

Introduction to Systems Biology (and why you should care)

BIOINF 524/525

3/21/2017

Module logistics

- Network analysis in systems biology (Lecture 3/21, Lab 3/23)
- High-throughput sequencing data (Lecture 3/28, Lab 3/30)
- Network inference and modeling (Lecture 4/4, Lab 4/6)
- Machine learning in systems biology (Lecture 4/11, Lab 4/13)

Module logistics

Lectures will focus on conceptual overview of goals and methods

Labs will include didactic material interspersed with exercises

Weekly homework will involve extension of lab exercises (due the day of the following lab session)

Grading is pass/fail and based on attendance and homework completion

Introduction to Systems Biology

BIOINF 524/525

3/21/2017

What is systems biology?
(and what can it do for me?)

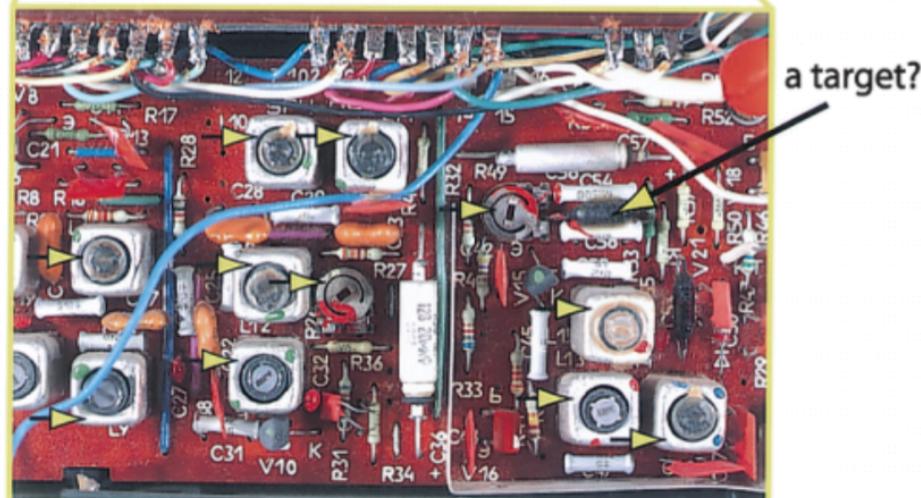
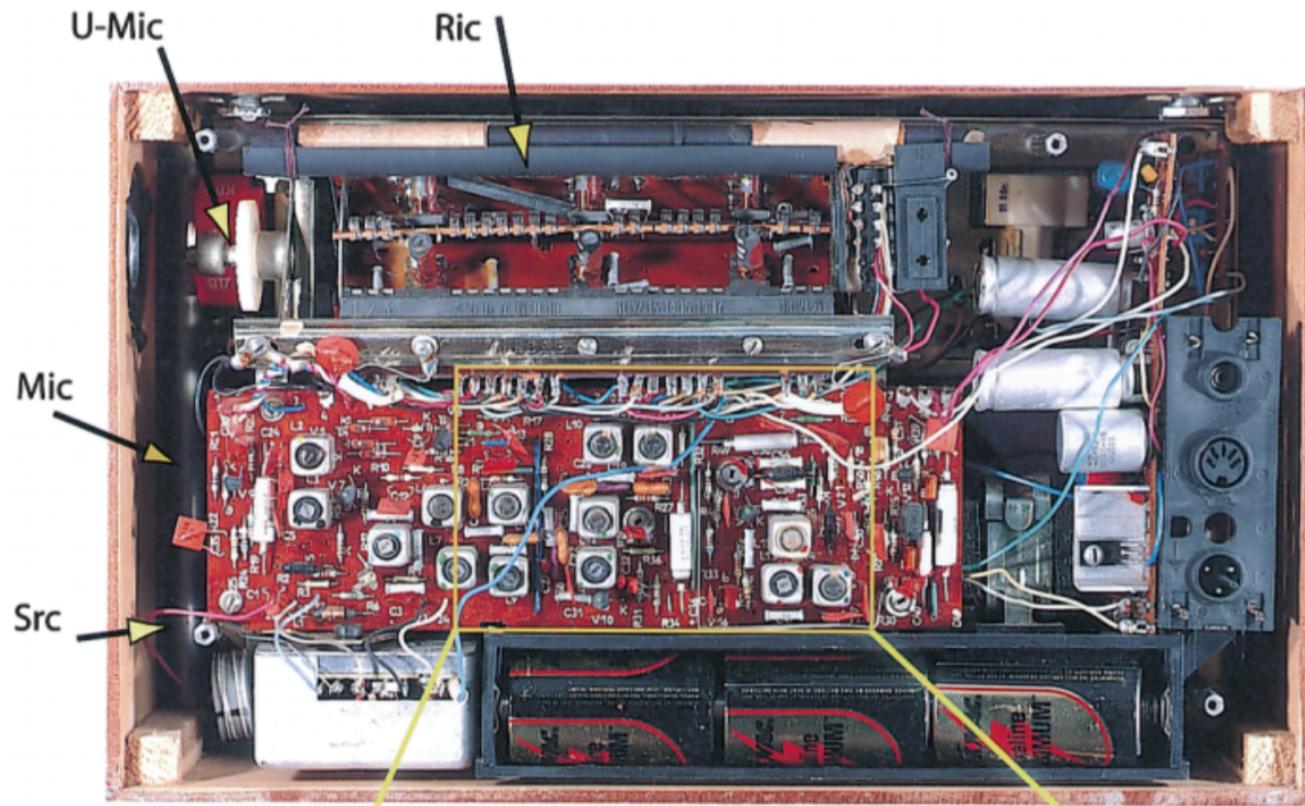
“[A]sk five biomedical researchers to define systems biology, and you’ll get 10 different answers . . . or maybe more”
--Christopher Wanjek

