection in lung cancer (Sesen et al., 2013)
- . . .

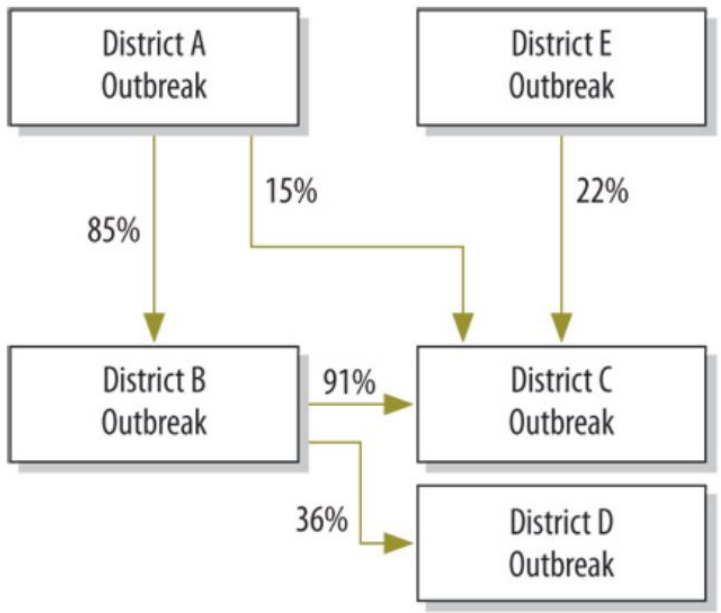

Figure: Simple Bayesian network model for the occurrence of a meningitis epidemic (Beresniak et al., 2011)

Bayesian Network Structure Learning

Identify a network that uncovers **conditional independence relations** (or **cause-effect relationships**) among the variables given the data set

Existing structure learning algorithms:

- Constraint-based algorithms: Markov Property
- Score-based algorithms: statistically motivated score
- Hybrid algorithms

Current Problems

For constraint-based methods,

- Sensitive to the failures in (conditional) independence tests

For score-based methods,

- NP-hard
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Time-consuming and less accurate on large-scale data sets!!!

Possible Solution

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Prior information

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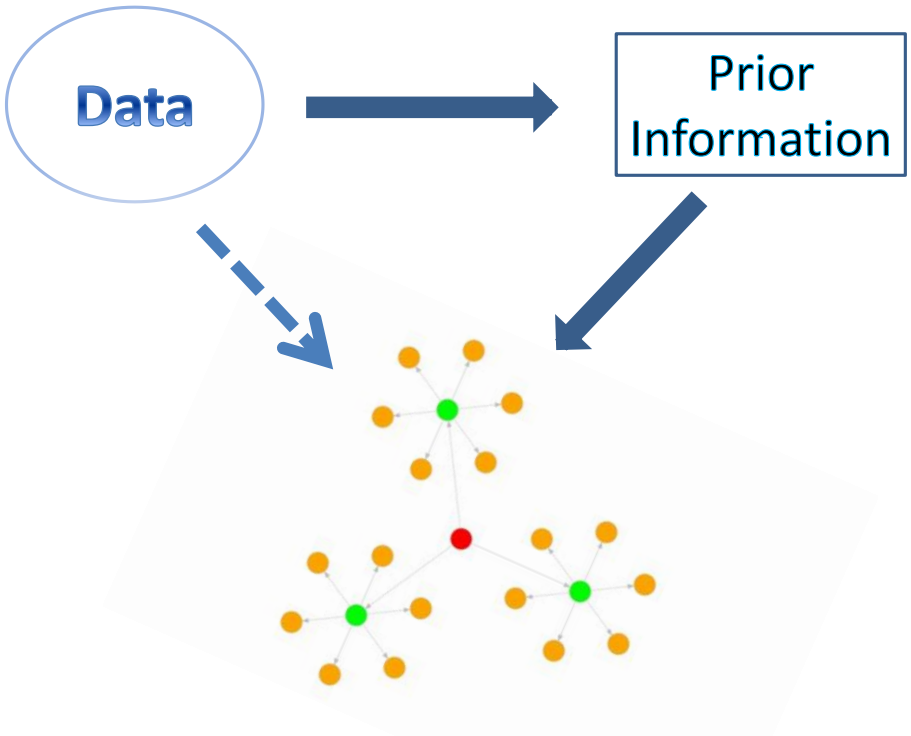
However, under real-world scenarios,

