

Differential study of the GRNs in the cancerous pathology & therapeutic response:

An **EVOLUTIONARY** approach based on
the **BAYESIAN NETWORKS**

PhD Student: NGUYEN, H.T. : LINA-COD

Supervisor: RAMSTEIN, G. : LINA-COD

Co-Director: JACQUES, Y. : INSERM-U892

Director: LERAY, P. : LINA-COD

This is a research project combining :
Bioinformatics, Machine learning and Statistics

The main goal of this presentation is to introduce in general :

- 1 a **machine learning** approach for **bioinformatics**
 - That is **Bayesian networks** (BN) for gene regulatory network (GRN) reconstruction
 - in order to infer the differentiation of the cytokine implication in **different experimental conditions**
- 2 an **evolutionary algorithm** (EA) for BN structure learning
 - Estimation of Distribution Algorithm (EDA)

- 1 Introduction
- 2 Machine learning for GRN reconstruction
- 3 EA for BN struture learning
- 4 Conclusion and Future Works

- 1 Introduction
- 2 Machine learning for GRN reconstruction
- 3 EA for BN struture learning
- 4 Conclusion and Future Works

Biology

- Found **IL-15** in recent years [Arena et al. 2000]
- This cytokine plays a critical role in the immune system
- It has **the similar action** to the others cytokines in this system

Question:

→ How is the **implication** of IL-15 in the **different experiments**?

Bioinformatics & Machine Learning

- **Microarray** allows to measure simultaneously the **expression level** of **thousands** of genes
- **Gene regulatory networks** (GRNs) allow to achieve the **regulation of gene expression**
- There are various **machine learning** methods proposed to reconstruct the GRNs
 - **Bayesian networks** (BNs) can solve major problems of this reconstruction

Question:

→ How can we use the **BNs** to infer the **implication** of IL-15 in the **different experiments**?

Problems & Solutions

"If there aren't any problems, we have only the solution"

Problem: Data

- **Heterogeneous** and **noisy**
- A **massive number** of variables (over 25.000 genes)
- But a **small number** of samples (dozen experiments)

Solution: Data

- **Public** database : to increase the number of samples
- **Normalization** : to normalize heterogeneous data
- **Bayesian networks** : to deal with noisy data, the massive number of variables

- 1 Introduction
- 2 Machine learning for GRN reconstruction
- 3 EA for BN struture learning
- 4 Conclusion and Future Works

Machine learning aproaches

for the reconstruction of the GRNs

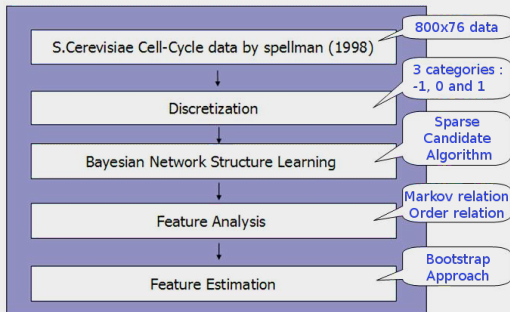
Overview:

- 1 **Clustering** [MacQueen, 1967]
- 2 **Boolean Networks** [Kauffman, 1969]
- 3 **Bayesian Networks**
 - Using BNs to Analyze Expression Data [Freidman et al., 2000]
 - Inferring Subnetworks from Expression Profiles [Pe'er et al., 2001]
 - **Our approach** : Using **a set of BNs** to infer the differential study of the cytokine in different experimental conditions

Bayesian networks

Using BNs to Analyze Expression Data [Freidman et al., 2000]

