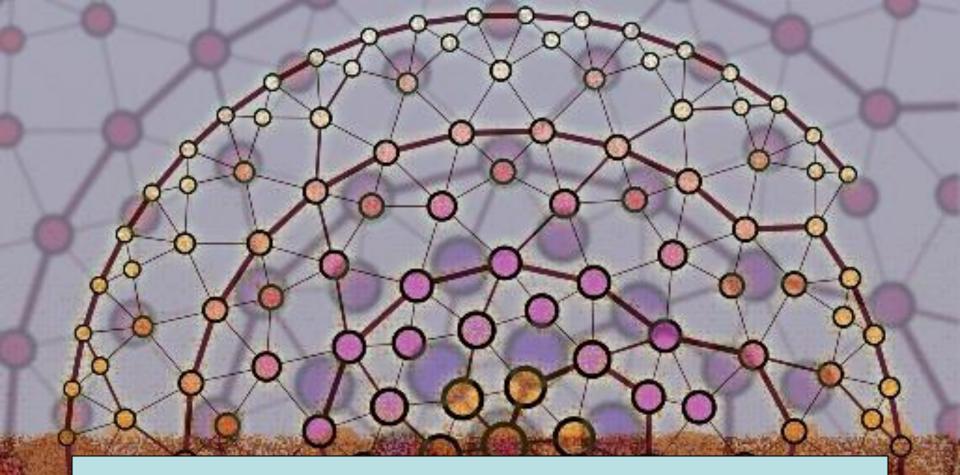
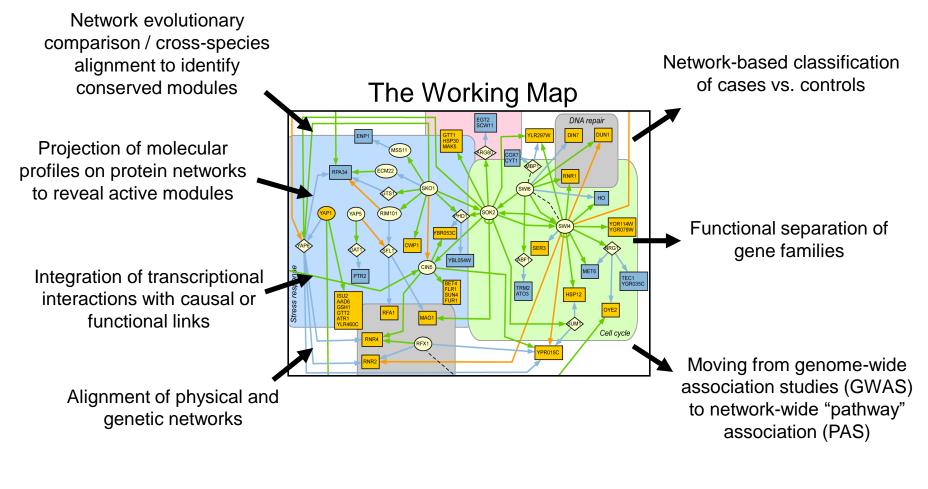
# Microsoft® Research Faculty Summit



## Pathway Association Analysis Trey Ideker UCSD

## A working network map of the cell



**Building networks** 

**Using networks** 

## www.cytoscape.org

#### Shannon et al. *Genome Research* 2003 Cline et al. *Nature Protocols* 2007

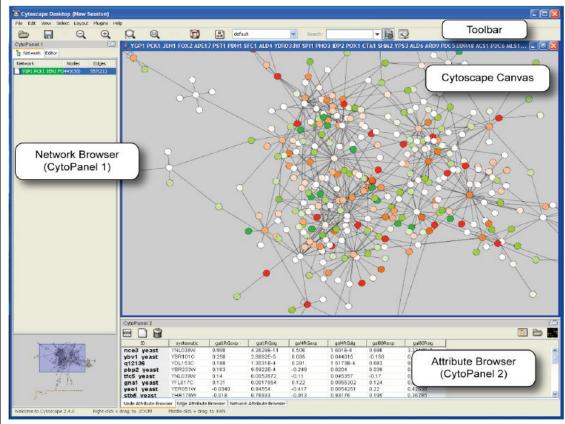
OPEN SOURCE Java platform for integration of systems biology data

- •Layout and query of interaction networks (physical and genetic)
- •Visual and programmatic integration of molecular state data (attributes)

•The ultimate goal is to provide the tools to facilitate all aspects of pathway assembly and annotation.

#### RECENT NEWS

•Version 2.6 released June 2008; Scalability+efficiency now equivalent to best commercial packages



- •The Cytoscape Consortium is a 501(c)3 non-for-profit in the State of California
- •The Cytoscape ® Registered Trademark awarded

JOINTLY CODED with Agilent, ISB, UMich, Pasteur, Sloan-Ketter., UCSF, Unilever, Toronto

