

# Network Analysis and Application

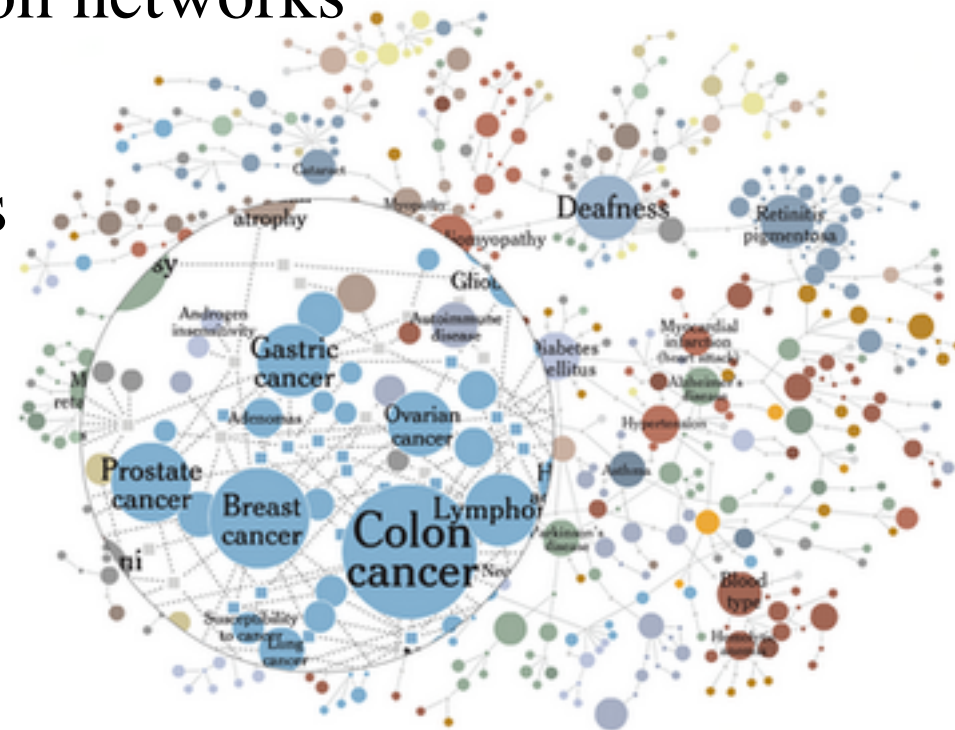
Yao Fu  
10-15-2012



# INTRODUCTION TO BIOLOGICAL NETWORKS

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- Characterization of **biological processes**
- Network examples
  - Protein-protein interaction networks
  - Metabolic network
  - Transcriptional networks
  - RNA networks
  - Co-expression network
  - Disease gene network
  - Signaling network...



Human Disease Network

# Protein Protein interaction Network

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- **Nodes** : Protein ; **Edges**: interactions.
- High throughput interaction screening methods:
  - Yeast two hybrid experiments (Y2H)
  - Protein complex purification (PCP)
- Database:

**BioGRID** 3.1



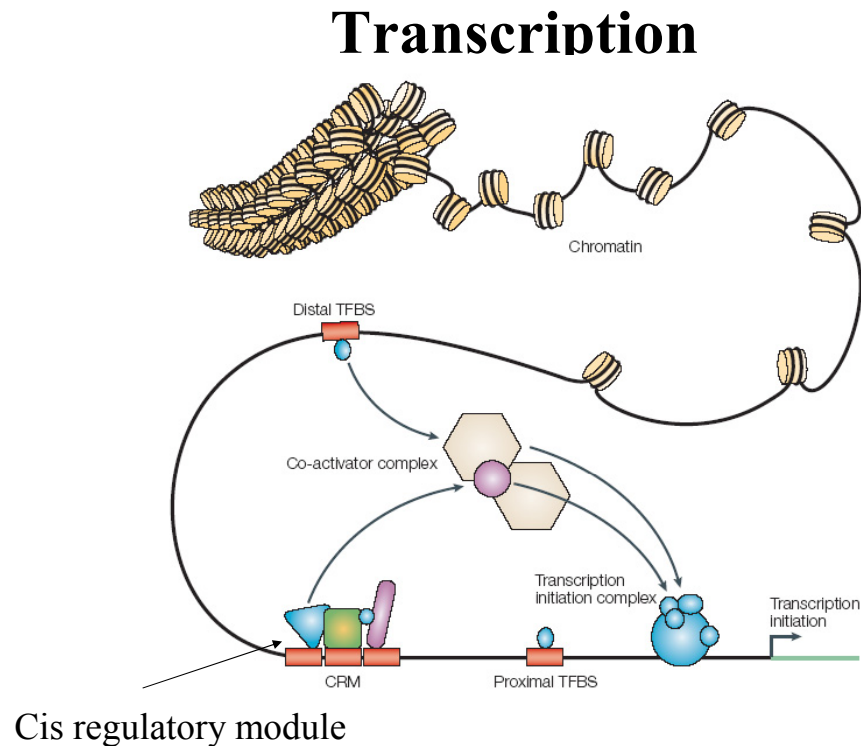
Database of Interacting Proteins



# Transcriptional Network

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- **Nodes:** Protein (transcription factors or target genes)
- **Edges:** (directed) from a transcription factor to a gene.



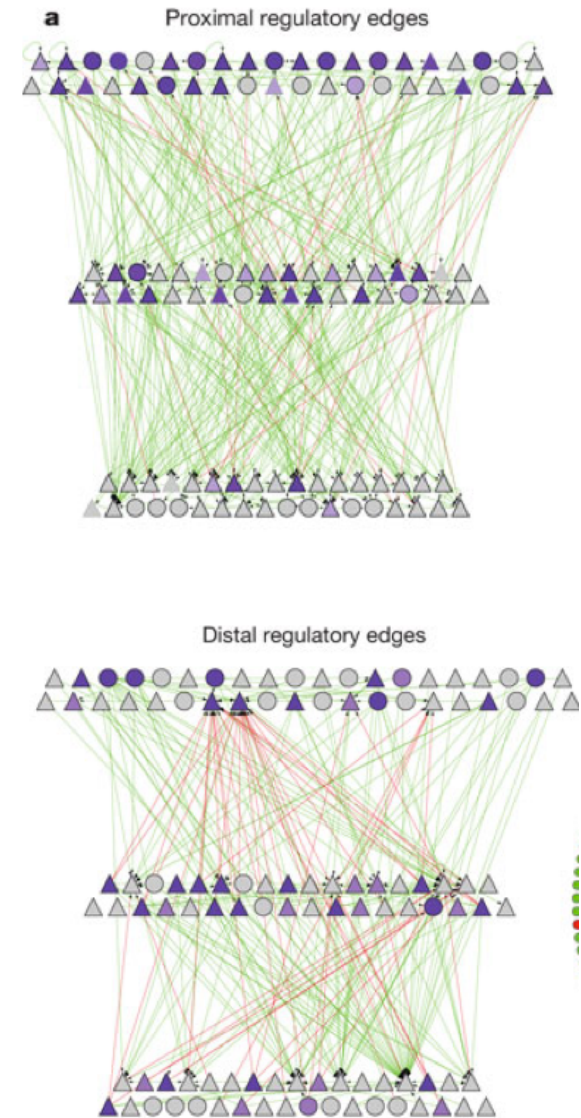
- **Experimental**

- Encode Chip-seq data

- **Computational**

- Identification of Transcription Factor Binding Sites

\* TRANSFAC® is the database on eukaryotic transcription factors, their genomic binding sites and DNA-binding profiles



M. Gerstein, et al., Nature (2012)

# Co-expression Network

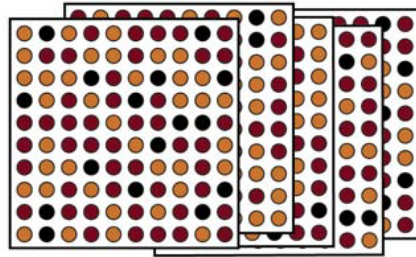
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- Describes the relation between the expression pattern of different genes
- **Nodes:** Genes
- **Edges:** Two vertices are connected if the corresponding genes have similar expression patterns.



