

Comparative Analysis of Molecular Interaction Networks

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Various parts of this work involve collaborations with William Goddard (CalTech), Priya Vashishtha, Rajiv Kalia, Aiichiro Nakano (USC), Yohan Kim and Shankar Subramaniam (UCSD), Eric Jakobsson (UIUC), Larry Scott (IIT), Vipin Kumar (UMN), Ahmed Sameh, Zhiyuan Li, Suresh Jagannatha, Mete Sozen (Purdue), Mehmet Koyuturk (Case Western)

This work is supported by National Institutes of Health, National Science Foundation, Department of Energy, Intel and Microsoft.

Outline

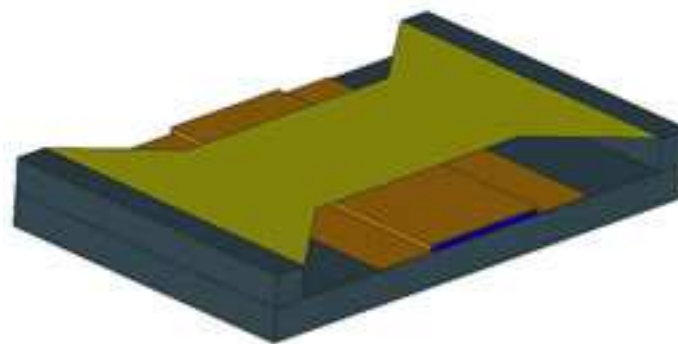
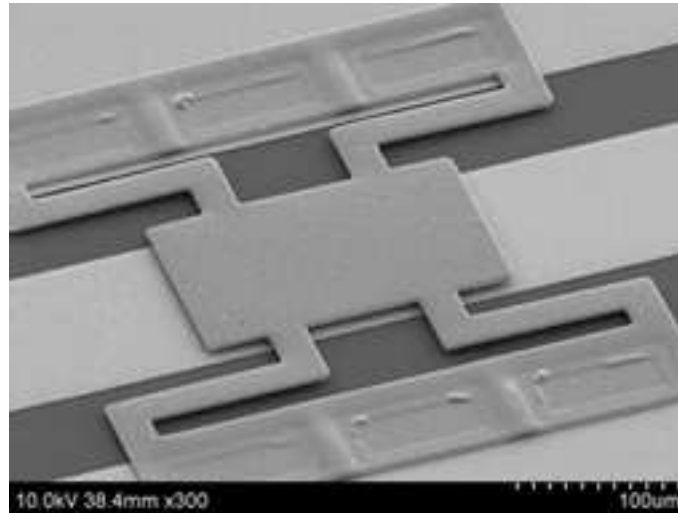
- Preamble: Who we are and what we do
- Molecular Interaction Networks
 - Modeling, evolution, problems, practical implications
- Algorithms for Analyzing Molecular Interaction Networks
 - *Analyzing biological networks for conserved molecular interaction patterns*
 - *Pairwise Alignment of protein-protein interaction networks*
 - *Probabilistic models/analyses for assessing statistical significance*
- Computational Synthesis of Interaction Networks
 - Inferring function from domain co-evolution
- Ongoing Work

Lab Overview

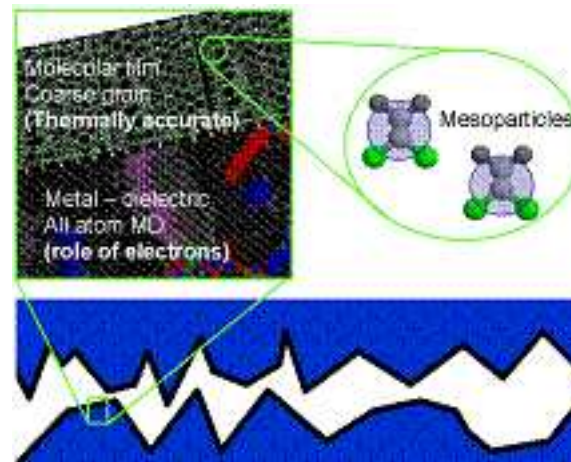
- Development of algorithmic and software substrates to solve fundamental problems in science and engineering.
- Research transcends software infrastructure (compilers, OS), algorithms (numerical and combinatorial), platforms (motes to petascale), and software (libraries to services).
- We focus on problems at the core of computing, but measure the value of our work in terms of its impact on science and engineering applications.
- All of our projects are in close collaboration with domain experts.

Lab Overview: Sample Projects

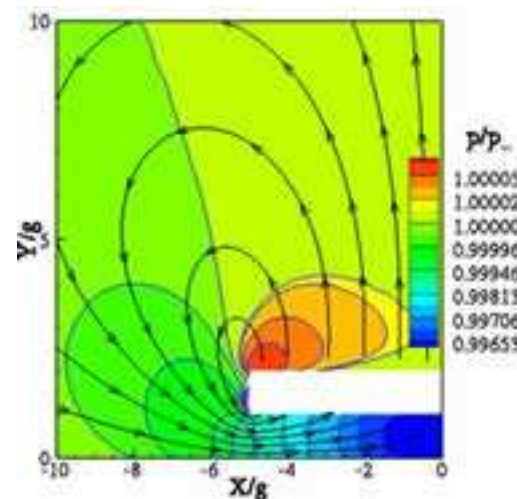
Simulation of Contacting MEMS (DoE/NNSA PRISM Center).



Contacting MEMS (DoE/NNSA PRISM)



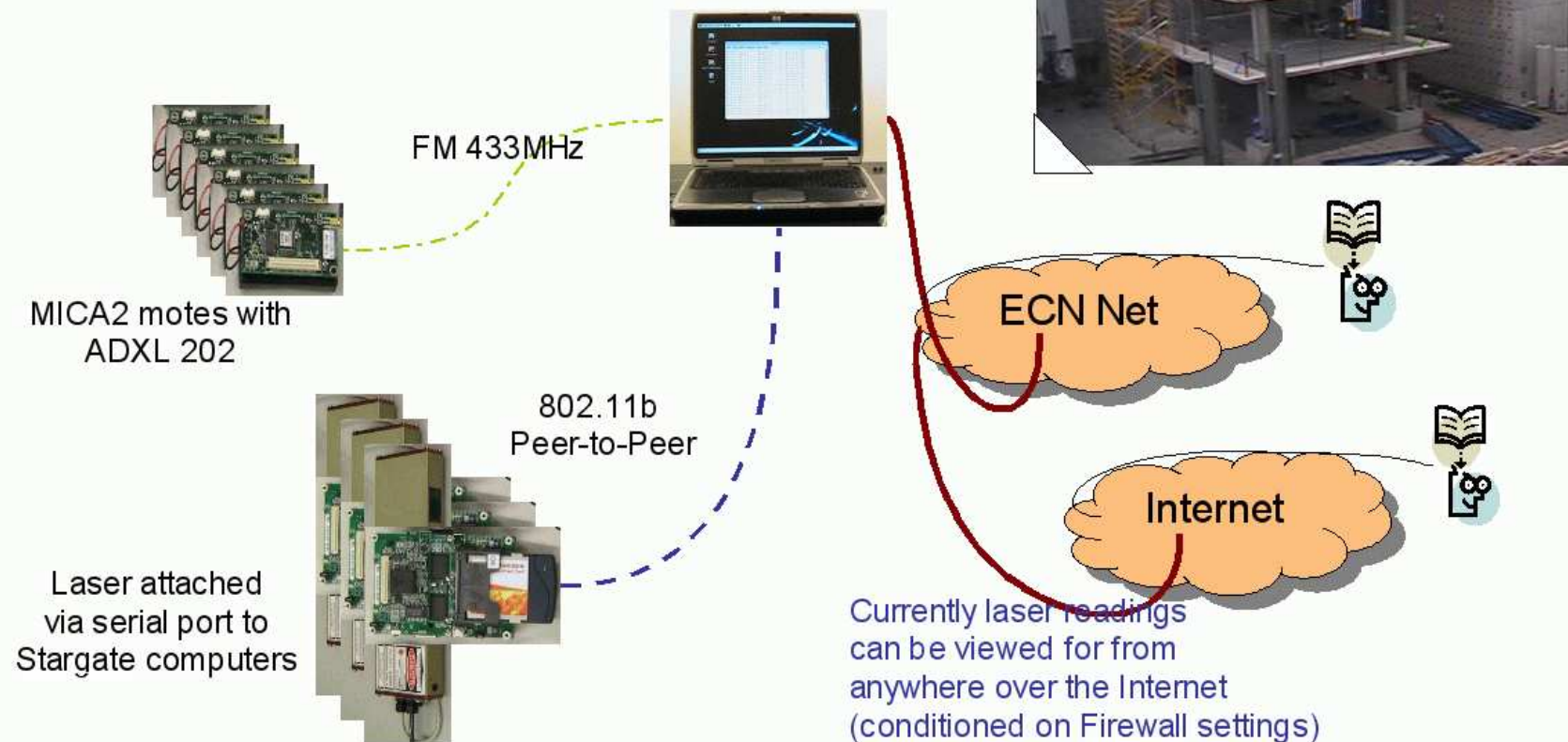
Multiresolution simulations of contact physics



Multiscale Models for Aerodynamic Damping

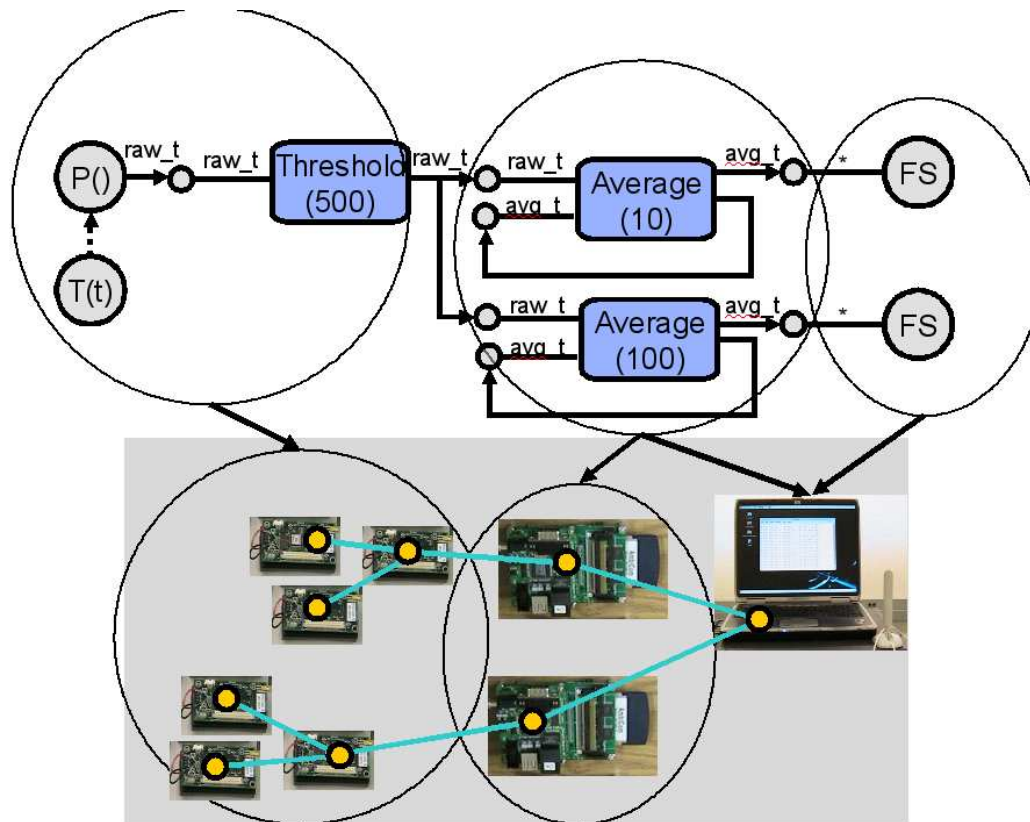
Model Reduction and Control of Large Structures (NSF)