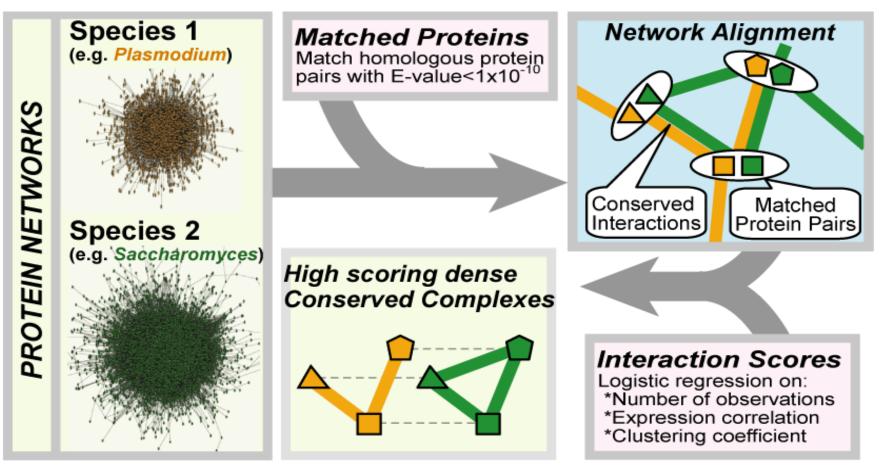
## Comparison of biological networks

## (Silpa Suthram with Roded Sharan, Richard Karp, and others)



## **Cross-comparison of networks:**

(1) Conserved regions in the presence vs. absence of stimulus(2) Conserved regions across different species

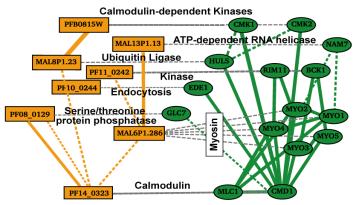


Kelley et al. *PNAS* 2003 Ideker & Sharan *Gen Res* 2008

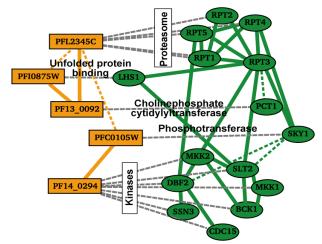
Suthram et al. *Nature* 2005 Sharan & Ideker *Nat. Biotech.* 2006 Sharan et al. RECOMB 2004 Scott et al. RECOMB 2005

## Plasmodium: a network apart?

#### [a] Endocytosis

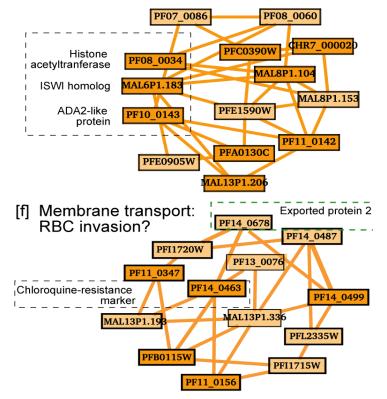


#### [b] Unfolded protein response



Conserved *Plasmodium /* Saccharomyces protein complexes

#### [e] Chromatin remodeling



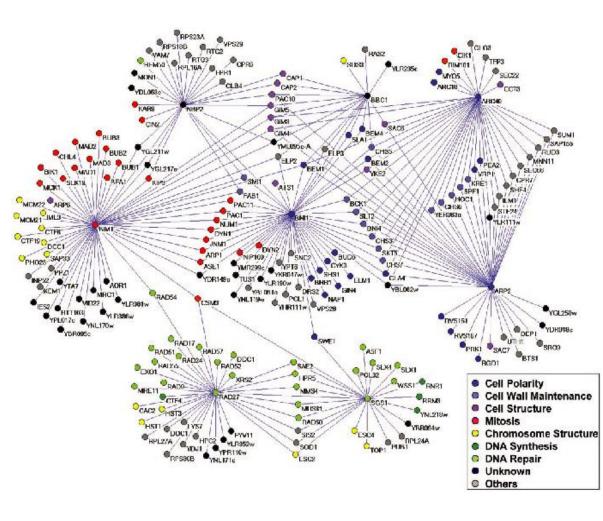
*Plasmodium*-specific protein complexes

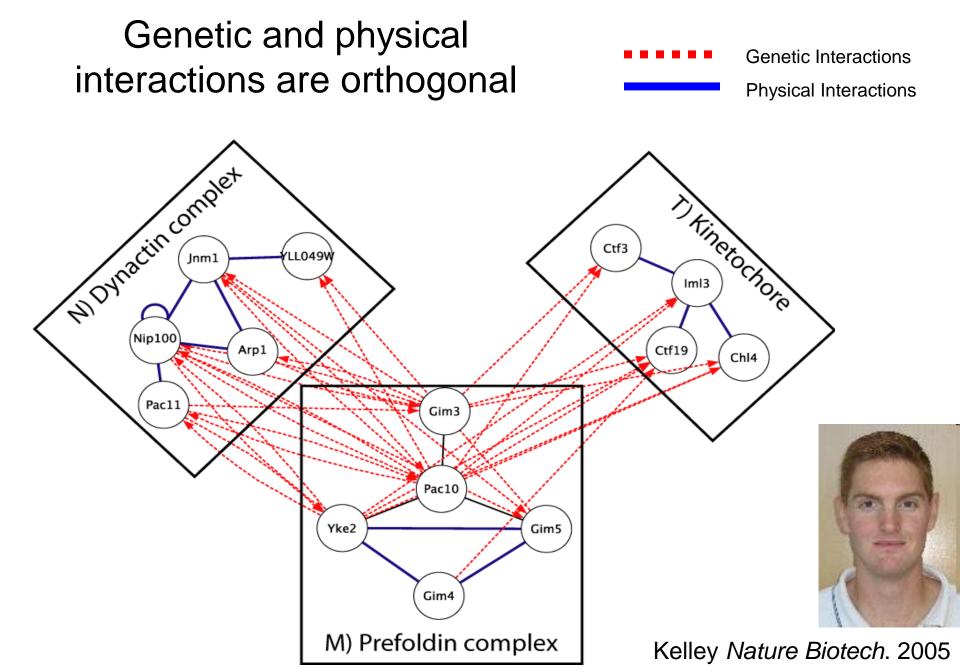
Suthram et al. *Nature* 2005 La Count et al. *Nature* 2005

