Bioinformatics 3

V7 – Function Annotation, Gene Regulation

Mon., Nov 5, 2012

Network Meta-Growth

Q: When I find a new protein and its (already known) partners in an experiment and I add that to a database, do I get a scale-free network?

Which proteins are in databases??? <=> the experimentally accessibly ones!!!

- \rightarrow costs for the experiment
- \rightarrow experience required for purification, methods, analysis...
- \rightarrow existing assays for similar proteins
- \rightarrow personal interests

(to get funding: preference for {cancer, HIV, Alzheimer...})

Higher probability to find proteins related to known ones

<=> growing network with preferential attachment

What Does a Protein Do?

The Comprehensive Enzyme Information System	TU Braunschweig Dept. of Bioinformatics
EC Explorer [SEARCH][BROWSE]	
 1 Oxidoreductases (4042 organisms) \$ 2 Transferases (3198 organisms) \$ 2.1 Transferring one-carbon groups (615 organisms) \$ 2.1.1 Methyltransferases (514 organisms) \$ 2.1.2 Hydroxymethyl-, formyl- and related transferases (82 organisms) \$ 2.1.3 Carboxy- and carbamoyltransferases (105 organisms) \$ 2.1.4 Amidinotransferases (32 organisms) \$ 2.1.4 Amidinotransferases (17 organisms) \$ 2.1.4.2 scyllo-inosamine-4-phosphate amidinotransferase (15 organisms) \$ 2.2 Transferring aldehyde or ketonic groups (91 organisms) \$ 2.3 Acyltransferases (925 organisms) \$ 2.4 Glycosyltransferases (925 organisms) \$ 2.5 Transferring alkyl or aryl groups, other than methyl groups (547 organisms) \$ 2.6 Transferring nitrogenous groups (377 organisms) \$ 2.7 Transferring sulfur-containing groups (1343 organisms) \$ 2.8 Transferring sulfur-containing groups (276 organisms) \$ 3 Hydrolases (4453 organisms) \$ 5 Isomerases (849 organisms) \$ 6 Ligases (686 organisms) \$ 	sms) 3 💽 🔗

Enzyme Classification scheme (from <u>http://www.brenda-</u> <u>enzymes.org</u>/)

MIPS FunCat

MIPS Functional Catalogue 001 METABOLISM ■ 002 ENERGY 004 STORAGE PROTEIN ■ **1**0 CELL CYCLE AND DNA PROCESSING **11 TRANSCRIPTION 12 PROTEIN SYNTHESIS** 14 PROTEIN FATE (folding, modification, destination) **16 PROTEIN WITH BINDING FUNCTION OR COFACTOR REQUIREMENT** (structural or catalytic) **18 W**18 REGULATION OF METABOLISM AND PROTEIN FUNCTION **1 0** 20 CELLULAR TRANSPORT, TRANSPORT FACILITIES AND TRANSPORT ROUTES **10030 CELLULAR COMMUNICATION/SIGNAL TRANSDUCTION MECHANISM 1 3 3 3 3 3 3 3 3 4 3 4 3 3 3 4 5 5 4 5 5 4 5 5 5 5 5 5 1 3**4 INTERACTION WITH THE ENVIRONMENT **W**38 TRANSPOSABLE ELEMENTS, VIRAL AND PLASMID PROTEINS 040 CELL FATE 043 CELL TYPE DIFFERENTIATION **0**45 TISSUE DIFFERENTIATION 047 ORGAN DIFFERENTIATION **0**70 SUBCELLULAR LOCALIZATION **1 0**73 CELL TYPE LOCALIZATION **075 TISSUE LOCALIZATION 077 ORGAN LOCALIZATION 0**98 CLASSIFICATION NOT YET CLEAR-CUT **0**99 UNCLASSIFIED PROTEINS

Classification Browser from http://mips.gsf.de/projects/funcat

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Digging Deeper



Details and Proteins

01 METABOLISM [Eukaryota Bacteria Archaea]

01.06 lipid, fatty acid and isoprenoid metabolism [Eukaryota Bacteria Archaea]

01.06.02 membrane lipid metabolism [Eukaryota Bacteria Archaea]

01.06.02.01 phospholipid metabolism [Eukaryota Bacteria Archaea]

DETAILED RESULTS:

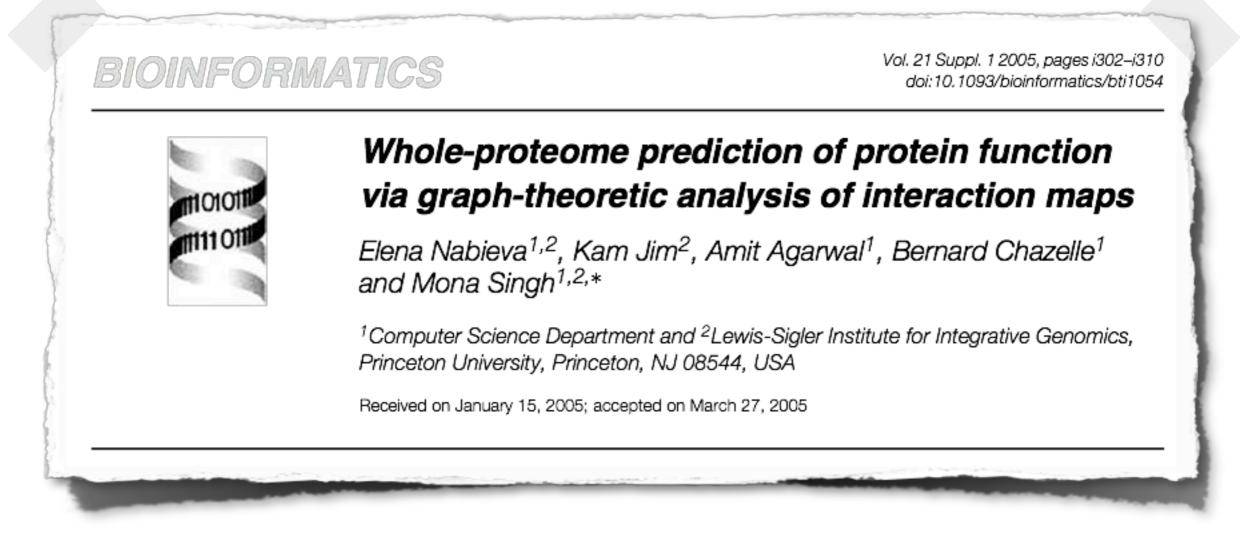
Number:	01.06.02.01
Description:	phospholipid metabolism
Explanation	-
EC number:	-
Taxonomy:	[Eukaryota Bacteria Archaea]
Reference Link:	-
Reference PMID:	-
Funlink:	-
GO mapping:	<u>GO:0008654</u>

Manually Annotated Proteins:

Organism	Proteins
Helicobacter pylori KE26695	<u>HP0190; HP0700; HP0215; HP0737; HP1071;</u> <u>HP0961; HP0871; HP1016; HP0201; Co-annotated-FunCats</u>
Saccharomyces cerevisiae	
Neurospora crassa	
Listeria monocytogenes EGD	<u>gi 16411389; gi 16410893; gi 16411991; gi 16409732; gi 16410732;</u> <u>gi 16410825; gi 16409367; gi 16411263;</u> <i>Co-annotated-FunCats</i>

http://mips.gsf.de/projects/funcat

Un-Classified Proteins?



Many unclassified proteins:

 \rightarrow estimate: ~1/3 of the yeast proteome not annotated functionally

 \rightarrow BioGRID: 4495 proteins in the largest cluster of the yeast physical interaction map.

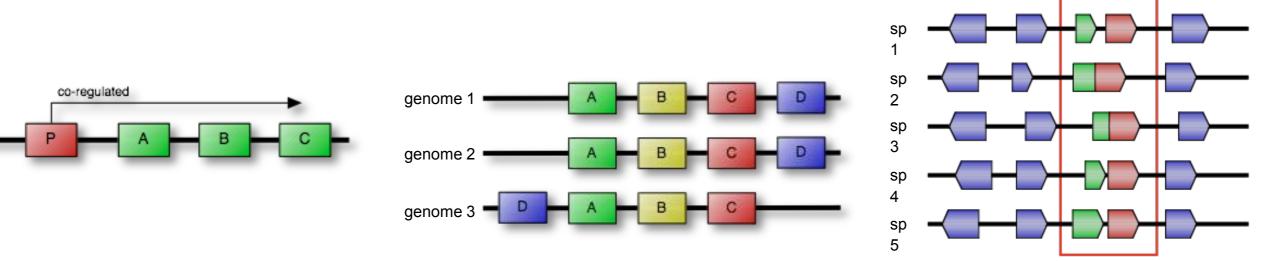
2946 have a MIPS functional annotation

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Partition the Graph

Large **PPI networks** were built from:

- HT experiments (Y2H, TAP, synthetic lethality, coexpression, coregulation, ...)
- predictions (gene profiling, gene neighborhood, phylogenetic profiles, ...)
- \rightarrow proteins that are functionally linked

