From Machine Learning to Learning Machines - A Perspective toward Personalized Medicine

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Introduction

- Learning Machines: A Bottom-up Approach with a Network
 - Analysis of Networks
 - From Networks to Personalized Medicine

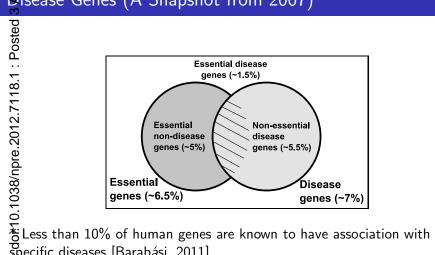
Precedings : doi:10.1038/npre.20設.7118.1 : Posted 3 Apr point uoi

the Interactomes

р вко Molecular Networks

- 20 Protein-protein Interaction Networks
 - Metabolic Networks
 - Regulatory Networks TF-gene Networks
 - Post-translational Networks Kinase-substrate Networks
- Protein-protein 1
 Metabolic Networks
 Regulatory Networks RNA Networks Chenotypic Networks RNA Networks - TF-miRNA Networks, miRNA-gene Networks
- Co-expression Net Co-expression Networks
- What is a Disease Network?

Disease Genes (A Snapshot from 2007)



specific diseases [Barab*á*si, 2011].

 SOF these ${\sim}19\%$ are known to be oncogenes (November 16, 2011; Cancer Genome Project).

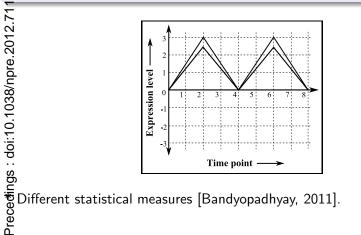
$\frac{1}{2}$ Framework of Co-expression Analysis

- Co-expression
- Differential Expression
- Differential Co-expression
- Co-expression Dynamics

Co-expression

Definition

Bairwise similarity pattern (spatial or temporal) of expression vectors.



Differential Expression

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Definition

arying patterns (spatial or temporal) of expression vectors in different SAM, t-test, etc.

Differential Co-expression

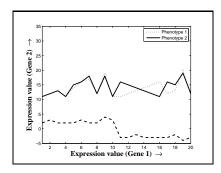
Pairwise varying dependence (spatial or temporal) between expression On/off case and gap/subsitut

On/off case and gap/subsitution case [Dettling, 2005].

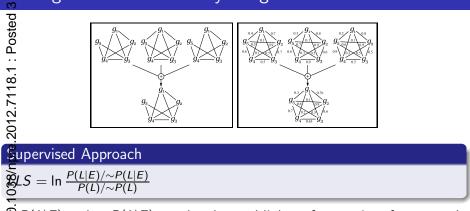
Eo-expression Dynamics

sted Definition

Pairwise varying dependence (spatial or temporal) between expression Sectors based on another expression vector. Vectors base Vectors Ve



Making Networks Robust by Integration



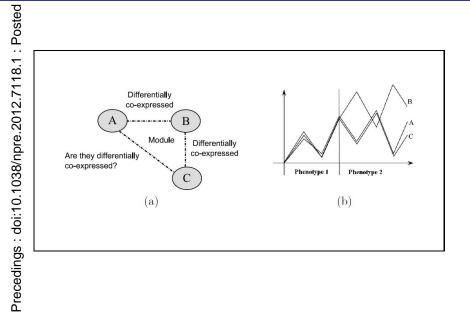
P(L|E) and $\sim P(L|E)$ are the observed linkage frequencies of annotated serves operating in the same and in different pathways, respectively, whereas P(L) and $\sim P(L)$ are the prior annotations [Lee, 2004].

