

Pathway & Network Analysis of Omics Data: Networks in Biology

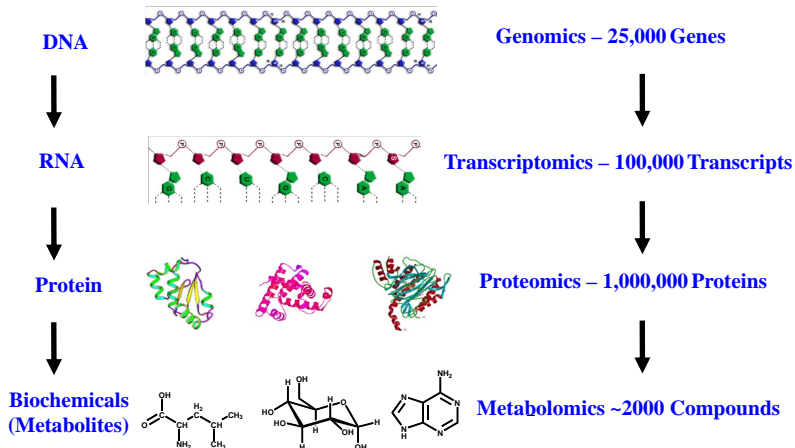
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Summer Institute for Statistical Genetics – Australia, 2017

Why Study Networks?

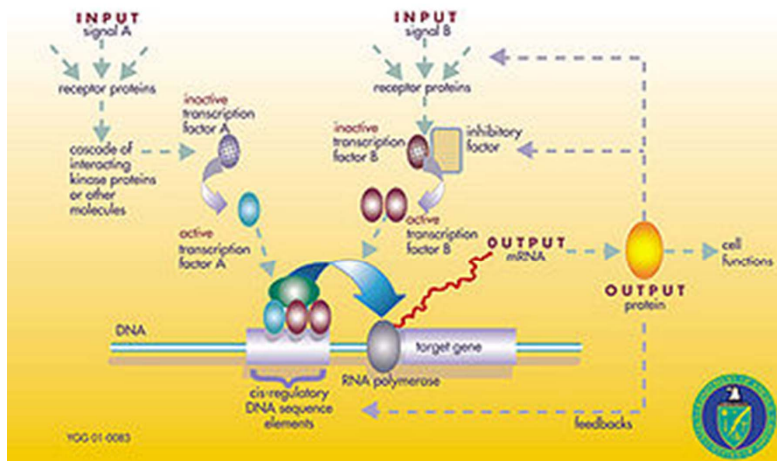
- ▶ Components of biological systems, e.g. genes, proteins, metabolites, interact with each other to carry out different functions in the cell.
- ▶ Examples of such interactions include signaling, regulation and interactions between proteins.
- ▶ We cannot understand the function and behavior of biological systems by studying individual components ($2 + 2 \neq 4!$).
- ▶ Networks provide an efficient representation of complex reaction in the cells, as well as basis for mathematical/statistical models for the study of these systems.

Central Dogma of Molecular Biology (Extended)