### Synthetic lethals and epistatic interactions in model species

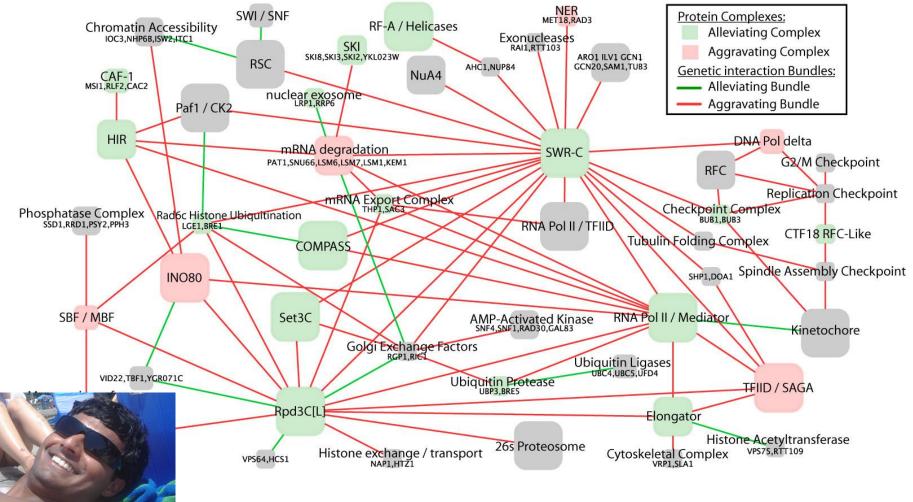
### **Genetic Interactions:**

- Classical method used to map pathways in model species
- Highly analogous to multi-genic interaction in human disease and combination therapy
- Thousands are being uncovered through systematic studies





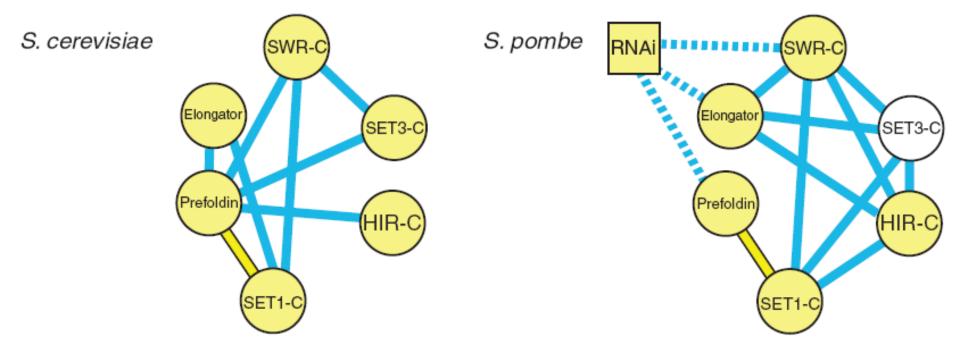
# Functional maps of protein complexes



#### Bandyopadhyay et al. PLoS Comp Bio 2008

Comparison of genetic interaction networks across budding and fission yeasts

Positive Genetic Interactions Negative Genetic Interactions



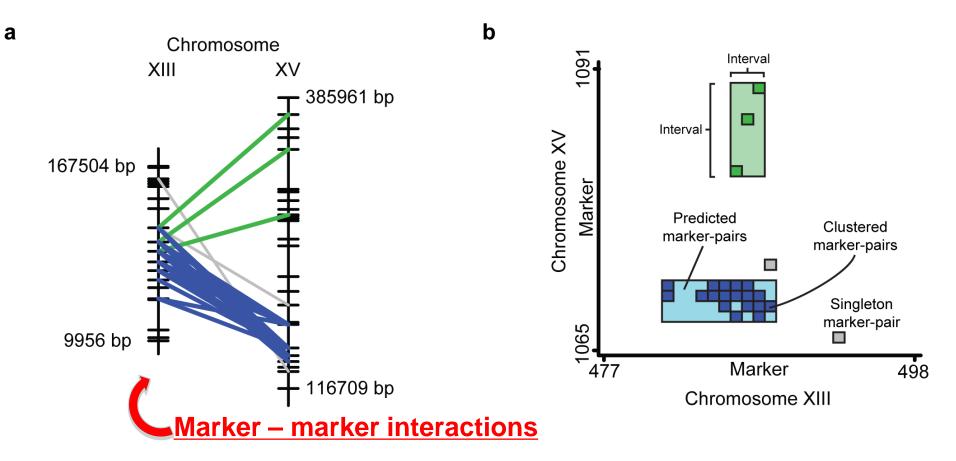


Assen Roguev, Sourav Bandyopadhyay, Nevan Krogan

Roguev et al. Science 322: 405 (2008)