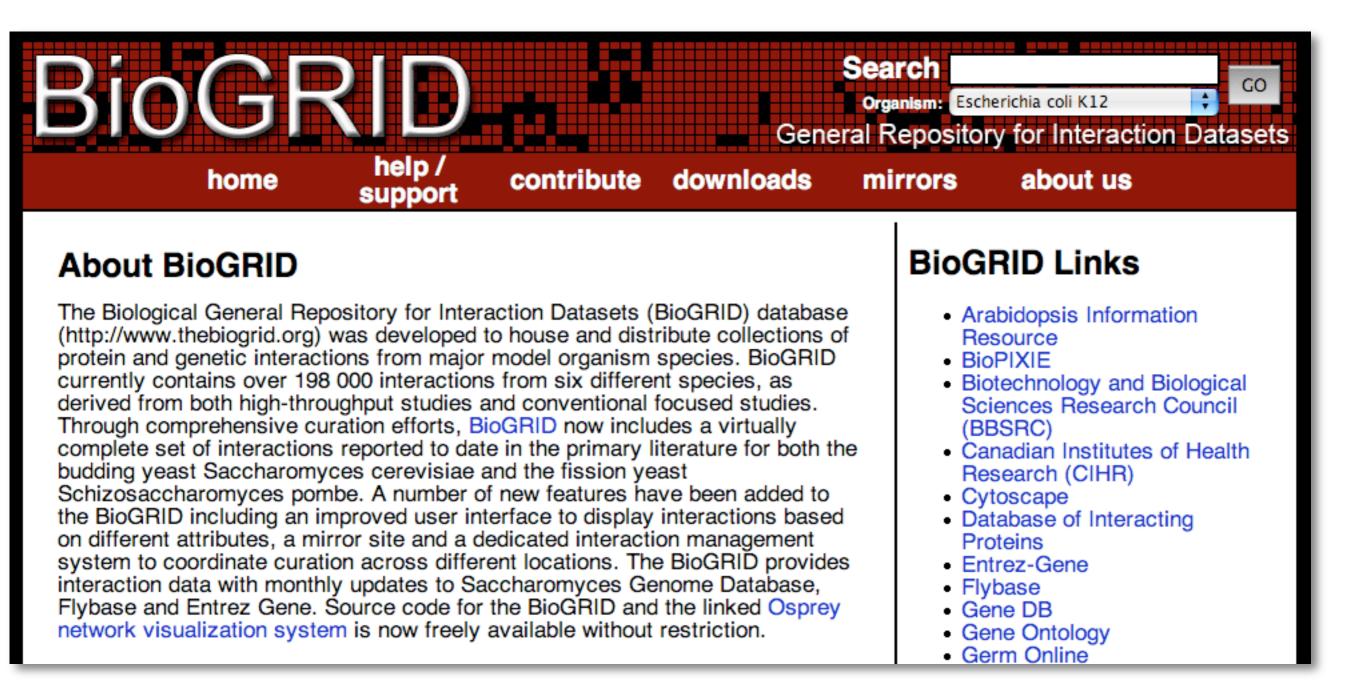


Identify unknown functions from clustering of these networks by, e.g.:

- shared interactions (similar neighborhood \rightarrow power graphs)
- membership in a community
- similarity of shortest path vectors to all other proteins (= similar path into the rest of the network)

Protein Interactions

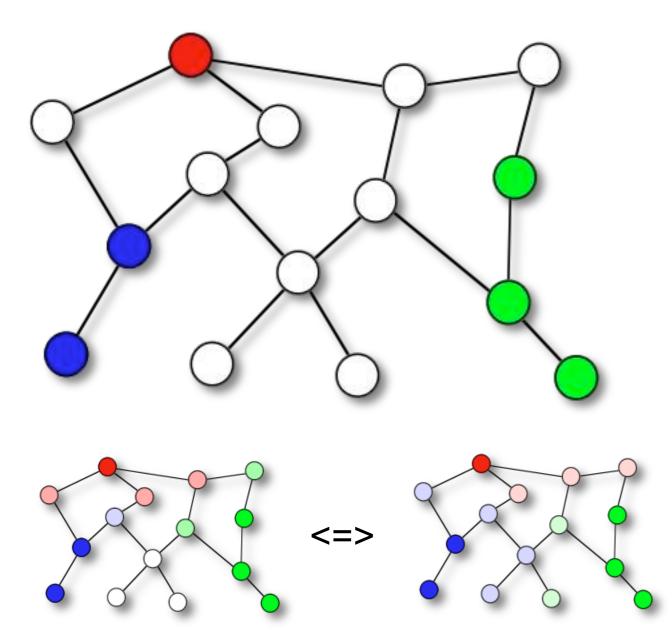
Nabieva et al used the *S. cerevisiae* dataset from GRID of 2005 (now BioGRID) \rightarrow 4495 proteins and 12 531 physical interactions in the largest cluster



http://www.thebiogrid.org/about.php

Function Annotation

Task: **predict** function (= functional annotation) for a protein from the **available** annotations



Similar:

How to **assign colors** to the white nodes?

Use information on:

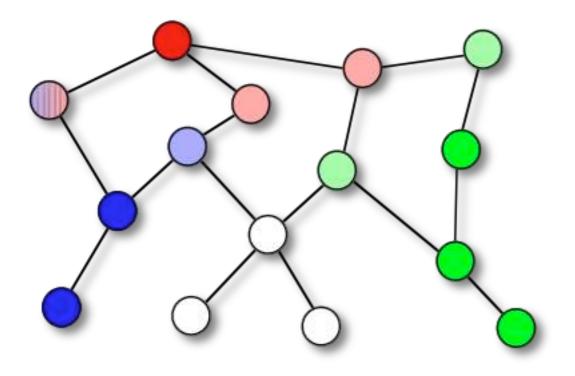
- distance to colored nodes
- local connectivity
- reliability of the links

• ...

Algorithm I: Majority

Schwikowski, Uetz, and Fields, "A network of protein–protein interactions in yeast" *Nat. Biotechnol.* **18** (2000) 1257

Consider all neighbors and **sum** up how often a certain **annotation occurs** \rightarrow score for an annotation = count among the direct neighbors \rightarrow take the 3 most frequent functions



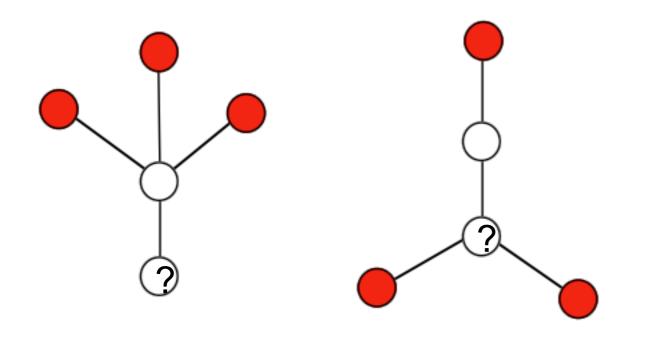
Majority makes only limited
 use of the local connectivity
 → cannot assign function to
 next-neighbors

For weighted graphs: \rightarrow weighted sum

Extended Majority: Neighborhood

Hishigaki, Nakai, Ono, Tanigami, and Takagi, "Assessment of prediction accuracy of protein function from protein–protein interaction data", *Yeast* **18** (2001) 523

Look for **overrepresented** functions within a given **radius** of 1, 2, or 3 links \rightarrow use as function score the value of a χ^2 -test



Neighborhood does not consider local network topology

Both examples are treated **identical** with r = 2

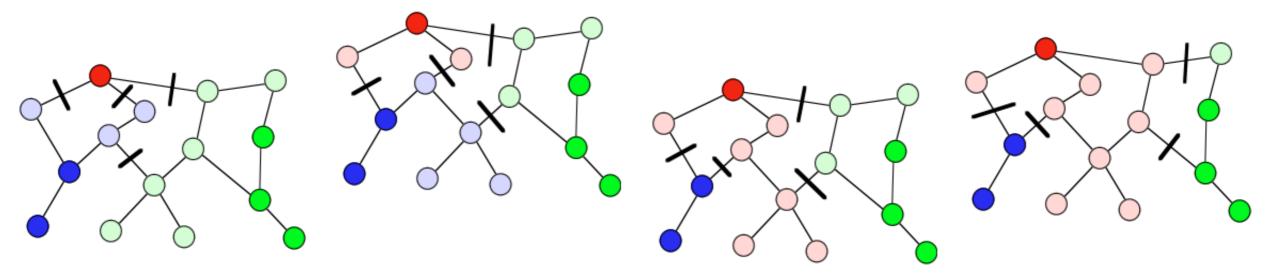
Neighborhood can not (easily) be generalized to weighted graphs!

Minimize Changes: GenMultiCut

Karaoz, Murali, Letovsky, Zheng, Ding, Cantor, and Kasif, "Whole-genome annotation by using evidence integration in functional-linkage networks" PNAS **101** (2004) 2888

"Annotate proteins so as to **minimize** the number of times that **different** functions are associated with **neighboring** proteins"

 \rightarrow generalization of the multiway *k*-cut problem for weighted edges, can be stated as an integer linear program (ILP)



Multiple possible solutions \rightarrow scores from **frequency** of annotations

Nabieva et al: FunctionalFlow

Extend the idea of "guilty by association"

 \rightarrow each annotated protein is a source of "function"-flow

- \rightarrow simulate for a few time steps
 - \rightarrow choose the annotation with the highest accumulated flow

Each node *u* has a reservoir $R_t(u)$, each edge a capacity constraint (weight) $w_{u,v}$

Initially: $R_0^a(u) = \begin{cases} \infty, & \text{if } u \text{ is annotated with } a, \\ 0, & \text{otherwise.} \end{cases}$ and $g_0^a(u,v) = 0$