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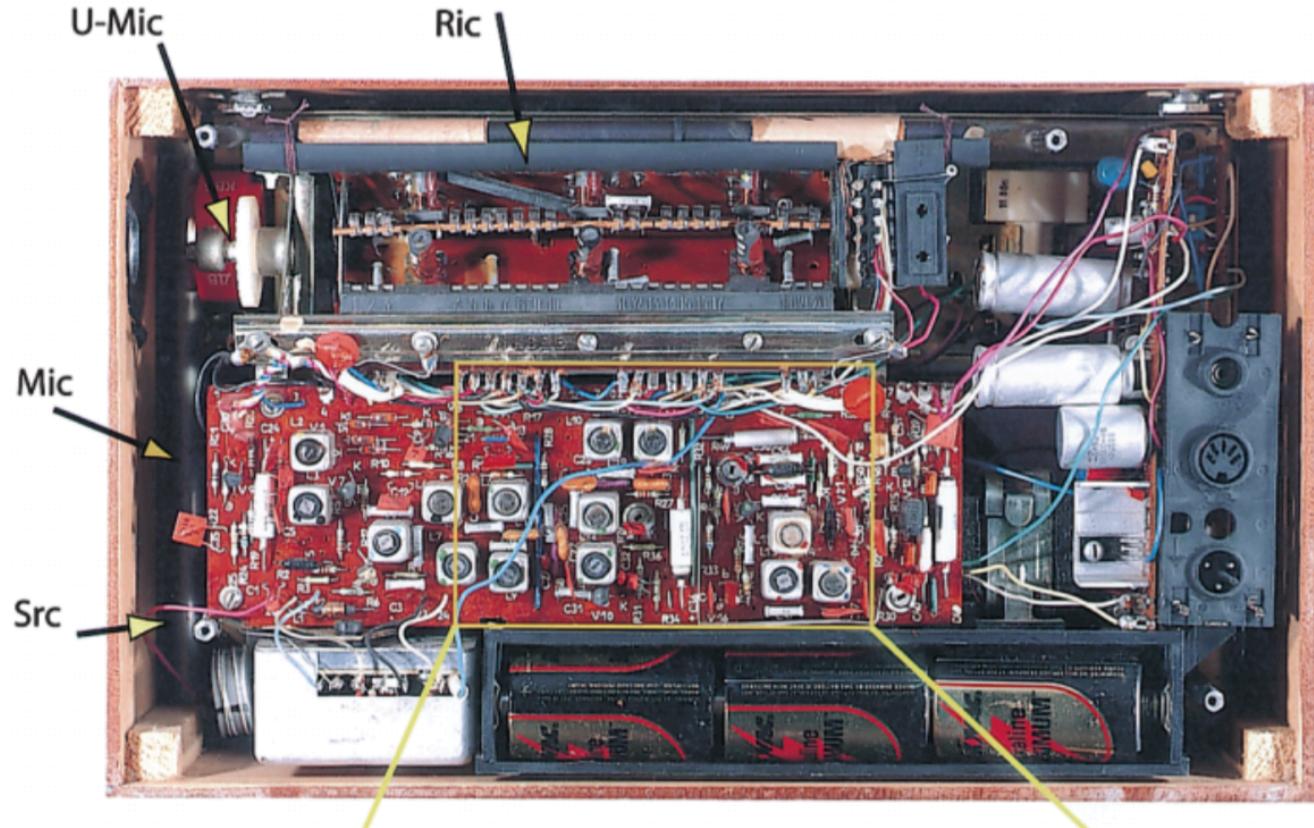
“[A] scientific approach that combines the principles of engineering, mathematics, physics, and computer science with extensive experimental data to develop a quantitative as well as a deep conceptual understanding of biological phenomena, permitting prediction and accurate simulation of complex (emergent) biological behaviors.”
--Dr. Ron Germain

Can a Biologist Fix a Radio?

Lazebnik, Y. Cancer Cell 2002
(slides via Michael Wolfe)



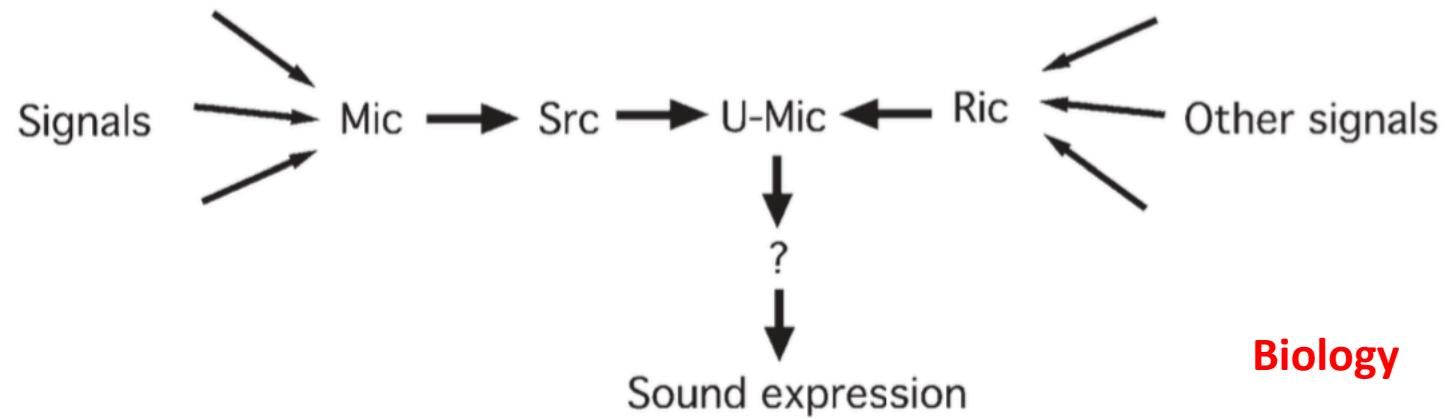
Lazebnik, Y. Cancer Cell 2002
(slides via Michael Wolfe)



"The first thing a biochemist would do with a radio would be to stick it in a Waring blender"
-Prof. Phil Andrews

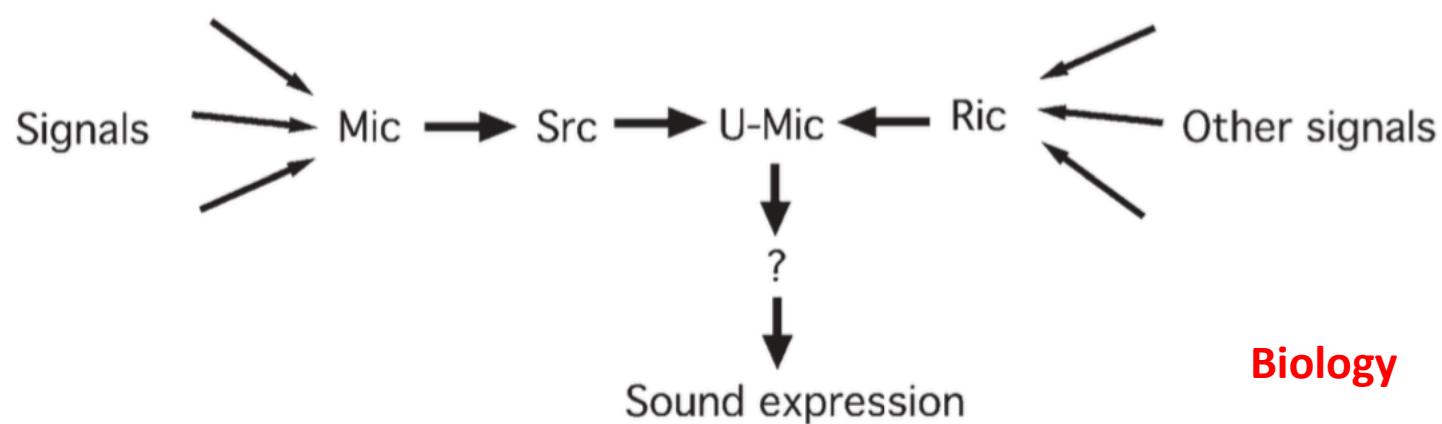
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A

