

# Estimating high-dimensional directed acyclic graphs with the PC-algorithm

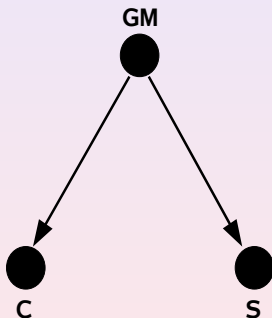
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# Overview

- 1 DAG and its skeleton
- 2 PC-algorithm
- 3 Consistency
- 4 Simulation
- 5 Application

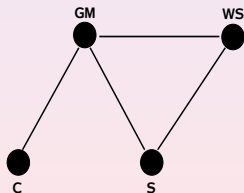
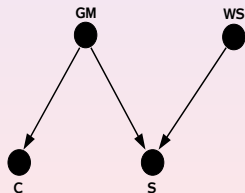
## Directed Acyclic Graphs (DAGs)



- Nodes: Random Variables
- Edges: Some Dependence
- Recursive factorization:  
 $f(GM, C, S) = f(GM)f(C|GM)f(S|GM)$
- We assume Multivariate Normal Distribution

## Directed Global Markov Property

- DAG implies conditional independence relations
- $C \perp S | GM \iff C, S$  are separated by  $GM$  in  $(G_{An(C \cup S | GM)})^m$



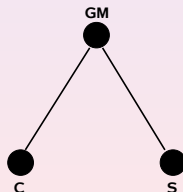
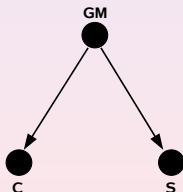
- Ancestral set
- Moralize
- Drop directions

# Faithfulness

Conditional independence relations implied by DAG  
=  
Conditional independence relations of distribution

## Skeleton of a DAG

- Ignore directions of arrows
- Edge between two nodes  $A$  and  $B \iff A, B$  are dependent given every subset of remaining nodes



# The PC-algorithm for finding a DAG

- **Finding the skeleton:**

Form complete graph  $G$

$l = -1$

repeat

$l = l + 1$

    repeat

        select (new) ordered pair of adjacent nodes  $A, B$  in  $G$

        select (new) neighborhood  $N$  of  $A$  with size  $l$  (if possible)

        if  $A, B$  are cond. indep. given  $N$

            save  $N$  in  $\mathbf{N}$

            delete edge  $A, B$  in  $G$

        until all ordered pairs have been tested

    until all neighborhoods are of size smaller than  $l$

- **Finding the DAG:** The skeleton can be directed using  $\mathbf{N}$  and four simple rules.

## Sample Version of the PC-algorithm

- Real World: Cond. Indep. Relations  $A \perp B|S$  are not known
- Instead: Test for partial correlation  $\rho_{AB|S} = 0$  (due to Gaussian assumption)

### Therefore:

Remove edge if test for  $\rho_{AB|S} = 0$  cannot be rejected for some  $S$  on level  $\alpha$ .



## Consistency: Assumptions

$n$ : Number of samples,  $p$ : Number of nodes

- Multivariate Normality, Faithfulness
- Nodes:  $p_n = O(n^a)$   $0 \leq a < \infty$  (**high-dimensional**)
- Max number of neighbors is  $O(n^{1-b})$   $0 < b \leq 1$  (**sparse**)
- Bounded partial correlations ( $0 < d < \frac{b}{2}$ ):  
 $\inf\{|\rho_{ij|\mathbf{k}}|; \rho_{ij|\mathbf{k}} \neq 0\} \geq c_n, c_n^{-1} = O(n^d)$  (**larger than  $\frac{1}{\sqrt{n}}$** )  
 $\sup\{|\rho_{ij|\mathbf{k}}|\} \leq M < 1$

## Consistency: Main Result

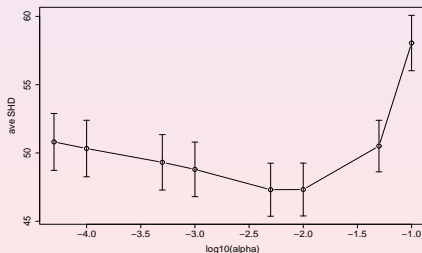
**Under these assumptions:**

There exists some  $\alpha_n \rightarrow 0$  ( $n \rightarrow \infty$ ) so that

$$P(\text{estimated DAG} = \text{true DAG}) = 1 - O(\exp(-Cn^{1-2d})) \rightarrow 1 \\ (n \rightarrow \infty) \quad \text{for } 0 < C < \infty$$

## Choice of $\alpha$

- Structural Hamming Distance (SHD) measures distance between estimated and true graph.
- Over a wide range of parameters the average SHD is minimized for significance levels between  $\alpha = 0.005$  and  $\alpha = 0.001$ .
- In practice: Either choose default values for  $\alpha$  or generate priority list of edges



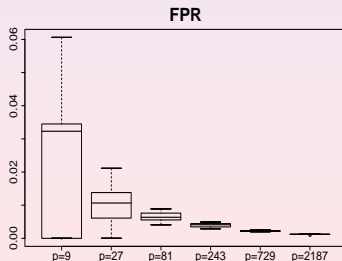
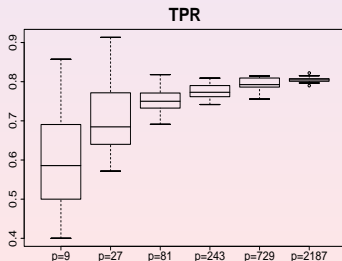
# Performance

**Computing Time:**  $p = 1000, n = 1000, E[N] = 8 \rightarrow t \sim 1h$

**Estimation:**

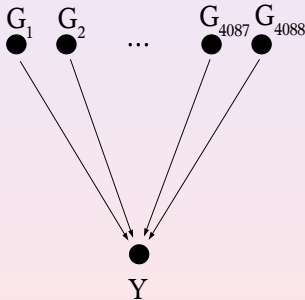
- Number of variables  $p$  increases exponentially
- Number of samples  $n$  increases linearly
- Expected size of neighborhood  $E[N] = \sqrt{n}$  increases sublinearly

Then: TPR increases, FPR decreases



## Application

### Production of Riboflavin (Vitamin $B_2$ ) in *Bacillus Subtilis*

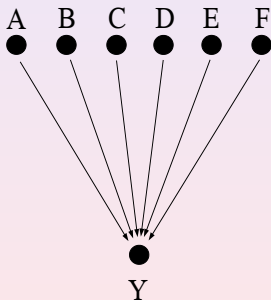


- **Goal:** Maximize output of Riboflavin  $Y$  by manipulating genes
- Data obtained by Affymetrix *B. subtilis* GeneChips from DSM Nutritional Products
- Number of Variables  $p = 4088$ , number of samples  $n = 50$

Which genes have an influence on  $Y$ ?

## Application 2

### Result



- Small number of stable candidates extracted
- They are a subset of genes found with other techniques (Lasso, Elastic Net, . . . )
- Findings promising from a biological point of view
- Experimental testing in progress

## Conclusion

- DAG, Skeleton, Dependence
- PC-algorithm finds true DAG/skeleton consistently (under some assumptions)
- PC-algorithm is fast for sparse graphs
- More information:  
M. Kalisch and P. Bühlmann  
Estimating High-Dimensional Directed Acyclic Graphs with the PC-algorithm  
JMLR 8 (2007)
- R-package `pcalg` for the PC-algorithm (including robust version)