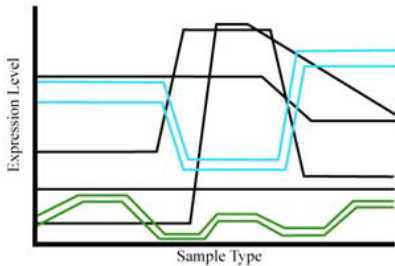
Figure 1

A Array Data



Data contains correlations

B Correlation Analysis



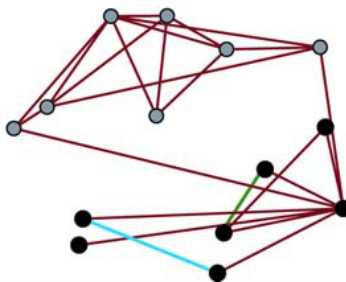
Correlation coefficients for all genes

C Correlation Matrix

	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12	G13	G14
G1	1	0.9	0.9	0.9	0.9	0.8	0.9	0.1	0.9	0.1	0.1	0.8	0.2	0.2
G2	0.9	1	0.9	0.3	0.3	0.7	0.0	0.5	0.3	0.1	0.1	0.2	0.4	0.3
G3	0.9	0.9	1	0.9	0.0	0.2	0.5	0.7	0.6	0.5	0.2	0.6	0.1	0.0
G4	0.9	0.3	0.9	1	0.5	0.3	0.6	0.3	0.0	0.5	0.1	0.2	0.2	0.6
G5	0.9	0.3	0.0	0.5	1	0.1	0.6	0.1	0.3	0.3	0.3	0.5	0.2	0.5
G6	0.8	0.7	0.2	0.3	0.1	1	0.9	0.2	0.1	0.1	0.5	0.3	0.1	0.1
G7	0.9	0.0	0.5	0.6	0.6	0.9	1	0.3	0.1	0.5	0.1	0.3	0.5	0.2
G8	0.1	0.5	0.7	0.3	0.1	0.2	0.3	1	0.9	0.9	0.9	0.8	0.8	0.9
G9	0.9	0.3	0.6	0.0	0.3	0.1	0.1	0.9	1	0.8	0.1	0.3	0.5	0.3
G10	0.1	0.1	0.5	0.5	0.3	0.1	0.5	0.9	0.8	1	0.8	1.0	0.2	0.3
G11	0.1	0.1	0.2	0.1	0.3	0.5	0.1	0.9	0.1	0.8	1	0.5	0.8	0.9
G12	0.8	0.2	0.6	0.2	0.5	0.3	0.3	0.8	0.3	1.0	0.5	1	0.8	0.1
G13	0.2	0.4	0.1	0.2	0.2	0.1	0.5	0.8	0.5	0.2	0.8	0.8	1	0.9
G14	0.2	0.3	0.0	0.6	0.5	0.1	0.2	0.9	0.3	0.3	0.9	0.1	0.9	1

Convert into Adjacency Matrix and Network

D Coexpression Network



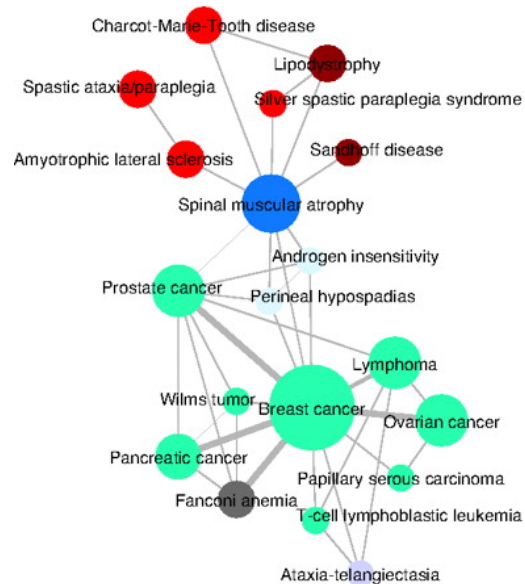
- Microarray gene expression data.
- Measure concordance of gene expression with a Pearson correlation.
- The Pearson correlation matrix is transformed to an adjacency matrix. Binary values in the adjacency matrix correspond to an un-weighted network.
- The adjacency matrix can be visualized by a graph.

# Disease Gene Networks

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- A bipartite graph with two sets of vertices.
- **Nodes**: One set represents disease; the other represents genes.
- **Edges**: A gene and a disease are connected if the gene is involved in the disease.

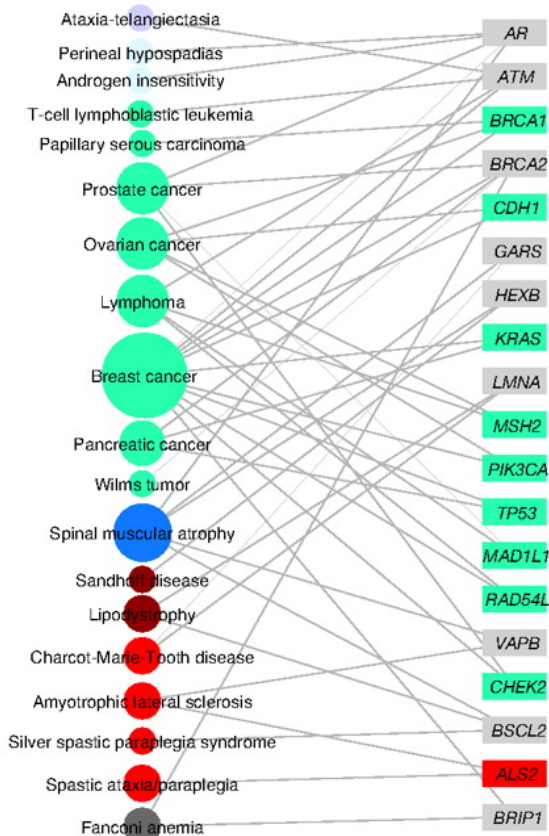
## Human Disease Network (HDN)