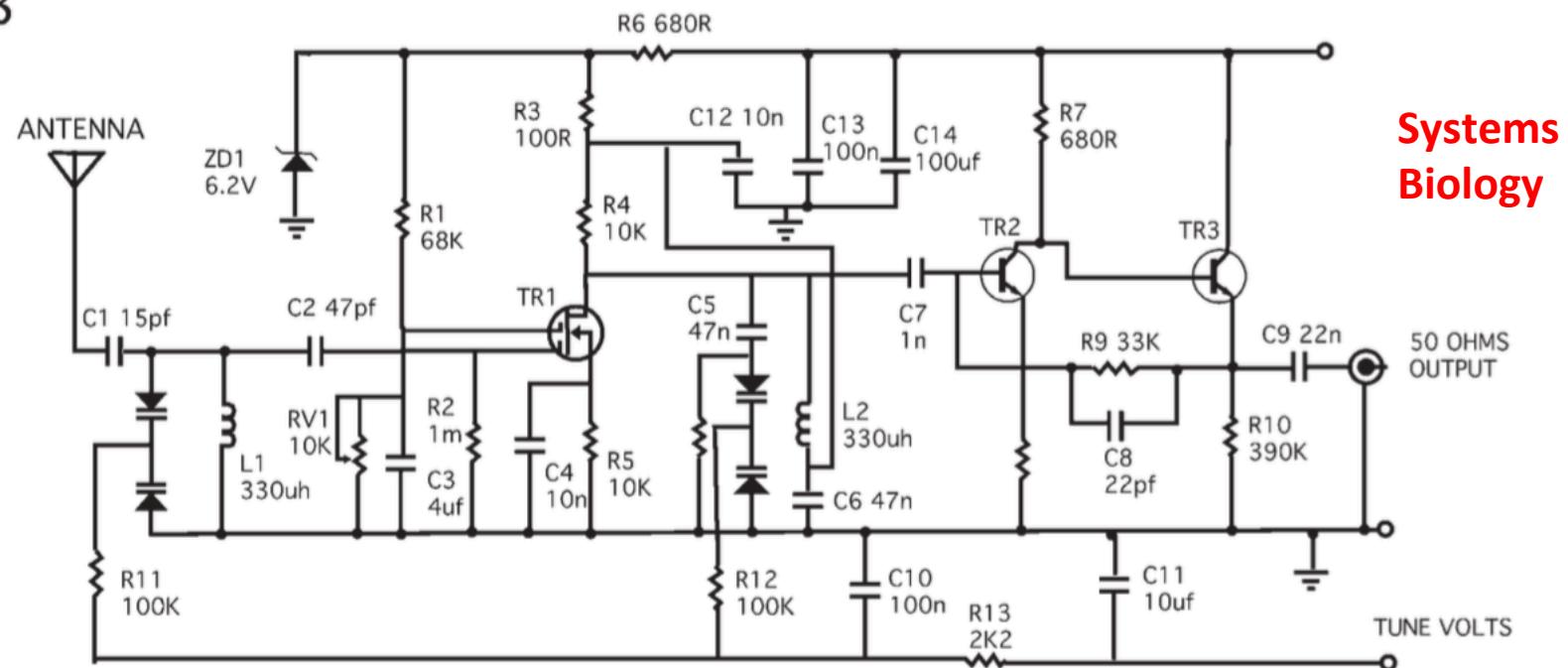


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A



B

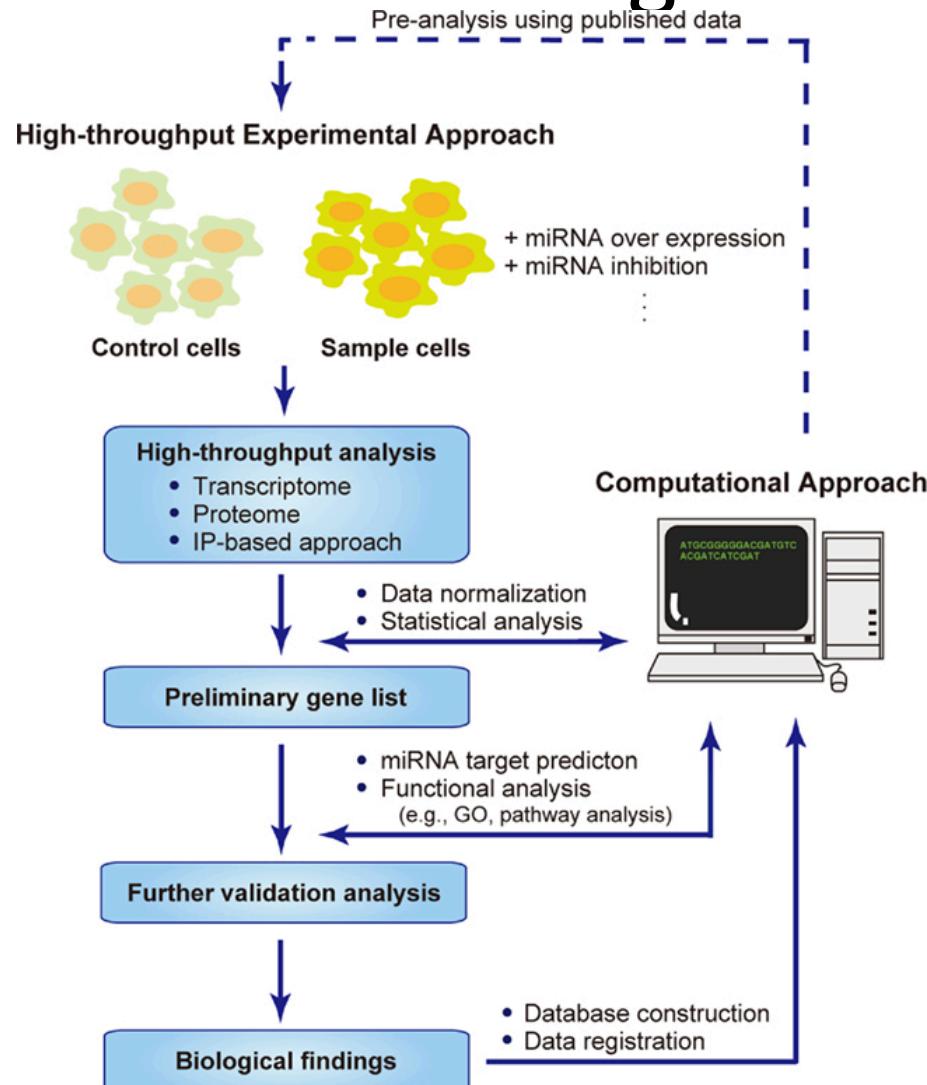


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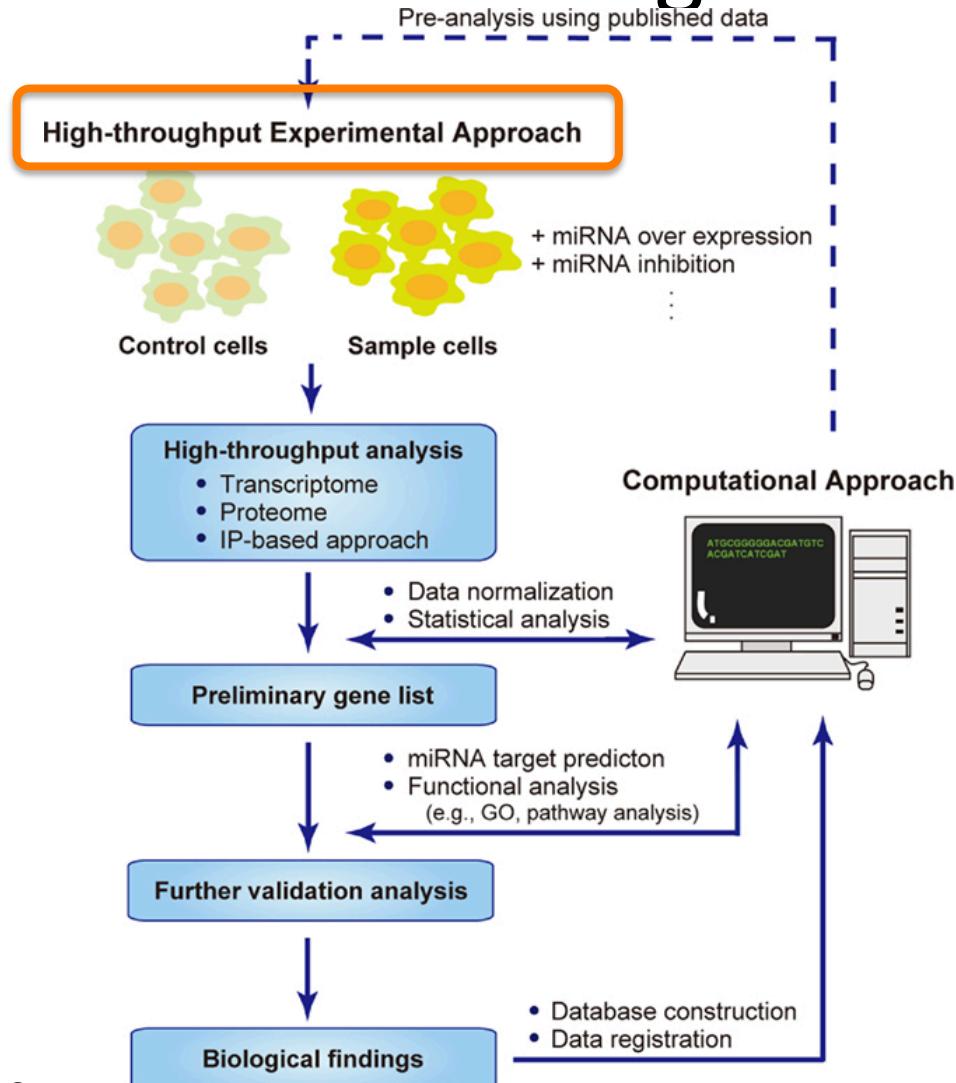
Guiding principles of systems biology

- Draw from physics and engineering to obtain quantitative descriptions