Pilot deployment at BOWEN labs

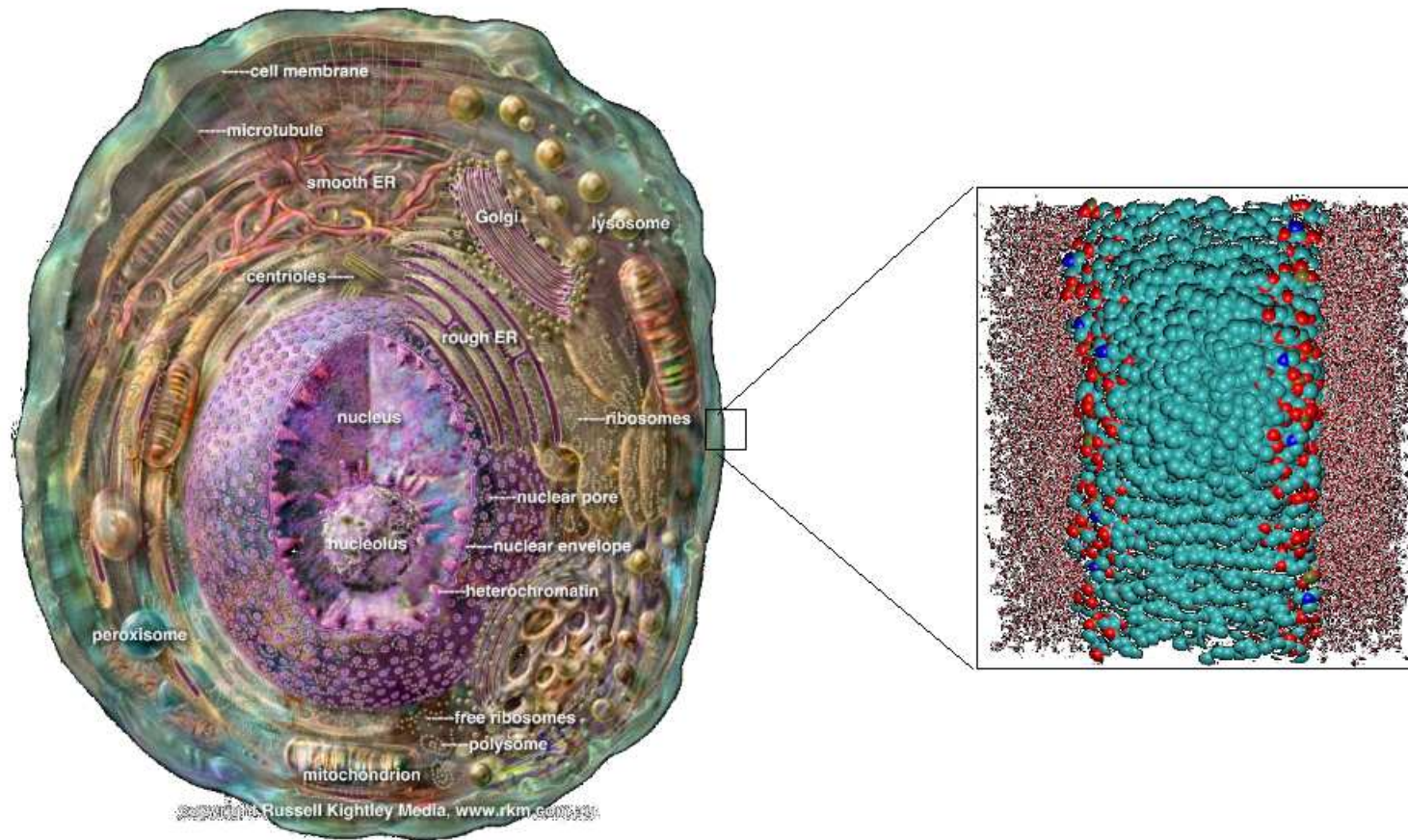


Model Reduction and Control of Large Structures

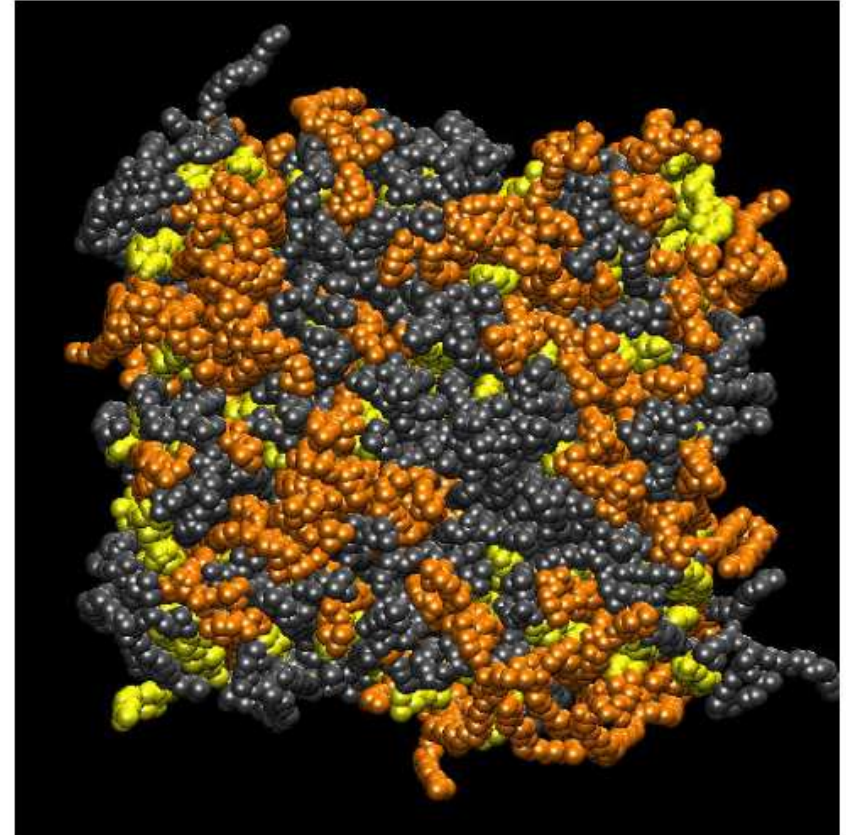
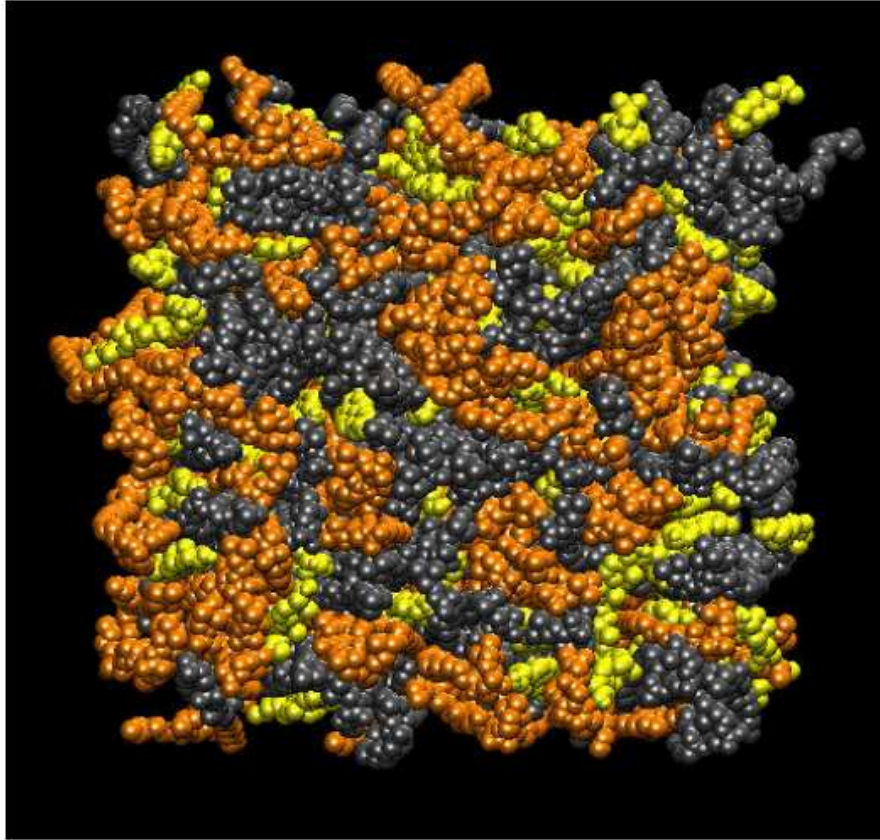
A critical component of embedded systems is the effort associated with application development. Our COSMOS environment fundamentally addresses this bottleneck.



Simulation of Biophysical Systems: Membranes (NIH)



Membrane Simulations (NIH)

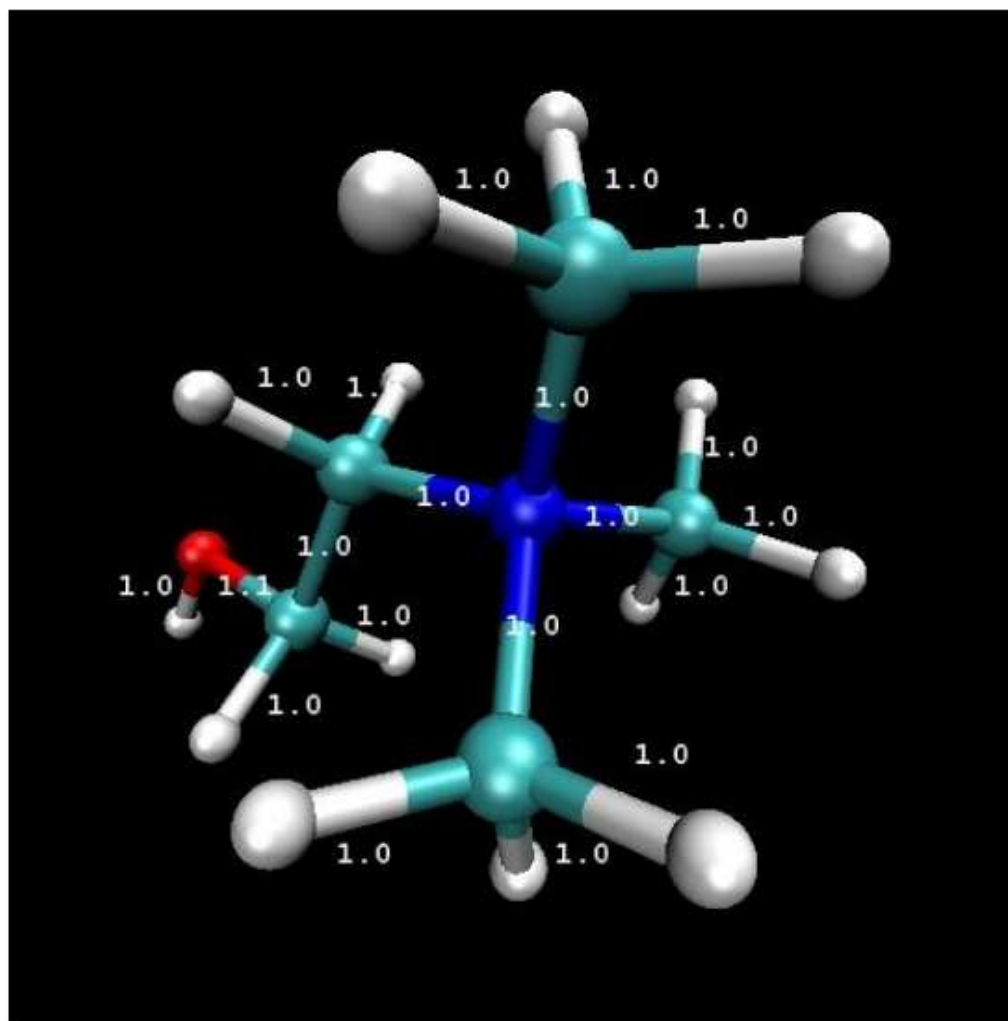


Ternary mixture: 100 DOPC, 100 18:0 SM, 100 CHOL, 10000 water (43500 atoms), 250 ns.

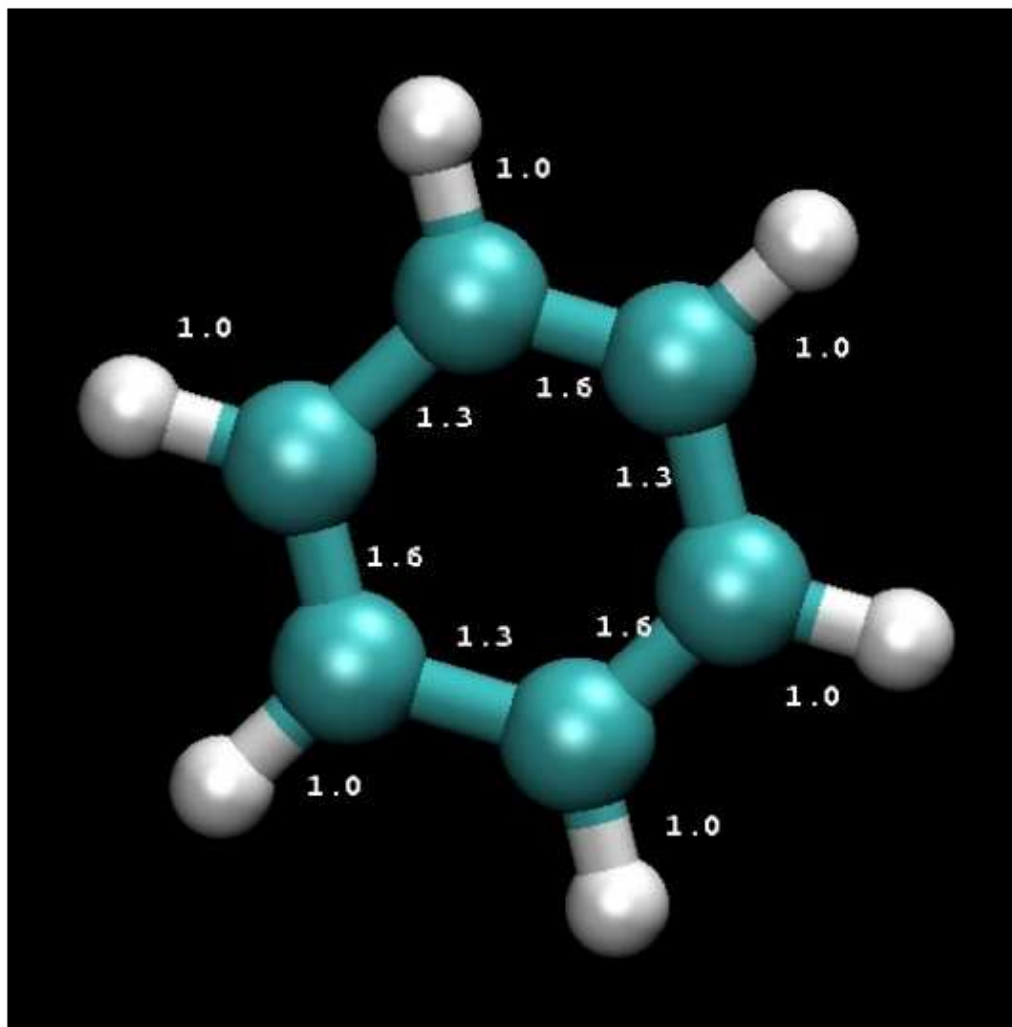
Simulation of Reactive Systems (DoE/SciDAC)

- Chemical reactions correspond to association and dissociation of chemical bonds.
 - Classical simulations cannot simulate reactions.
 - ab-initio methods calculate overlap of electron orbitals to investigate chemical reactions.
- ReaX force field postulates a classical bond order interaction to mimic the association and dissociation of chemical bonds.

Reactive Simulations: Bond Order of Choline



Reactive Simulations: Bond Order of Benzene



Other Ongoing Projects

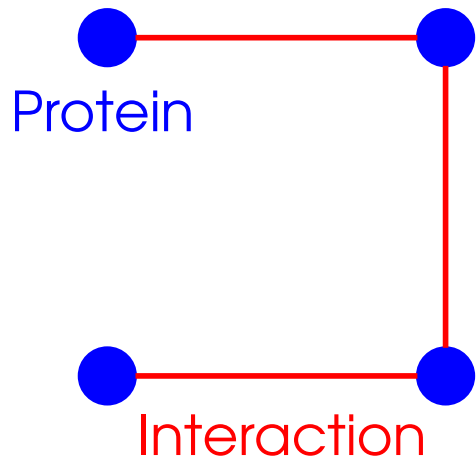
- Scaling solvers to petaFLOPS (DARPA/HPCS) and Next-Generation Solvers (NSF/CISE).
- Algorithmic Asynchrony and Scaling (NSF/CISE).
- Affinity scheduling and multicores (NSF/CISE).
- Speculation and Multicore Architectures (Intel).
- Transactions and Parallelism (Microsoft).

Outline

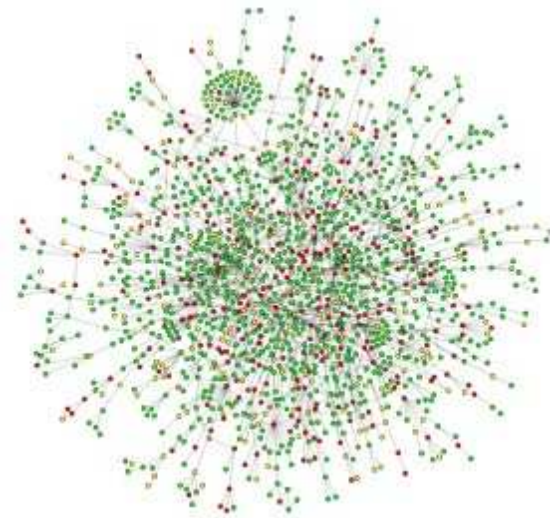
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Protein-Protein Interaction (PPI) Networks

- Interacting proteins can be identified via high-throughput screening
 - Two-hybrid
 - Mass spectrometry
 - Tandem affinity purification (TAP)



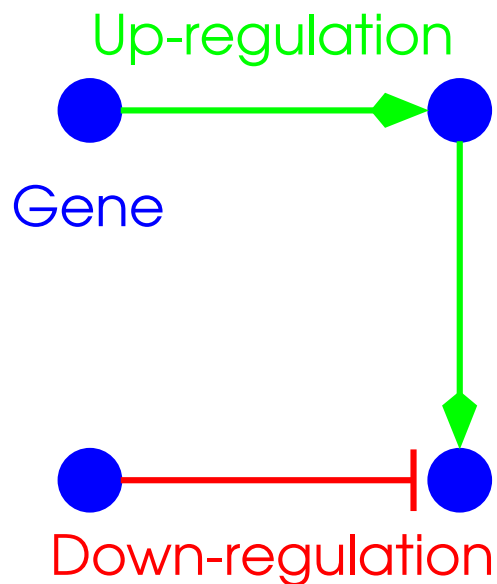
Undirected Graph Model



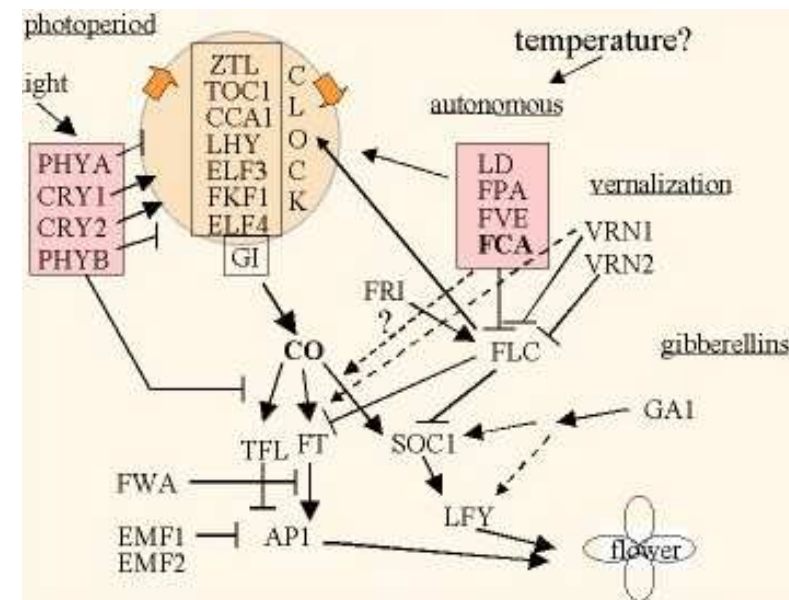
S. Cerevisiae PPI network
(Jeong et al., *Nature*, 2001)

