Inference methods

- Probabilistic methods
  - Clustering analysis
  - Data mining
  - Bayesian networks

- Deterministic methods
  - Continuous – Differential equations
  - Discrete - Boolean

Four steps in clustering analysis

- Pair-wise correlation analysis
  - Time-series data
  - Spatial data
- Gene co-expression network
- Clustering of genes
- Predicting protein-protein interaction

Drawback: No insight into the causal relationship

Pair-wise similarities between expression profiles:

- Pearson correlation
- Squared Pearson correlation coefficient
- Spearman rank correlation
- Jacknife correlation coefficient
- Euclidean distance

Clustering algorithms:

- Bottom-up approach
  - Hierarchical clustering
- Top-down approach

Local clustering algorithm

Qian et al. (2001) JMB, 314, 1053-1066
Oncogenic signaling network

Construction of weighted gene co-expression network based on pairwise Pearson correlations

Hierarchical clustering to detect groups or modules.

Elucidation of directionality

\[
SR = \frac{\min(|b_{YX}|, |b_{XY}|)}{\max(|b_{YX}|, |b_{XY}|)}.
\]

\(b_{YX}, b_{XY}\): regression slopes
e.g. \(b_{YX} = 1.004\) and \(b_{XY} = 0.976\)

Directionality is assigned to those edges for which 
\(SR = 0\)

\(\text{If } SR = \frac{|b_{YX}|}{|b_{XY}|} \Rightarrow Y \rightarrow X; \text{ If } SR = \frac{|b_{XY}|}{|b_{YX}|} \Rightarrow X \rightarrow Y, \text{ SR}_{XY} = 0.97\)

Data mining

- Extract information based on the statistical co-occurrence.

Algorithm searched for the co-occurrence of pair of genes resulting in the edge generation according to the user defined threshold.

Network retrieved by the query ‘DNA repair’

Bayesian networks

- These protocols are used for sparse datasets
- Probabilistic approach which is capable of handling noise
- The approach is based on the statistical properties of dependence and conditional independence in the data
- Estimate the confidence in the different features of the network
- Insight into the causal influence
Bayesian analysis

• Bayes’ theorem = \( P(A|B) = \frac{(P(B|A)P(A))}{(P(B))} \alpha L(A|B)P(A) \)

\( P(B) \) – normalizing constant (NC)

Posterior = \( \frac{(\text{Prior} \times \text{Likelihood})}{\text{NC}} \)

Steps in Bayesian analysis

• Define state of the system
  – random variable
  – known information

• Find conditional probability of each node
  – Directed acyclic graph representation of possible causal relationships

\[ I(A; E) \]
\[ I(B; D | A, E) \]
\[ I(C; A, D, E | B) \]
\[ I(D; B, C, E | A) \]
\[ I(E; A, D) \]

Continued…

• Find joint distribution
  – A set of local joint probability distributions that statistically convey these relationships

• The distribution yielding highest Bayesian score is chosen as the best fit to the data. Benchmarks for weighting are typically obtained from likelihood.

\[ P(A, B, C, D, E) = P(A)P(B|A)P(C|B)P(D|A)P(E). \]

• Bayesian analysis produces multiple candidate networks
• The links can be established randomly or heuristically
• Iterative search algorithms are employed, e.g. genetic algorithm

Local map for the gene SVS1

Deterministic Methods for Network Inference

A deterministic inference correlates the rate of change in expression level of each gene with the levels of other genes by finding the functional or logical forms of these interdependence relationships.