- Aim to describe and predict biological behavior
- Identify organizing principles and minimal functional examples of common biological motifs
- Emphasis on connections of components as well as their individual behavior

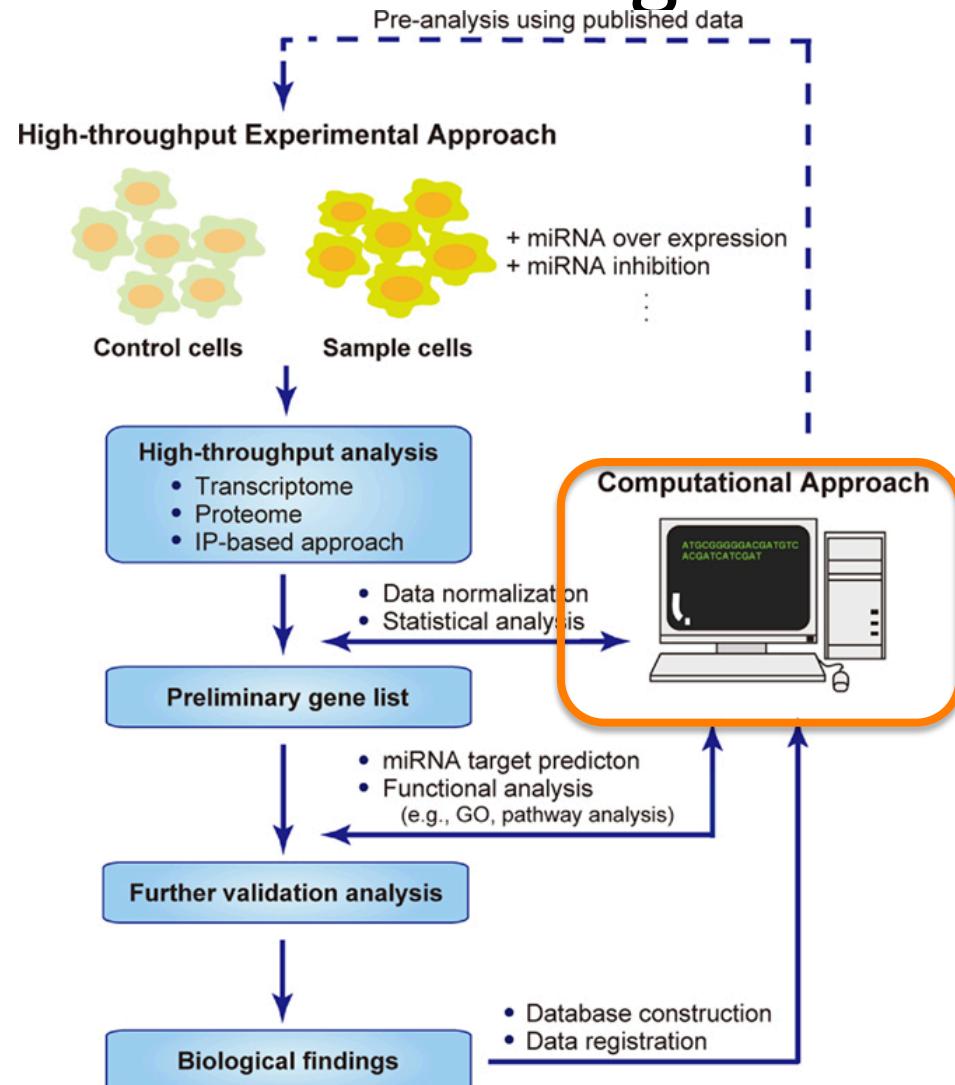
Example in action: discovery of microRNA targets