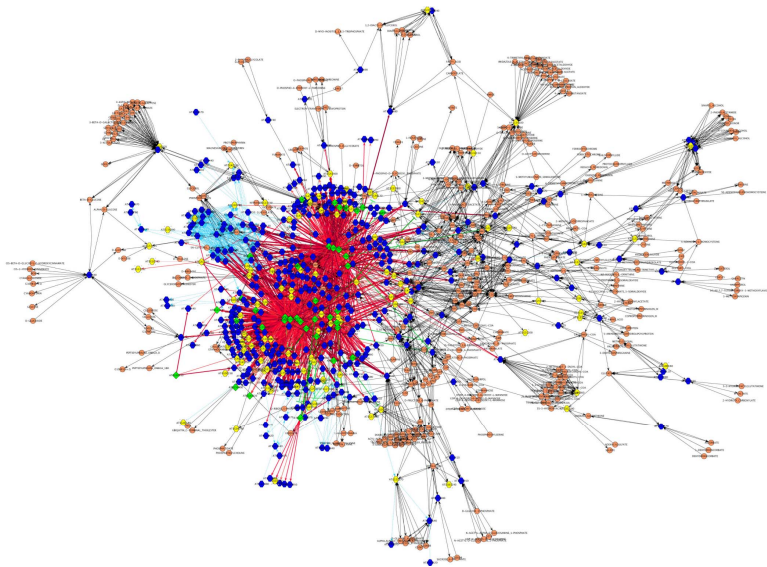


Networks in Biology: Gene Regulatory Interactions

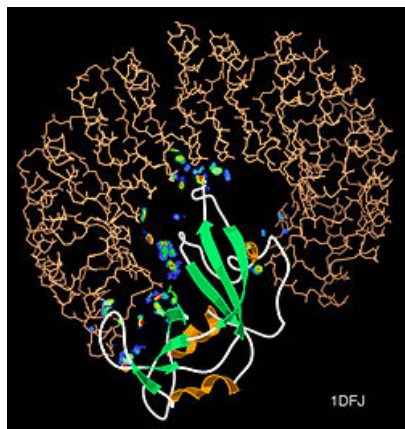
A GENE REGULATORY NETWORK



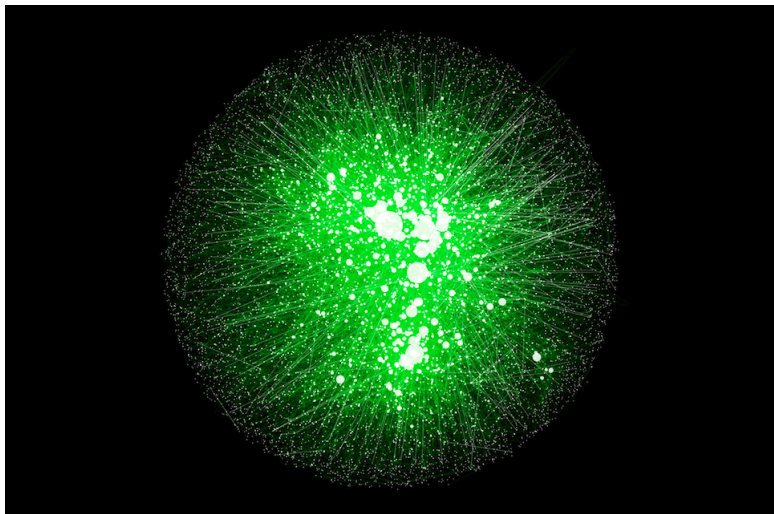
Networks in Biology: Gene Regulatory Networks



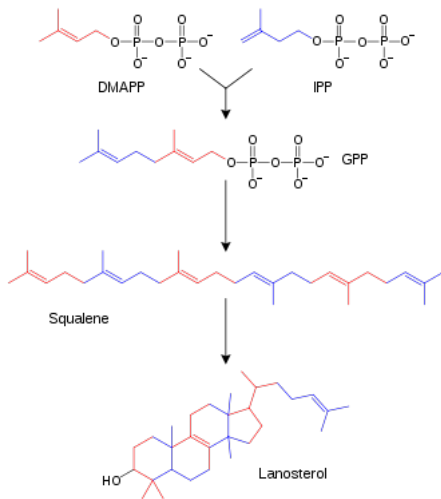
Networks in Biology: Protein-Protein Interactions



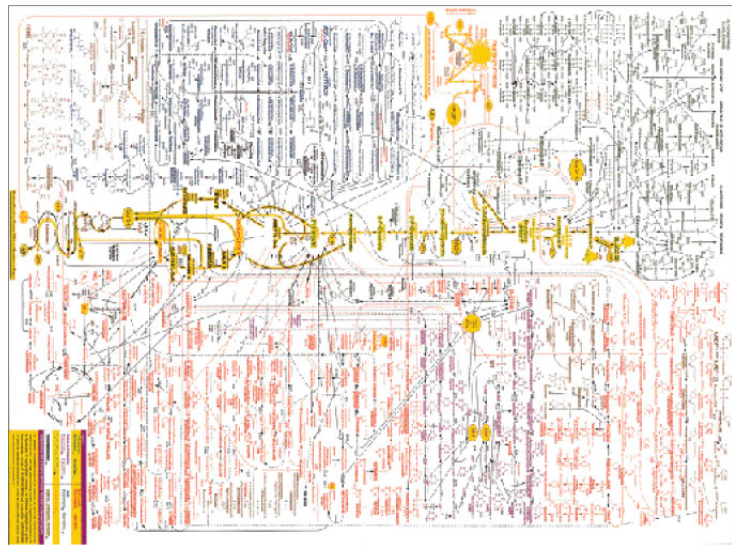
Networks in Biology: Protein-Protein Interaction (PPI) Networks



Networks in Biology: Metabolic Reactions



Networks in Biology: Metabolic Pathways



But Do Networks Matter?