1. Expert knowledge may be scarce
2. A structure, an ordering of nodes, or distribution knowledge of nodes and arcs cannot be specified

Our Expectation

1. Generate prior information (existence of arcs) from data
2. Improve time efficiency, accuracies, or both



Motivation

1. Cluster-tree decomposition in the “Sparse Candidate” algorithm (Friedman et al., 1999)

2. Dividing the super-structure (a pre-assumed skeleton for the network) into clusters (Kojima et al., 2010)

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Why not group similar variables into clusters and learn the within-cluster and between-cluster arcs in two steps?

Outline of the Algorithm (Step 1)

Two-Step Clustering-Based Bayesian Network Structure Learning Strategy

- Data set $\mathcal{D} = \{X_1, X_2, ..., X_N\}$ with N variables
- The number of clusters: K (Parameter)

Step 1:

1: Compute the dissimilarity matrix.
2: Carry out clustering analysis via *average linkage agglomerative clustering method* and cut the dendrogram into K groups (clusters).
3: Learn Bayesian network structures within each cluster using a traditional algorithm A[1].

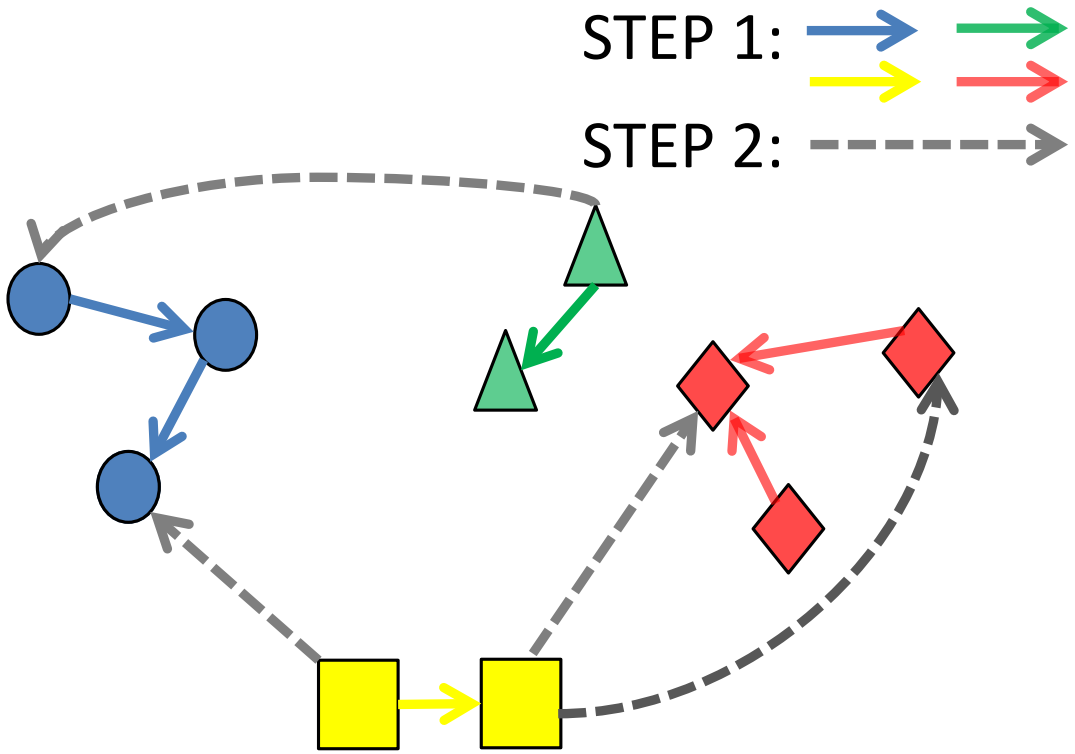
[1] This could be any traditional structure learning algorithm, like the Grow-Shrink algorithm (Margaritis, 2003).

Outline of the Algorithm (Step 2)

Step 2:

1: Apply the algorithm A again on all variables with the retained arcs to combine clusters.

Output: Bayesian network structure learned from the data set $\mathcal{D}$.