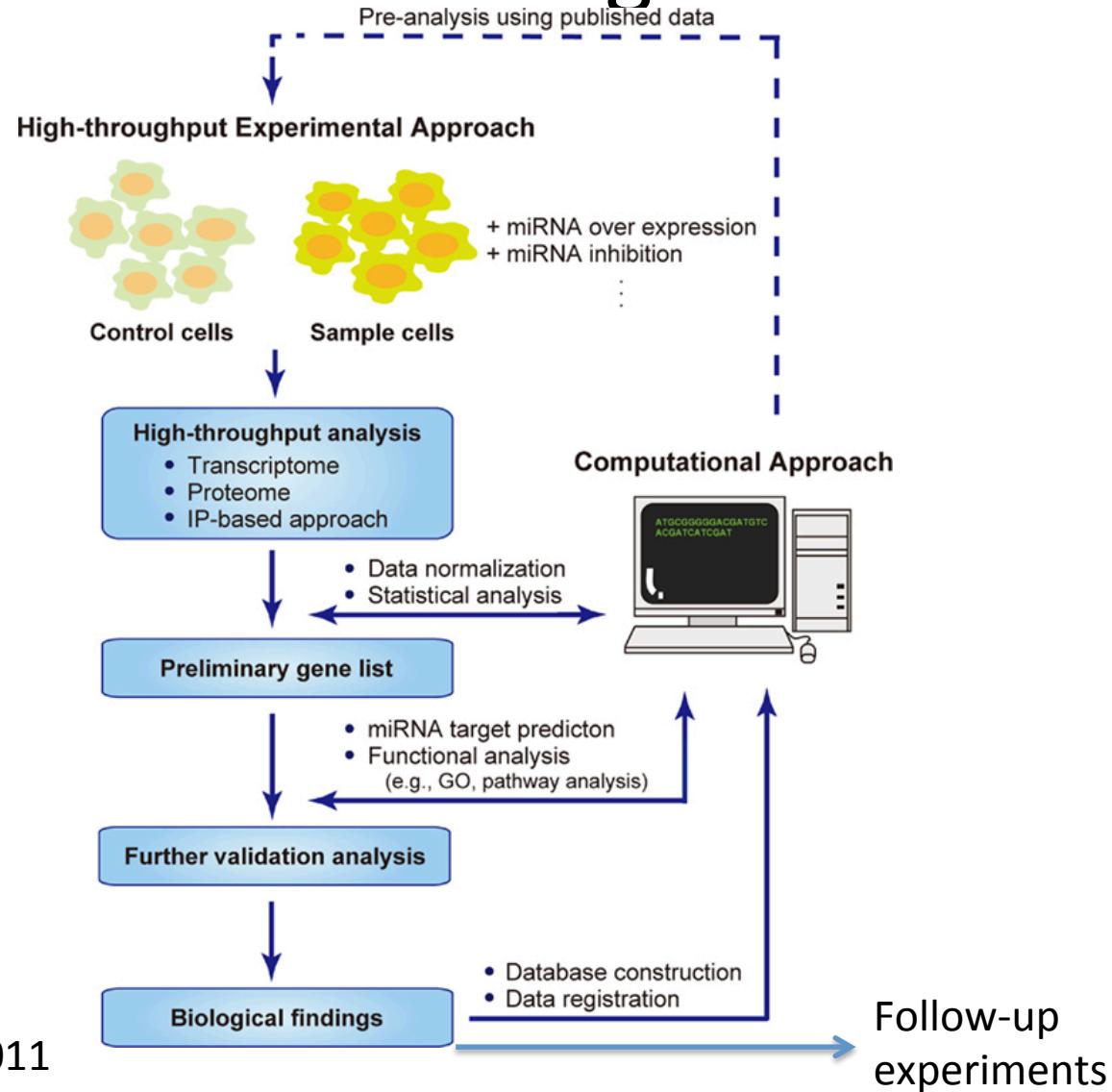
Example in action: discovery of microRNA targets



Example in action: discovery of microRNA targets



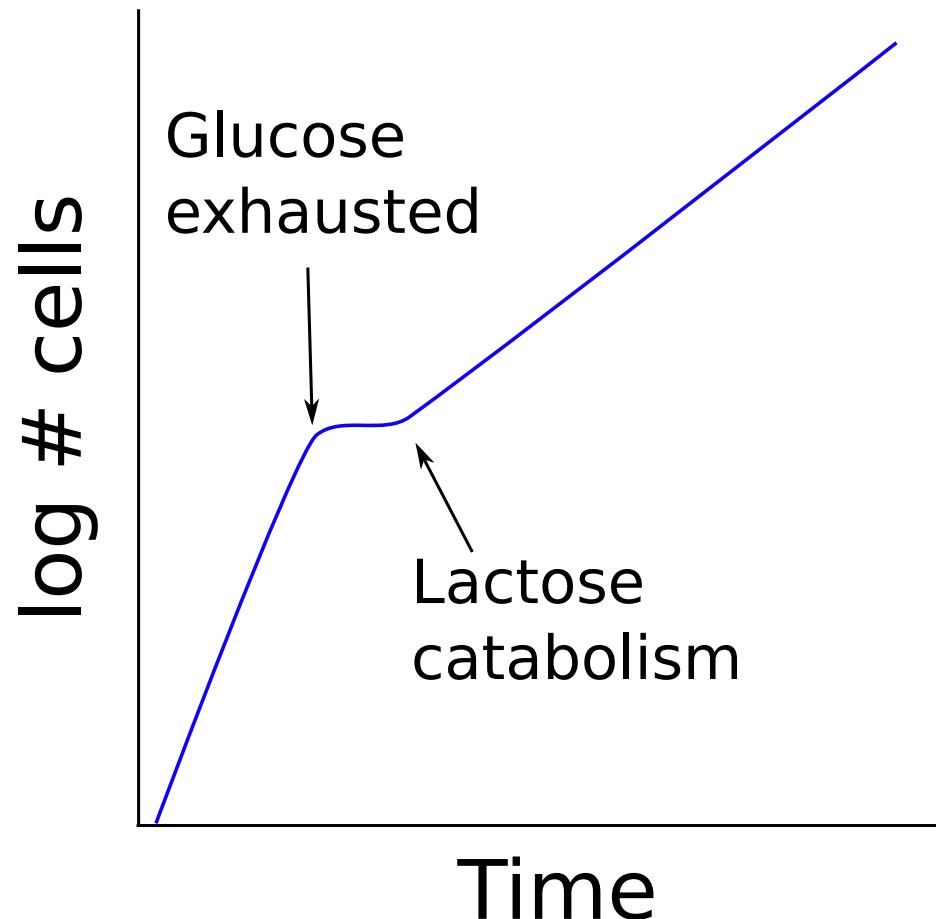
Example in action: discovery of microRNA targets