- ▶ They Do!
- ▶ Recent studies have linked changes in gene/protein networks with many human diseases.

Systems Biology and Emerging Technologies

Gene Networks and microRNAs Implicated in Aggressive Prostate Cancer

Liang Wang,¹ Hui Tang,² Venugopal Thayanithy,³ Subbaya Subramanian,³ Ann L. Oberg,² Julie M. Cunningham,¹ James R. Cerhan,² Clifford J. Steer,⁴ and Stephen N. Thibodeau¹

¹Departments of Laboratory Medicine and Pathology and ²Health Sciences Research, Mayo Clinic, Rochester, Minnesota; and Departments of ³Laboratory Medicine and Pathology, ⁴Medicine, and Genetics, Cell Biology, and Development, University of Minnesota, Minneapolis, Minnesota

Estrogen-Regulated Gene Networks in Human Breast Cancer Cells: Involvement of E2F1 in the Regulation of Cell Proliferation

Joshua D. Stender, Jonna Frasor, Barry Komm, Ken C. N. Chang, W. Lee Kraus, and Benita S. Katzenellenbogen

Departments of Biochemistry (J.D.S.) and Molecular and Integrative Physiology (J.F., B.S.K.), University of Illinois at Urbana-Champaign, Urbana, Illinois 61801-3704; Women's Health and Musculoskeletal Biology (B.K., K.C.N.C.), Wyeth Research, Collegeville, Pennsylvania 19426; and Department of Molecular Biology and Genetics (W.L.K.), Cornell University, Ithaca, New York 14853-4203



A Transcriptional Signature and Common Gene Networks Link Cancer with Lipid Metabolism and Diverse Human Diseases

Heather A. Hirsch,^{1,7} Dimitrios Iliopoulos,^{1,7} Amita Joshi,^{1,7} Yong Zhang,² Savina A. Jaeger,³ Martha Bulyk,^{3,4,5} Philip N. Tschlis,⁶ X. Shirley Liu,² and Kevin Struhl^{1,*}

¹Department of Biological Chemistry and Molecular Pharmacology, Harvard Medical School, Boston, MA 02115, USA

²Department of Biostatistics and Computational Biology, Dana Farber Cancer Institute, Harvard School of Public Health, Boston, MA 02115, USA

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⁷These authors contributed equally to this work

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But Do Networks Matter?

And, incorporating the knowledge of networks **improves our ability to find causes of complex diseases.**

Molecular Systems Biology 3; Article number 140; doi:10.1038/msb4100180

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www.molecularsystemsbiology.com

REPORT

Network-based classification of breast cancer metastasis

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¹ Bioinformatics Program, University of California San Diego, La Jolla, CA, USA, ² Department of Bioengineering, University of California San Diego, La Jolla, CA, USA,

³ Department of Bio and Brain Engineering, Korea Advanced Institute of Science and Technology, Daejeon, Korea and ⁴ Cancer Genetics Program, Moores Cancer Center, University of California San Diego, La Jolla, CA, USA

⁵ These authors contributed equally to this work

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Why Do We Need Network Inference?

- ▶ Despite progress, our knowledge of interactions in the genome is limited.
- ▶ The entire genome is a vast landscape, and **experiments for discovering networks are very expensive**
- ▶ From a statistical point of view, **network estimation is related to estimation of covariance matrices**, which has many independent applications in statistical inference and prediction (*more about this later*)
- ▶ Finally, and perhaps most importantly, **gene and protein networks are dynamic** and changes in these networks have been attributed to complex diseases.