Gene Regulatory Networks

- Expression of genes is dynamically orchestrated through genes controlling each other's transcription
 - Computationally induced from gene expression data and/or sequence level analysis



Boolean Network
Model

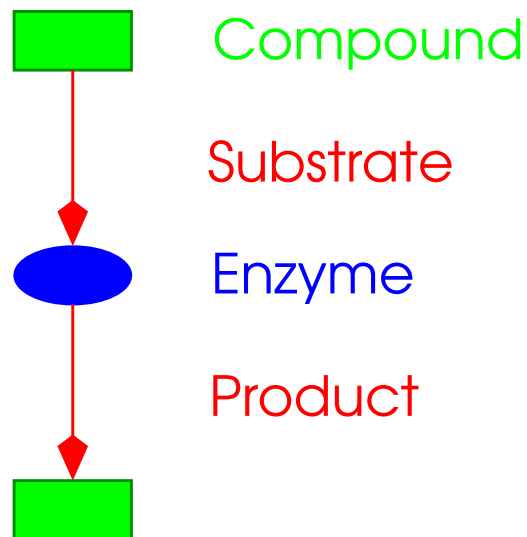


Genetic network that controls
flowering time in *A. thaliana*

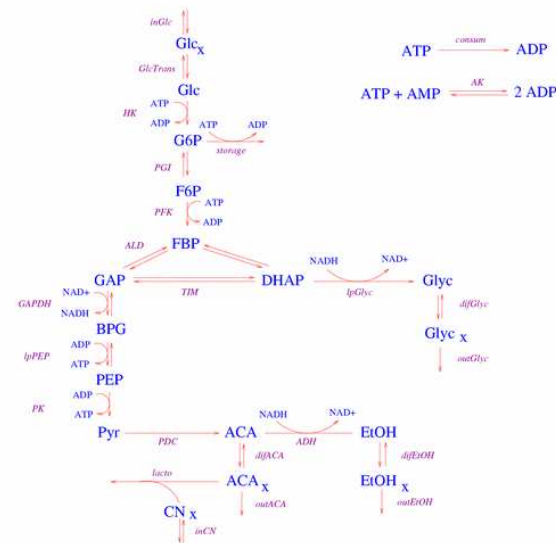
(Blazquez et al, *EMBO Reports*, 2001)

Metabolic Pathways

- Chains of reactions that perform a particular metabolic function
 - Reactions are linked to each other through substrate-product relationships
 - Experimentally derived & computationally extended



Directed Hypergraph Model



Glycolysis pathway in *S. Cerevisiae*
(Hynne et al., *Biophys. Chem.*, 2001)

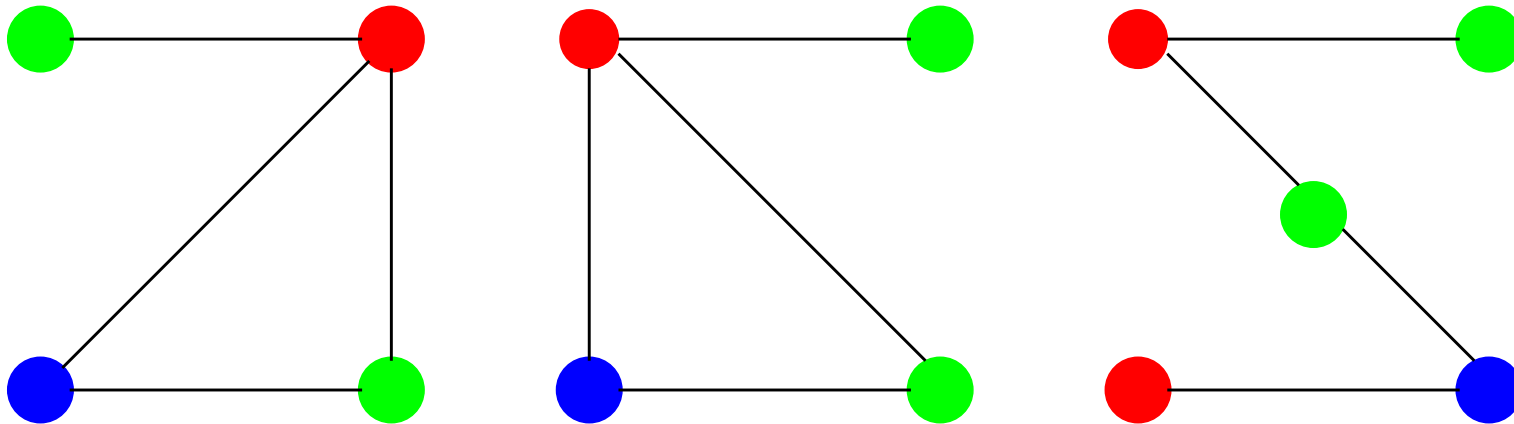
Evolution of Molecular Interactions

- “Evolution thinks modular” (*Vespignani, Nature Gen., 2003*)
- Cooperative tasks require all participating units
 - Selective pressure on preserving interactions & interacting proteins
 - Interacting proteins follow similar evolutionary trajectories (*Pellegrini et al., PNAS, 1999*)
- Orthologs of interacting proteins are likely to interact (*Wagner, Mol. Bio. Evol., 2001*)
 - Conservation of interactions may provide clues relating to conservation of function
- Modular conservation and alignment hold the key to critical structural, functional, and evolutionary concepts in systems biology

Conserved Interaction Patterns

- Given a collection of interaction networks (belonging to different species), find **sub-networks** that are **common** to an **interesting** subset of these networks (Koyutürk, Grama, & Szpankowski, *ISMB*, 2004)
 - A sub-network is a group of interactions that are tied to each other (**connected**)
 - **Frequency**: The number of networks that contain a sub-network, is a coarse measure of **statistical significance**
- Computational challenges
 - How to **relate** molecules (proteins) in different organisms?
 - Requires solution of the intractable **subgraph isomorphism** problem
 - Must be scalable to potentially **large** number of networks
 - Networks are **large** (in the range of $10K$ edges)

Graph Analysis



Network database



Interaction patterns that are common to all networks

Relating Proteins in Different Species

- Ortholog Databases
 - PPI networks: COG, Homologene, Pfam, ADDA
 - Metabolic pathways: Enzyme nomenclature
 - Reliable, but conservative
 - Domain families rely on domain information, but the underlying domains for most interactions are unknown \Rightarrow Multiple node labels
- Sequence Clustering
 - Cluster protein sequences and label proteins according to this clustering
 - Flexible, but expensive and noisy
- Labels may span a large range of functional relationships, from protein families to ortholog groups
 - Without loss of generality, we call identically labeled proteins as orthologs

Problem Statement

- Given a set of **proteins** V , a set of **interactions** E , and a **many-to-many** mapping from V to a set of **ortholog groups** $\mathcal{L} = \{l_1, l_2, \dots, l_n\}$, the corresponding interaction network is a **labeled graph** $G = (V, E, \mathcal{L})$.
 - $v \in V(G)$ is associated with a set of ortholog groups $L(v) \subseteq \mathcal{L}$.
 - $uv \in E(G)$ represents an interaction between u and v .
- S is a **sub-network** of G , i.e., $S \sqsubseteq G$ if there is an **injective** mapping $\phi : V(S) \rightarrow V(G)$ such that for all $v \in V(S)$, $L(v) \subseteq L(\phi(v))$ and for all $uv \in E(S)$, $\phi(u)\phi(v) \in E(G)$.

Computational Problem

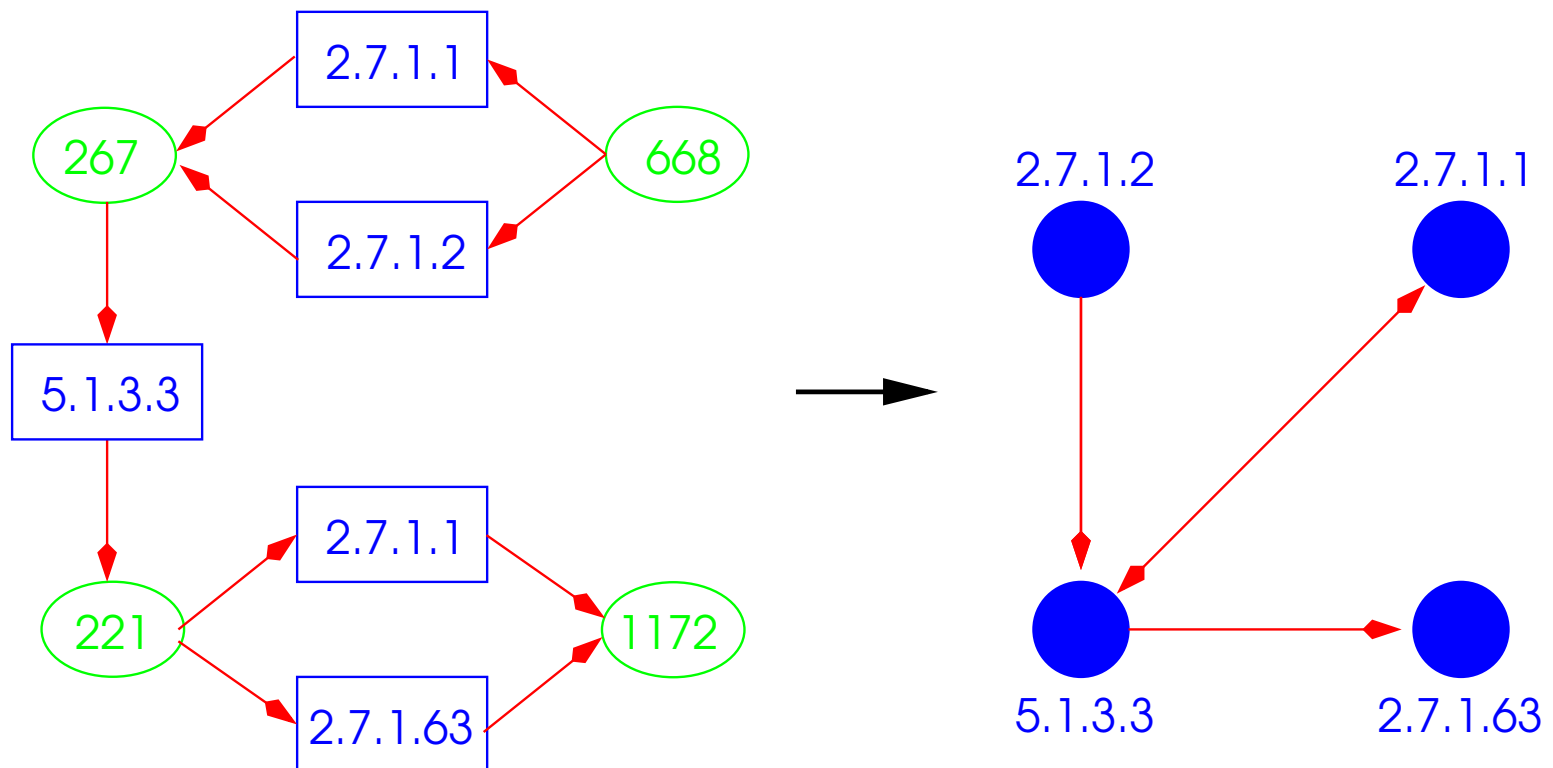
- Conserved sub-network discovery
 - **Instance:** A set of interaction networks $\mathcal{G} = \{G_1 = (V_1, E_1, \mathcal{L}), G_2 = (V_2, E_2, \mathcal{L}), \dots, G_m = (V_m, E_m, \mathcal{L})\}$, each belonging to a different organism, and a **frequency** threshold σ^* .
 - **Problem:** Let $H(S) = \{G_i : S \sqsubseteq G_i\}$ be the **occurrence** set of graph S . Find all **connected** subgraphs S such that $|H(S)| \geq \sigma^*$, i.e., S is a **frequent** subgraph in \mathcal{G} and for all $S' \supset S$, $H(S) \neq H(S')$, i.e., S is **maximal**.

Algorithmic Insight: Ortholog Contraction

- Contract orthologous nodes into a single node
- No subgraph isomorphism
 - Graphs are uniquely identified by their edge sets
- Key observation: Frequent sub-networks are preserved \Rightarrow No information loss
 - Sub-networks that are frequent in general graphs are also frequent in their ortholog-contracted representation
 - Ortholog contraction is a powerful pruning heuristic
- Discovered frequent sub-networks are still biologically interpretable!
 - Interaction between proteins becomes interaction between ortholog groups

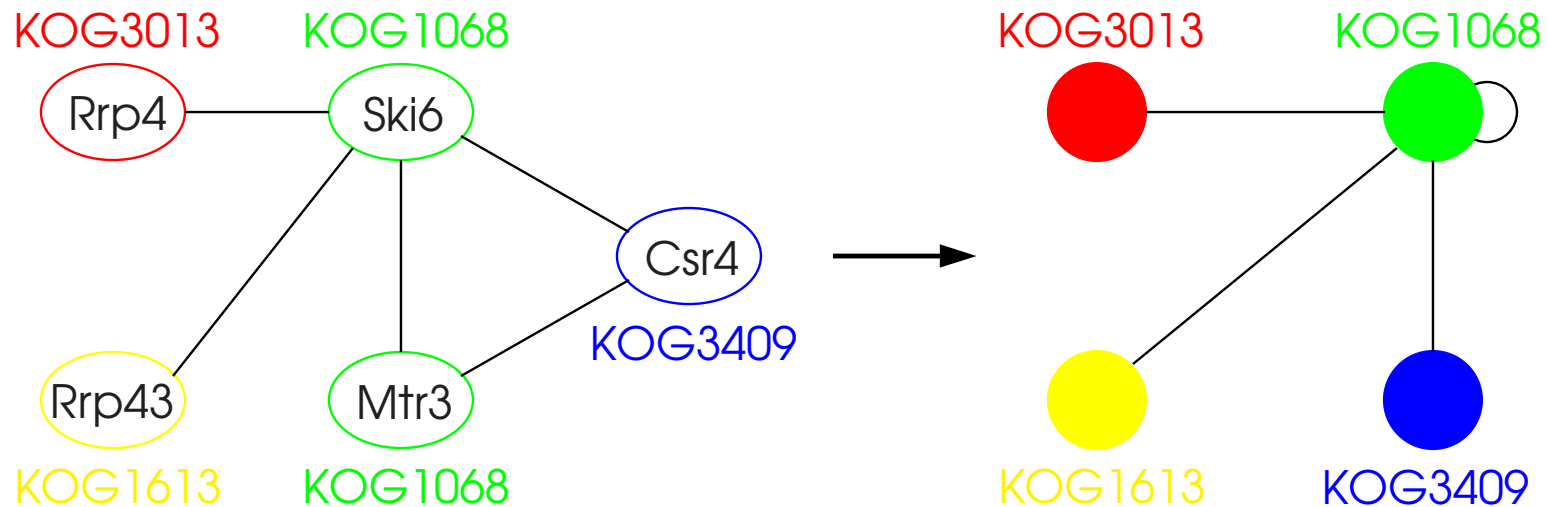
Ortholog Contraction in Metabolic Pathways

- Directed hypergraph \rightarrow uniquely-labeled directed graph
 - Nodes represent enzymes
 - Global labeling by enzyme nomenclature (EC numbers)
 - A directed edge from one enzyme to the other implies that the second consumes a product of the first