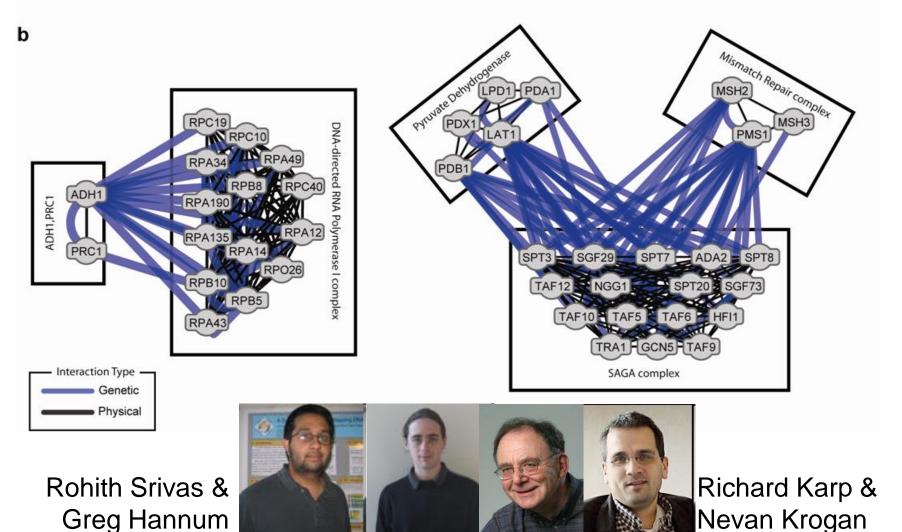
# Network-based approaches to identify genetic interactions in gene association studies

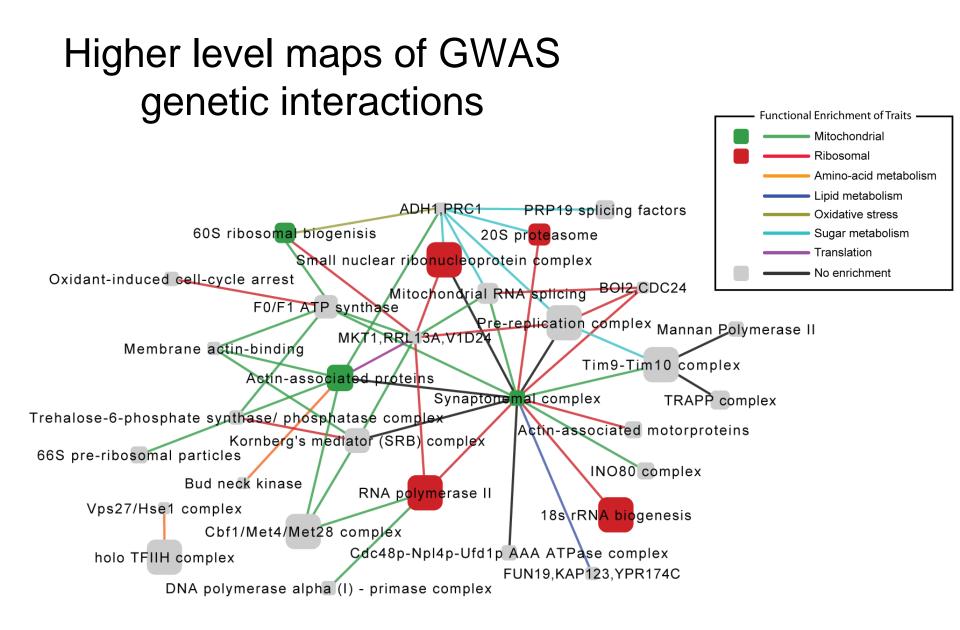
## Genetic interactions occur frequently in Genome Wide Association Studies (GWAS)



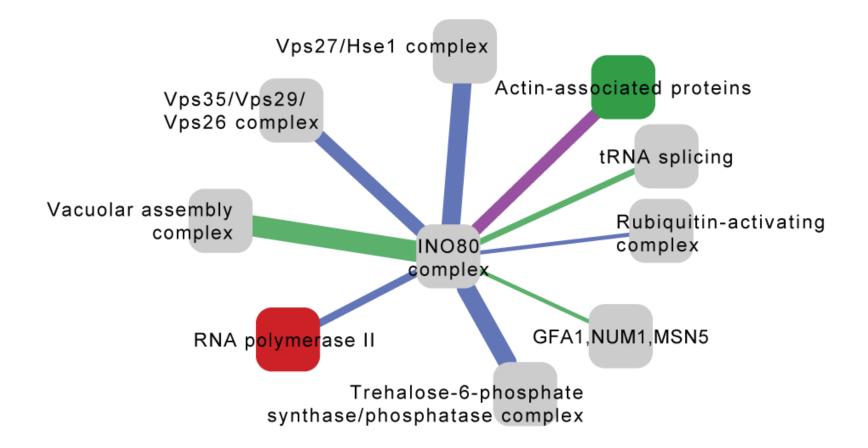
But they are impossible to find. Marker-marker interactions are very difficult to identify in GWAS data due to lack of statistical power.