Dissimilarity Metric

Data sets with only discrete variables:

- Negative *mutual information*

Data sets with only continuous variables:

- *1-(Pearson's) correlation*

Hybrid data sets: See our paper for details.

Accuracy and Time Efficiency Evaluation

Accuracy metric (Metz, 1978):

$$Accuracy = \frac{\sum True\ Positive + \sum True\ Negative}{\sum Total\ Population}$$

Time efficiency metric:

Average elapsed times of repeated experiments

Traditional Structure Learning Algorithms

Constraint-based:

- Grow-Shrink (GS) algorithm (Margaritis, 2003)
- Incremental Association Markov Blanket (IAMB) algorithm (Tsamardinos et al., 2003a)
- Interleaved Incremental Association (Inter-IAMB) algorithm (Yaramakala and Margaritis, 2005)

Score-based:

- Hill-Climbing (HC) algorithm
- Tabu greedy search (TABU) algorithm

Hybrid:

- Max-Min Parents and Children (MMPC) algorithm (Tsamardinos et al., 2003b)

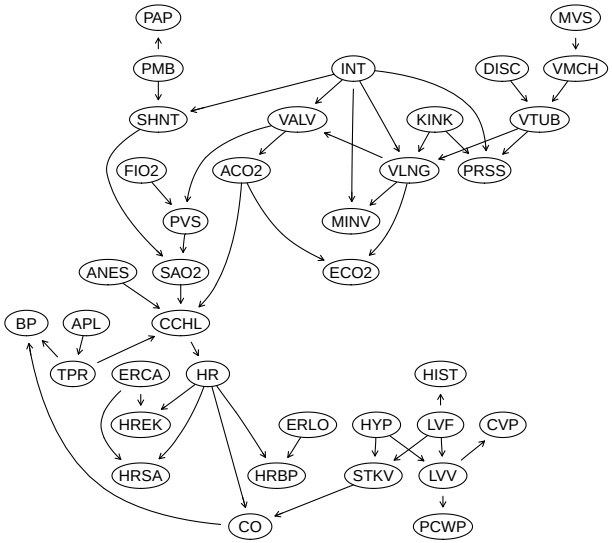
Accuracy Comparisons (I)

Methods	"asia"	"insurance"	"alarm"	"hepar2"
GS	**0.9096** (0.8918)	**0.9309** (0.9263)	**0.9662** (0.9602)	**0.9763** (0.9753)
IAMB	**0.9084** (0.8896)	**0.9287** (0.9218)	**0.9715** (0.9686)	**0.9747** (0.9741)
Inter-IAMB	**0.9082** (0.8936)	**0.9281** (0.9208)	**0.9716** (0.9689)	**0.9748** (0.9742)
MMPC	**0.8557** (0.8546)	**0.9259** (**0.9259**)	**0.9649** (0.9646)	**0.9732** (0.9728)
HC	**0.9766** (**0.9766**)	**0.9328** (0.9293)	**0.9768** (0.9724)	**0.9824** (0.9822)
TABU	**0.9664** (0.9657)	**0.9422** (0.9312)	**0.9788** (0.9744)	**0.9814** (0.9810)

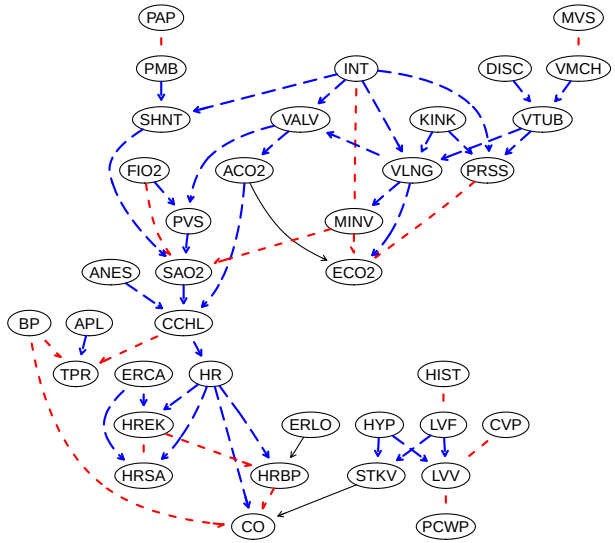
Table: TSCB Strategy vs Embedded Traditional Algorithms (inside round brackets).