Then: downhill flow with capacity contraints

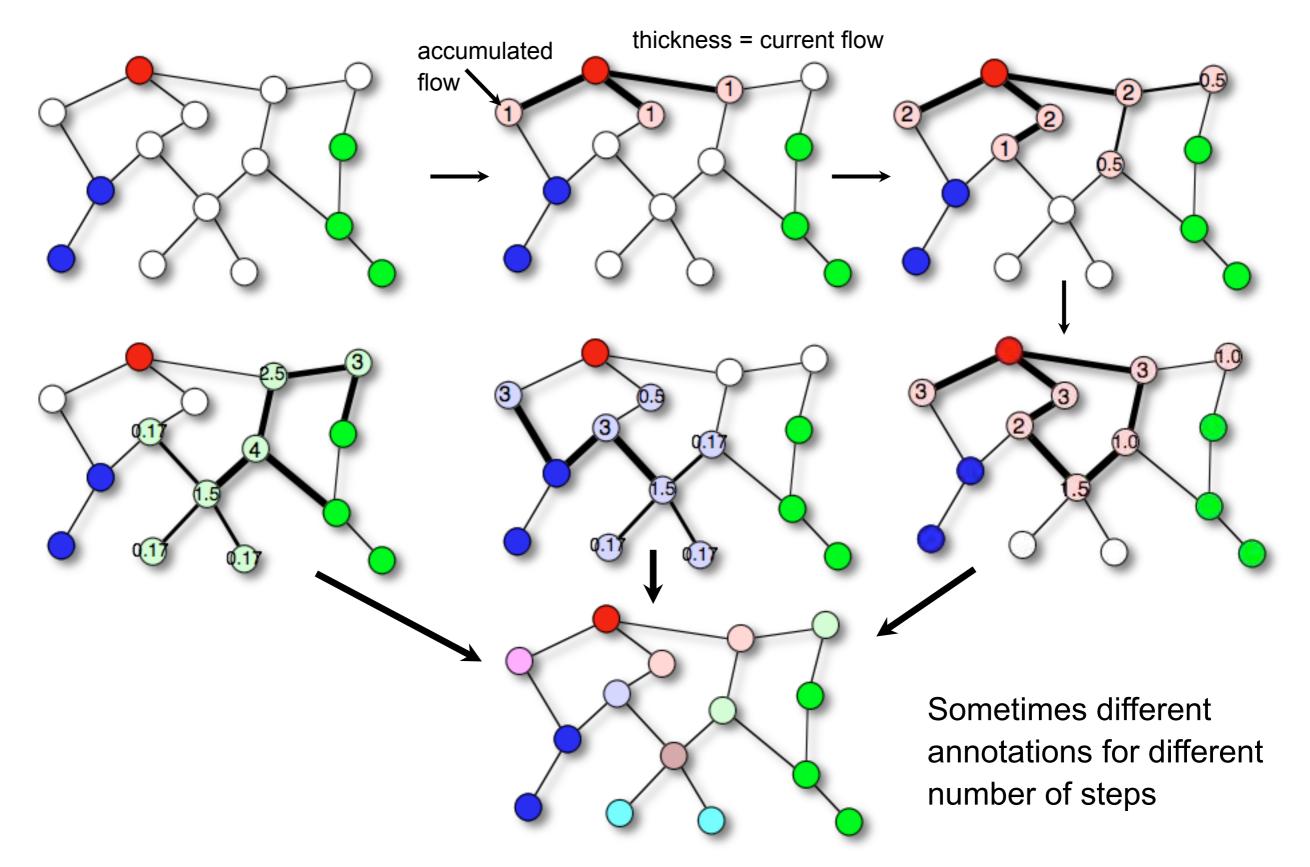
 $g_t^a(u,v) = \begin{cases} 0, & \text{if } R_{t-1}^a(u) < R_{t-1}^a(v) \\ \min\left(w_{u,v}, \frac{w_{u,v}}{\sum_{(u,y) \in E} w_{u,y}}\right), & \text{otherwise.} \end{cases}$

Score from accumulated in-flow: $f_a(u) = \sum_{t=1}^d \sum_{v:(u,v)\in E} g_t^a(v,u)$

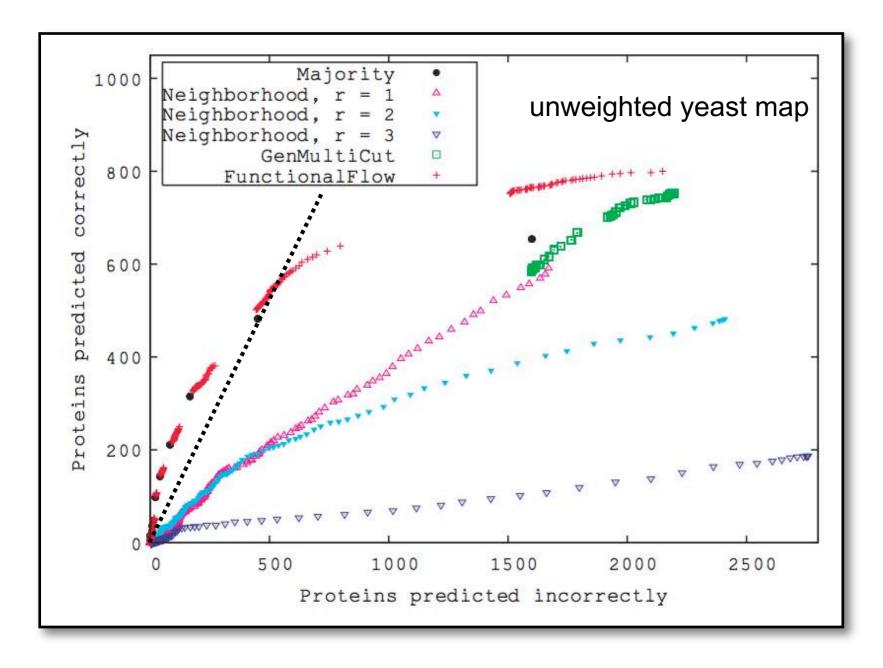
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An Example



Comparison



For FunctionalFlow: six propagation steps (diameter of the yeast network \approx 12)

Change score threshold for accepting annotations \rightarrow ratio TP/FP

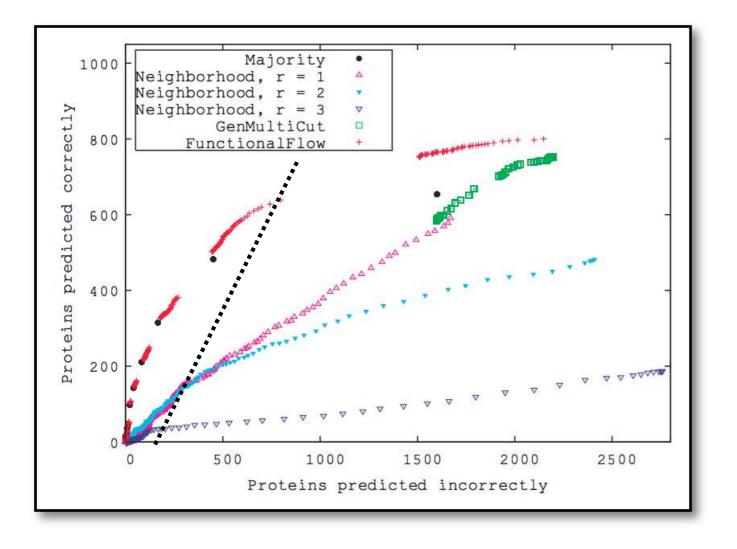
→ FunctionalFlow performs best in the high-confidence region

 \rightarrow many false predictions!!!

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Nabieva et al, Bioinformatics 21 (2005) i302

Comparison Details

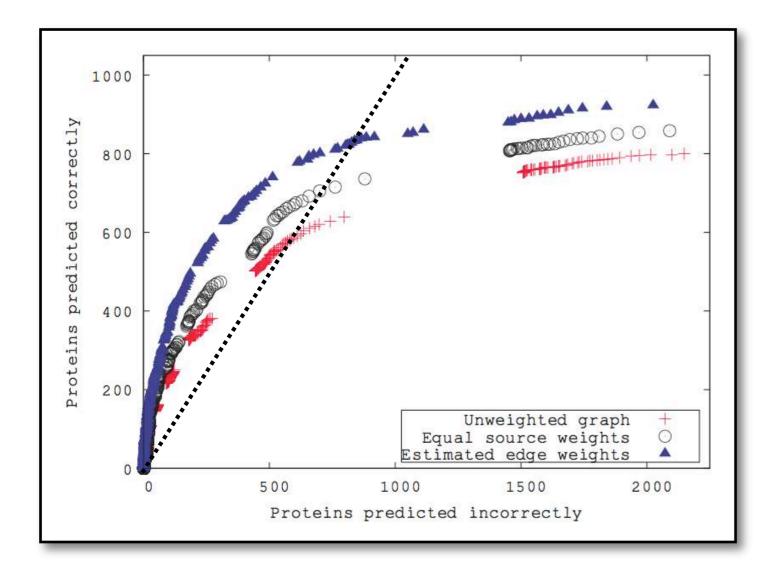


Multiple runs (solutions) of FunctionalFlow (with slight random perturbations of the weights) → increases prediction accuracy Majority vs. Neighborhood @ *r* = 1 → counting neighboring annotations is more effective than χ²-test

Neighborhood with r = 1 or 2 comparable to FunctionalFlow for high-confidence region, performance decreases with increasing $r \rightarrow bad$ idea to **ignore** local connectivity

Weighted Graphs

Performance of FunctionalFlow with differently weighted data:



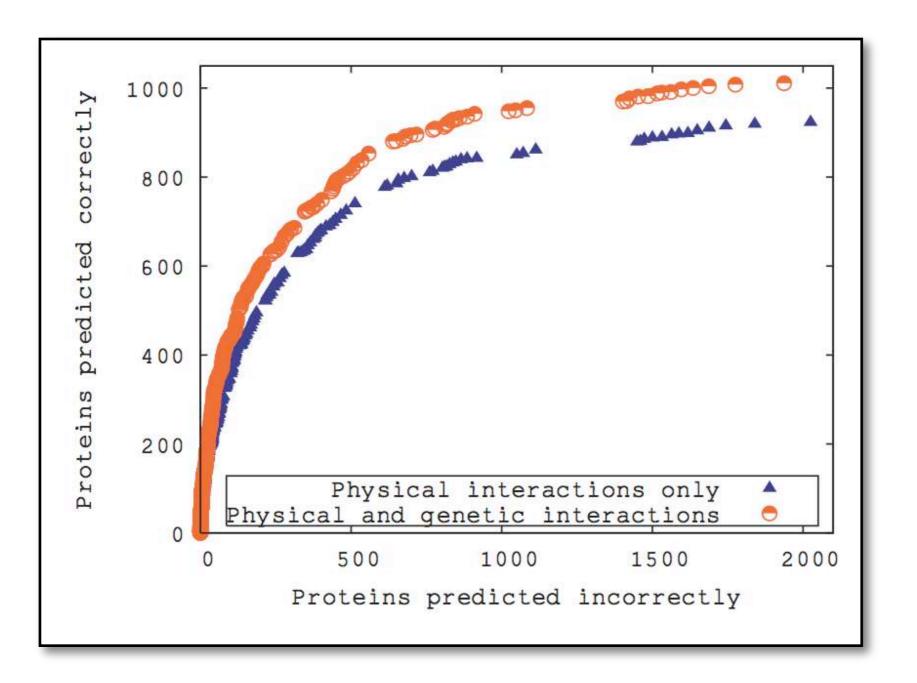
Compare:

- unweighted
- weight 0.5 per experiment
- weight for experiments according to (estimated) reliability

Largest improvement

→ individual experimental reliabilities

Additional Information



(Note the clever choice of symbols in the plot...)

Use **genetic linkage** to modify the edge **weights** → better performance (also for Majority and GenMultiCut)

Summary: Static PPI-Networks

"Proteins are **modular machines**" <=> How are they related to each other?

- Understand "Networks" prototypes (ER, SF, ...) and their properties (*P(k), C(k),* clustering, ...)
- 2) Get the data

experimental and theoretical techniques (Y2H, TAP, co-regulation, ...), quality control and data integration (Bayes)

3) Analyze the data

compare P(k), C(k), clusters, ... to prototypes \rightarrow highly modular, clustered with sparse sampling \rightarrow PPI networks are not scale-free

4) Predict missing information

network structure combined from multiple sources \rightarrow functional annotation

Next step: environmental changes, cell cycle

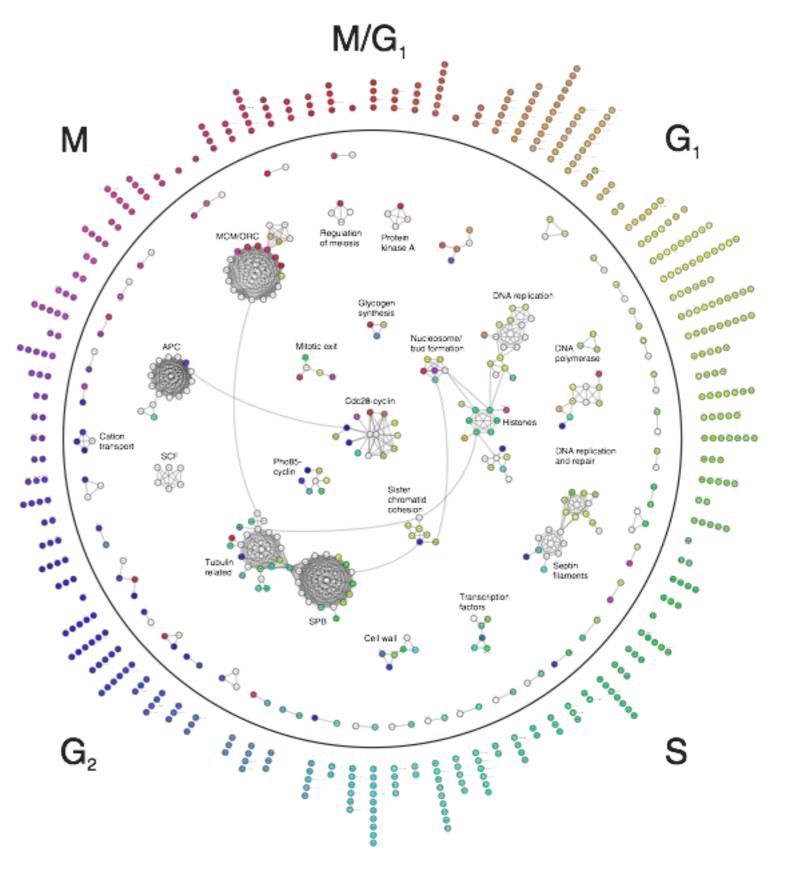
 \rightarrow changes (dynamics) in the PPI network – how and why?

Turn, Turn, Turn...

From Lichtenberg et al, Science 307 (2005) 724:

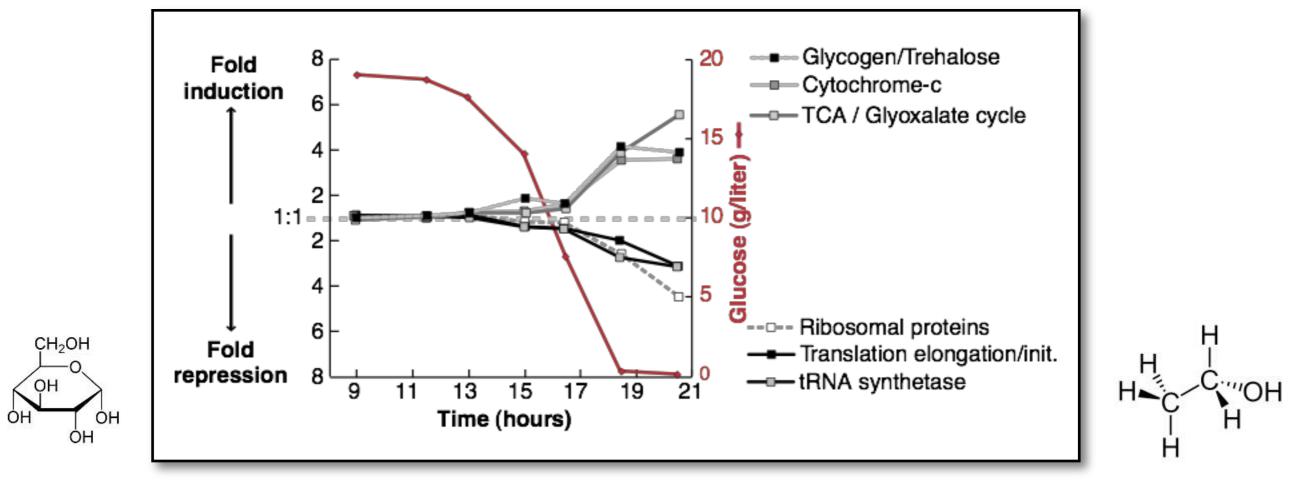
 \rightarrow certain proteins only occur during well-defined phases in the cell cycle

 \rightarrow how is protein expression regulated?



External Triggers

Re-routing of metabolic fluxes during the diauxic shift in *S. cerevisiae* \rightarrow changes in protein abundances (measured via mRNA levels)



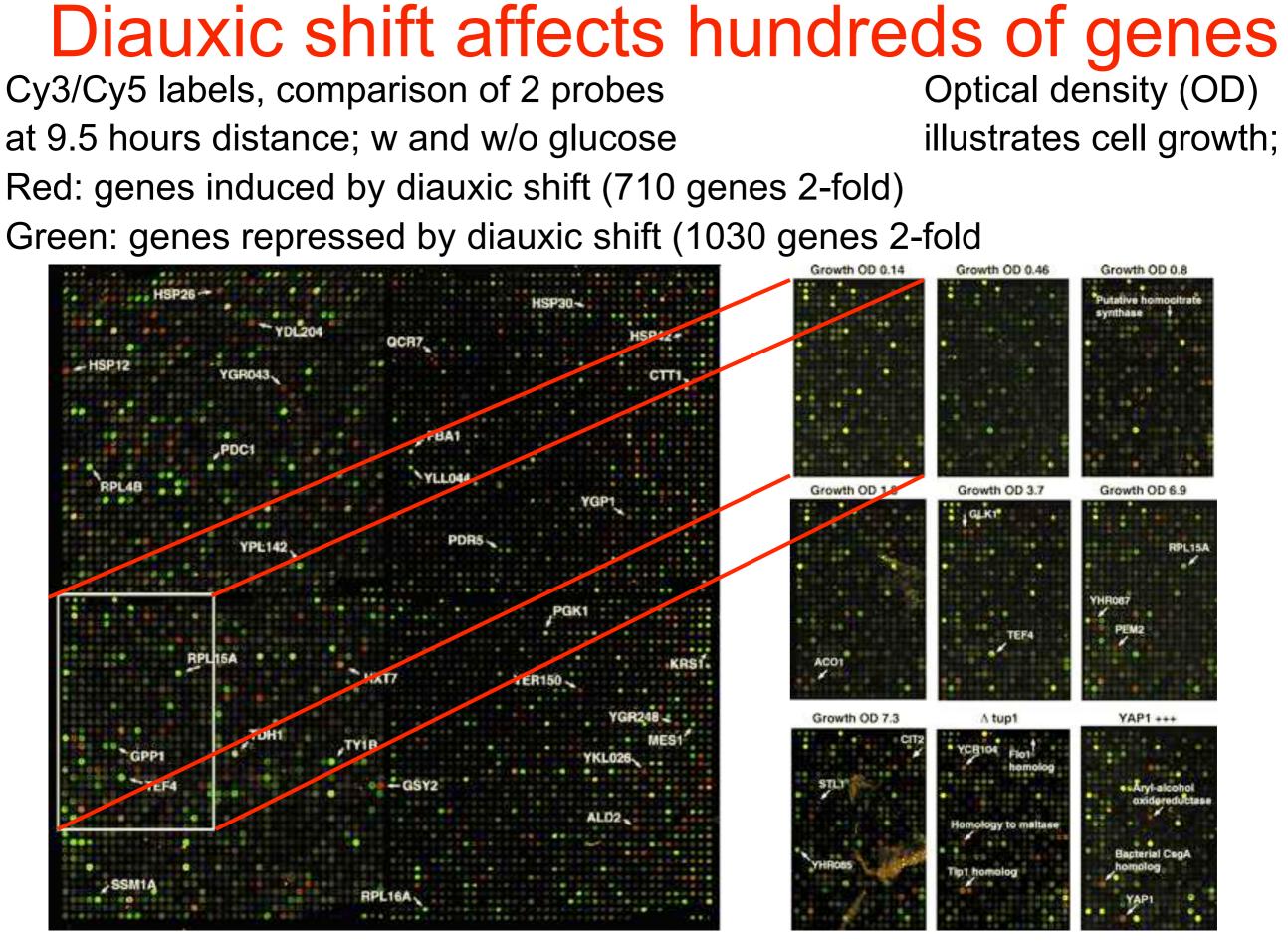
 anaerobic fermentation:

 fast growth on glucose → ethanol

 Diauxic shift

Note: "quorum sensing" — different bacteria have different strategies

DeRisi et al., Science 278 (1997) 680

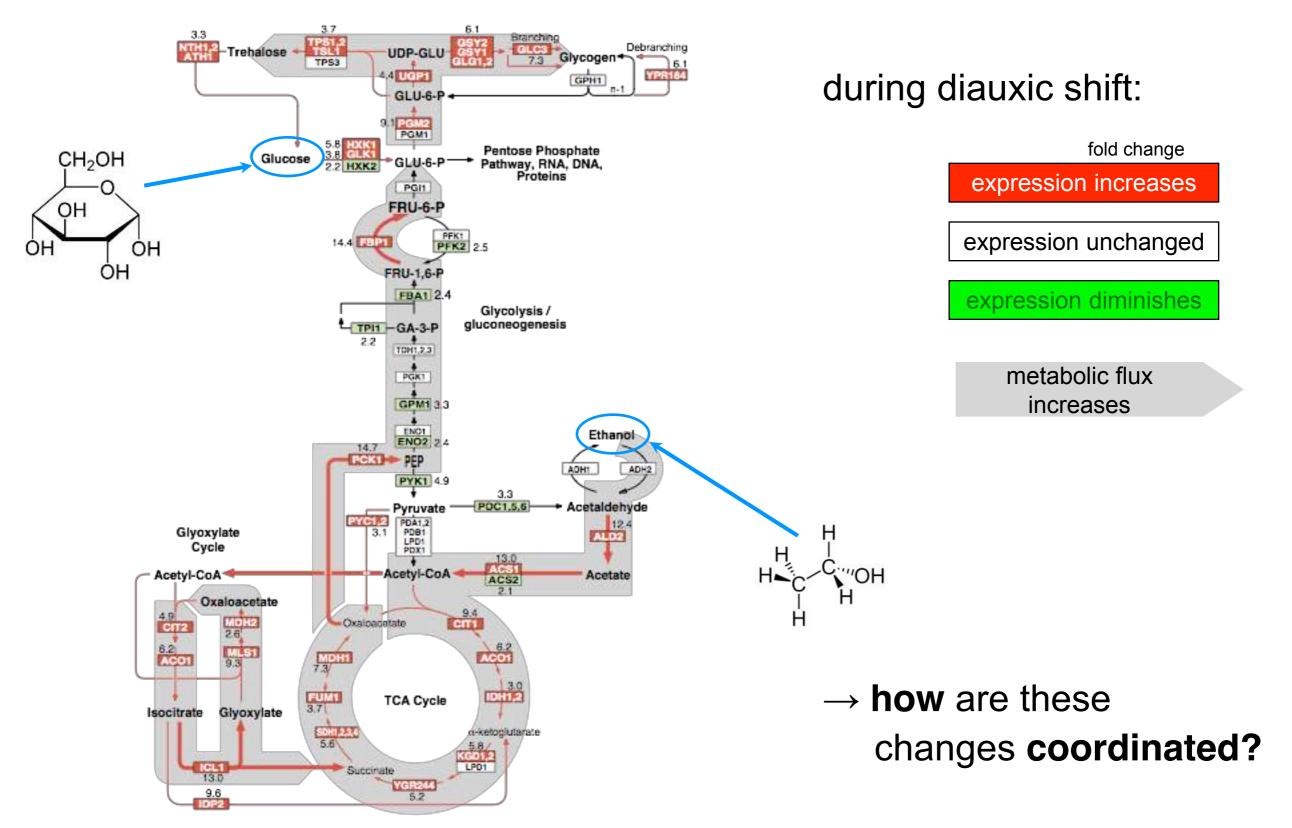


DeRisi et al., *Science* **278** (1997) 680

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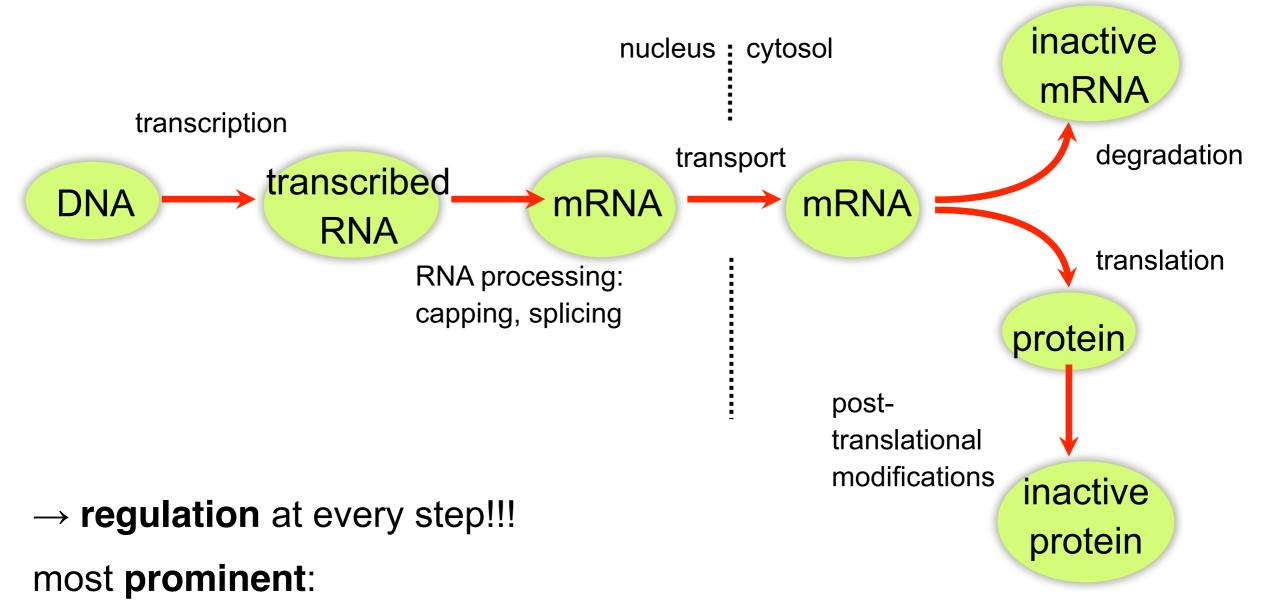
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Flux Re-Routing



Gene Expression

Sequence of processes: from DNA to functional proteins

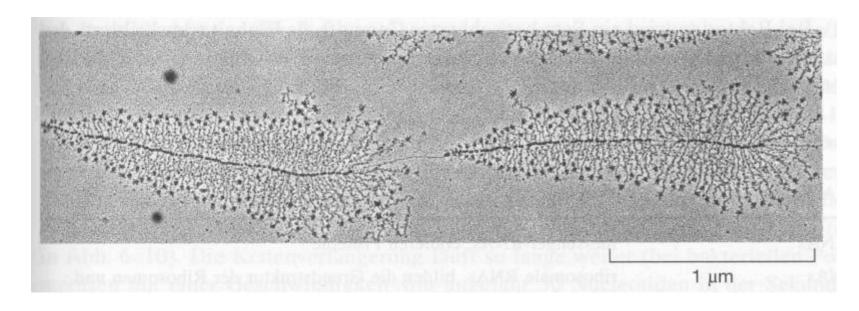


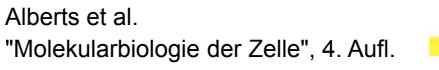
activation or repression of the transcription initiation

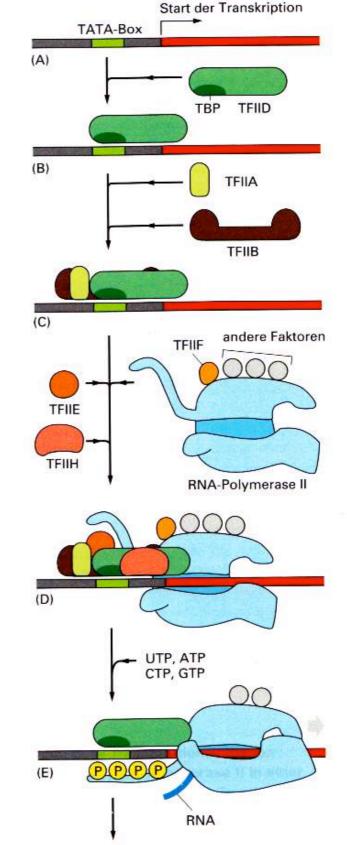
Transcription Initiation

In eukaryotes:

- several general transcription factors
 have to bind
- specific enhancers or repressors may bind
- then the RNA polymerase binds
- and starts transcription





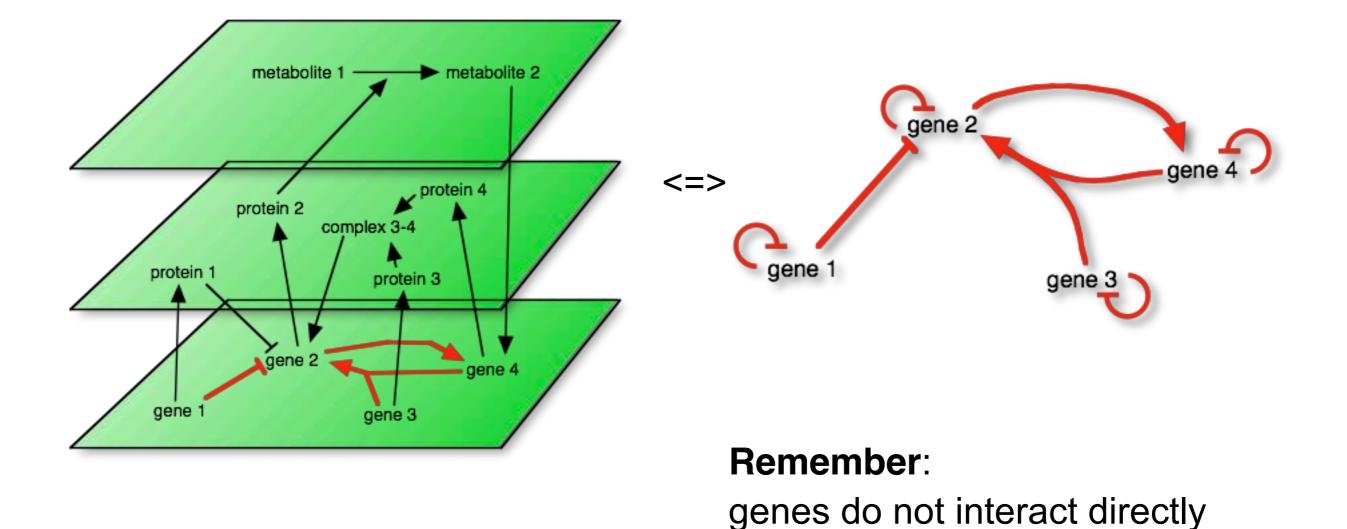


TRANSKRIPTION

Layers upon Layers

Biological regulation via proteins and metabolites

<=> Projected regulatory network

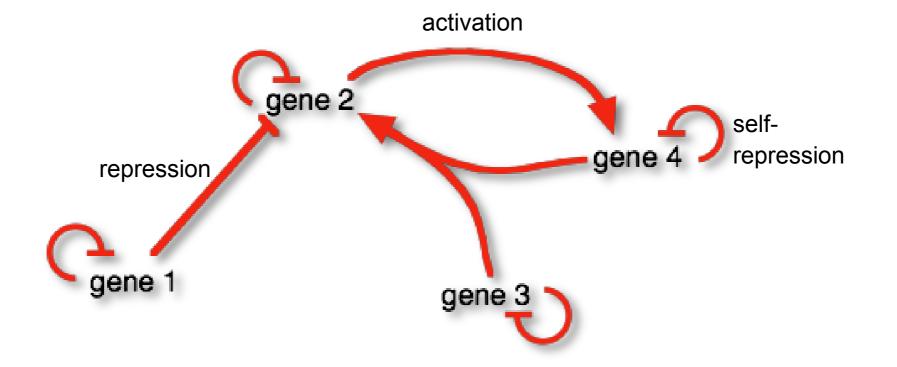


Conventions for GRN Graphs

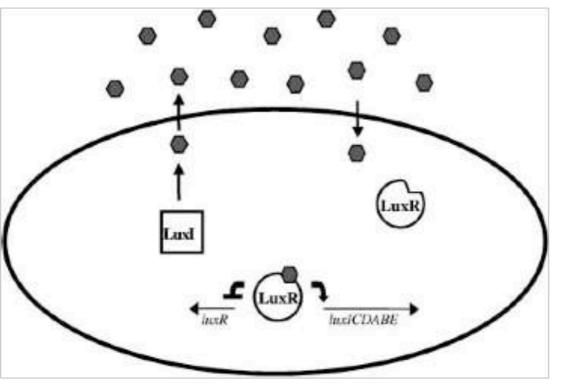
Nodes: genes that code for proteins which catalyze products \dots \rightarrow everything projected onto respective gene

Gene regulation networks have "cause and action" \rightarrow **directed** networks

A gene can enhance or suppress the expression of another gene \rightarrow **two types** of arrows



Luminescence in V. fischeri



Miller, Bassler, 2001

V. fischeri lives in symbiotic association with eukaryotic hosts.

Function: generate light

Squid: camouflage against moon light

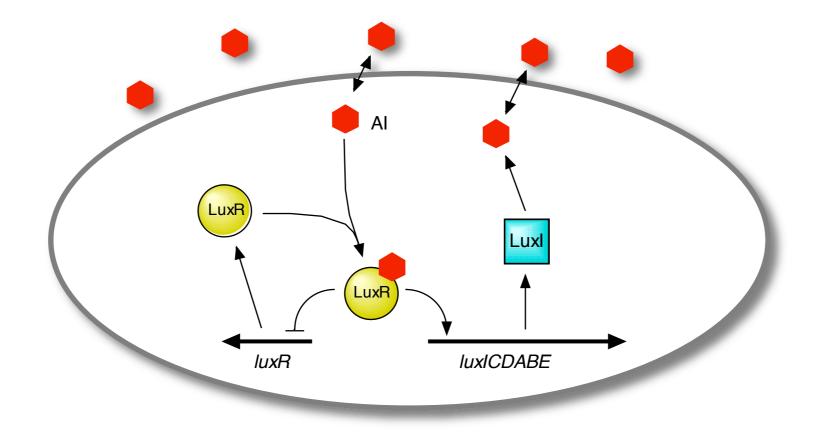
Fish *Monocentris japonicus*: attracts a mate by light seduction

Figure 1 The Vibrio fischeri LuxI/LuxR quorum sensing circuit. There are five luciferase structural genes (luxCDABE) and two regulatory genes (luxR and luxI) required for quorum sensing-controlled light emission in V. fischeri. The genes are arranged in two adjacent but divergently transcribed units. luxR is transcribed to the left, and the *luxICDABE* operon is transcribed to the right. The LuxI protein (square) is responsible for synthesis of the HSL autoinducer N-(3-oxohexanoyl)-homoserine lactone (hexagons). As the cell-population density increases, the concentration of the autoinducer increases both intra- and extracellularly. At a critical autoinducer concentration, the LuxR protein (circle) binds the autoinducer. The LuxR-autoinducer complex binds at the *luxICDABE* promoter and activates transcription of this operon. This action results in an exponential increase in autoinducer synthesis via the increase in transcription of luxI and an exponential increase in light production via the increase in transcription of *luxCDABE*. The LuxR-autoinducer complex also binds at the *luxR* promoter, but in this case the complex represses the transcription of luxR. This negative action compensates for the positive action at the *luxICDABE* promoter. The oval represents a bacterial cell.

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The Complete Picture?

Sketch from Miller & Bassler used to explain the mechanism:

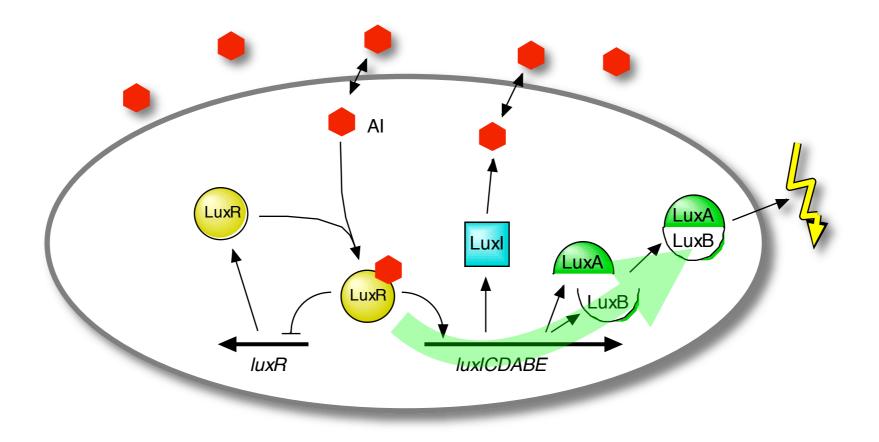


What is **missing**?