Ortholog Contraction in PPI Networks

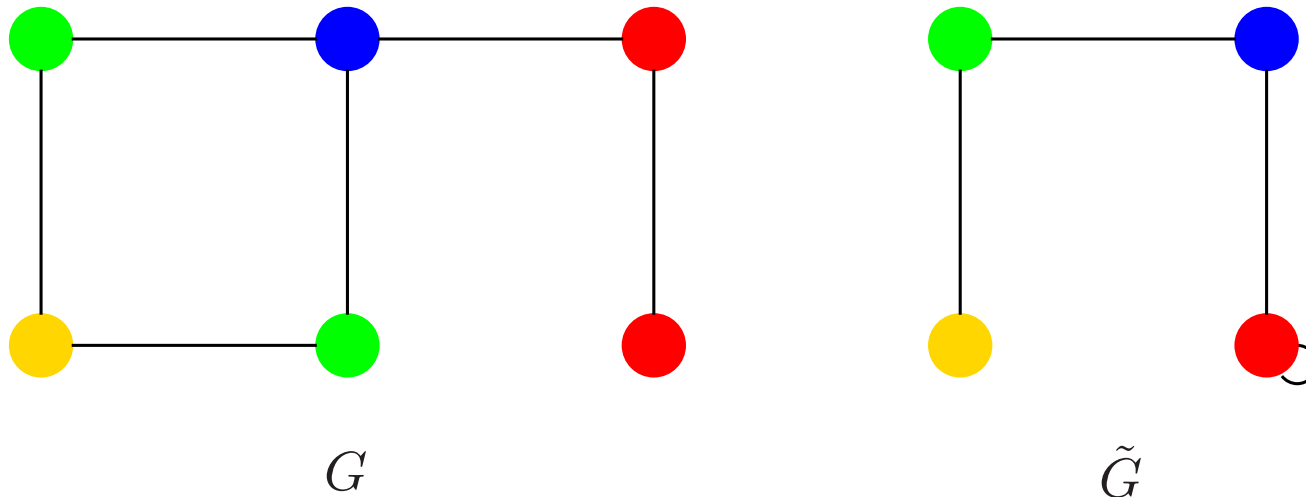
- Interaction between **proteins** → Interaction between **ortholog groups** or **protein families**



Preservation of Sub-networks

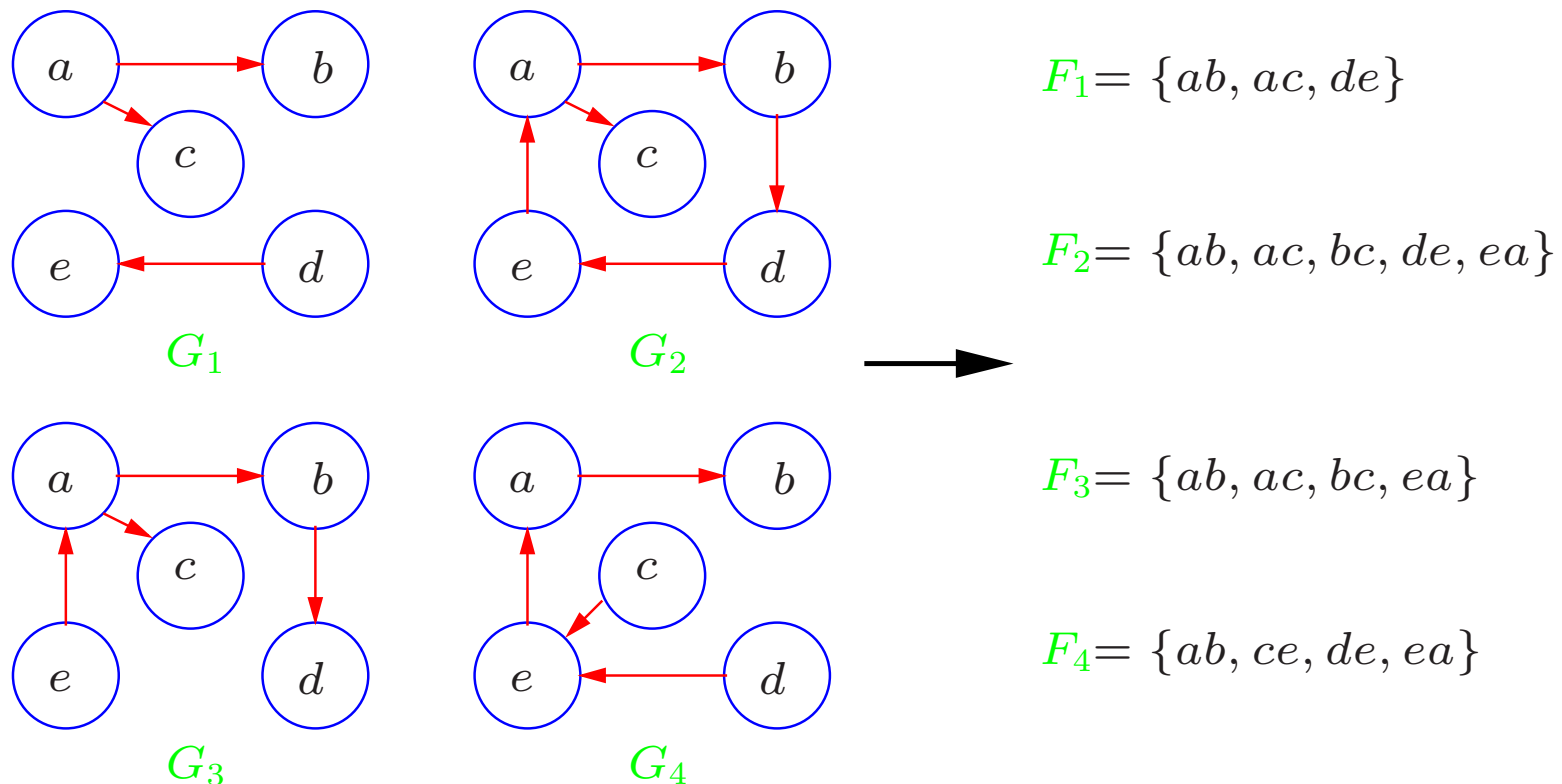
Theorem: Let \tilde{G} be the ortholog-contracted graph obtained by contracting the orthologous nodes of network G . Then, if S is a subgraph of G , \tilde{S} is a subgraph of \tilde{G} .

Corollary: The ortholog-contracted representation of any frequent sub-network is also frequent in the set of ortholog-contracted graphs.



Simplifying the Graph Analysis Problem

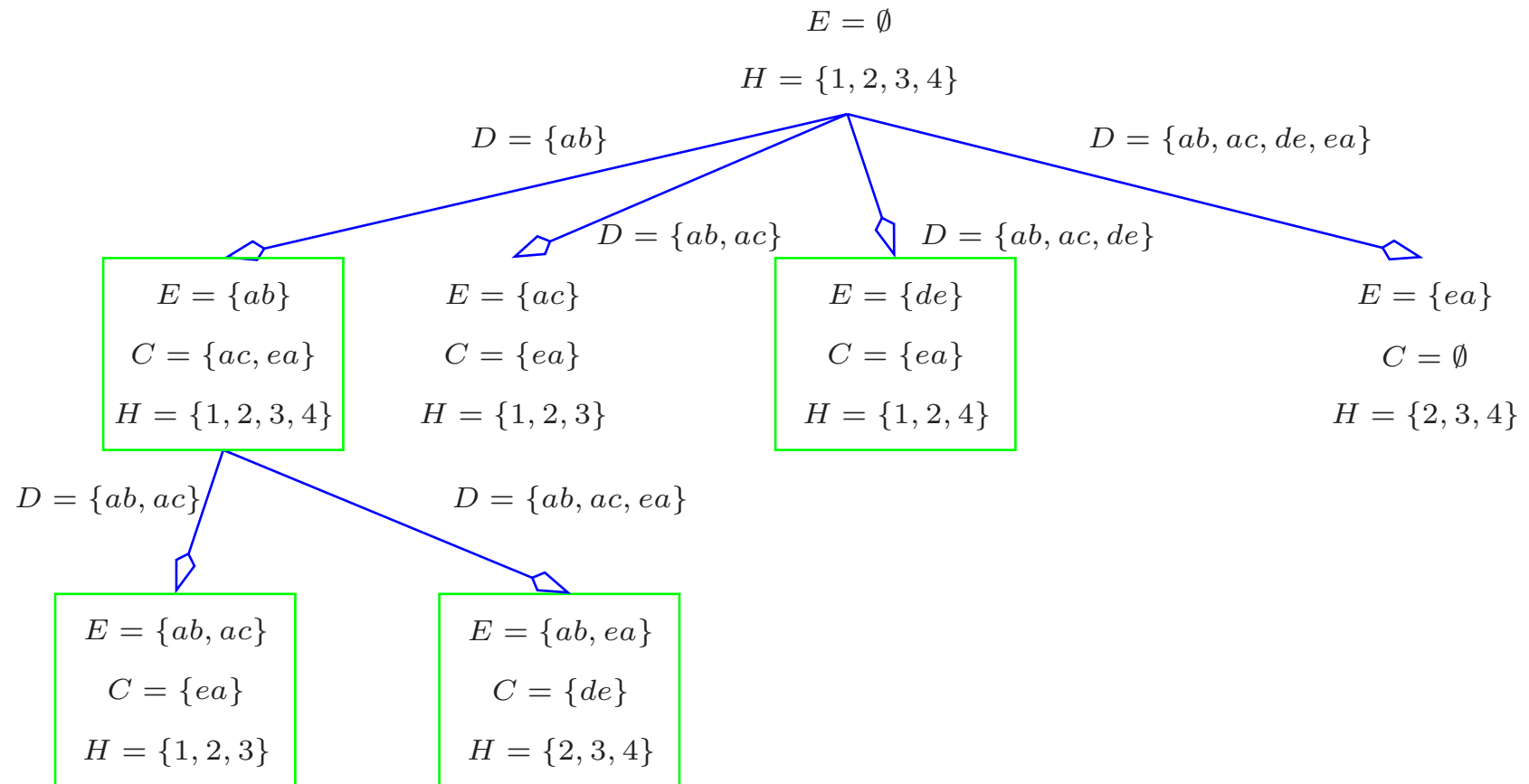
- **Observation:** An ortholog-contracted graph is uniquely determined by the set of its edges.
 - Conserved **Sub-network** Discovery Problem \rightarrow Frequent **Edge set** Discovery Problem



Extending Frequent Itemset Mining to Graph Analysis

- Given a set of transactions, find sets of items that are frequent in these transactions
 - Extensively studied in data mining literature
- Algorithms exploit downward closure property
 - An edge set is frequent only if all of its subsets are frequent
 - Generate edge sets (sub-networks) from small to large, pruning supersets of infrequent sets
- No redundancy
- No subgraph enumeration

MULE: Analyzing Ortholog-Contracted Networks

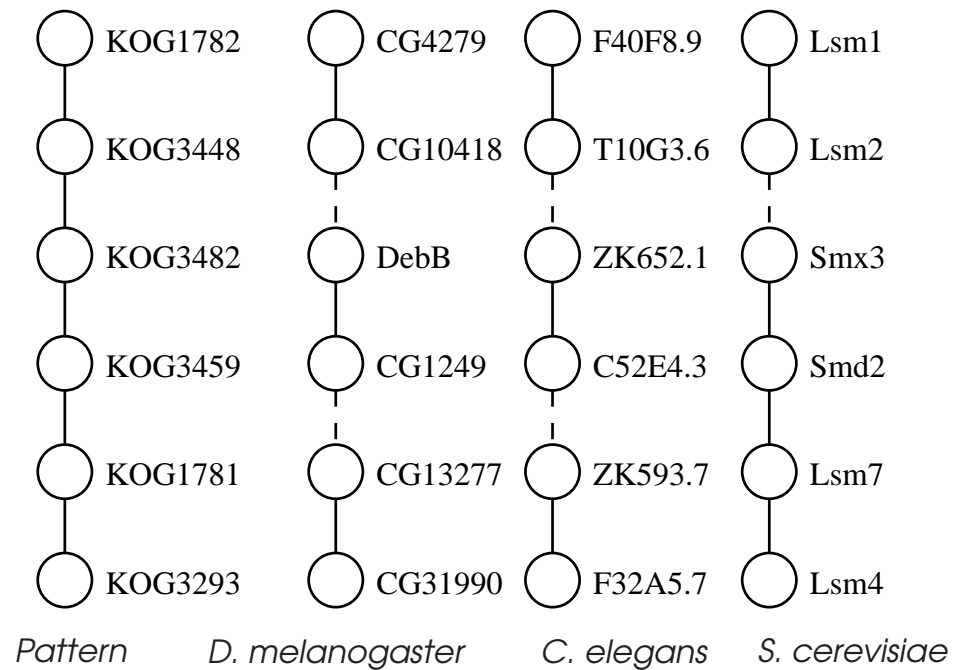


Sample run of MULE for identifying maximal sub-networks that are common to at least 3 organisms

Results: Analyzing PPI Networks

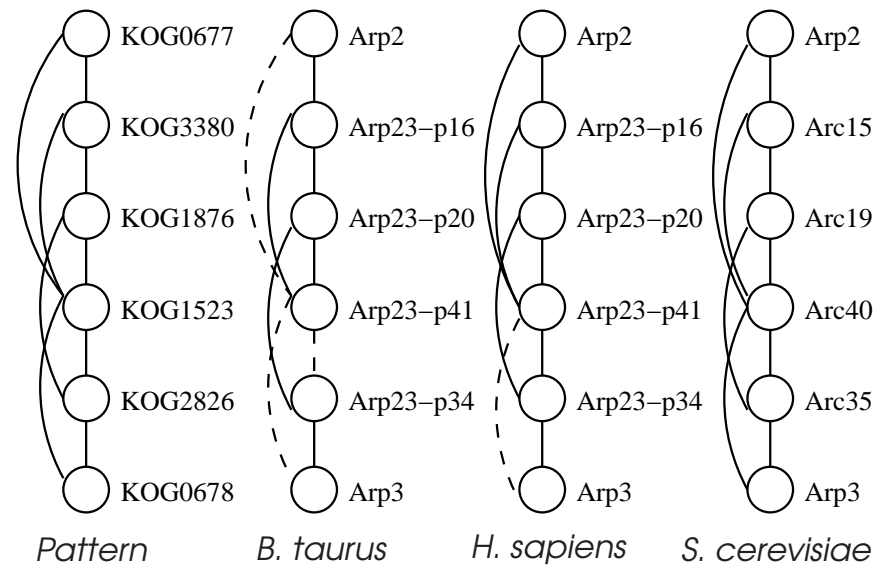
- PPI networks for 9 eukaryotic organisms derived from BIND and DIP
 - *A. thaliana*, *O. sativa*, *S. cerevisiae*, *C. elegans*, *D. melanogaster*, *H. sapiens*, *B. taurus*, *M. musculus*, *R. norvegicus*
 - # of proteins ranges from 288 (*Arabidopsis*) to 8577 (*fruit fly*)
 - # of interactions ranges from 340 (*rice*) to 28829 (*fruit fly*)
- Ortholog contraction
 - Group proteins according to existing COG ortholog clusters
 - Merge Homologene groups into COG clusters
 - Cluster remaining proteins via BLASTCLUST
 - Ortholog-contracted *fruit fly* network contains 11088 interactions between 2849 ortholog groups
- MULE is available at
<http://www.cs.purdue.edu/pdsl/>