Architecture of system proposed by Freidman et al., 2000



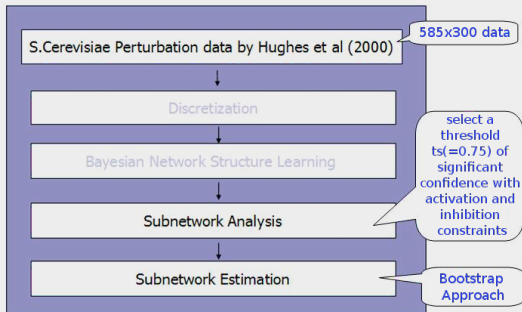
Open problems:

Continuous data, discretization method, temporal expression data, causal patterns, biological knowledge

Bayesian networks

Inferring Subnetworks from Expression Profiles [Pe'er et al., 2001]

Architecture of system proposed by Pe'er et al., 2001



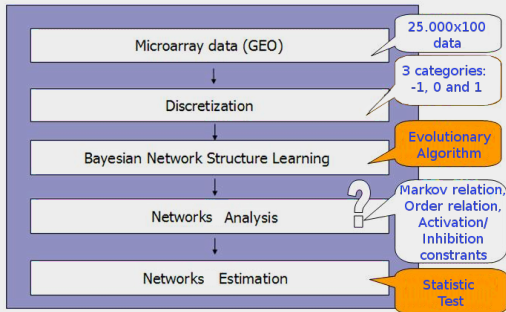
Open problems:

Latent factors that interact with several observed genes,
 biological knowledge

Bayesian networks

Our approach

Our architecture of system (overview) :



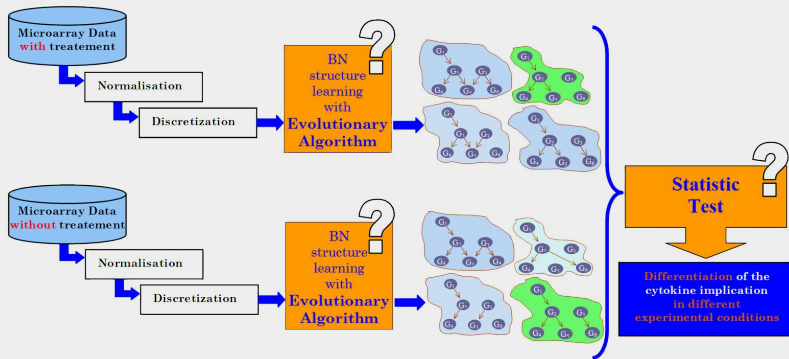
Open problems:

More detail in "**Future Works**" section

Bayesian networks

Our approach

Our architecture of system (detail)



- 1 Introduction
- 2 Machine learning for GRN reconstruction
- 3 EA for BN struture learning
- 4 Conclusion and Future Works

BN structure learning

Different approaches

Different approaches to learn the structure of BNs

- From an **expert**
- **Constraint-based**: find in the data for conditional independence relations, then construct graphical structures for these relations
- **Search-Scoring** : search in the space of legal structures for the BNs that maximize the score
 - **Evolutionary Algorithm**:
 - Genetic Algorithm (GA)
 - **Estimation of Distribution Algorithm** (EDA)

Evolutionary Algorithm

and its representative EDA (Estimation of Distribution Algorithm)

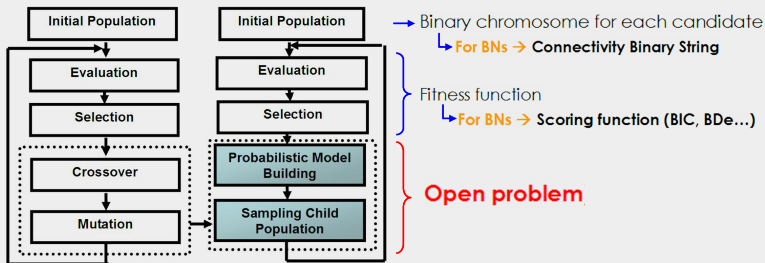
EA : What and why?

- "EA is a subset of evolutionary computation, a **population-based** heuristic optimization algorithm"
- EA allow to maintain a **set of interesting solutions**

EDA : What and why?