- emitted light signal
- degradation of AI and proteins
- threshold
- details of the "reactions"

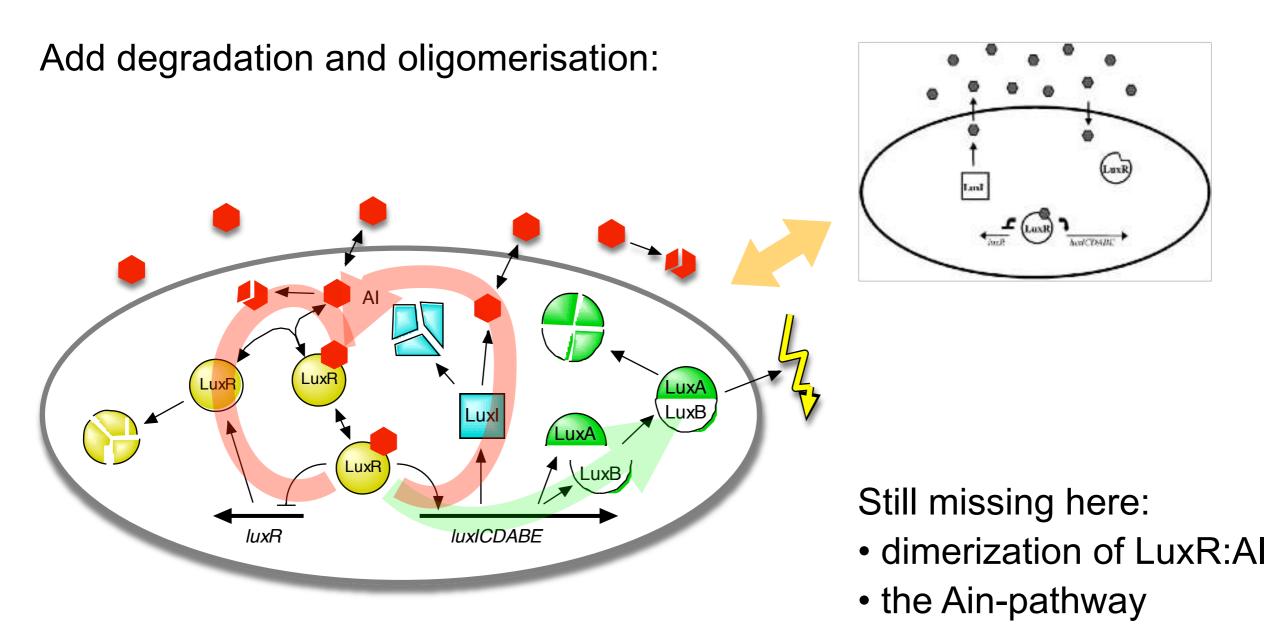
A Slightly More Complete Picture

Add luminescence $LuxA + LuxB \rightarrow luciferase \rightarrow light$



Beware: the picture contains **different reaction mechanisms** (various associations, transcription + translation, diffusion, ...)

Still not the Complete Picture



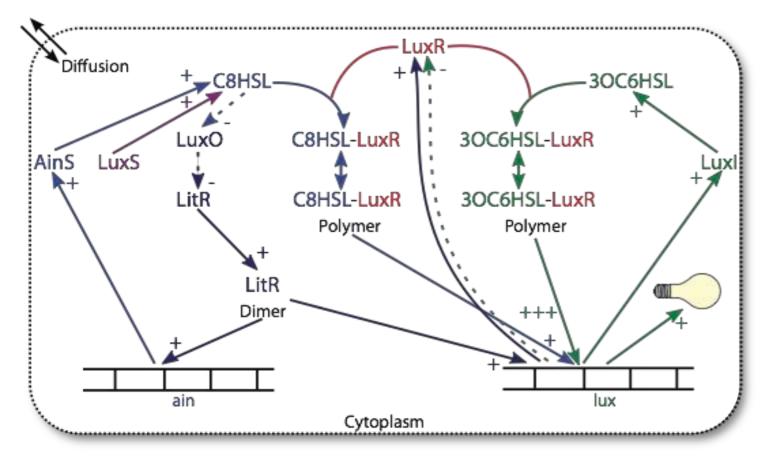
Modeling problem in biology:

 \rightarrow convert hand-waving **verbal descriptions** into consistent models

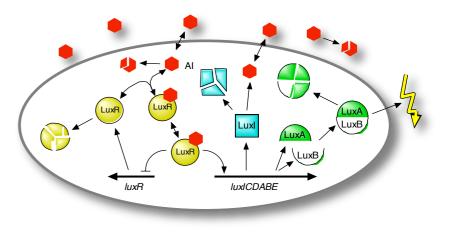
And There is One More Detail...

- two auto-inducers: 30C6HSL and C8HSL
- two genes (ain and lux)

But: the model is still incomplete

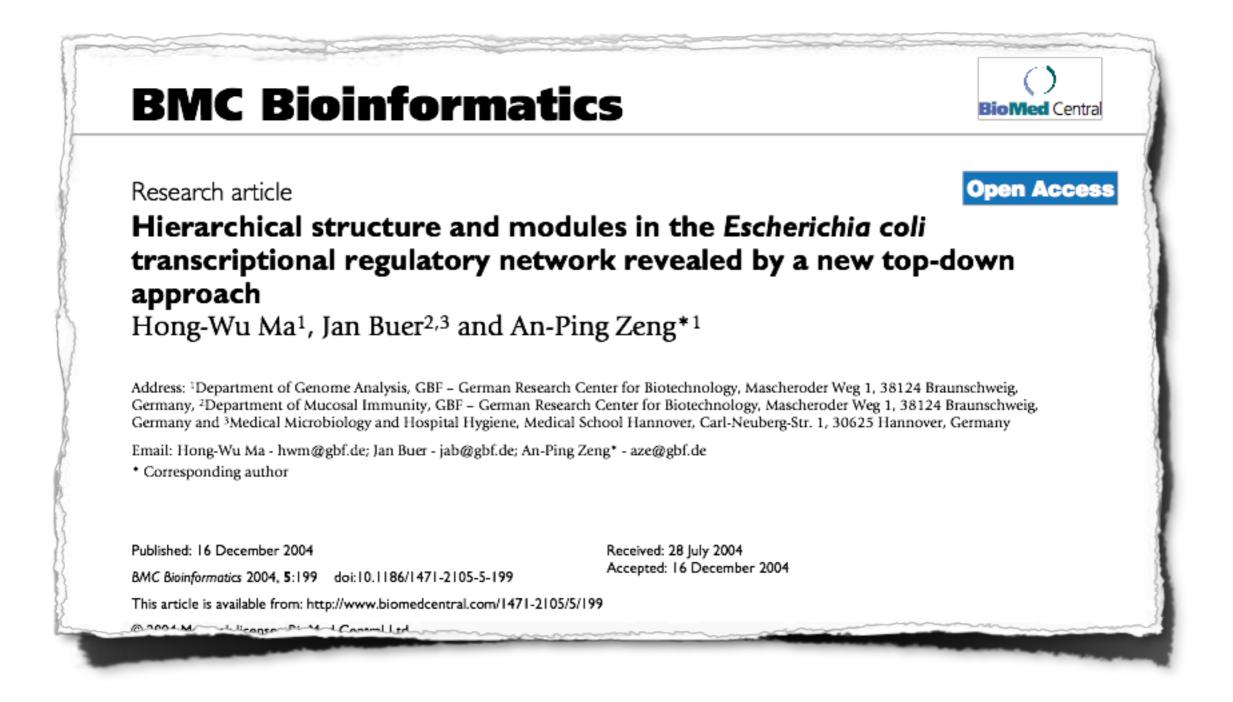


Nadine Schaadt, BSc. thesis



- → which of all these reactions are important for the dynamic behavior of the system?
- \rightarrow is everything known?
- → systemic model? → interactions with cellular environment
 - \rightarrow predictions?

E. coli Regulatory Network

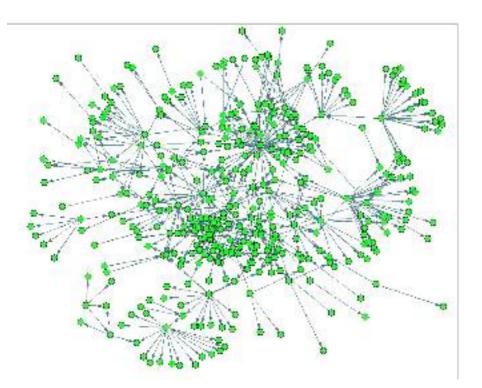


BMC Bioinformatics 5 (2004) 199

Hierarchies

Largest WCC: 325 operons (3/4 of the complete network)

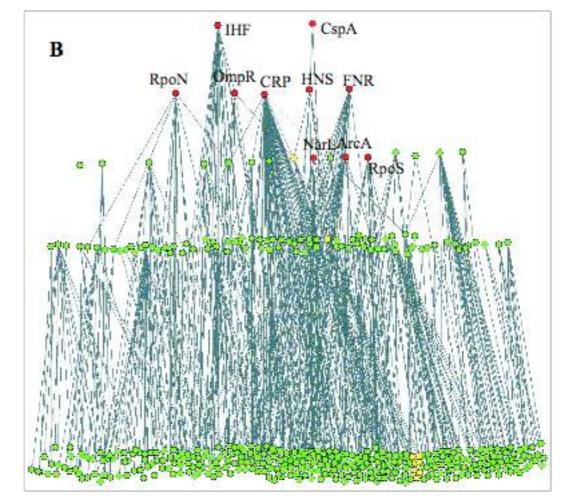
WCC = weakly connected component (ignore directions of regulation)



Network from standard layout algorithm

Lowest level: operons that code for TFs with only autoregulation, or no TFs

Next layer: delete nodes of lower layer, identify TFs that do not regulate other operons in this layer (only lower layers) Continue ...