# GWAS genetic interactions also run between physical networks and pathways





# GWAS interactions can be verified by inducing epistasis using classical genetics



Sponsors NIGMS NIEHS NIMH NSF Packard Foundation Agilent Unilever Pfizer

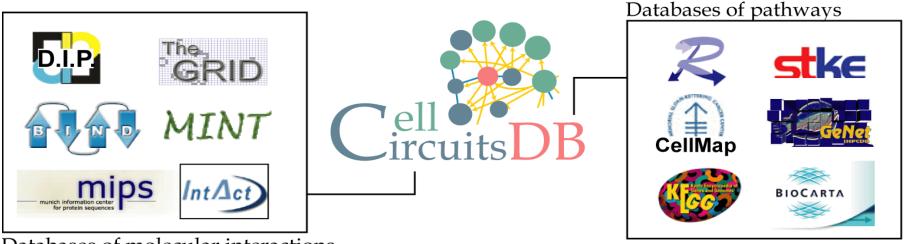
<u>**Collaborators**</u> (UCSD) Richard Kolodner Tom Kipps David Perkins Steve Briggs Lorraine Pillus Jean Wang

<u>**Collaborators**</u> (external) Nevan Krogan (UCSF) Richard Karp (UC Berkeley) Roded Sharan (Tel Aviv) Bas van Steensel (NKI) Sumit Chanda (Burnham) Howard Fox (Scripps) Curt Wittenberg (Scripps) Russ Finley (Wayne State) Doheon Lee (KAIST) Gary Bader (U Toronto) The Cytoscape Team





# http://CellCircuits.org



Databases of molecular interactions

Increasing certainty and biological relevance

# Network modules and modulebased classification

## Querying biological networks for "Active Modules"

#### Color network nodes (genes/proteins) with:

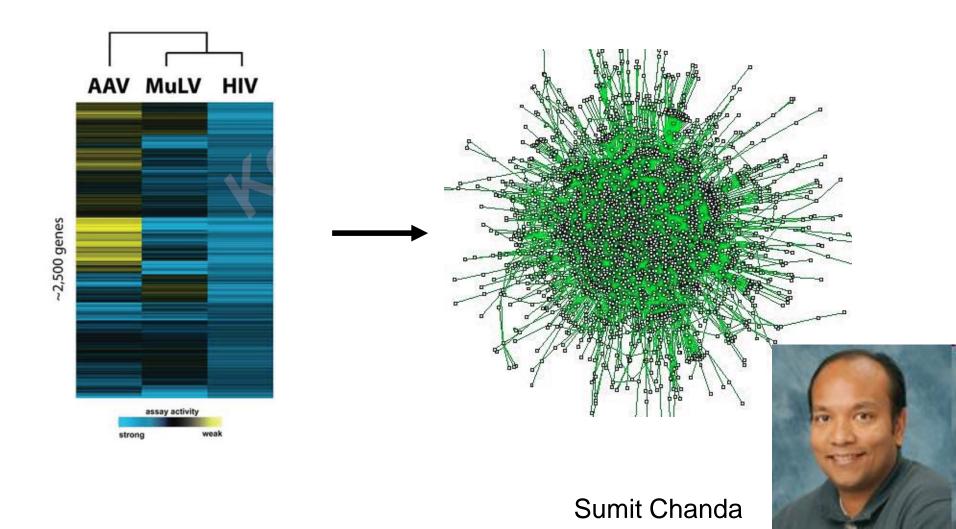
Patient expression profile Protein states Patient genotype (SNP state) Enzyme activity RNAi phenotype

Interaction Database Dump, aka "Hairball"

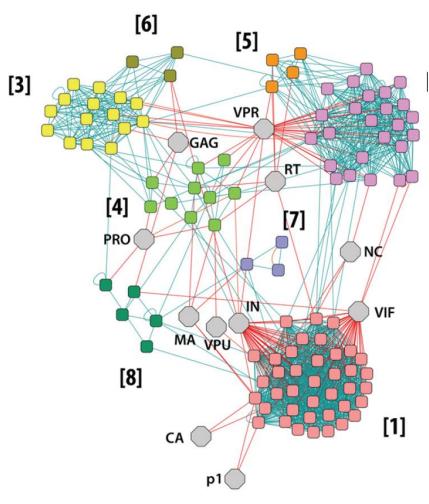


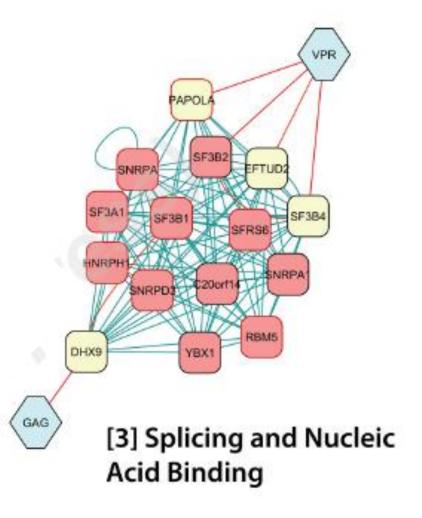
### Ideker et al. *Bioinformatics* (2002)