Insupervised Approach

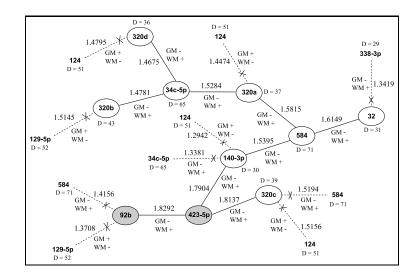
$$\Psi_c(i,j) = \sqrt[\alpha]{\sum_{k=1}^n \xi_k(i,j) W_k(i,j)^{\alpha}}$$


```
Degree: Disease biomolecules avoid hubs
                                   Modularity: Biomolecules specific to a disease form
Modularity: Biomolecules specific to a disease form
i modules
  Sharing: Diseases having common biomolecules show
  phenotypic similarity
  Closeness: Causal pathways coincide with the connectors
  of known disease-subnetworks
  Solution
  Solution
  Multiple Machine Learning Machines
  Machine Learning
  Machine
  Machine Learning
  Mac
```

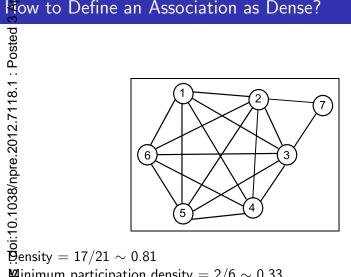
Bifferential Co-expression to Module Finding



Bifferentially Co-expressed Switching Tree



How to Define an Association as Dense?



Minimum participation density = $2/6 \sim 0.33$

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A Dense Module

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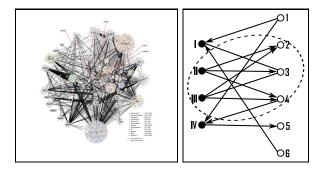
Association density of a vertex

Given a weighted graph $G = (V, E, \Omega)$, the association density, μ_{v_i/V^N} , of evertex v_i of G with respect to a vertexlet V^N (such that $v_i \notin V^N$), is defined as the ratio of the sum of the edge weights between v_i and each of the vertices belonging to V^N , and the cardinality of the set V^N . Thus, the essociation density of a vertex v_i with respect to the vertexlet V^N is emputed as $\mu_{v_i/V^N} = \frac{\sum_{v_j \in V^N} \Omega_{v_i v_j}}{N}$.

Association density of a vertexlet

The association density of a vertexlet V^N is defined to be the minimum of the association density of every vertex belonging to the vertexlet with espect to the vertexlets of order (N-1). So, the association density of a vertexlet V^N is given by $\mu_{V^N} = \min_{v_i \in V^N} \left(\mu_{v_i/V^N - \{v_i\}} \right)$.

Regulatory Network Analysis



BClique

BDBClique is a fully connected subgraph $G' = (V'_1, V'_2, E') \subseteq G$ of a **\overline{\mathbf{a}}** rected bipartite graph G such that either $i \in V'_1, j \in V'_2, \forall (i, j) \in E'$ or $\overset{\mathbf{0}}{E} \in V'_2, j \in V'_1, \forall (i,j) \in E'.$

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Machine Learning to Learning Machines

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	Endogenous	Exoge
TF combinations	complex	sim
Path length	long	sho
TF outdegree	Low	Hi
Significant motifs	FFLs	single
TF interconnectedness	High	Lc
Table: Topologica nbe, 2004].	l properties of Ne	tworks.
	Path length TF outdegree Significant motifs TF interconnectedness	EndogenousTF combinationscomplexPath lengthlongTF outdegreeLowSignificant motifsFFLsTF interconnectednessHighTable:Topological properties of Nenbe, 2004].

Exogenous

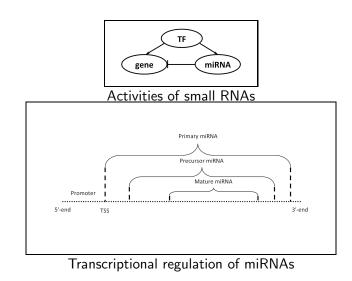
simple

short High

single input

Low

Strengthening the Network Analysis



grugs and Biomarkers

being the second second

-Prepare integrative network models

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Cildentify potential multi-node signatures

A test case of cancer metastasis is proposed pursuing the 'seed and soil' minciple [Erler, 2009].

Nore focus on aberrations and pathways

Fildentify the genetic aberrations and the master regulators that drive foliferation, survival, metastasis, and drug resistance

...Model the adaptive/feedback mechanisms that thwart the efficacy of Botent drugs

 $\frac{1}{2}$ Predict additional target pathways for combinatorial drug treatment

🖉 [Ray, 2010, Pe'er, 2011].

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THANK YOU