Conserved Protein Interaction Patterns



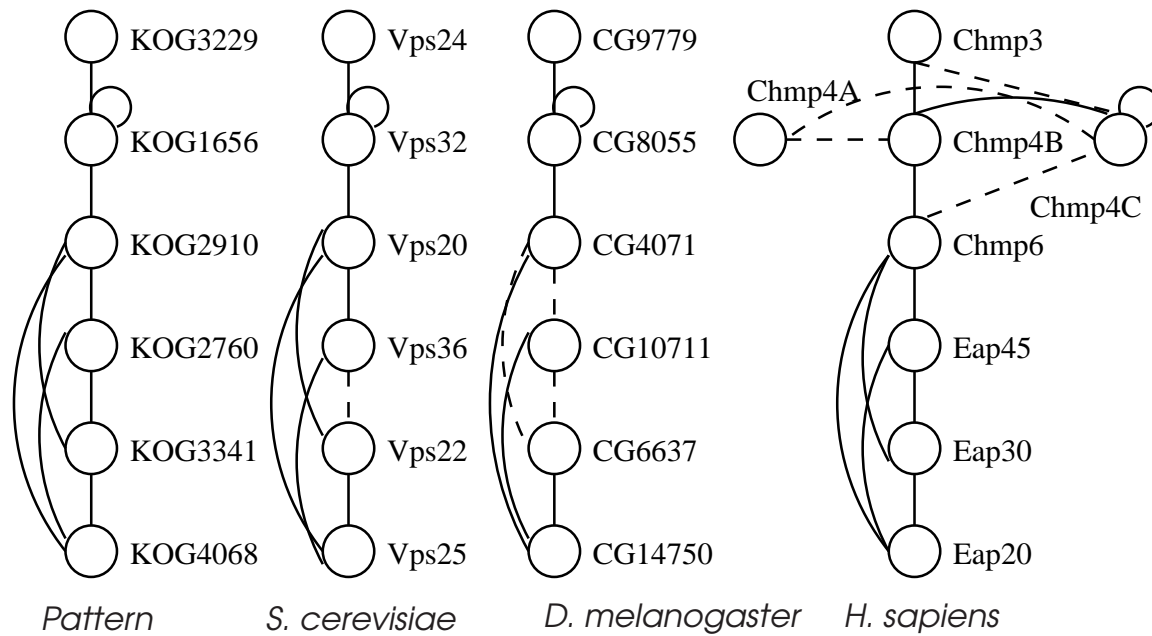
Small nuclear ribonucleoprotein complex ($p < 2e - 43$)

Conserved Protein Interaction Patterns



Actin-related protein Arp2/3 complex ($p < 9e - 11$)

Conserved Protein Interaction Patterns



Endosomal sorting ($p < 1e - 78$)

Runtime Characteristics

Comparison with isomorphism-based algorithms

FSG (Kuramochi & Karypis, *IEEE TKDE*, 2004), **gSpan** (Yan & Han, *KDD*, 2003)

Dataset	Minimum Support (%)	Runtime (secs.)	FSG		Runtime (secs.)	MULE	
			Largest pattern	Number of patterns		Largest pattern	Number of patterns
Glutamate	20	0.2	9	12	0.01	9	12
	16	0.7	10	14	0.01	10	14
	12	5.1	13	39	0.10	13	39
	10	22.7	16	34	0.29	15	34
	8	138.9	16	56	0.99	15	56
Alanine	24	0.1	8	11	0.01	8	11
	20	1.5	11	15	0.02	11	15
	16	4.0	12	21	0.06	12	21
	12	112.7	17	25	1.06	16	25
	10	215.1	17	34	1.72	16	34

Extraction of contracted patterns

Glutamate metabolism, $\sigma = 8\%$				Alanine metabolism, $\sigma = 10\%$			
Size of contracted pattern	Extraction time (secs.)		Size of extracted pattern	Size of contracted pattern	Extraction time (secs.)		Size of extracted pattern
	FSG	gSpan			FSG	gSpan	
15	10.8	1.12	16	16	54.1	10.13	17
14	12.8	2.42	16	16	24.1	3.92	16
13	1.7	0.31	13	12	0.9	0.27	12
12	0.9	0.30	12	11	0.4	0.13	11
11	0.5	0.08	11	8	0.1	0.01	8
Total number of patterns: 56				Total number of patterns: 34			
Total runtime of FSG alone: 138.9 secs.				Total runtime of FSG alone :215.1 secs.			
Total runtime of MULE+FSG: 0.99+100.5 secs.				Total runtime of MULE+FSG: 1.72+160.6 secs.			
Total runtime of MULE+gSpan: 0.99+16.8 secs.				Total runtime of MULE+gSpan: 1.72+31.0 secs.			

Discussion

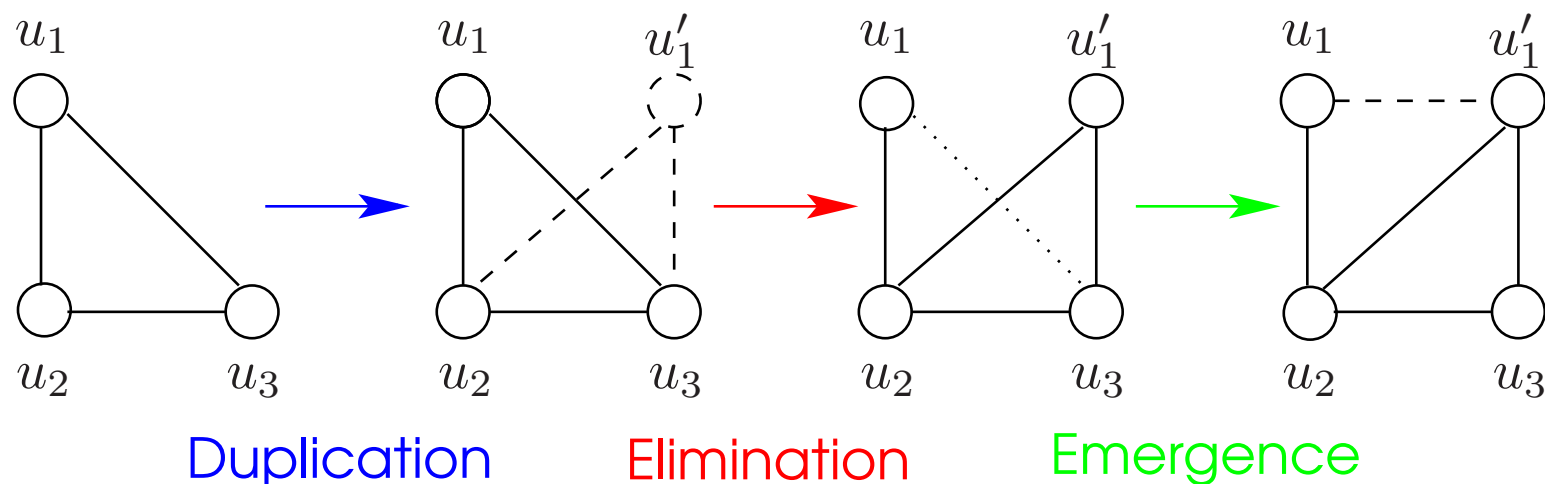
- Ortholog contraction is **fast & scalable**
 - Graph cartesian product based methods (Sharan et al., *PNAS*, 2004), (Koyutürk et al., *RECOMB*, 2005) create m^n product nodes for an ortholog group that has m proteins in each of n organisms
 - Ortholog contraction represents the same group with only n contracted nodes
 - Isomorphism-based graph analysis algorithms **do not scale** to large networks
- Ortholog contraction implicitly **accounts for noise** by eliminating false positives by thresholding frequency, and false negatives by contraction
- Frequency-based approach is **not** easily extensible to **weighted** graphs (Zhou et al., *ISMB*, 2005)

Alignment of PPI Networks

- Given two PPI networks that belong to two different organisms, identify sub-networks that are **similar** to each other
 - **Biological implications**
 - **Mathematical modeling**
- Existing algorithms
 - PathBLAST aligns **pathways** (linear chains) to simplify the problem while maintaining biological meaning (**Kelley et al., PNAS, 2004**)
 - NetworkBLAST compares **conserved complex model** with **null model** to identify significantly conserved subnets (**Sharan et al., J. Comp. Biol., 2005**)
- Our approach (**Koyutürk et al., RECOMB, 2005**) (**Koyutürk et al., J. Comp. Biol., 2006**)
 - Guided by **models of evolution**
 - **Scores** evolutionary events
 - Identifies sets of proteins that induce **high-scoring sub-network pairs**

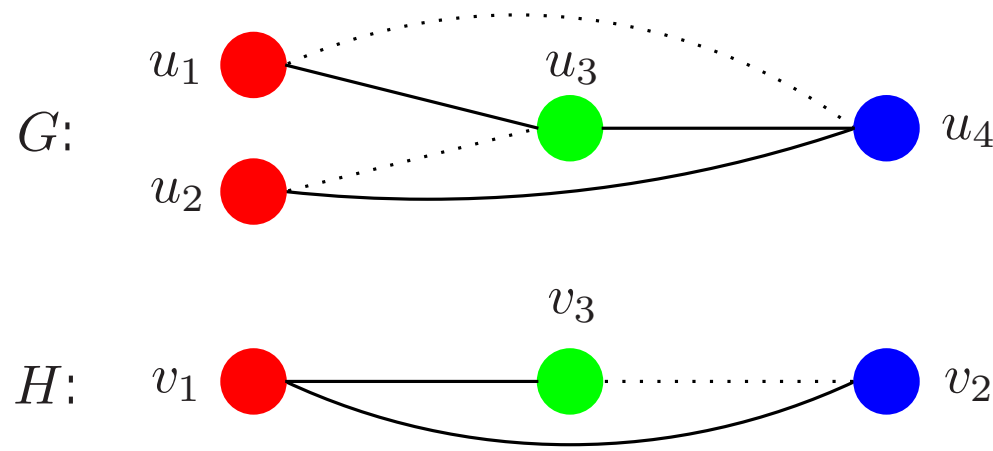
Evolution of PPI Networks

- Duplication/divergence models for the evolution of protein interaction networks
 - Interactions of duplicated proteins are also duplicated
 - Duplicated proteins rapidly lose interactions through mutations
- Allows defining and scoring evolutionary events as graph-theoretical concepts



Match, Mismatch, and Duplication

- Evolutionary events as graph-theoretic concepts
 - A **match** $\in \mathcal{M}$ corresponds to two pairs of homolog proteins from each organism such that both pairs interact in both PPIs. A match is associated with **score** μ .
 - A **mismatch** $\in \mathcal{N}$ corresponds to two pairs of homolog proteins from each organism such that only one pair is interacting. A mismatch is associated with **penalty** ν .
 - A **duplication** $\in \mathcal{D}$ corresponds to a pair of homolog proteins that are in the same organism. A duplication is associated with **score** δ .



Scoring Matches, Mismatches and Duplications

- Quantizing similarity between two proteins
 - Confidence in two proteins being orthologous
 - BLAST E-value: $S(u, v) = \log_{10} \frac{p(u, v)}{p_{random}}$
 - Ortholog clustering: $S(u, v) = c(u)c(v)$
- Match score
 - $\mu(uu', vv') = \bar{\mu} \min\{S(u, v), S(u', v')\}$
- Mismatch penalty
 - $\nu(uu', vv') = \bar{\nu} \min\{S(u, v), S(u', v')\}$
- Duplication score
 - $\delta(u, u') = \bar{\delta}(\hat{\delta} - S(u, u'))$
 - $\hat{\delta}$ specifies threshold for sequence similarity to be considered functionally conserved

Pairwise Alignment of PPIs as an Optimization Problem

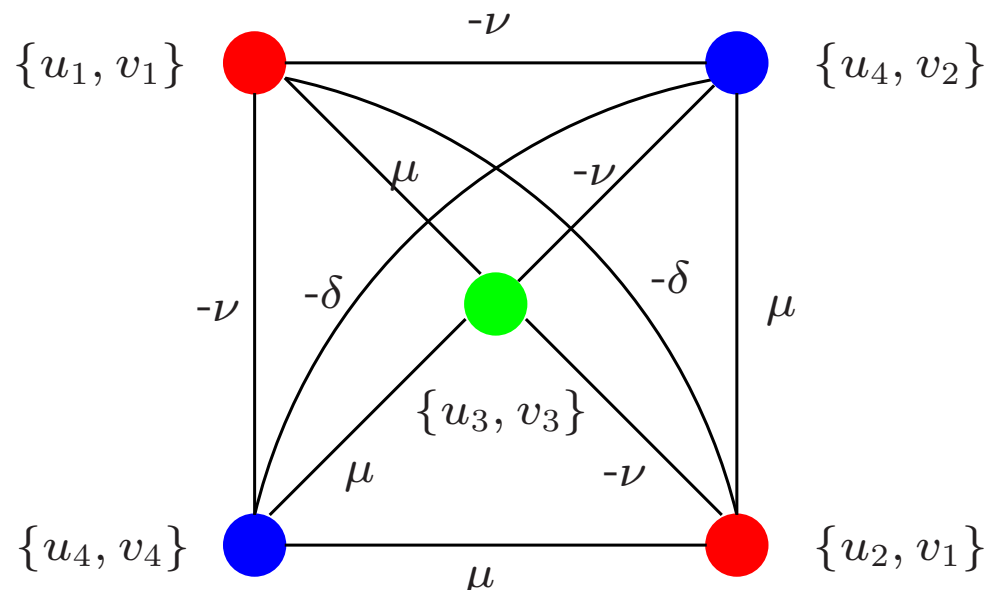
- Alignment score:

$$\sigma(\mathcal{A}(P)) = \sum_{M \in \mathcal{M}} \mu(M) - \sum_{N \in \mathcal{N}} \nu(N) + \sum_{D \in \mathcal{D}} \delta(D)$$

- Matches are rewarded for conservation of interactions
 - Duplications are rewarded/penalized for functional conservation/differentiation after split
 - Mismatches are penalized for functional divergence (what about experimental error?)
- Scores are functions of similarity between associated proteins
- Problem: Find all protein subset pairs with significant alignment score
 - High scoring protein subsets are likely to correspond to conserved modules
- A graph equivalent to BLAST

Weighted Alignment Graph

- $G(V, E)$: V consists of all pairs of homolog proteins $\mathbf{v} = \{u \in U, v \in V\}$
- An edge $\mathbf{v}\mathbf{v}' = \{uv\}\{u'v'\}$ in E is a
 - **match edge** if $uu' \in E$ and $vv' \in V$, with weight $w(\mathbf{v}\mathbf{v}') = \mu(uv, u'v')$
 - **mismatch edge** if $uu' \in E$ and $vv' \notin V$ or vice versa, with weight $w(\mathbf{v}\mathbf{v}') = -\nu(uv, u'v')$
 - **duplication edge** if $S(u, u') > 0$ or $S(v, v') > 0$, with weight $w(\mathbf{v}\mathbf{v}') = \delta(u, u')$ or $w(\mathbf{v}\mathbf{v}') = \delta(v, v')$



Maximum Weight Induced Subgraph Problem

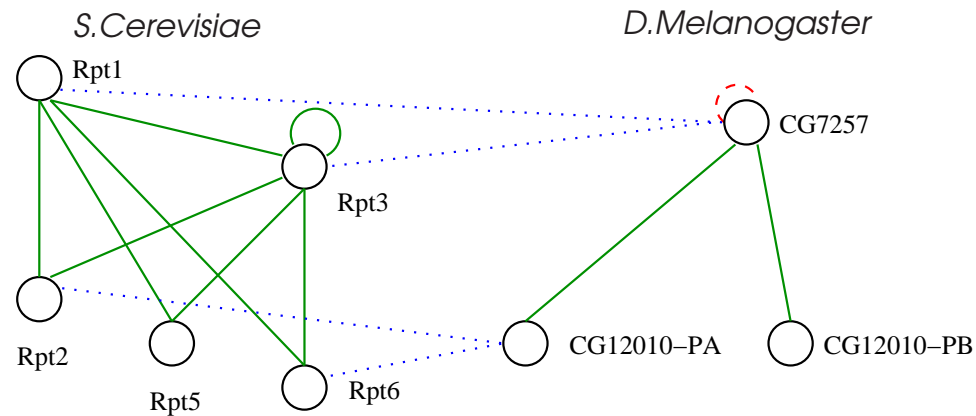
- **Definition:** (MAWISH)
 - Given graph $\mathcal{G}(\mathcal{V}, \mathcal{E})$ and a constant ϵ , find $\tilde{\mathcal{V}} \subseteq \mathcal{V}$ such that $\sum_{\mathbf{v}, \mathbf{u} \in \tilde{\mathcal{V}}} w(\mathbf{vu}) \geq \epsilon$.
 - NP-complete by reduction from Maximum-Clique
- **Theorem:** (MAWISH \equiv Pairwise alignment)
 - If $\tilde{\mathcal{V}}$ is a solution for the MAWISH problem on $\mathcal{G}(\mathcal{V}, \mathcal{E})$, then $P = \{\tilde{U}, \tilde{V}\}$ induces an alignment $\mathcal{A}(P)$ with $\sigma(\mathcal{A}) \geq \epsilon$, where $\tilde{\mathcal{V}} = \tilde{U} \times \tilde{V}$.
- **Solution:** Local graph expansion
 - Greedy graph growing + iterative refinement
 - Linear-time heuristic
- Source code available at
<http://www.cs.purdue.edu/pdsl/>

