Multiscale Bootstrap Analysis of Gene Networks Based on Bayesian Networks and Nonparametric Regression

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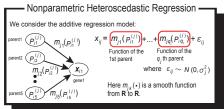
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Introduction

The Bayesian network [2, 3, 4] is a very powerful tool for estimating the gene network from microarray expression profiles. The estimated network is often susceptible to statistical sampling error, and thus Imoto et al. [3, 4] evaluated the reliability of estimation by calculating the bootstrap probabilities for the edges connecting genes. The bootstrap method, however, underestimates the probability values, and it sometimes leads to false "discovery". For improving the accuracy of the bootstrap probability, we propose the application of the newly developed multiscale bootstrap [5, 6] to the gene network estimation.

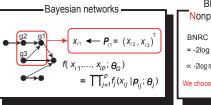
Method

1. Nonlinear Bayesian Network Model



- DAG encoding the Markov assumption. (DAG : Directed acyclic graph
- · The joint density can be computed by the product of the conditional densities.
- 2. How can we capture the nonlinear relation-
- ships between genes?

 3. How can we choose the optimal graph?



BNRC(Bayesian network and Nonparametric Regression Criterion)

= $-2\log \pi(G) \int \prod_{i=1}^{n} f(\mathbf{x}_{i} | \theta_{G}) \pi(\theta_{G} | \lambda_{G}) d\theta_{G}$ $\propto -2\log \pi(G) - r \log(2\pi n^{-1}) + \log \left| J_{\lambda}(\hat{\boldsymbol{\theta}}_{G}) \right| - 2nI_{\lambda}(\hat{\boldsymbol{\theta}}_{G} | \mathbf{X}_{n})$

We choose the graph that minimizes the value of BNRC

2. Bootstrap and Multiscale Bootstrap **Edge Intensity**

We measure the intensity of the edge by the bootstrap and multiscale bootstrap method. In the multiscale bootstrap method, we generate replicates $\boldsymbol{\chi}_{n'}^*$ = $(\boldsymbol{x}_1^*,\ldots,\boldsymbol{x}_n^*)$ for several n' values from the original gene expression data \boldsymbol{X}_n = ($\mathbf{x}_1, \ldots, \mathbf{x}_n$). In other words, we alter the number of arrays from n to n'in the bootstrap replication. We will take n' values with n'/n = 0.5, 0.6, 0.7, 0.8,0.9, 1.0, 1.1, 1.2, 1.3, 1.4, in the example shown later. We call $\tau = \sqrt{n/n'}$ scale

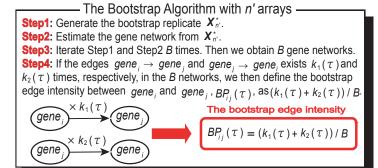
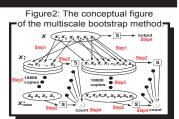


Figure1: The conceptual figure of the bootstrap method

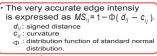
The bootstrap method

- We take n' = n.
- The bootstrap edge intensity can be written as BP (1).



The multiscale bootstrap method

We calculate $\mathit{BP}_{ij}(\tau)$ with several τ values by altering n'/n.

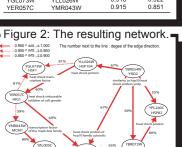


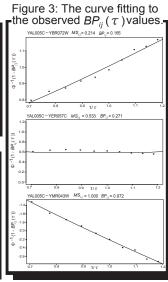
We estimate d_{ij} and C_{ij} by fitting the theoretical curve $BP_{ij}(\tau) = 1 - \Phi(d_{ij}/\tau + c_{ij}\tau)$ to the observed $BP_{ij}(\tau)$ values calculated to the observed $BP_{ij}(\tau)$ values calculated by the multiscale bootstrap method.

Result

- · We applied the proposed method to S.cervisiae gene expressin data.
- · We focusd on 9 genes, which are involved or putatively involved in the heat shock response
- We took B = 10000.

Table 1: Gene pairs with high multiscale bootstrap intensities. YBR072W YPL240C YFR0570 YLL026W 0.998 YAL005C YMR043W YI I 026W YBR054W 0.996 YBL075C YPL2400 0.978 YBR054W 0.885 0.642 YGL073W YGL073W





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