- "EDA is an **outgrowth** of genetic algorithm. In EDA a population may be approximated with a **probability distribution** and new candidate solutions can be obtained by sampling this distribution"
- EDA allows to maintain a **set of interesting solutions** with **the good probabilistic distributions**
→ This could be useful for a **statistic test** after

EDA & GA : Case study for BN structure learning



Other Names of EDA :

- **PMBGAs** (Probabilistic Model Building Genetic Algorithms)
- **DEAs** (Distribution Estimation Algorithms)
- **IDEAs** (Iterated Density Estimation Algorithms)

EDA is categorised into three groups :

1. Univariate EDA

- **PBIL** (Population Based Incremental Learning) [Baluja, 1994]
- **UMDA** (Univariate Marginal Distribution Algorithm) [Mühlenbein et al., 1996]
- **cGA** (Compact Genetic Algorithm) [Hariket et al., 1998]

2. Bivariate EDA

- **MMIC** (Mutual Information Maximization for Input Clustering) [Bonet et al., 1997]
- **COMIT** (Combining Optimizers with Mutual Information Trees) [Baluja, 1997]
- **BMDA** (Bivariate Marginal Distribution Algorithm) [Pelikan et al., 1999]

3. Multivariate EDA

- **ECGA** (Extended Compact Genetic Algorithm) [Harik, 1999]
- **EBNA** (Estimation of Bayesian Networks Algorithm) [Etzeberria et al., 1999]
- **FDA** (Factorized Distribution Algorithm) [Mühlenbein et al., 1999]
- **LFDA** (Learning Factorized Distribution Algorithm) [Mühlenbein et al., 1999]
- **BOA** (Bayesian Optimization Algorithm) [Pelikan et al., 2000]

- 1 Introduction
- 2 Machine learning for GRN reconstruction
- 3 EA for BN struture learning
- 4 Conclusion and Future Works

Conclusions and Future Works

Conclusions

Conclusions :

- The goal of this work is **differential analysis** :
 - 1 BNs reconstruct GRNs
 - 2 EAs maintain a set of good BNs
 - 3 Comparison the obtained BNs in different experiments

Future Works :

- **Theory** : Which type of EDA can be used? May the statistic test be a good approach?
- **Implementation** : A module of BN structure learning by EA with **ProBT(C)** and **EO library** (Evolving Objects)
- **Experimentation** : Test this module with **GEO** (Gene Expression Omnibus) data

Researchers



RAMSTEIN Gerard

Laboratoire d'Informatique de Nantes-Atlantique, France
Equipe « **C**onnaissances et **D**ecisions »



LERAY Philippe

Laboratoire d'Informatique de Nantes-Atlantique, France
Equipe « **C**onnaissances et **D**ecisions »



JACQUES Yannick

Centre de Recherche en Cancerologie Nantes/Angers, France
Equipe « **C**ytokines et **R**eccepteurs »



HUYNH Xuan-Hiep

Laboratoire d'Informatique de Université de Cantho, Vietnam
Equipe « **G**énie **L**ogiciel »

NGUYEN H.T.
nguyen-ht@univ-nantes.fr

Appendix

Representation for a BN in the evolutionary methods

Ideas:

Each possible candidate of BNs is represented by an $n \times n$ connectivity string C_{ij}

$$c_{ij} = \begin{cases} 1 & \text{if } j \text{ is a parent of } i, \\ 0 & \text{otherwise.} \end{cases}$$

For each chromosome, we represent an individual of the population by the string :

$$C_{11}C_{21} \dots C_{n1} \ C_{12}C_{22} \dots C_{n2} \ \dots \ C_{1n}C_{2n} \dots C_{nn}$$

Example



Chromosome :
010 001 000

(a)



Chromosome :
010 001 100

(b)

Appendix

Example of a simple EDA for the BN structure learning

Example