Networks: A Short Premier

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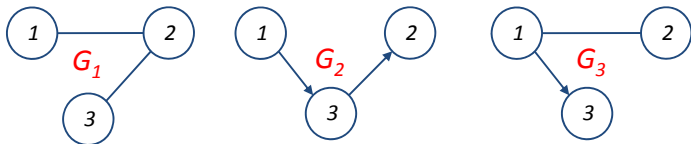
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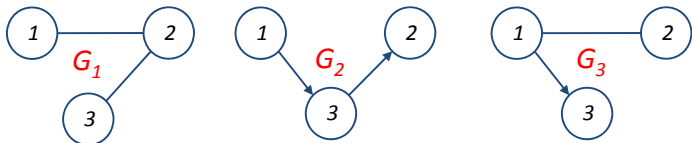
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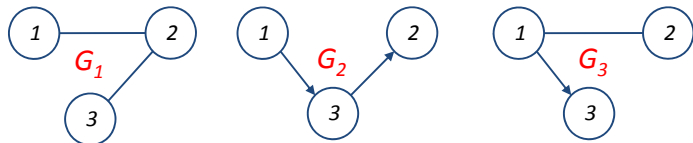
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- ▶ The **edges** are:

$$E_1 = \{1 - 2, 2 - 3\}$$

$$E_2 = \{1 \rightarrow 3, 3 \rightarrow 2\}$$

$$E_3 = \{1 - 2, 1 \rightarrow 3\}$$

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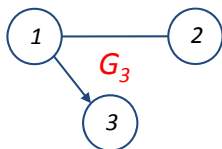
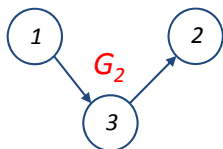
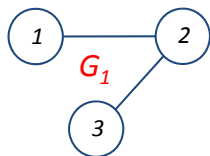
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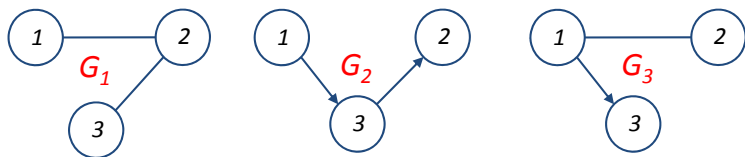
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- ▶ For **undirected edges**, we add a **1** in both directions

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$$A = \begin{bmatrix} 0 & \mathbf{1} & 0 \\ \mathbf{1} & 0 & \mathbf{1} \\ 0 & \mathbf{1} & 0 \end{bmatrix} \quad A = \begin{bmatrix} 0 & 0 & \mathbf{1} \\ 0 & 0 & 0 \\ 0 & \mathbf{1} & 0 \end{bmatrix} \quad A = \begin{bmatrix} 0 & \mathbf{1} & \mathbf{1} \\ \mathbf{1} & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

What Do Edges in Biological Networks Mean?

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- ▶ In **metabolic networks**, an edge between compound i and j often means that *the two compounds are involved in the same reaction*, meaning that they are generated at relative rates.
- ▶ Thus, edges represent some type of **association among genes, proteins or metabolites**, defined generally to include *linear or nonlinear* associations; more later....

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- ▶ In practice, we observe n measurements of each of the variables (genes/proteins/ metabolites) for say different individuals, and want to determine which variables are connected, or use their connection for statistical analysis

An Overview of Methods for Network Inference

Two general classes of network inference methods :

- ▶ Methods based on **marginal measures of association**:
 - ▶ Co-expression Networks (uses linear measures of association)
 - ▶ Methods based on **mutual information** (can accommodate non-linear associations)
- ▶ Methods based on **conditional measures of association**:
 - ▶ Methods assuming (multivariate) normality (glasso, etc)
 - ▶ Generalizations to allow for nonlinear dependencies

Our Plan

In the remainder of this module, we will cover the following topics

- ▶ Methods for **reconstructing undirected networks**
 - ▶ Marginal association (co-expression) nets (WGCNA, ARACNE)
 - ▶ Conditional independence graphs (CIGs)
- ▶ **Network analysis** (and more on WGCNA)
- ▶ Methods for **reconstructing directed networks**
 - ▶ Bayesian Networks (basic concepts, reconstruction algorithm)
 - ▶ Reconstructing directed networks from time-course data and perturbation screens (time permitting)
- ▶ Network-based **pathway enrichment analysis**
- ▶ Network-based **omics data integration**