Organizing principles of biological networks

The lac operon, viewed four ways

The lac operon, viewed four ways



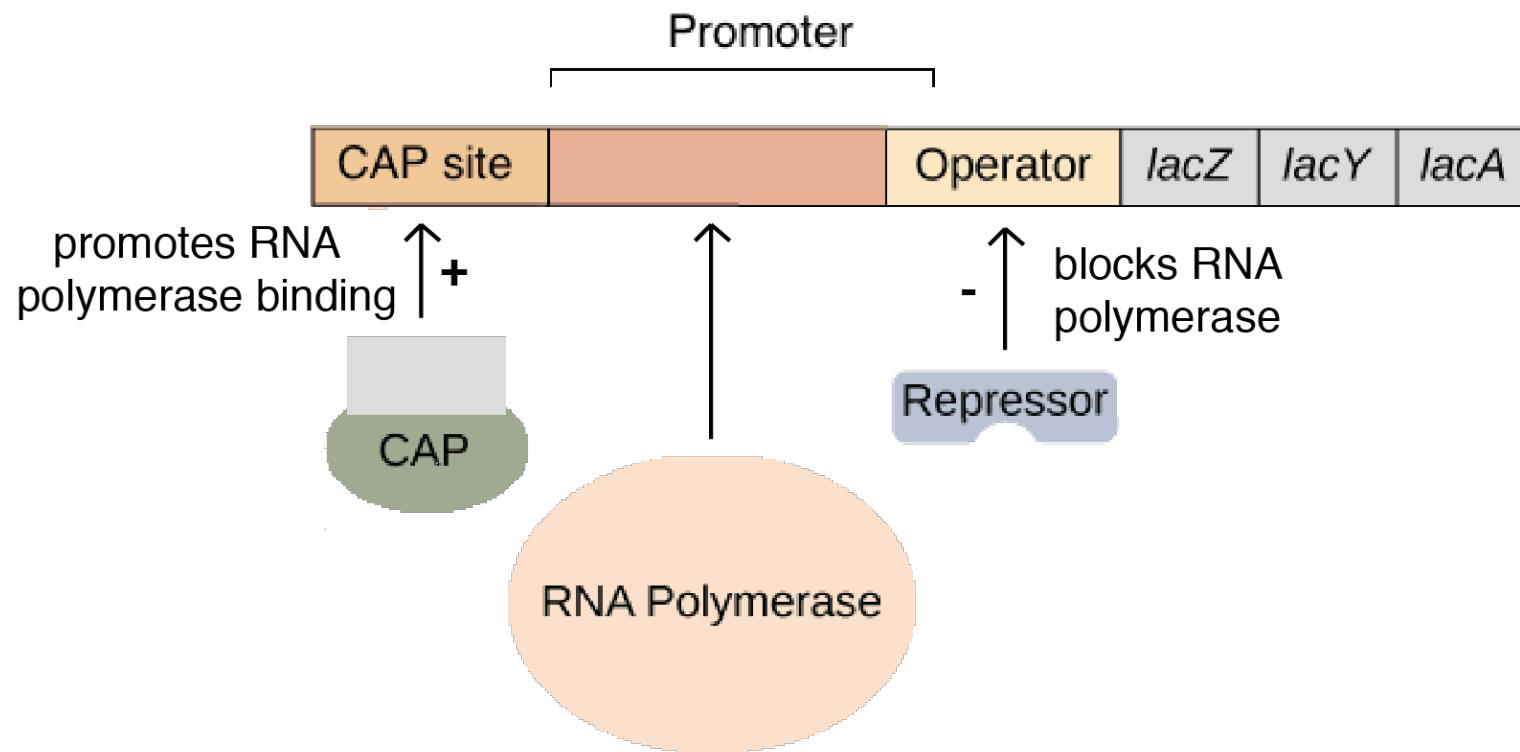
The lac operon, viewed four ways



Genetics

The lac operon, viewed four ways

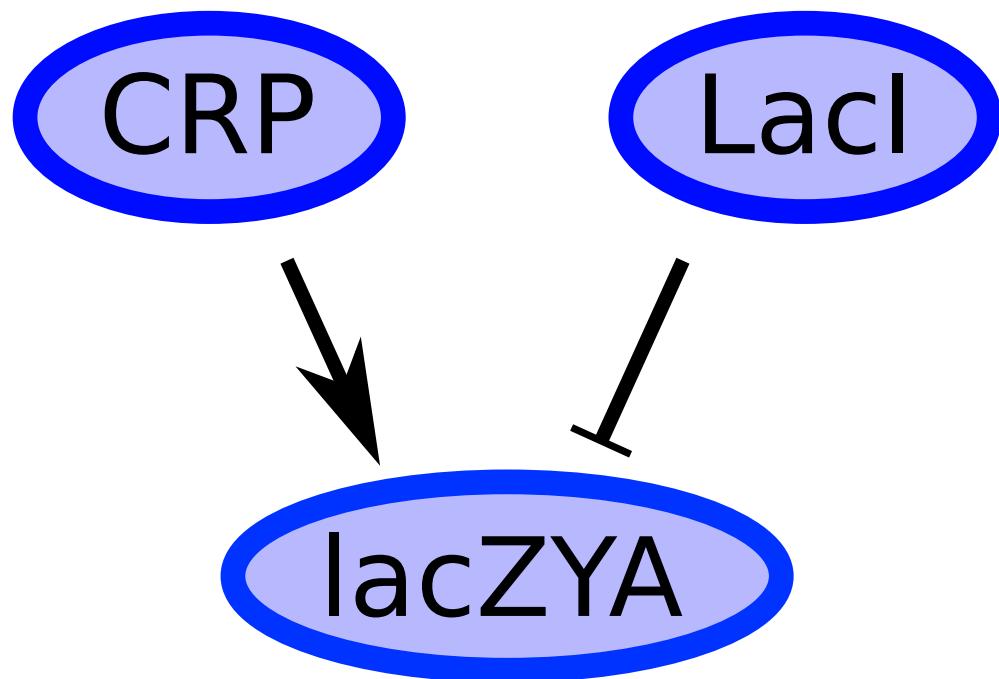
The *lac* operon:



Molecular biology

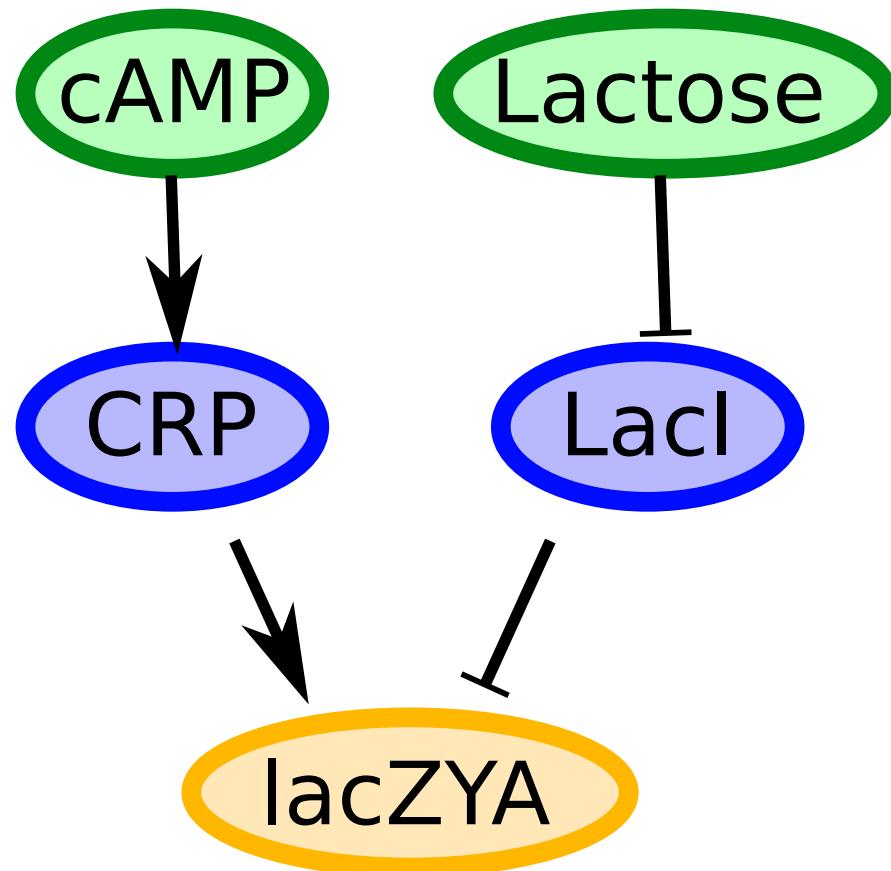
(Image from Khan Academy)