(Loosely) Two classes of deterministic inference methods:

1) Continuous;
2) Discrete

Continuous Methods

- Identified as: systems of linear or nonlinear differential equations in which, for example, rate of change of expression of $X_i(t)$ is a linear combination of concentrations of all other $X_j(t)$:

$$\frac{dX_i(t)}{dt} = \sum_{j=1}^{N} w_{ij} X_j(t)$$

- Pros and cons:
  - can be quite accurate;
  - accuracy increases as number of experimental time points increases;
  - computational intractability quickly becomes an issue

- Have been used to infer gene-regulatory networks in:

An Example: Inferring gene-regulatory networks in B. subtilis

A Linear Model of Network Inference

Microarray data

$$\frac{dX_i(t)}{dt} = \sum_{j=1}^{N} w_{ij} X_j(t)$$

To be solved for

$w_{ij} > 0 \Rightarrow activation$ of $i$ by $j$

$w_{ij} < 0 \Rightarrow inhibition$ of $i$ by $j$


Optimization

Maximizing Sparseness

$$\min \sum_{i,j} (w_{ij}^a + w_{ij}^b)$$

subject to

$$w_{ij}^a \sum_{k=1}^{N} w_{ik} v_k = w_{ij}^b \quad \forall i, j = 1, 2, \ldots, N$$

$$w_{ij}^a \geq 0, w_{ij}^b \geq 0 \quad \forall i, j = 1, 2, \ldots, N$$

Dense network

Sparse network

Post Optimization

Sparseness

Maximizing Sparseness
Discrete Methods

- **Identified as:** Boolean and other logic-based methods that predict discrete regulatory relationships, e.g.,

A set of nodes $V=\{v_1,\ldots,v_n\}$ and a list of Boolean functions $F=\{f_1,\ldots,f_n\}$ where a Boolean function $f_i(v_{i1},\ldots,v_{ik})$ with $k$ specified input nodes is assigned to node $x_i$.

**Pros and cons:**

- More computationally-tractable than continuous methods;
- Less accurate than continuous methods.

Much practical application is currently focused on developing and implementing algorithms for large-scale inference: e.g. REVEAL (REVerse Engineering ALgorithm)


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An Example: Boolean protocol for network inference

**Boolean network basics...**

A Boolean network $G(V,F)$ consists of a set of nodes, $V=\{v_1,\ldots,v_n\}$, representing genes, and a list of Boolean functions, $F=\{f_1,\ldots,f_n\}$.

A Boolean function, $f_i(v_{i1},\ldots,v_{ik})$, with inputs from specified nodes, $v_{i1},\ldots,v_{ik}$, is assigned to each node $v_i$, and this function gives the logical rules (AND, OR, AND NOT, etc...) for the ways in which nodes $v_{i1},\ldots,v_{ik}$ will interact.

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**A picture (no inference yet)**

![Boolean network diagram]

**RULES**

$v'_1 = v_1$, $v'_2 = v_2$, AND $v'_3 = \text{NOT } v_3$

<table>
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<th>INPUT</th>
<th>OUTPUT</th>
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<tbody>
<tr>
<td>$v_1$</td>
<td>$v_1'$</td>
</tr>
<tr>
<td>$v_2$</td>
<td>$v_2'$</td>
</tr>
<tr>
<td>$v_3$</td>
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**An algorithm for inferring a Boolean network**

[Almeida, T. and Myano, S. Pac. Symp. on Biocomputing 4, 17-28 (1999)]

1) For each node $v_i \in V$, execute STEP 2.
2) If there is a triplet $(v_i,v_{i1},v_{i2})$, satisfying $O_j = f_i(v_{i1},v_{i2},O_j)$ for all $j=1,\ldots,m$, where $O_j$ and $I_j$ are state outputs and inputs, take $f_i$ as a Boolean function assigned to $v_i$ and take $v_{i1}, v_{i2}$ as input nodes to $v_i$.
2) Enumerate all triplets $(v_i,v_{i1},v_{i2})$ satisfying $O_j = f_i(v_{i1},v_{i2},O_j)$ for all $j=1,\ldots,m$.

What do STEPS 2 and 2' actually mean?!!!
Three Examples

- Inference methods that bridge the gap between probabilistic and deterministic approaches, usually by incorporating some type of stochastic process (variability, uncertainty) into the inference algorithm.

• Pros and cons:
  - Arguably most accurate and realistic network inference methods;
  - Amount of training data and computational time make methods prohibitive for large networks;

For Example: Probabilistic Boolean Inference

- $N$ Boolean functions are assigned to each node, each with some probability of being selected to advance the state of the node; a machine-learning algorithm must be used to update the state of each node at each time point.