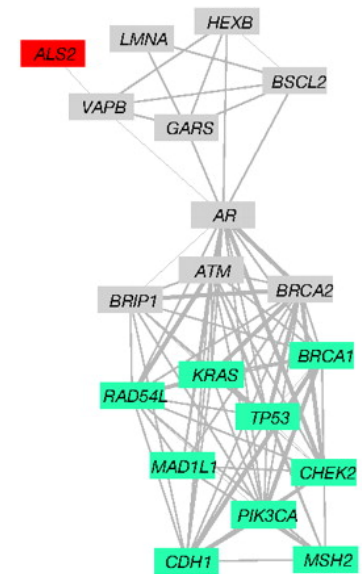
## DISEASOME

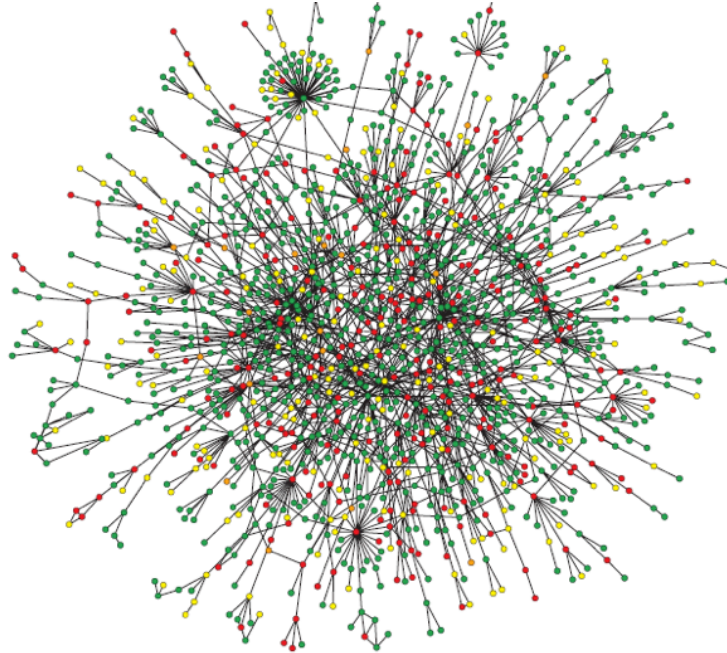
### disease phenotype

### disease genome



## Disease Gene Network (DGN)





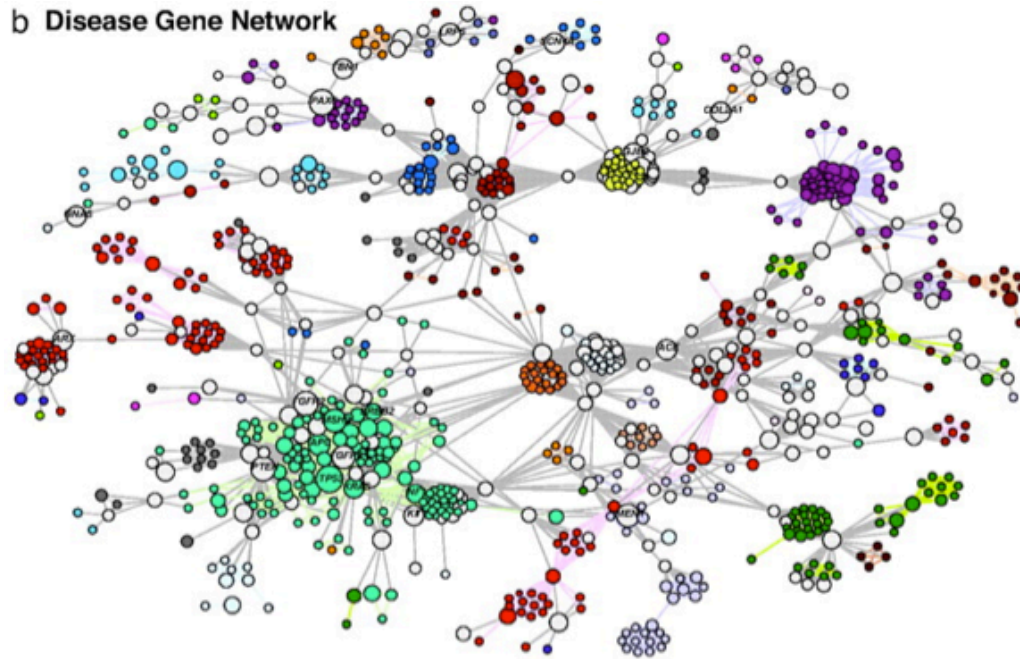
What we make out of the hairball



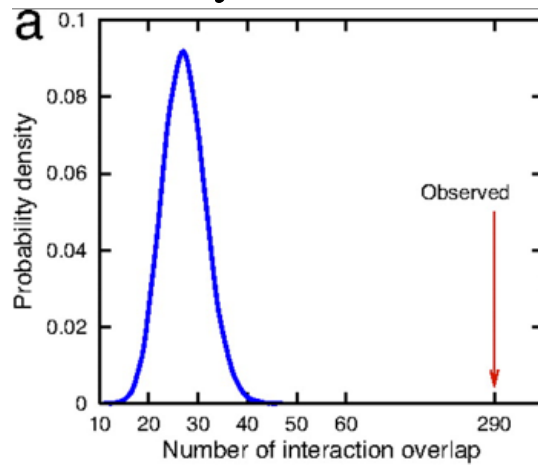
- 13



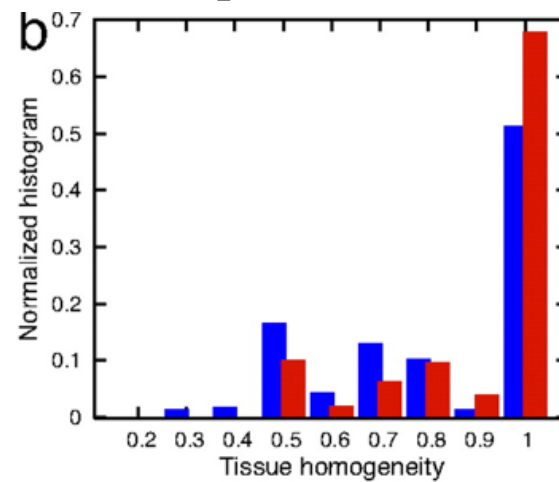
**b Disease Gene Network**



✧ Physical interaction



✧ Express in same tissue



# DYNAMICS OF NETWORK

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✧ Networks are not static

- Date and party hubs

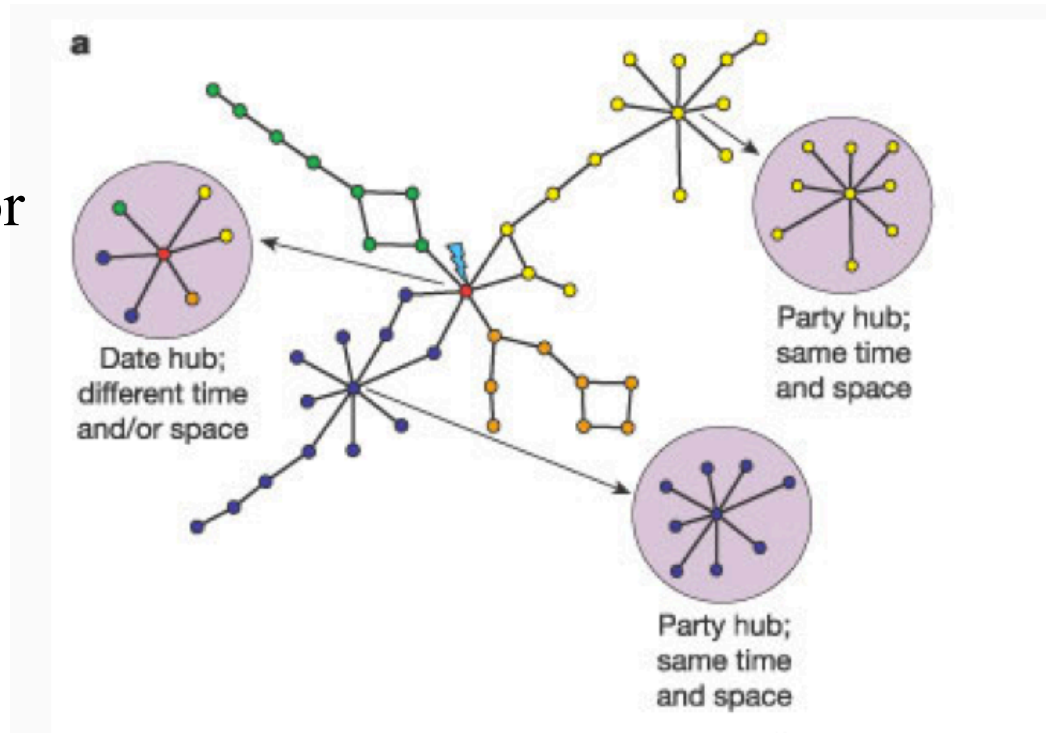
✧ Networks change during evolution

- Network rewiring



“Party hubs”: interact with their partners simultaneously.