# Projection of RNAi phenotypes onto a network of human-human & human-HIV protein interactions



## Network modules associated with infection





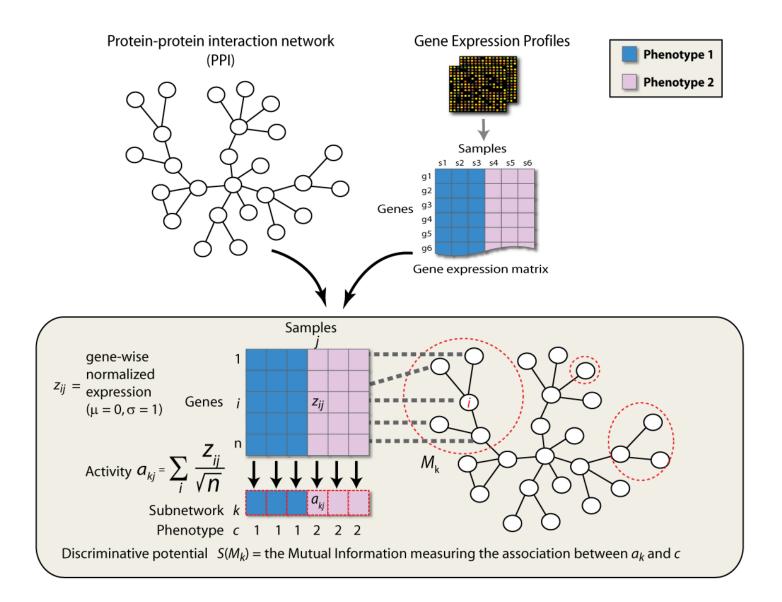
Konig et al. Cell. 2008

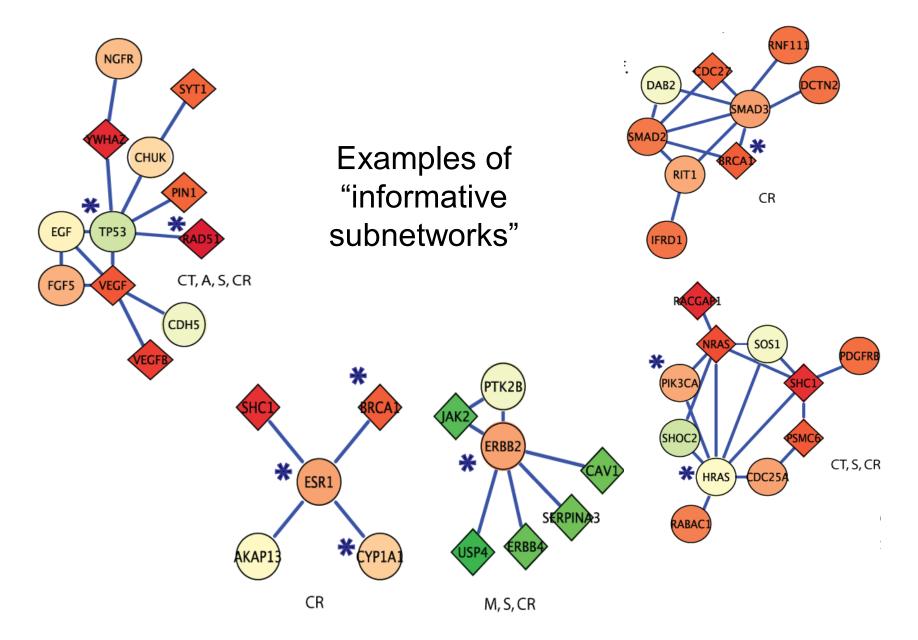
# Using protein networks for diagnostics / classification

Han Yu Chuang with Tom Kipps and Steve Briggs (UCSD) Eunjung Lee & Doheon Lee (KAIST)



### Protein network diagnosis of breast cancer metastasis





Chuang et al. Molecular Systems Biology 2007

## LETTERS

#### nature biotechnology

#### February 2009

# Dynamic modularity in protein interaction networks predicts breast cancer outcome

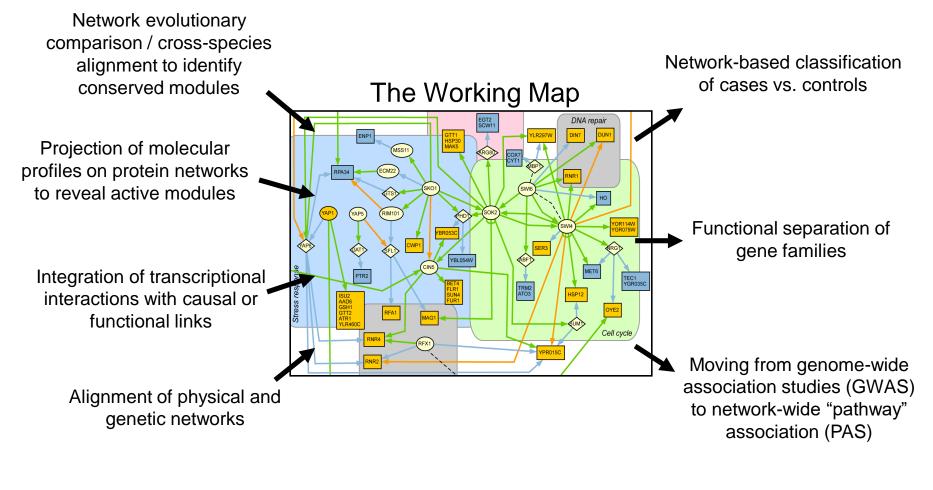
Ian W Taylor<sup>1,2</sup>, Rune Linding<sup>1,3</sup>, David Warde-Farley<sup>4,5</sup>, Yongmei Liu<sup>1</sup>, Catia Pesquita<sup>6</sup>, Daniel Faria<sup>6</sup>, Shelley Bull<sup>1,7</sup>, Tony Pawson<sup>1,2</sup>, Quaid Morris<sup>4,5</sup> & Jeffrey L Wrana<sup>1,2</sup>