The lac operon, viewed four ways



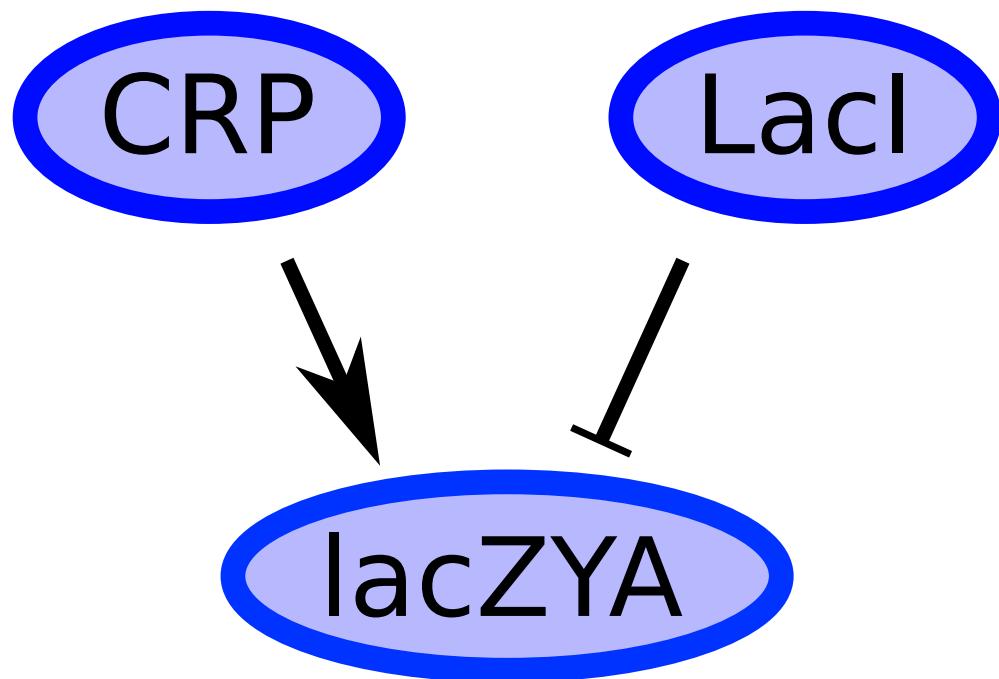
Graph theory

The lac operon, viewed four ways



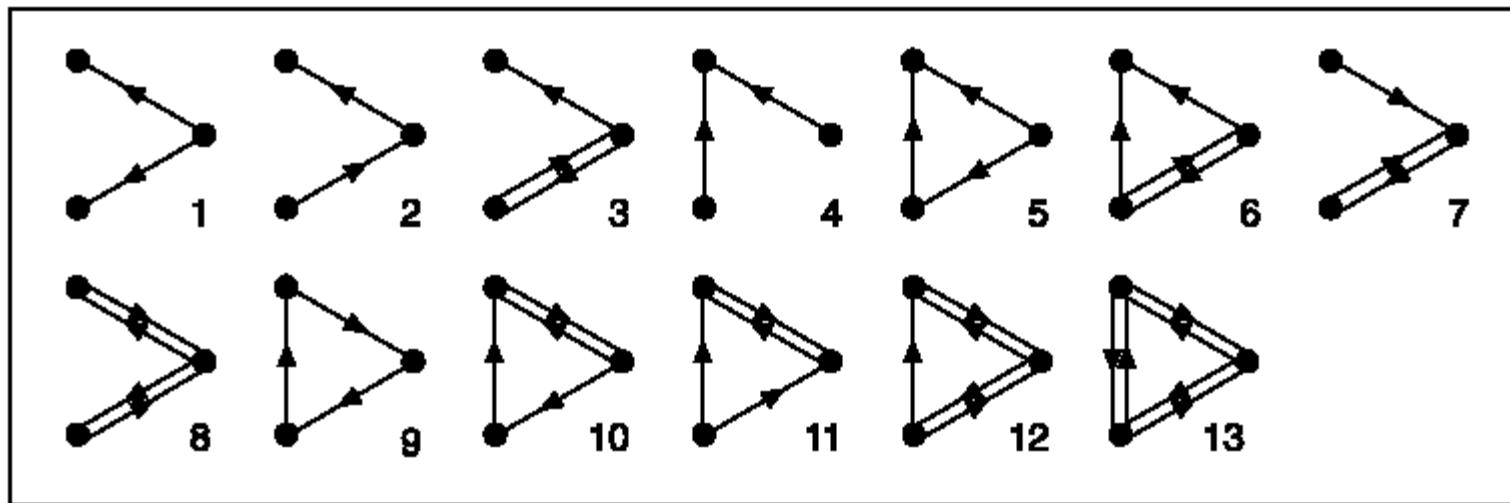
Graph theory

The lac operon, viewed four ways



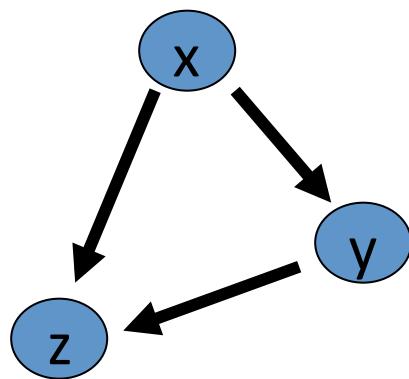
Graph theory

Network motifs yield specific biological functions

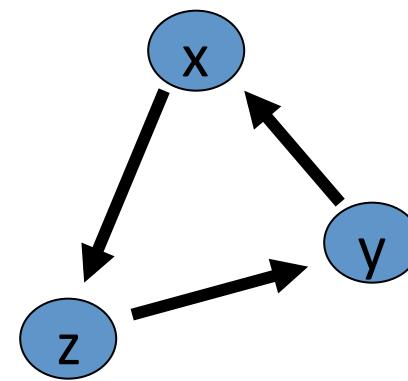


(U. Alon, *An Introduction to Systems Biology*)

Network motifs yield specific biological functions



Feed-forward loop



3-node feedback loop
(cycle)

(U. Alon, *An Introduction to Systems Biology*)

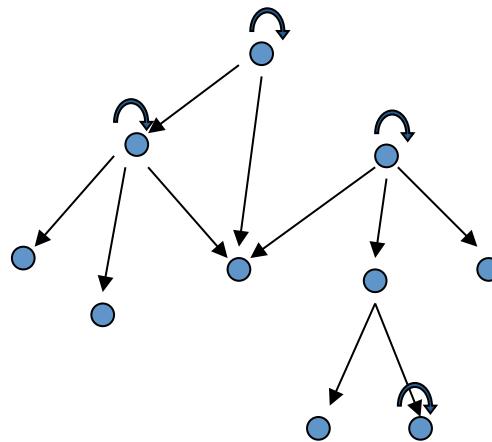
Network motifs yield specific biological functions

How do we find over-represented network motifs?

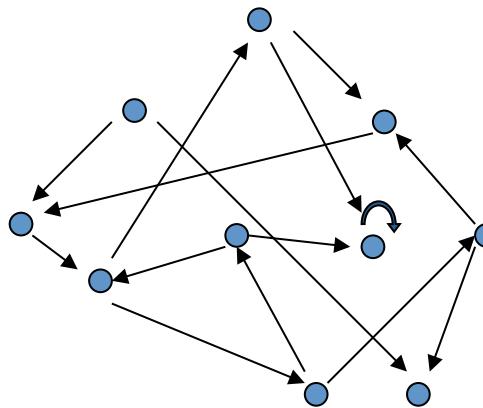
Network motifs yield specific biological functions

How do we find over-represented network motifs?