“Date hubs”: bind their partners at different times or locations

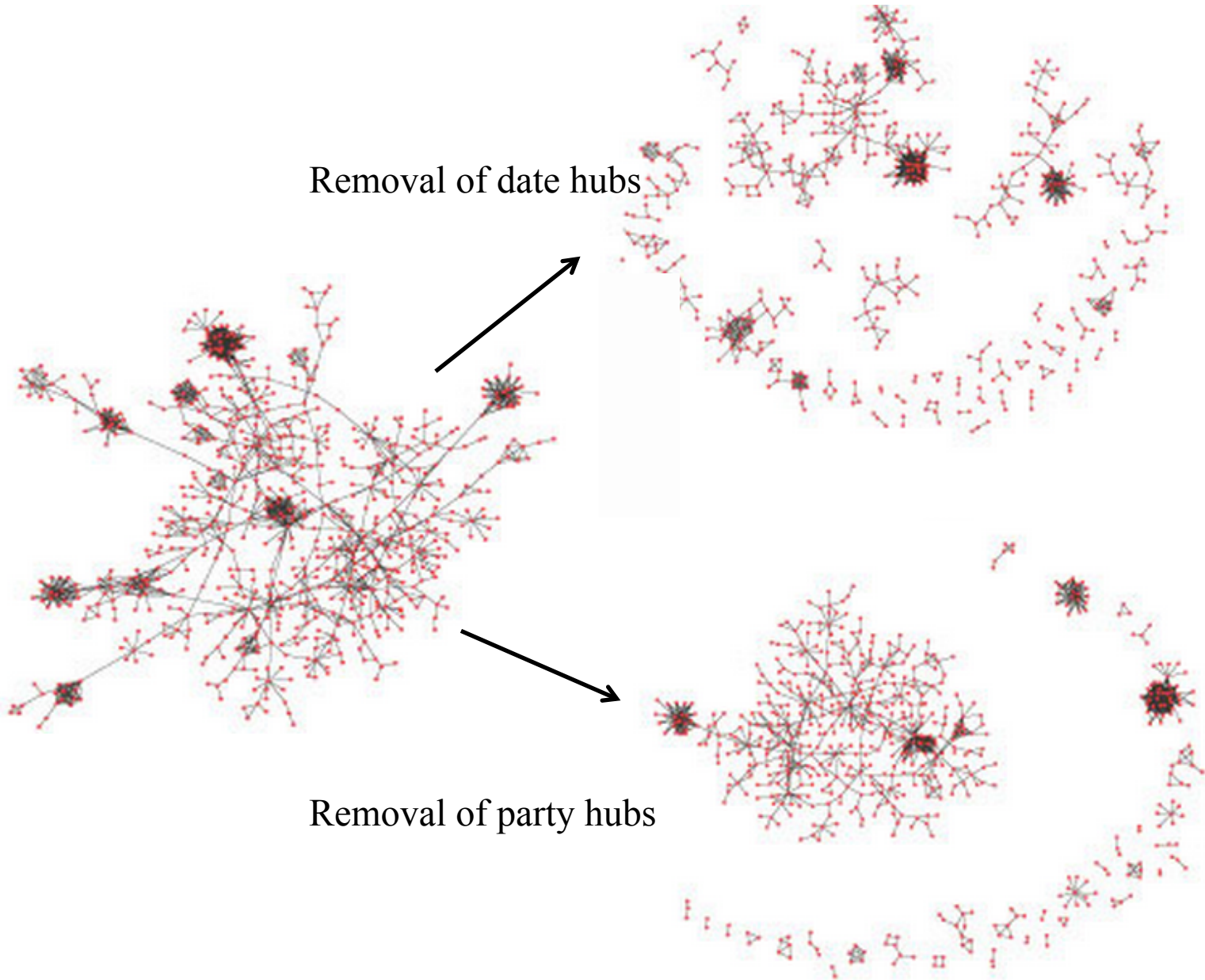


Yeast PPI (color - Mutual similarity in mRNA expression )

c

Removal of date hubs

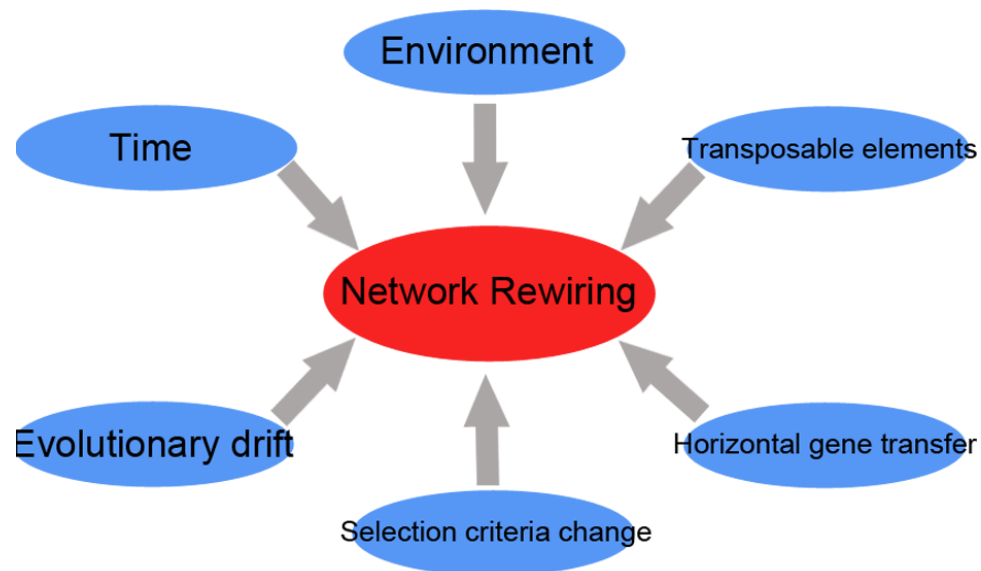
Removal of party hubs



# Network rewiring

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- How do biological interaction networks change overtime?
- Two ways to look at this:
  - What forces lead to gain and loss of nodes and edges?
  - Evolutionary selective pressure favors the network that represents the most fit phenotype.