Changes in the biochemical wiring of oncogenic cells drives phenotypic transformations that directly affect disease outcome. Here we examine the dynamic structure of the human protein interaction network (interactome) to determine whether changes in the organization of the interactome can be used to predict patient outcome. An analysis of hub proteins identified intermodular hub proteins that are co-expressed with their interacting partners in a tissue-restricted manner and intramodular hub proteins that are co-expressed with their interacting partners in all or most tissues. Substantial differences in biochemical structure were observed between the two types of hubs. Signaling domains were found more often in intermodular hub proteins, which were also more frequently associated with oncogenesis. Analysis of two breast cancer patient cohorts revealed that altered modularity of the human interactome may be useful as an indicator of breast cancer prognosis.

of hubs centered over increasing average PCC values (Fig. 1a, red asterisks). Randomly reassigning the expression data to different gene products in the same network resulted in an approximately normal distribution of PCC values (Fig. 1a, black dashed line). The shoulder (marked with a black asterisk) is largely due to strongly correlated gene products that have a high probability of reforming interactions with their true interactors when randomized (data not shown). We observed a similar multi-modal distribution using a literature-curated source alone<sup>4</sup> (Supplementary Fig. 1b) or a different high-confidence human PPI database<sup>5</sup> (Supplementary Fig. 1c).

The human interactome thus has two classes of hubs. One class displays low correlation of co-expression with its partners. We call these hubs intermodular hubs, as first proposed for the yeast interactome<sup>6,7</sup>. A second class, termed intramodular hubs, displays more highly correlated patterns of co-expression (Fig. 1a). These features reflect a modular architecture. Restricting the analysis to interactions