Alignment of Yeast and Fruit Fly PPI Networks

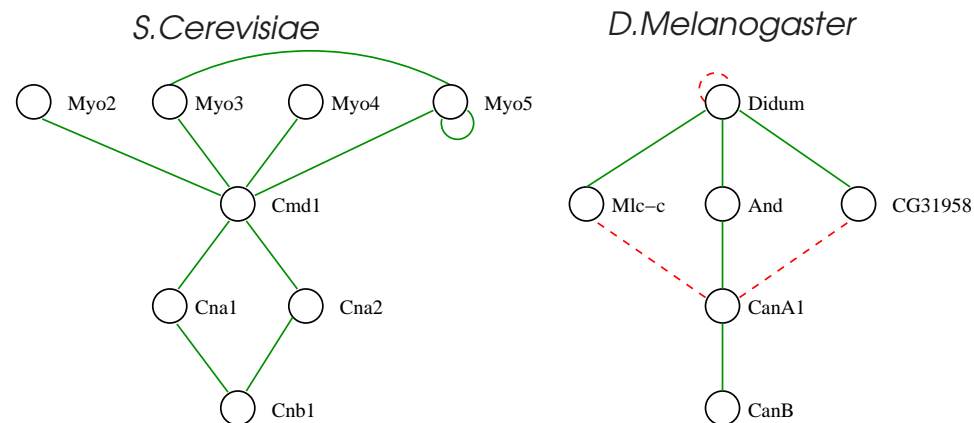
Rank	Score	<i>z</i> -score	# Proteins	# Matches	# Mismatches	# Dups.
1	15.97	6.6	18 (16, 5)	28	6	(4, 0)
	protein amino acid phosphorylation (69%) JAK-STAT cascade (40%)					
2	13.93	3.7	13 (8, 7)	25	7	(3, 1)
	endocytosis (50%) / calcium-mediated signaling (50%)					
5	8.22	13.5	9 (5, 3)	19	11	(1, 0)
	invasive growth (sensu <i>Saccharomyces</i>) (100%) oxygen and reactive oxygen species metabolism (33%)					
6	8.05	7.6	8 (5, 3)	12	2	(0, 1)
	ubiquitin-dependent protein catabolism (100%) mitosis (67%)					
21	4.36	6.2	9 (5, 4)	18	13	(0, 5)
	cytokinesis (100%, 50%)					
30	3.76	39.6	6 (3, 5)	5	1	(0, 6)
	DNA replication initiation (100%, 80%)					

Subnets Conserved in Yeast and Fruit Fly

Proteasome regulatory particle subnet



Calcium-dependent stress-activated signaling pathway



Discussion

- Comparison to other approaches: NetworkBlast (Sharan et al., *PNAS*, 2005), NUKE (Novak et al., *Genome Informatics*, 2005)
 - Much **faster** than NetworkBLAST, but provides **less coverage**
 - Comparable to NUKE depending on speed vs coverage trade-off
- Scores evolutionary events
 - **Flexible**, allows incorporation of different evolutionary models, experimental bases, target structures
 - Somewhat **ad-hoc**, what is a good weighting of scores?

Analytical Assessment of Statistical Significance

- What is the **significance** of a **dense** component in a network?
- What is the **significance** of a **conserved** component in multiple networks?
- Existing techniques
 - Mostly computational (e.g., Monte-Carlo simulations)
 - Compute probability that **the** pattern exists rather than **a** pattern with **the property** (e.g., size, density) exists
 - **Overestimation of significance**

Random Graph Models

- Interaction networks generally exhibit **power-law** property (or exponential, geometric, etc.)
- Analysis simplified through **independence** assumption (Itzkovitz et al., *Physical Review*, 2003)
- Independence assumption may cause problems for networks with **arbitrary degree distribution**
- $P(uv \in E) = d_u d_v / |E|$, where d_u is expected degree of u , but generally $d_{\max}^2 > |E|$ for PPI networks
- Analytical techniques based on simplified models (Koyutürk, Grama, Szpankowski, *RECOMB*, 2006)
 - **Rigorous analysis** on $G(n, p)$ model
 - Extension to piecewise $G(n, p)$ to **capture network characteristics** more accurately

Significance of Dense Subgraphs

- A subnet of r proteins is said to be ρ -dense if $F(r) \geq \rho r^2$, where $F(r)$ is the number of interactions between these r proteins
- What is the expected size of the largest ρ -dense subgraph in a random graph?
 - Any ρ -dense subgraph with larger size is statistically significant!
- $G(n, p)$ model
 - n proteins, each interaction occurs with probability p
 - Simple enough to facilitate rigorous analysis
 - If we let $p = d_{\max}/n$, largest ρ -dense subgraph in $G(n, p)$ stochastically dominates that in a graph with arbitrary degree distribution
- Piecewise $G(n, p)$ model
 - Few proteins with many interacting partners, many proteins with few interacting partners
 - Captures the basic characteristics of PPI networks
 - Analysis of $G(n, p)$ model immediately generalized to this model

Largest Dense Subgraph

- **Theorem:** If G is a random graph with n nodes, where every edge exists with probability p , then

$$\lim_{n \rightarrow \infty} \frac{R_\rho}{\log n} = \frac{1}{\kappa(p, \rho)} \quad (pr.), \quad (1)$$

where

$$\kappa(p, \rho) = \rho \log \frac{\rho}{p} + (1 - \rho) \log \frac{1 - \rho}{1 - p}. \quad (2)$$

More precisely,

$$P(R_\rho \geq r_0) \leq O \left(\frac{\log n}{n^{1/\kappa(p, \rho)}} \right), \quad (3)$$

where

$$r_0 = \frac{\log n - \log \log n + \log \kappa(p, \rho)}{\kappa(p, \rho)} \quad (4)$$

for large n .

Piecewise $G(n, p)$ model

- The size of largest dense subgraph is still proportional to $\log n / \kappa$ with a constant factor depending on **number of hubs**
- **Model:**

$$P(uv \in E(G)) = \begin{cases} p_h & \text{if } u, v \in V_h \\ p_l & \text{if } u, v \in V_l \\ p_b & \text{if } u \in V_h, v \in V_l \text{ or } u \in V_l, v \in V_h \end{cases}$$

- **Result:**
Let $n_h = |V_h|$. If $n_h = O(1)$, then $P(R_n(\rho) \geq r_1) \leq O\left(\frac{\log n}{n^{1/\kappa(p_l, \rho)}}\right)$,
where

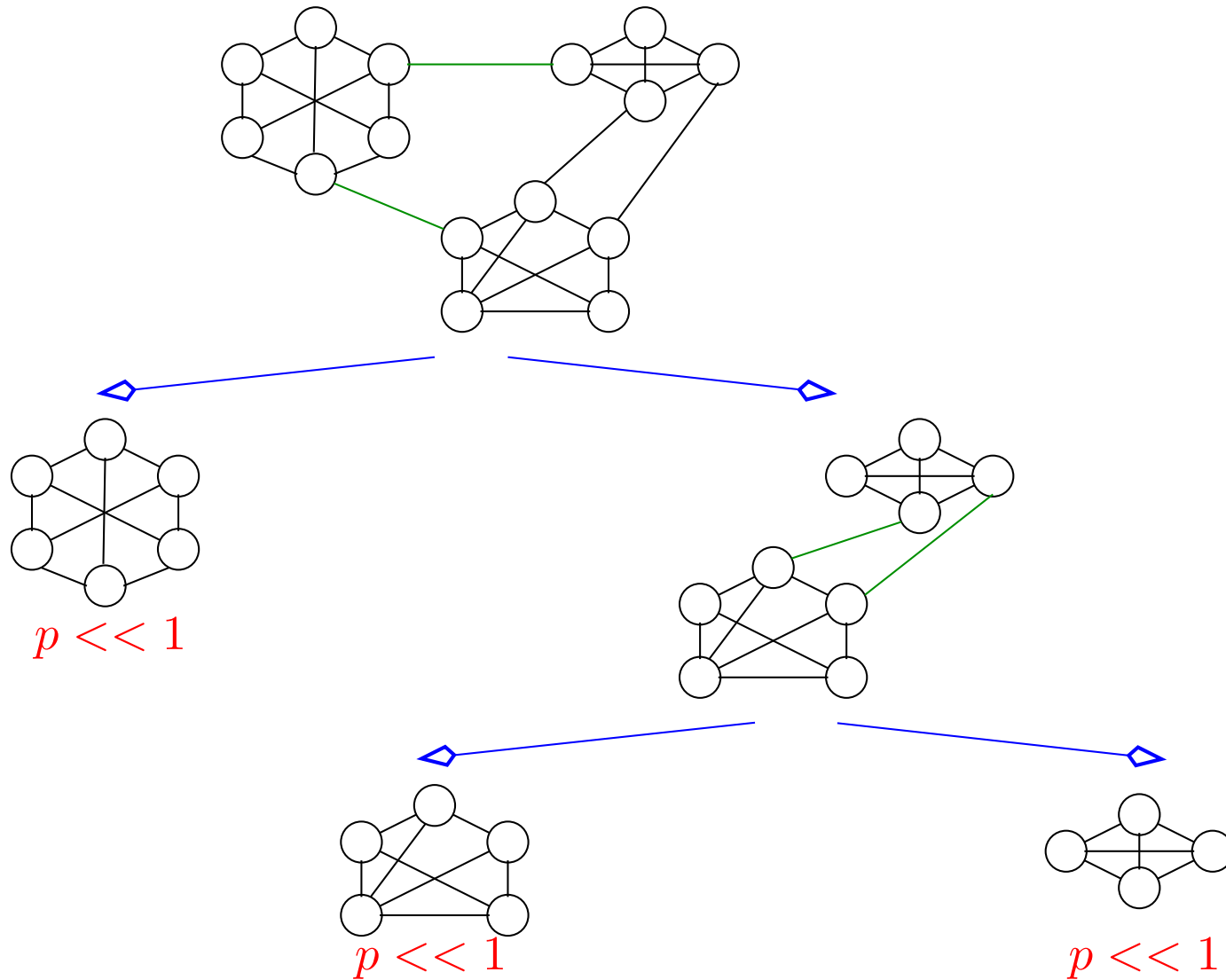
$$r_1 = \frac{\log n - \log \log n + 2n_h \log B + \log \kappa(p_l, \rho) - \log e + 1}{\kappa(p_l, \rho)}$$

and $B = \frac{p_b q_l}{p_l} + q_b$, where $q_b = 1 - p_b$ and $q_l = 1 - p_l$.

Algorithms Based on Statistical Significance

- Identification of **topological modules**
- Use **statistical significance** as a **stopping criterion** for graph clustering heuristics
- HCS Algorithm (*Hartuv & Shamir, Inf. Proc. Let., 2000*)
 - Find a minimum-cut bipartitioning of the network
 - If any of the parts is **dense enough**, record it as a dense cluster of proteins
 - Else, further partition them recursively
- **SIDES**: Use **statistical significance** to determine whether a subgraph is sufficiently dense
 - For given number of proteins and interactions between them, we can determine whether those proteins induce a significantly dense subnet

SIDES Algorithm



SIDES is available at <http://www.cs.purdue.edu/pds1>

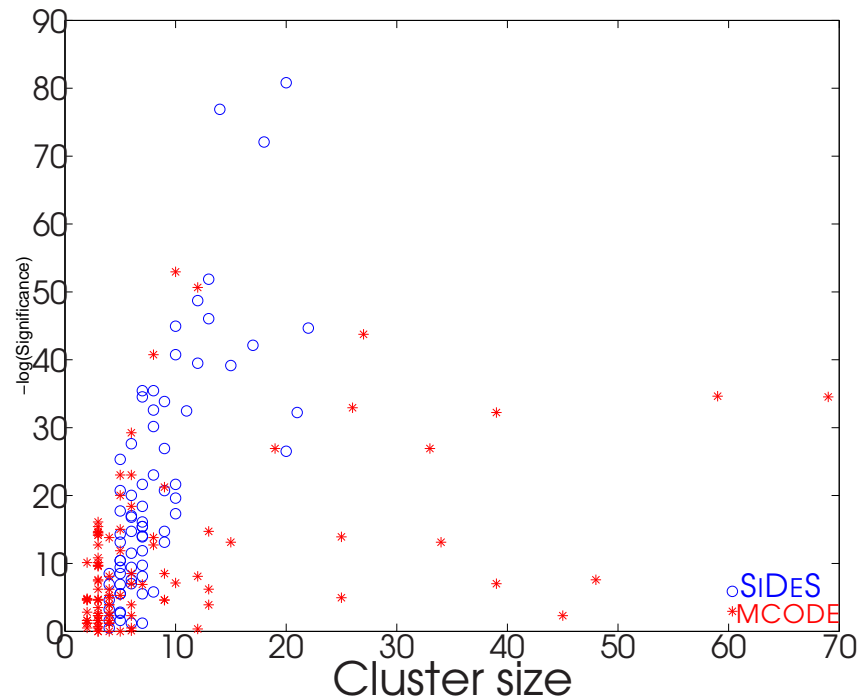
Performance of SIdES

- Biological relevance of identified clusters is assessed with respect to **Gene Ontology (GO)**
 - Estimate the statistical significance of the **enrichment** of each GO term in the cluster
- **Quality** of the clusters with respect to GO annotations
 - Assume cluster C containing n_C genes is associated with term T that is attached to n_T genes and n_{CT} of genes in C are attached to T
 - **specificity** = $100 \times n_{CT}/n_C$
 - **sensitivity** = $100 \times n_{CT}/n_T$

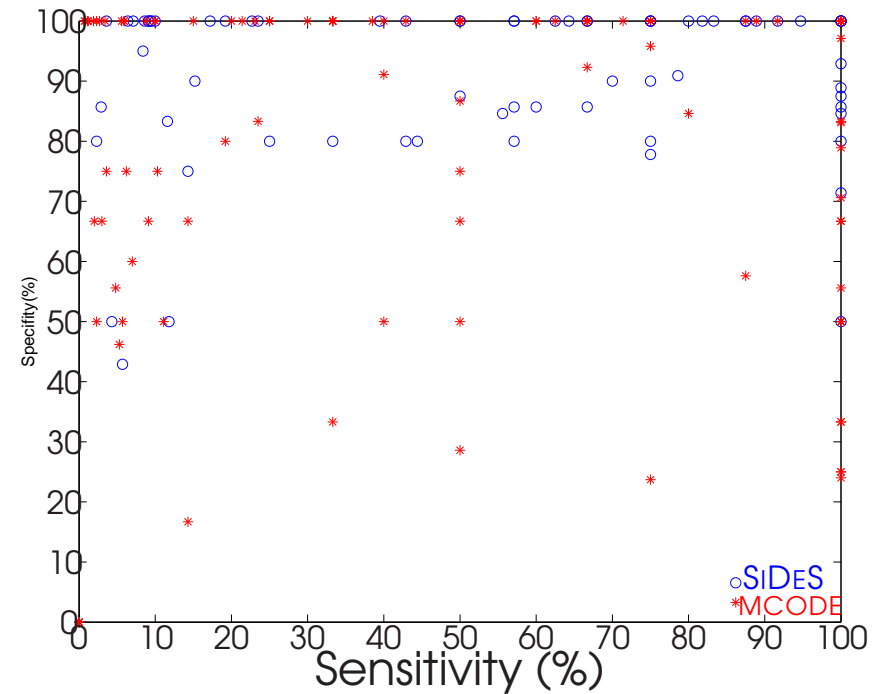
	SIdES			MCode		
	Min.	Max.	Avg.	Min.	Max.	Avg.
Specificity (%)	43.0	100.0	91.2	0.0	100.0	77.8
Sensitivity (%)	2.0	100.0	55.8	0.0	100.0	47.6