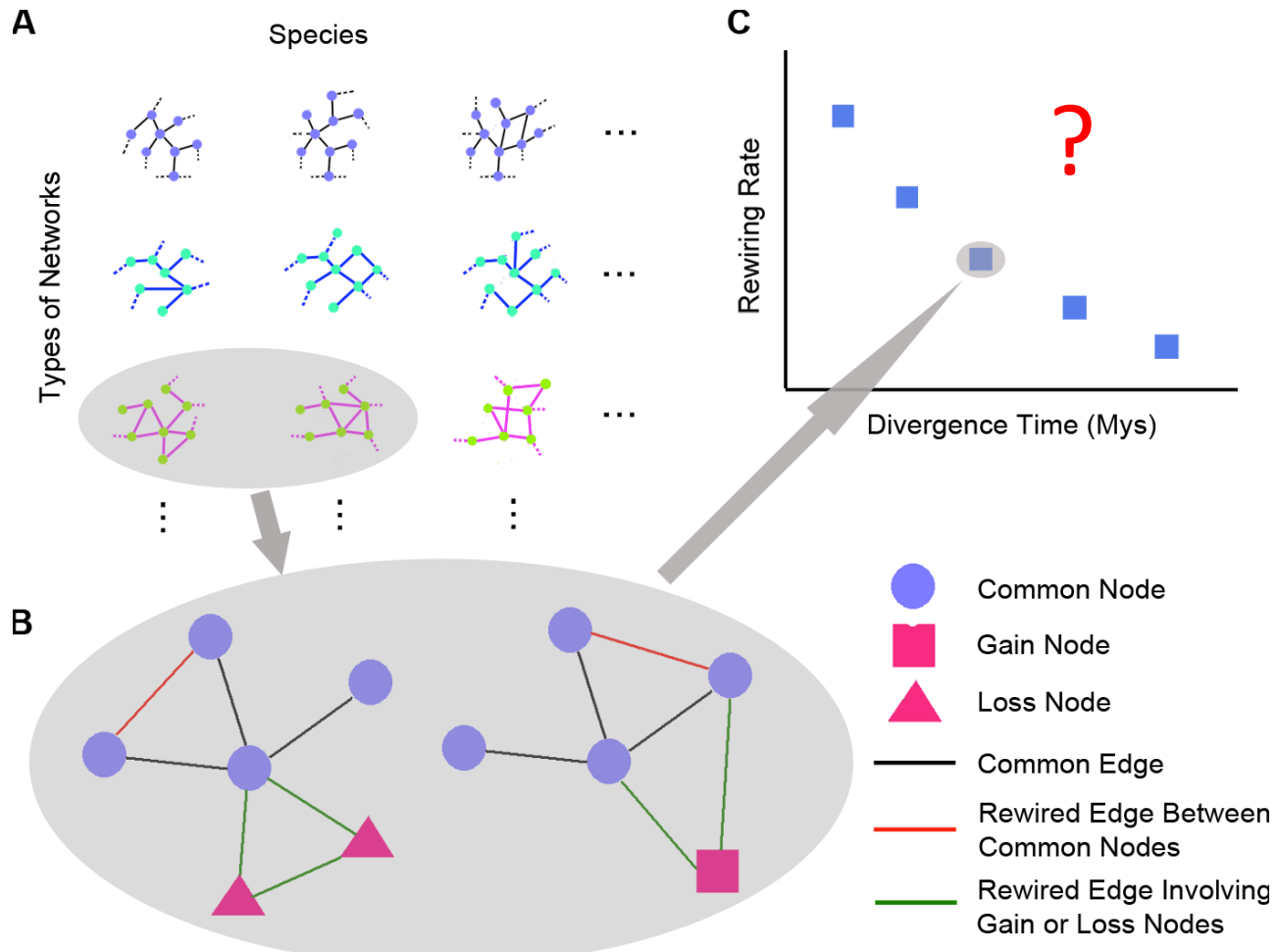
# Measuring the Evolutionary Rewiring of Biological Networks

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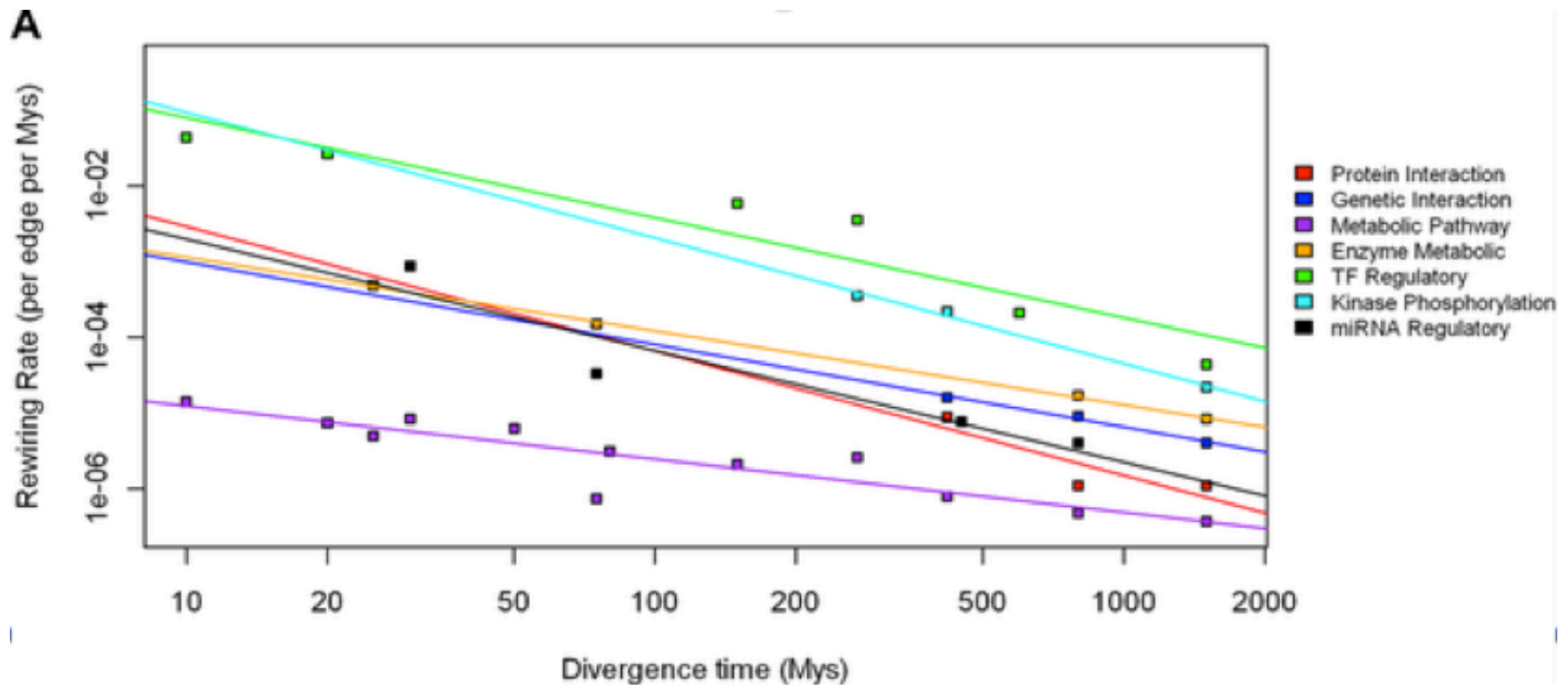
Chong Shou<sup>1</sup>, Nitin Bhardwaj<sup>2</sup>, Hugo Y. K. Lam<sup>1</sup>, Koon-Kiu Yan<sup>2</sup>, Philip M. Kim<sup>3</sup>, Michael Snyder<sup>4</sup>, Mark B. Gerstein<sup>1,2,5\*</sup>

 To **add a note**, highlight some text. [Hide notes](#)  
 [Make a general comment](#)