Accuracy Comparisons (II)

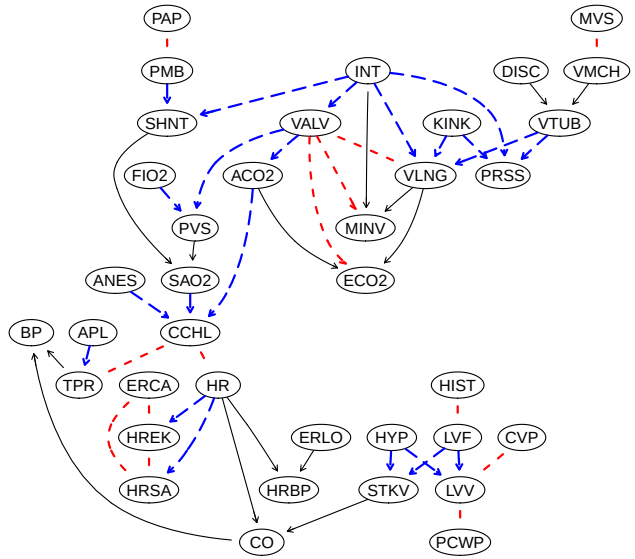
Network Configurations of the “alarm” Data Set.



(a) Actual Network



(b) Learned by the GS Algorithm



(c) Learned by the TSCB Strategy

Red dashed line: *False Positive*; Blue dashed line: *False Negative*.

Time Comparisons

Mean Elapsed Times / s	"asia"	"insurance"	"alarm"	"hepar2"
Clustering	0.00230	0.00788	0.01076	0.04432
Within clusters	0.00464	0.01670	0.05012	0.04744
Between clusters	0.00962	0.16420	0.24640	1.46168
TSCB	0.01656	**0.18878**	**0.30728**	**1.55344**
Traditional	**0.01010**	0.19362	0.35900	1.65584

Table: Mean Elapsed Times Comparison.

Sampling repeated times: 50; Recording repeated times: 10;
Experiments repeated times: $50 \times 10 = \mathbf{500}$.

Contributions

- An automatic way to generate prior information from data
- A wide range of Bayesian network structure learning algorithms can be improved
  1. Accuracy
  2. Time efficiency

Future work

1. Small clusters (≤ 3 variables) $\sim$ "network motifs" (Milo et al., 2002) ?

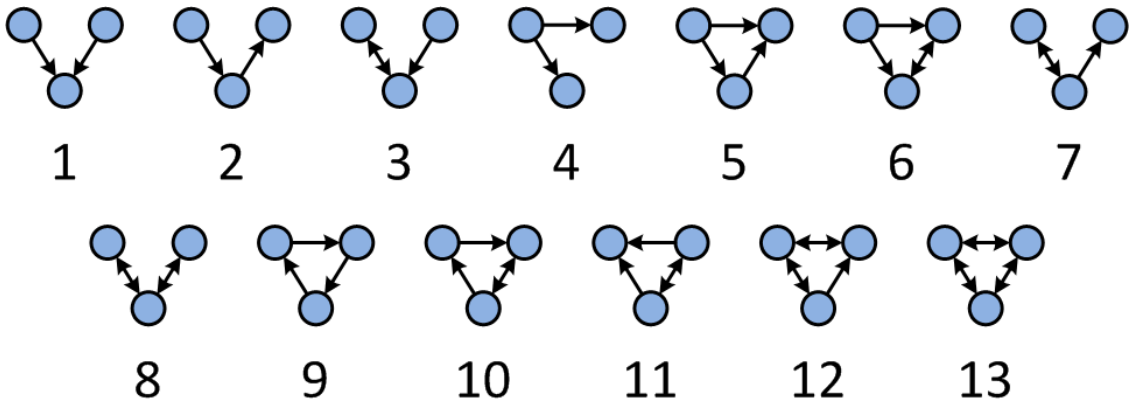


Figure: All 13 types of three-node connected subgraphs (Milo et al., 2002)

2. Existence of latent variables $\Rightarrow$ TSCB strategy ?
3. . . .

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Thank you!

Suggestions, Comments, Questions?