Comparison of SIdES with MCode (Bader & Hogue, *BMC Bioinformatics*, 2003)

Performance of SIDES



Size vs Significance



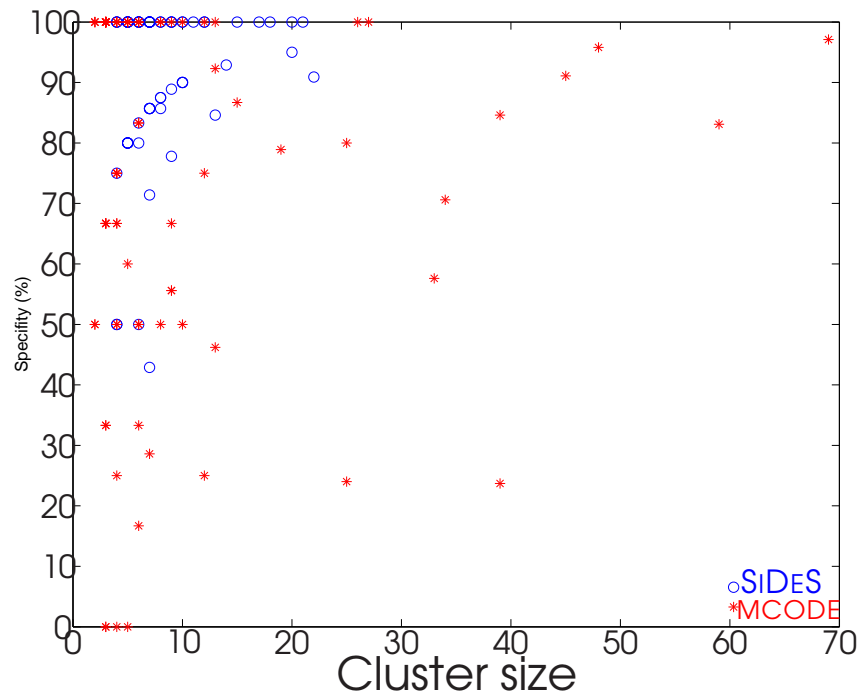
Sensitivity vs Specificity

Correlation

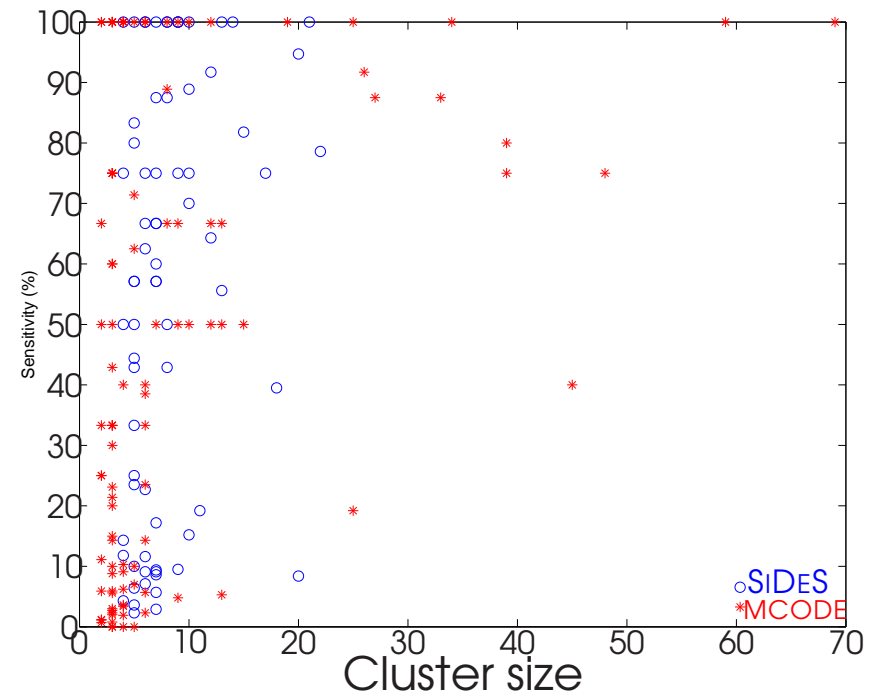
SIDES: 0.76

MCODE: 0.43

Performance of SiDES



Size vs Specificity



Size vs Sensitivity

Correlation

SiDES: 0.22
MCODE: -0.02

SiDES: 0.27
MCODE: 0.36

Functional Annotation of Biochemical Pathways

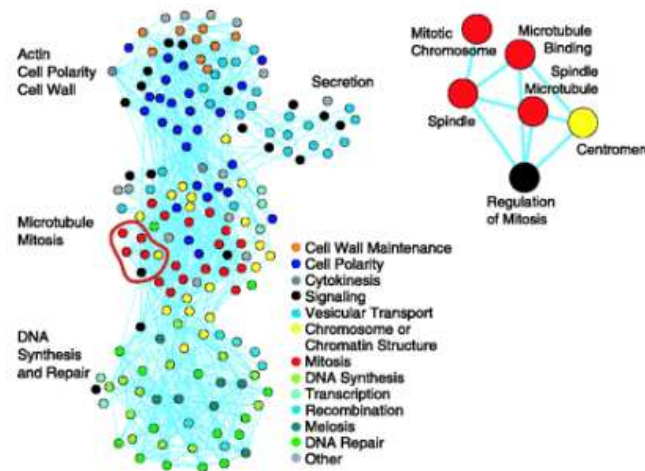
- Identifying Significant Pathways
- Annotations and Metrics
- Application to Protein/Domain Interaction Networks
- Implementation and Results

Molecular Annotation

- Functional annotation of genes provides an understanding of the underlying principles
 - Molecular function: role of a gene.
 - Biological process: processes a gene is involved in.
 - Cellular component: localization of genes product.
- Gene Ontology provides a library of molecular annotations (we refer to each annotation class as a functional attribute).

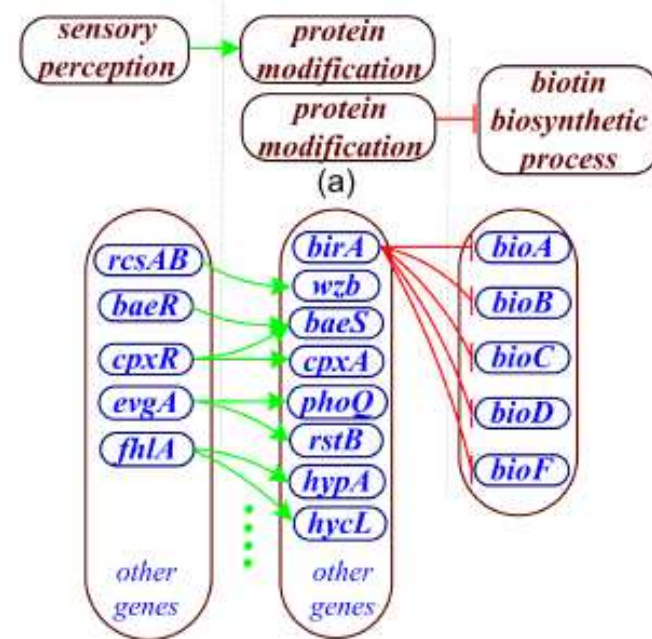
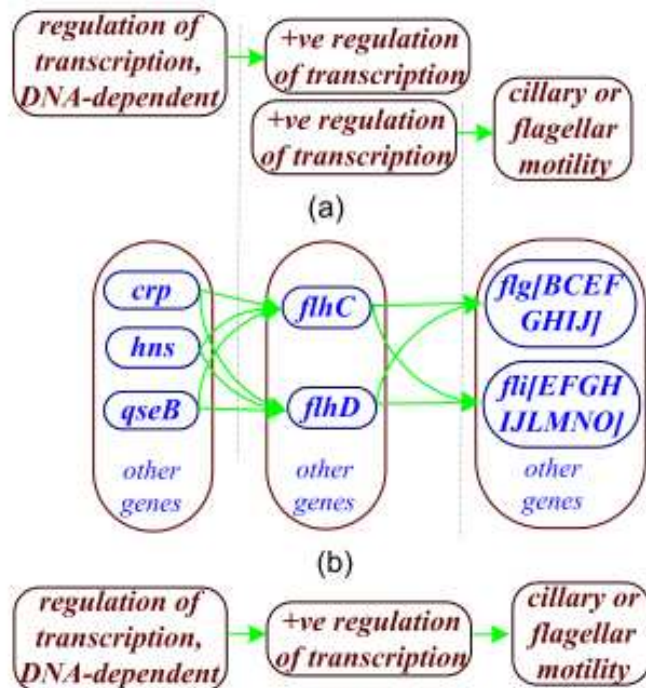
From Molecules to Systems

- Networks are species-specific
- Annotation is at the molecular level
- Map networks from gene space to function space (can generate a library of annotated modular (sub-) networks)



Network of Gene Ontology terms based on significance of pairwise interactions in yeast synthetic gene array (SGA) (Tong et al., Science, 2004)

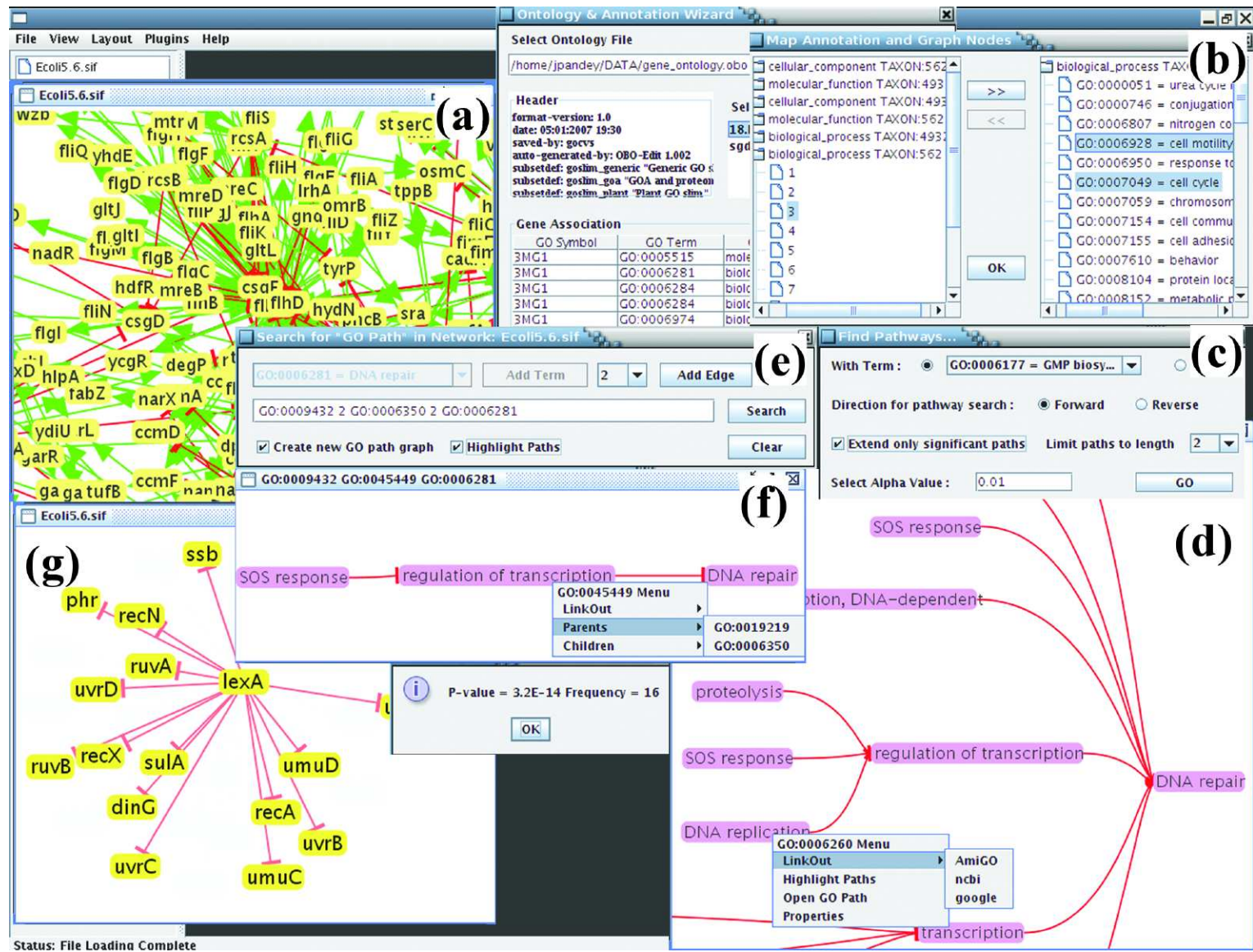
Indirect Regulation



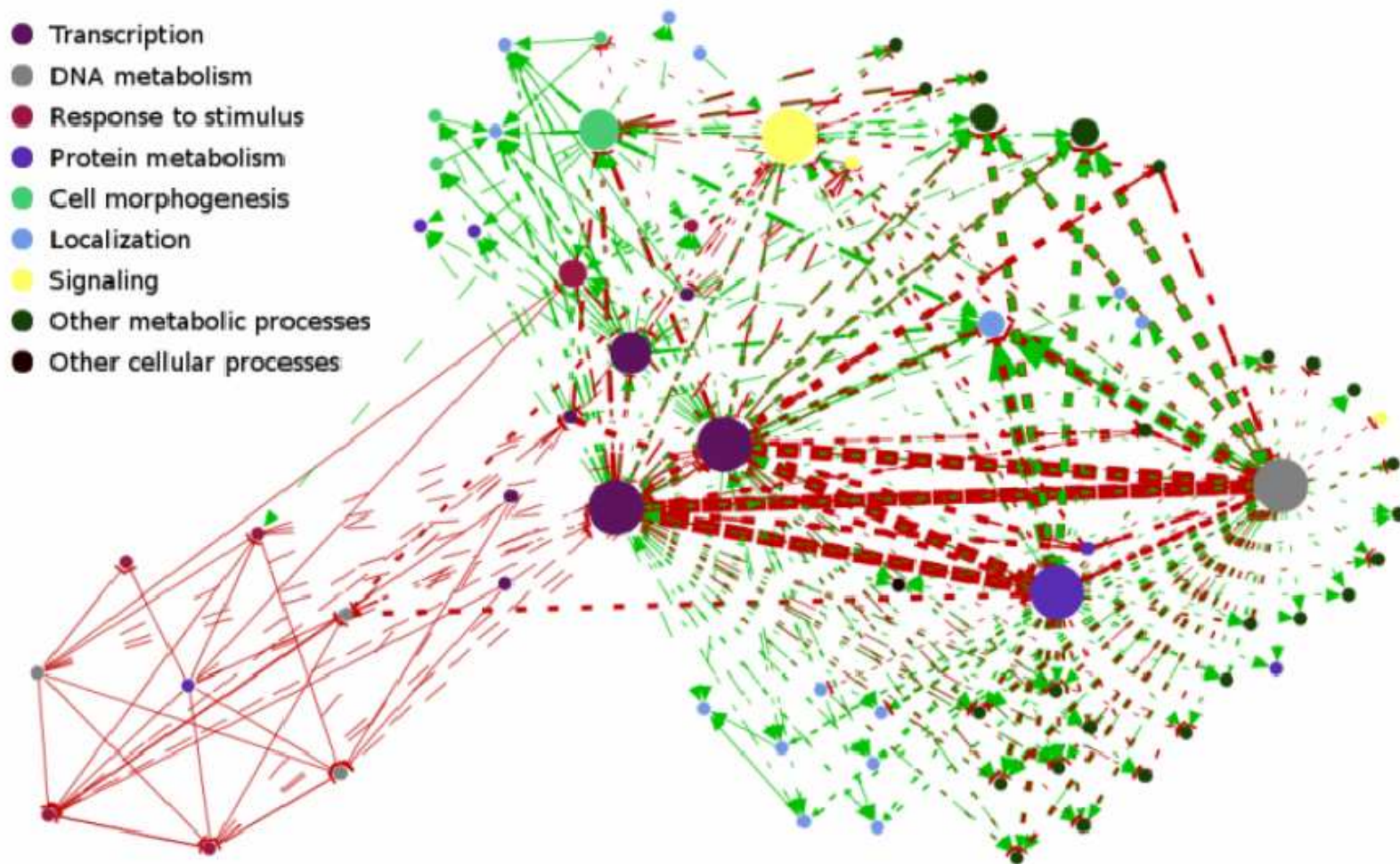
Key Results

- Statistically interpretable measures of significance are not monotonic.
- There is no monotonicity in the GO space either.
- Develop an alternate (weaker) measure of significance that builds on modularity of sub-components.
- Need to short-circuit common terms (transcription factors, DNA binding genes, etc.)
- Comprehensive software infrastructure built on these results.