- Sought to compare interaction network from various species and reconstruction of evolutionary history
  - Analogous to studying the evolutionary history of genes by comparing versions from different species



$$\text{Rewiring rate} = \frac{R}{C \times \text{Time divergence}}$$



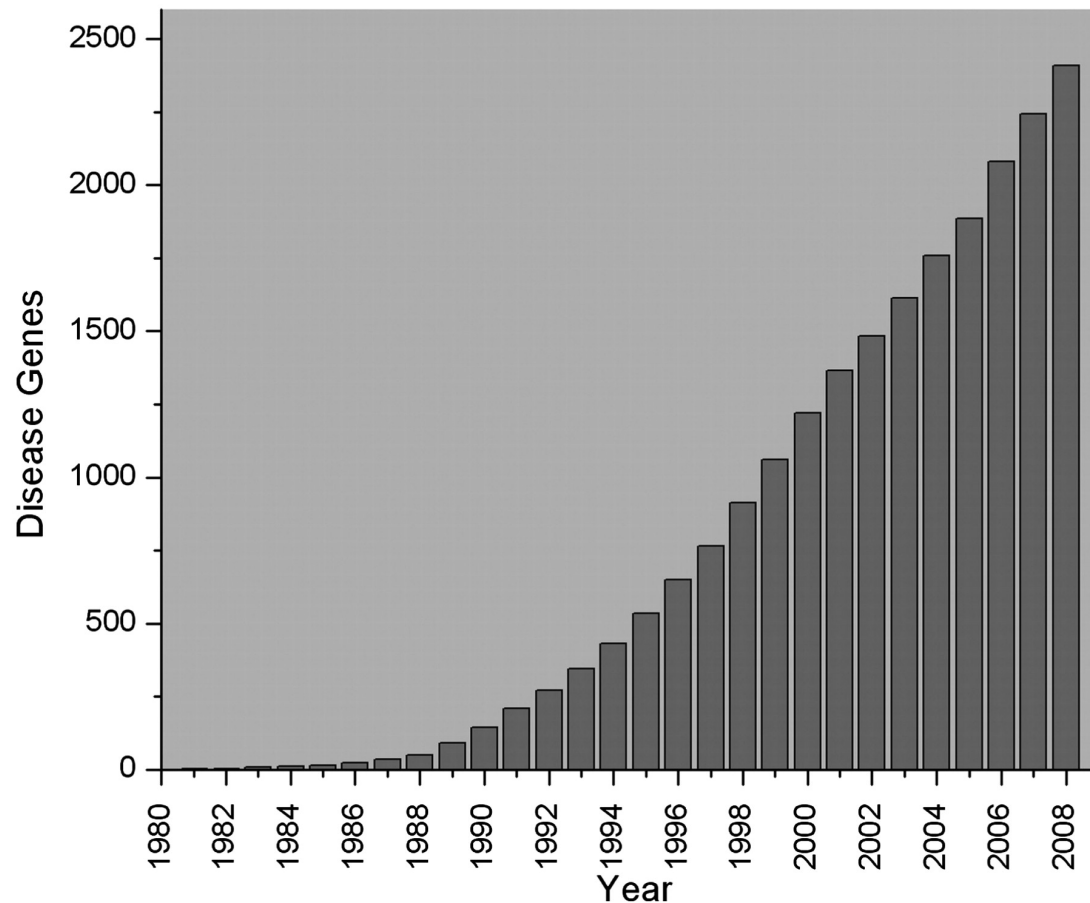
Transcription regulatory > Kinase phosphorylation > Protein interaction > Metabolic interaction

Shou C, Bhardwaj N, Lam HYK, Yan K-K, et al. (2011) Measuring the Evolutionary Rewiring of Biological Networks. PLoS Comput Biol 7(1): e1001050. doi:10.1371/journal.pcbi.1001050  
<http://www.ploscompbiol.org/article/info:doi/10.1371/journal.pcbi.1001050>

# NETWORK APPLICATION IN DISEASE

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## Histogram of cumulative growth of disease gene discovery.



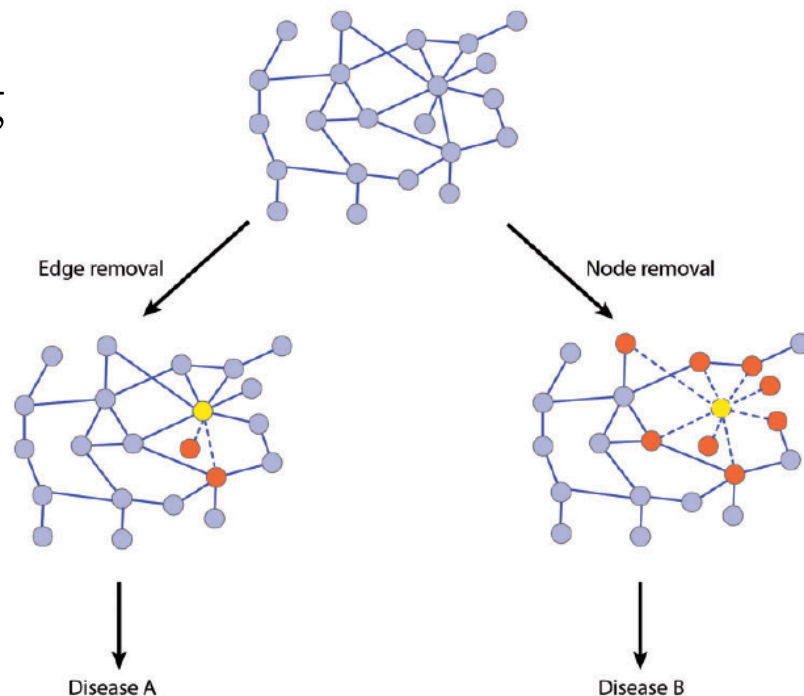
The majority of disease genes still remain underneath the tip of the iceberg.

Kann M G Brief Bioinform 2010;11:96-110



# GWAS approach

- Genome-wide association studies (GWAS) are powerful in mapping disease genes.
  - Low resolution: multiple genes in the disease-associated loci.
  - Perturbation of molecular networks by the gene causes the disease