Network with all regulatory edges pointing downwards

 \rightarrow a few global regulators (•) control all the details

Ma et al., BMC Bioinformatics 5 (2004) 199

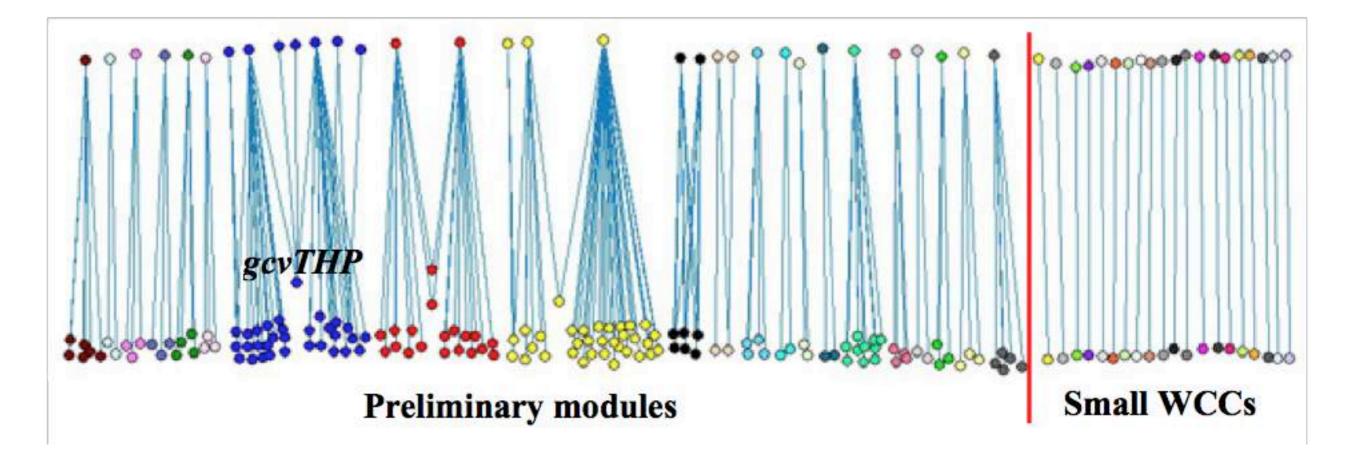
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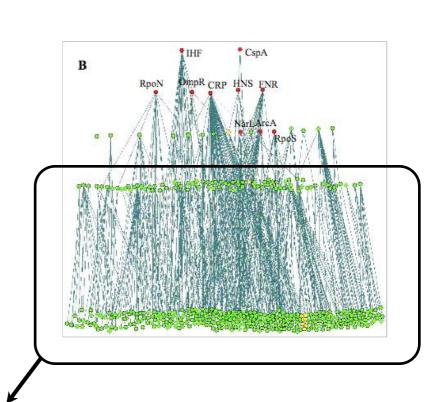
Global Regulators in E. coli

Global regulator	directly regulated Operons	Total regulated operons	Modules regulated	Function
IHF	21	39	15	integration host factor
CspA	2	24	5	Cold shock protein
CRP	72	112	21	cAMP receptor protein
FNR	22	38	16	anaerobic regulator, regulatory gene for nitrite and nitrate reductases, fumarate reductase
HNS	7	22	5	DNA-binding global regulator; involved in chromosome organization; preferentially binds bent DNA
OmpR	6	20	3	Response regulator for osmoregulation; regulates production o membrane proteins
RpoN	12	17	4	RNA polymerase sigma 54 subunit
RpoS	14	24	8	stationary phase sigma factor
ArcA	20	21	6	Response regulator protein represses aerobic genes under anaerobic growth conditions and activates some anaerobic gene
NarL	3	15	5	Two-component regulator protein for nitrate/nitrite response

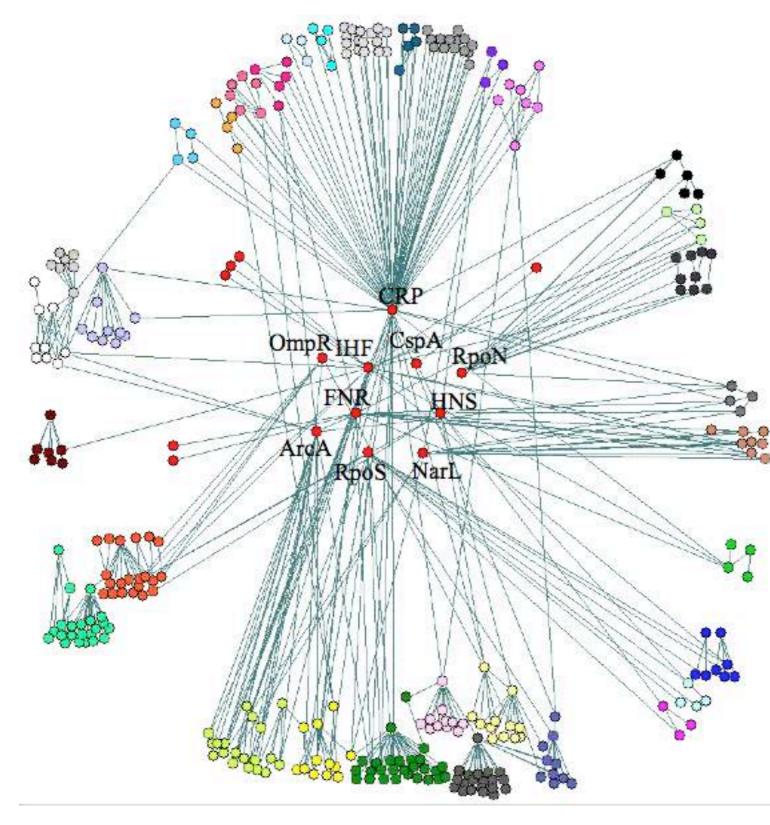
Modules

Remove top three layers and determine WCCs \rightarrow just a few modules





Putting it back together



The ten global regulators are at the core of the network,

some hierarchies exist between the modules

Naming a few!

Table 2: Functional investigation of modules identified.							
index	Operons included	Biological function description					
I	aceBAK, acs, adhE, fruBKA, fruR, icdA, iclMR, mlc, ppsA, ptsG, ptsHI_crr, pykF	Hexose PTS transport system, PEP generation, Acetate usage, glyoxylate shunt					
2	acnA, fþr, fumC, marRAB, nfo, sodA, soxR, soxS, zwf	Oxidative stress response					
3	ada_alkB, aidB, alkA, ahpCF, dps, gorA, katG, oxyR	Oxidative stress response, Alkylation					
4	alaWX, aldB, argU, argW, argX_hisR_leuT_proM, aspV, dnaA, leuQPV, leuX, lysT_valT_lysW, metT_leuW_ginUW_metU_glnVX, metY_yhbC_nusA_infB, nrdAB, pdhR_aceEF_lpdA, pheU, pheV, proK, proL, proP, sdhCDAB_b0725_sucABCD, serT, serX, thrU_tyrU_glyT_thrT, thrW, tyrTV, valUXY_lysV, yhdG_fis	rRNA, tRNA genes, DNA synthesis system, pyruvate dehydrogenase and ketoglutarate dehydrogenase system					
5	araBAD, araC, araE, araFGH, araJ	Arabinose uptake and usage					
6	argCBH, argD, argE, argF, argI, argR, carAB	Arginine usage, urea cycle					
7	caiF, caiTABCDE, fixABCX	Carnitine usage					
8	clpP, dnaKJ, grpE, hfiB, htpG, htpY, ibpAB, lon, mopA, mopB, rpoH	Heat shock response					
9	codBA, cvpA_purF_ubiX, glnB, glyA, guaBA, metA, metH, metR, prsA, purC, purEK, purHD, purL, purMN, purR, pyrC, pyrD, speA, ycfC_purB, metC, metF, metJ	Purine synthesis, purine and pyrimidine salvage pathway, methionine synthesis					
10	cpxAR, cpxP, dsbA, ecfl, htrA, motABcheAW, ppiA, skp_lpxDA_fabZ, tsr, xprB_dsbC_recJ	Stress response, Conjugative plasmid expression, cell motility and Chemotaxis					
11	dctA, dcuB_fumB, frdABCD, yjdHG	C4 dicarboxylate uptake					
12	edd_eda, gntKU, gntR, gntT	Gluconate usage, ED pathway					
13	csgBA, csgDEFG, envY_ompT, evgA, gcvA, gcvR, gcvTHP, gltBDF, ilvIH, kbl_tdh, livJ, livKHMGF, Irp, lysU, ompC, ompF, oppABCDF, osmC, sdaA, serA, stpA	Amino acid uptake and usage					
14	fdhF, fhIA, hycABCDEFGH, hypABCDE	Formate hydrogenlyase system					
15	flgAMN, flgBCDEFGHIJ, flgKL, flgMN, flhBAE, flhDC, fliAZY, fliC, fliDST, fliE, fliFGHIJK, fliLMNOPQR, tarTapcheRBYZ	Flagella motility system					
16	ftsQAZ, rcsAB, wza_wzb_b2060_wcaA_wcaB	Capsule synthesis, cell division					
17	gdhA, glnALG, glnHPQ, nac, putAP	Glutamine and proline utilization					
18	gImUS, manXYZ, nagBACD, nagE	Glucosamine, mannose utilization					
19	glpACB, glpD, glpFK, glpR, glpTQ	Glycerol phosphate utilization					
20	lysA, lysR, tdcABCDEFG, tdcR	Serine, threonine usage					
21	TEC malk have all maipo mals malt malz	Maltose willinging					

Summary

- Static PPI networks:
- \rightarrow topology, measures, data sources, ...
- Changes during cell cycle, adaptation to environmental changes, ...
- \rightarrow Gene Regulation
 - \rightarrow many biological steps
 - \rightarrow often modeled on the gene level only

Next lecture:

- Regulatory motifs
 - \rightarrow static and dynamic behavior