Narada Functionality



Narada Network Annotation



Ongoing Work

- Domain identification and domain-domain networks.
- (Sub)Network phylogenies.
- Network inference and stability.

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- M. Koyuturk, W. Szpankowski, and A. Grama, Assessing significance of connectivity and conservation in protein interaction networks, *Journal of Computational Biology*, 14(6), 747-764, 2007.
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- M. Koyuturk, Y. Kim, U. Topkara, S. Subramaniam, W. Szpankowski, and A. Grama, Pairwise Alignment of Protein Interaction Networks, *Journal of Computational Biology*, 13(2), 182-199, 2006.
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- M. Koyutürk, A. Grama and W. Szpankowski, Pairwise Local Alignment of Protein Interaction Networks Guided by Models of Evolution, RECOMB 2005.

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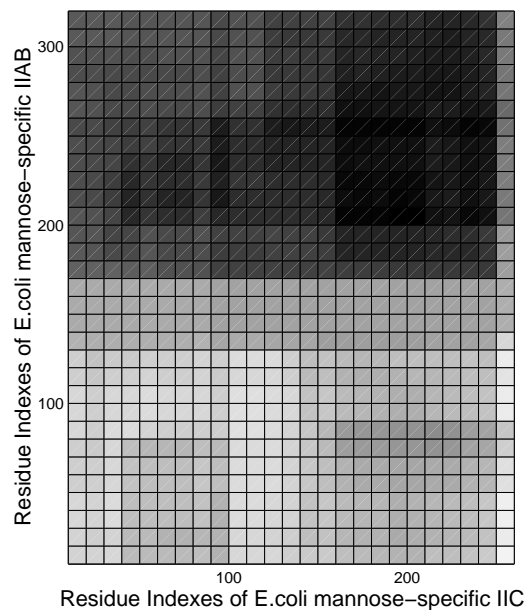
Thank you!

Phylogenetic Analysis for Predicting Interactions

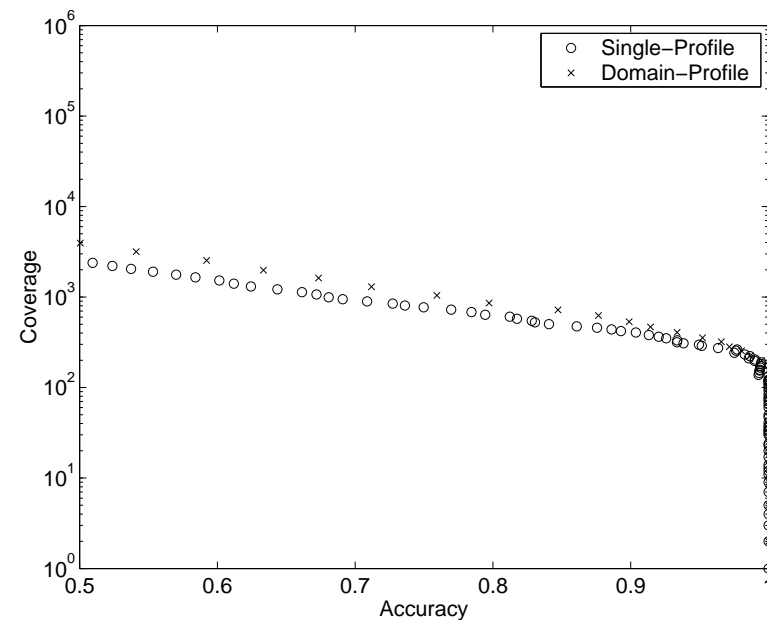
- Functionally related proteins are likely to have co-evolved
 - Construct **phylogenetic profile** for each genome: Vector of E-values signifying existence of an orthologous protein in each organism
 - Identify **pairwise functional associations** based on mutual information between phylogenetic profiles (**Pellegrini et al., PNAS, 1999**)
 - **Mutual information:**
$$I(X, Y) = H(X) - H(X|Y) = \sum_x \sum_y p(x, y) \log(p(x, y)/p(x)p(y))$$
 - Shown to identify functionally associated protein pairs at a coarser level than high-throughput methods
- However, **domains**, **not proteins**, co-evolve
 - How can we incorporate domain information to enhance performance of phylogeny-based interaction prediction?

Inferring Function from Domain Co-evolution

- Residue-level phylogenetic analysis (Kim, Koyutürk, Topkara, Grama, & Subramaniam, *Bioinformatics*, 2006)
 - No a-priori knowledge about domains
 - Construct residue phylogenetic profiles from local alignment results
 - Construct mutual information matrix
 - High-information contiguous submatrices that are sufficiently large correspond to putative co-evolved domains



Mutual Information Matrix



Single vs. Domain Profile

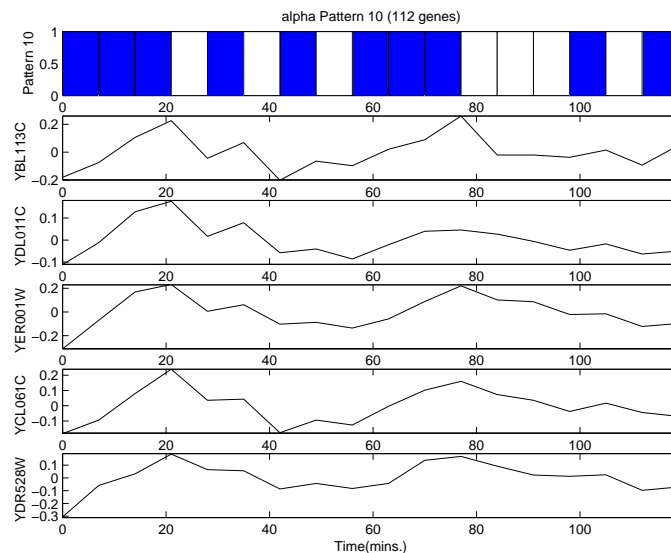
Conclusion

- A lot to learn from comparative network analysis
- We have fast algorithms
- We need
 - Enhanced & more detailed network models
 - High quality & comprehensive data
 - Detailed statistical models

Other Work on Pattern Identification

- PROXIMUS: Non-orthogonal decomposition of binary matrices
(Koyutürk, Grama, Ramakrishnan, *IEEE TKDE*, 2005)
 - Find a compact set of vectors that represent the entire matrix
 - Recursive decomposition through rank-one approximations
 - Fast (linear-time) iterative heuristics for computing approximations
 - Source code available at
<http://www.cs.purdue.edu/homes/pdsl/>

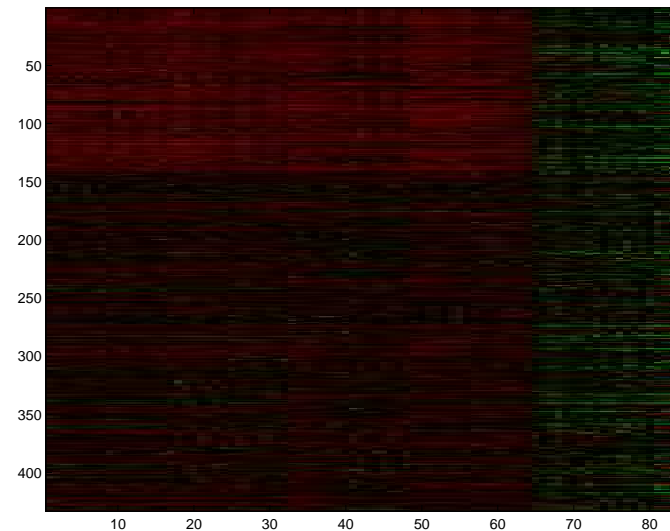
Patterns of regulation



“Algorithms for bounded-error correlation of high dimensional data in microarray experiments”

(Koyutürk, Grama, Szpankowski: *CSB'03*)

Biclustering

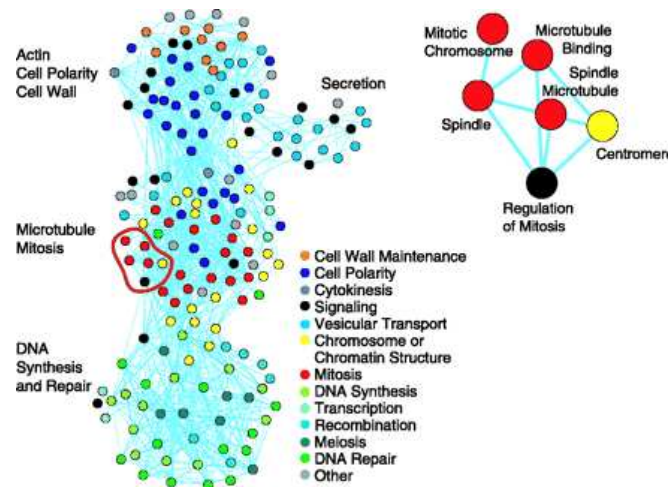


“Biclustering gene-feature matrices for statistically significant dense patterns”

(Koyutürk, Grama, Szpankowski: *CSB'04*.)

Identifying "Canonical" Regulatory Pathways

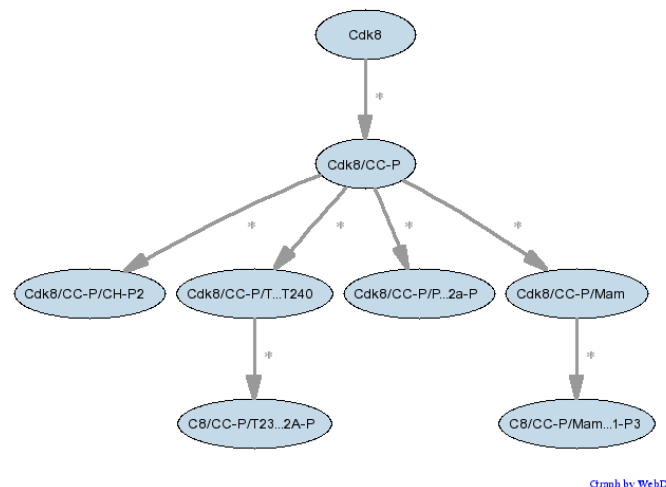
- Can we derive rules in terms of **GO terms**, e.g., $P_i \rightarrow P_j \dashv P_k$?
 - **Statistical challenge**: Such patterns have to be **significantly** abundant
 - **Computational challenge**: When statistical significance is the basis (as opposed to **frequency**), **monotonicity** properties (e.g., downward closure) no longer hold!
 - **Our approach**: **conditional significance**, i.e., evaluate significance of a pattern based on the background constructed by its substructures
- **Final goal**: Database of (computationally derived) canonical modules and pathways



A network of GO terms (Tong et al., *Science*, 2004)

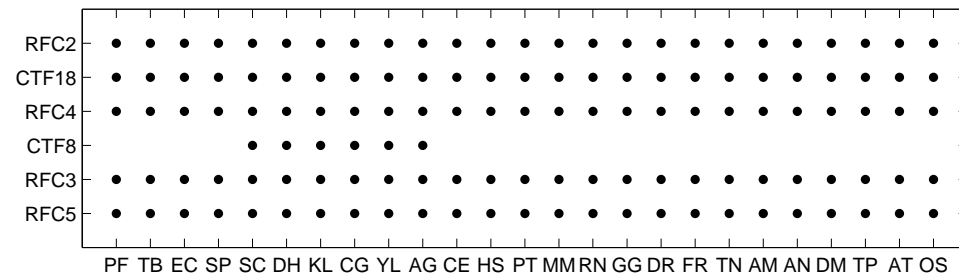
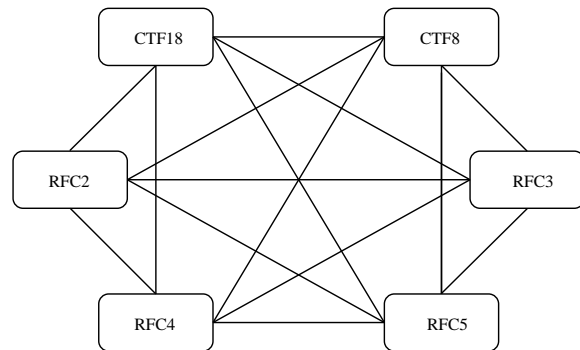
Cell as a State Machine

- **Signaling pathways** can be modeled as a series of **transitions** between **states** of protein or peptide molecules, non-protein molecules, (non-)protein complexes, and modules
 - **Signaling Gateway** provides a database of network states for proteins, a mirror is available to our group via our collaboration with S. Subramaniam
- Constructing signaling pathways from state information for individual molecules
 - **Smallest common supergraph** problem
 - Identification of **specified pathways**



State diagram for Cdk8 protein (from Molecule Pages)

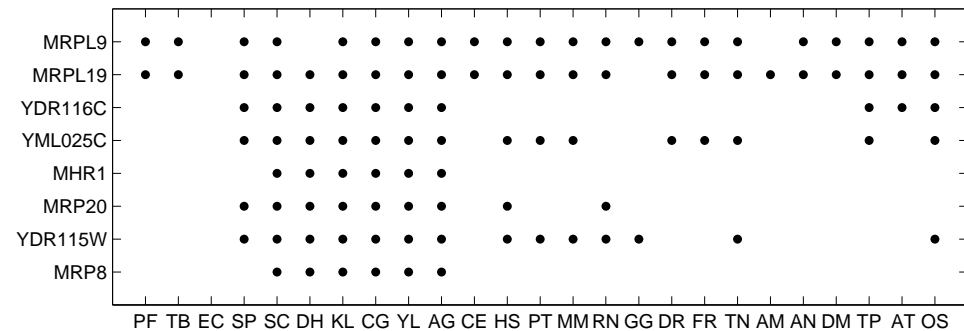
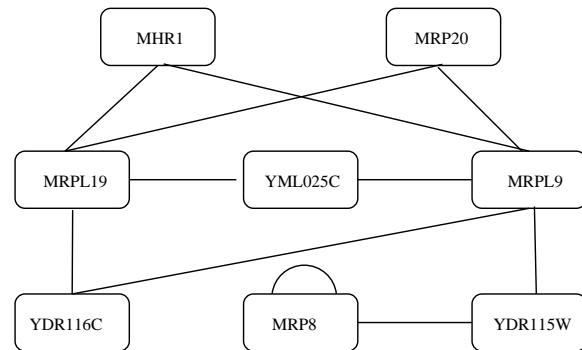
Modular Phylogenetics



Replication Factor C complex identified on yeast PPI network by
 MCODE (Bader & Hogue, *BMC Bioinformatics*, 2003) algorithm
 and the phylogenetic profiles of its proteins on
 25 eukaryotic genomes

Conserved in all eukaryotic species!

Modular Phylogenetics



A component of **mitochondrial ribosome** identified on yeast PPI network by **MCODE** algorithm and the **phylogenetic profiles** of its proteins on 25 eukaryotic genomes

Conserved in only yeast species!

- Models and algorithms for quantifying, analyzing, and evaluating modular conservation and divergence across species