X Wang, et al., 2011

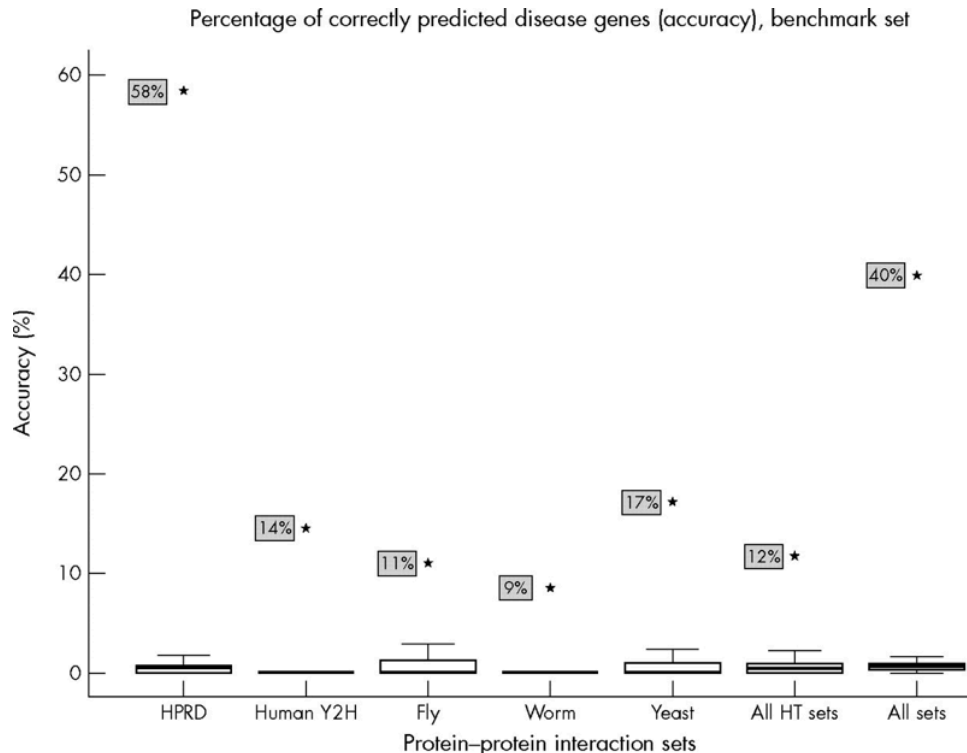
# Network Approach

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- Basis: genes associated with the same or similar diseases, tend to reside in the same neighborhood in networks and form physical and/or functional modules.

# Linkage method

- Predict disease-causing genes in known disease loci by counting the number of known causative genes in direct neighbors.



- 10 fold enrichment in disease genes compared to random.
- Restricting genes to those in same cellular compartment as known disease genes, 1000 fold enrichment.

# Disease sub-networks method

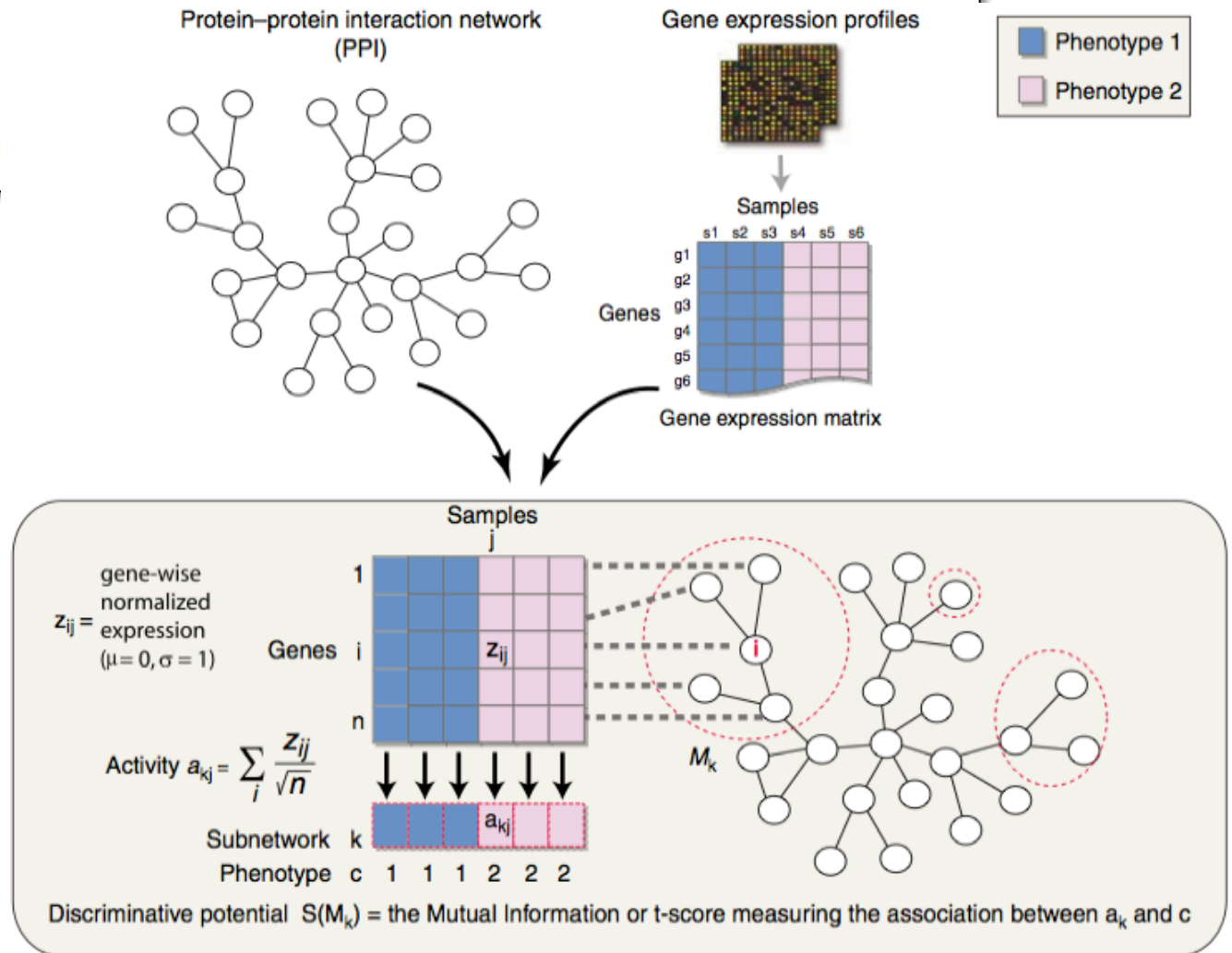
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- Assumption: disease-associated genes form sub-network
- Approach: find a sub-network that contains most of the disease-associated genes.