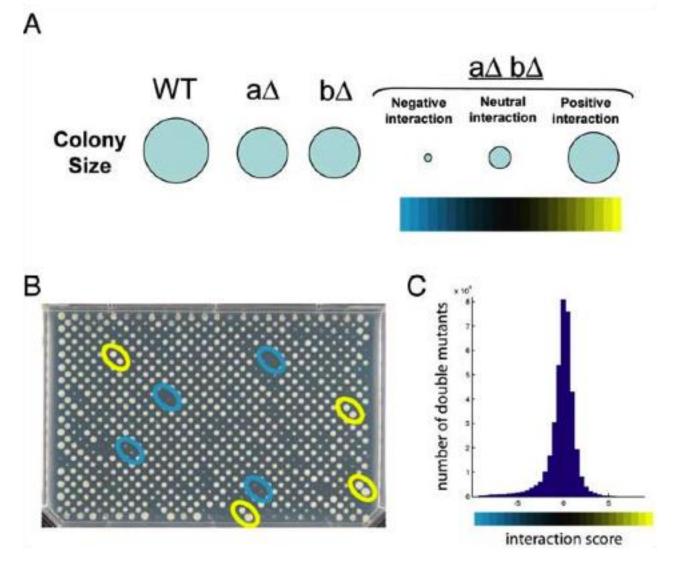
## Assembling a working network map

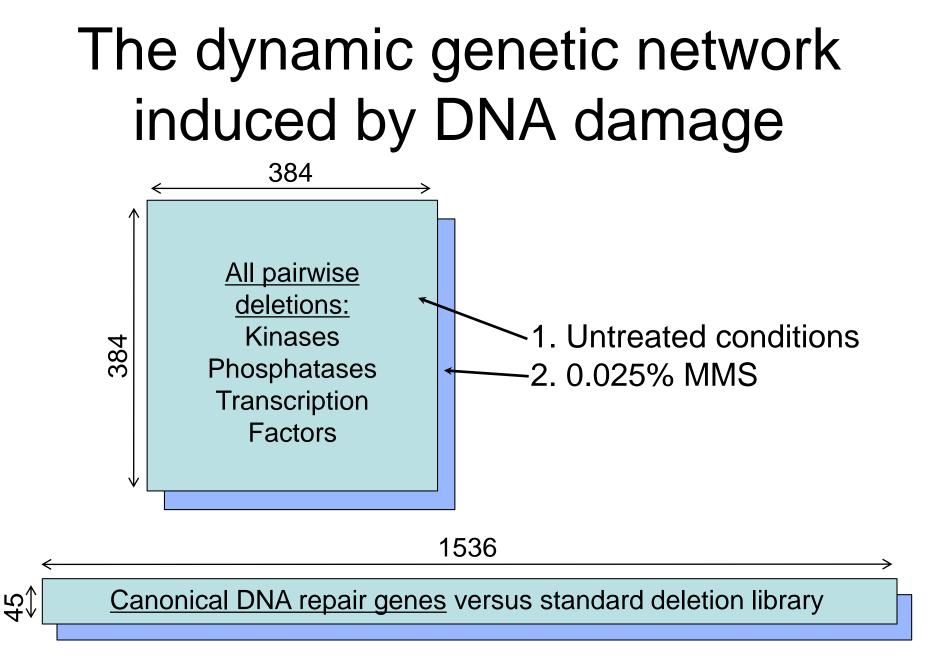


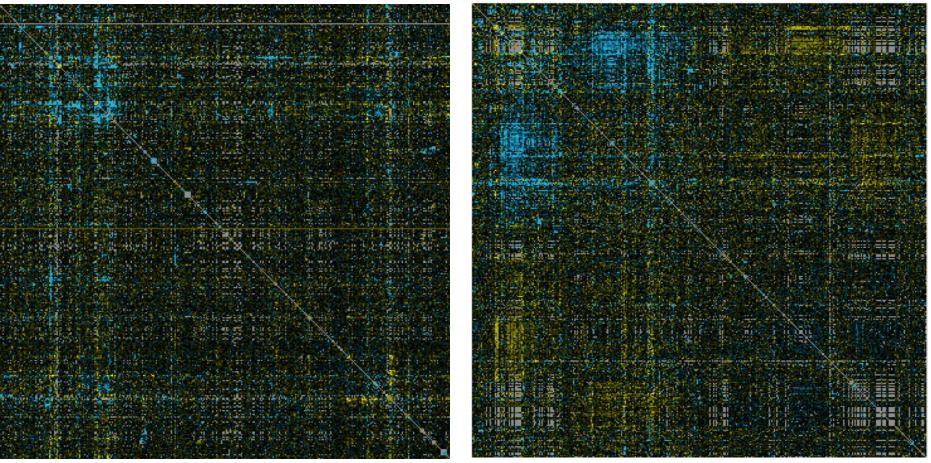
**Building networks** 

**Using networks** 

# Measuring genetic interactions



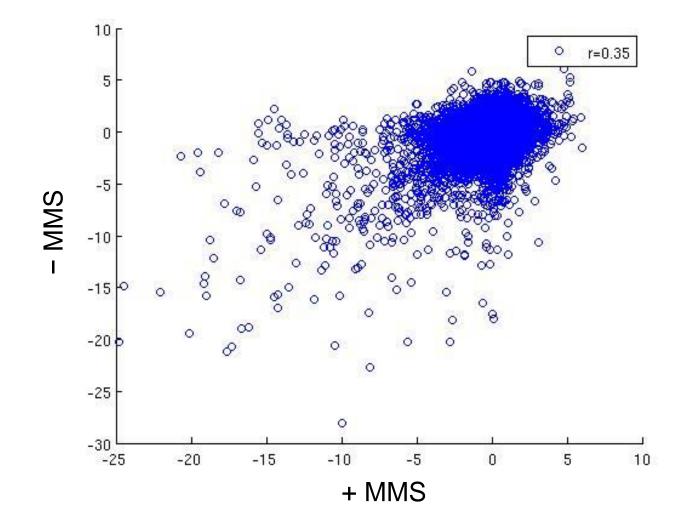




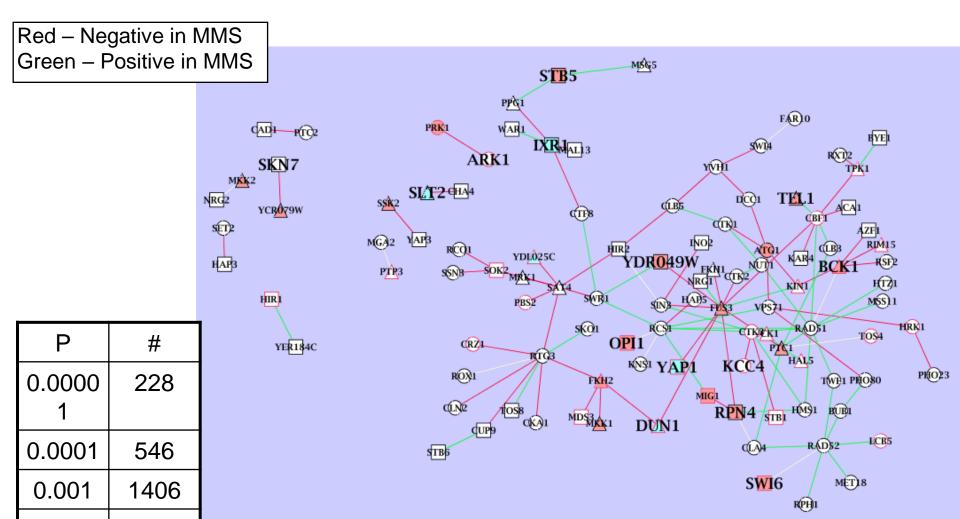
- MMS

+ MMS

# How in the world should we process these data ????



# One answer: Develop statistics to identify only the differences



## Known targets of TEL1 / ATM

	Genetic Interaction Score −MMS ⇒ +MMS	Pearson Correlation −MMS ⇒ +MMS
DUN1		-0.03 ⇒ 0.4 ***
CBF1	-2.8 ⇒ 1.05 ***	0.03 ⇒ 0.31 **
SOK2		0.05 ⇒ 0.12
SUM1		0.03 ⇒ 0.20 *
*** < 0.00001, ** < 0.001, * < 0.05		