# Network-based classification of breast cancer metastasis

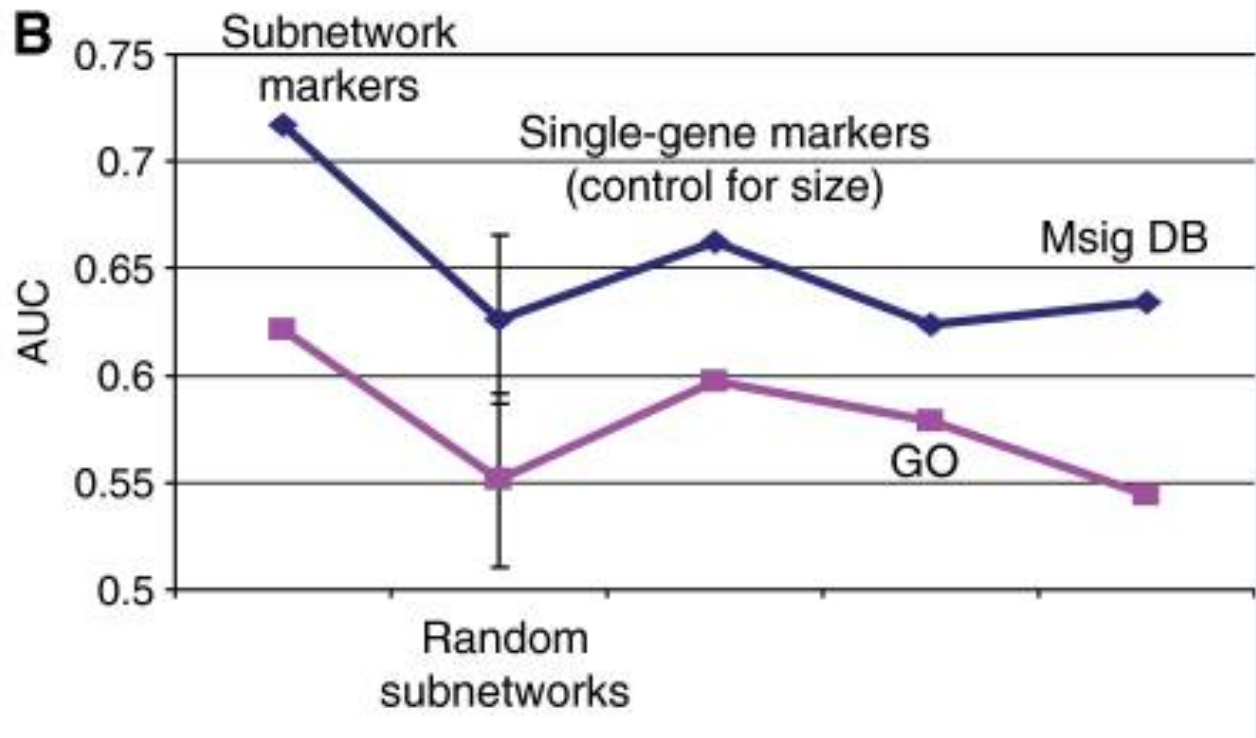
Han-Yu Chuang<sup>1,5</sup>, Eunjung

Han-Yu Chuang  
Eunjung Lee  
Yu-Tsueng Liu  
Doheon Lee  
Trey Ideker



# Disease sub-networks

- Sub-networks markers outperformed single-gene markers.



# Diffusion-based methods

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- Measure how connected each gene in the network is to the known disease genes (global distance measure).
  - The idea is that genes with greater “reachability” from known disease genes are more likely to be implicated in the disease.

# Diffusion methods: random walk

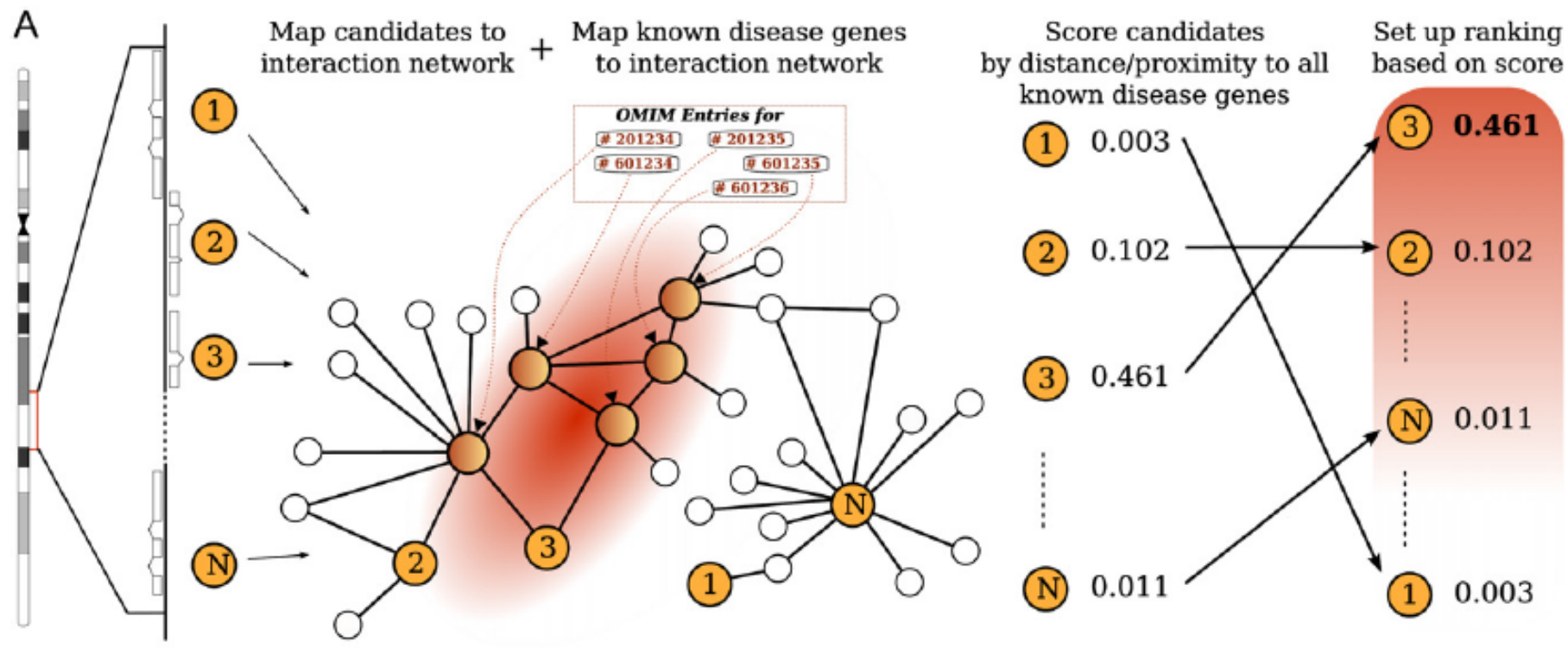
- Start a random walker at one of the known disease gens, let it wonder the network.
  - 1) To start, random pick a disease gene  $S$ , with equal probability  $p^0$
  - 2) From current node, randomly selected a neighbor node.
  - 3) In every time step, restart the walk from disease nodes, with probability  $r$ .

$$p^{t+1} = (1 - r)Wp^t + rp^0$$

$p^t$  : probability vector of random walker being at each node at time t.

$W$  : Matrix of transition probabilities.





Kohler S and Robinson PN, AJHG, 2011

# Comparison of methods

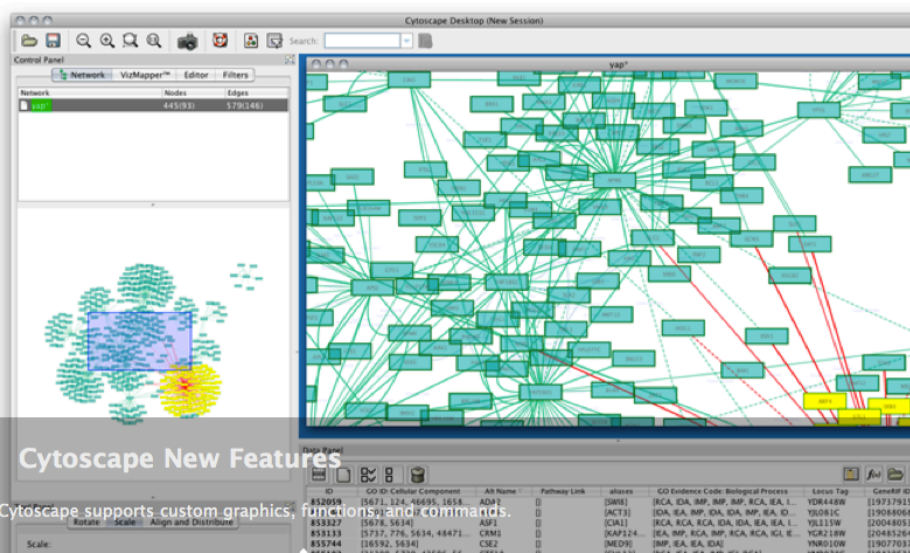
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Not surprising that a comparative study of these methods, ranking them by predictive power, produces the following rankings:

1. Diffusion-based methods
2. Disease sub-networks
3. Linkage methods

# Cytoscape

## Cytoscape: An Open Source Platform for Complex Network Analysis and Visualization



**Cytoscape New Features**  
Cytoscape supports custom graphics, functions, and commands.