‘Real’ Network



Randomized network
(Erdos – Renyi model)



$N=10$ nodes

$E= 14$ edges

$E_s=4$ self-edges

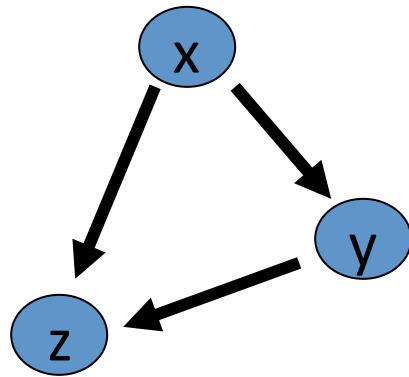
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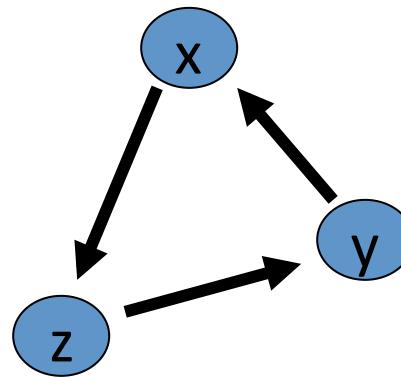
$E_s=1$ self-edge

(U. Alon, *An Introduction to Systems Biology*)

Example: Comparison of two 3-node network motifs

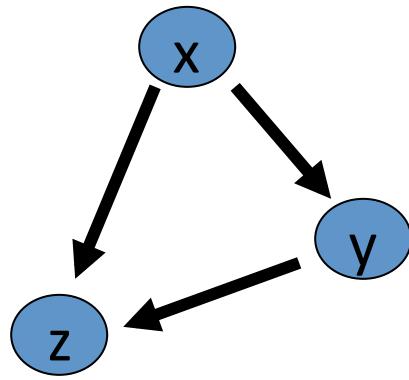


Feed-forward loop

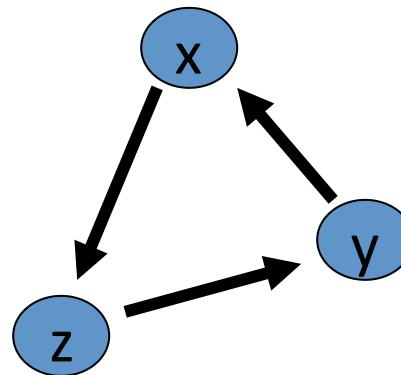


3-node feedback loop
(cycle)

Example: Comparison of two 3-node network motifs



Feed-forward loop

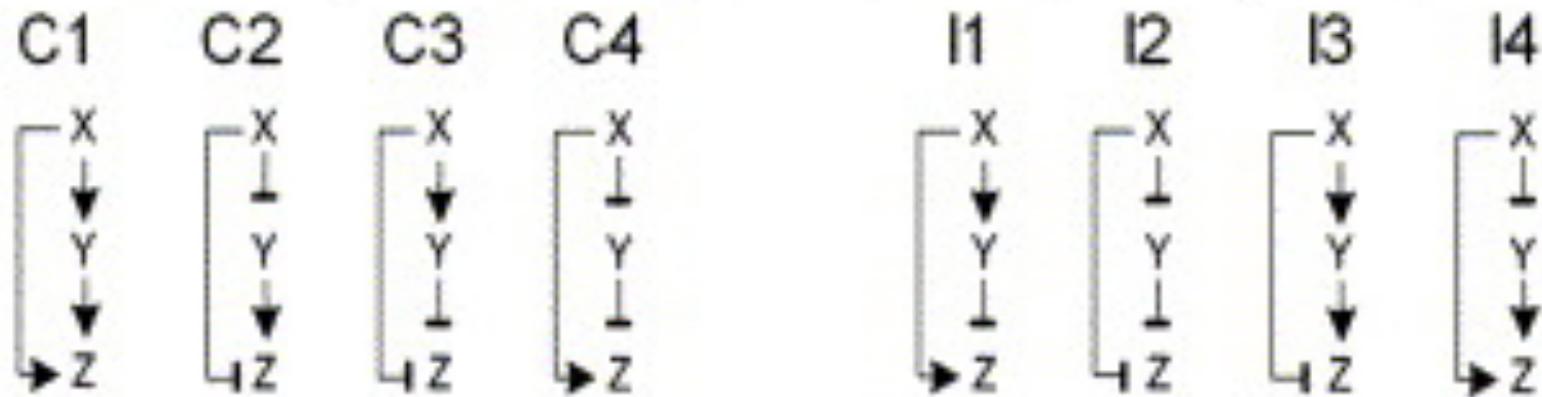


3-node feedback loop
(cycle)

	Feed-forward loop	3-node Feedback loop
<i>E. Coli</i>	42	0
Random network	1.7 +/- 1.3	0.6 +/- 0.8
Degree-preserving random network	7 +/- 5	0.2 +/- 0.6

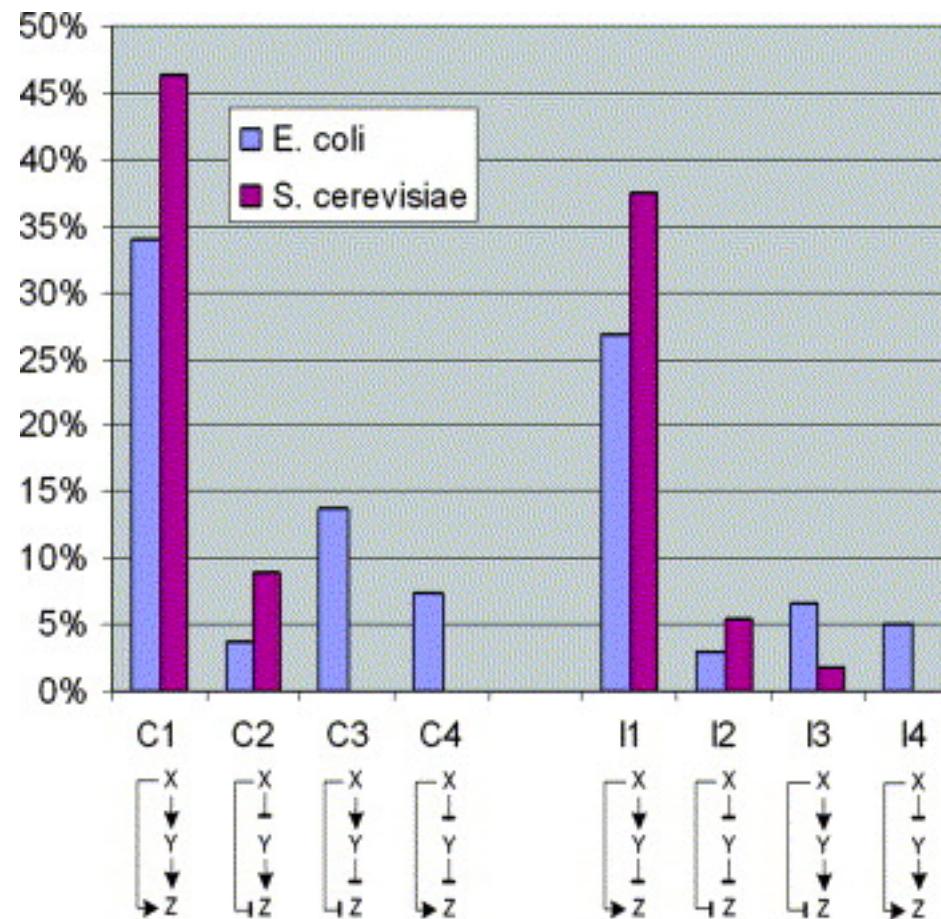
(U. Alon, *An Introduction to Systems Biology*)

Different feed-forward loops implement distinct functions



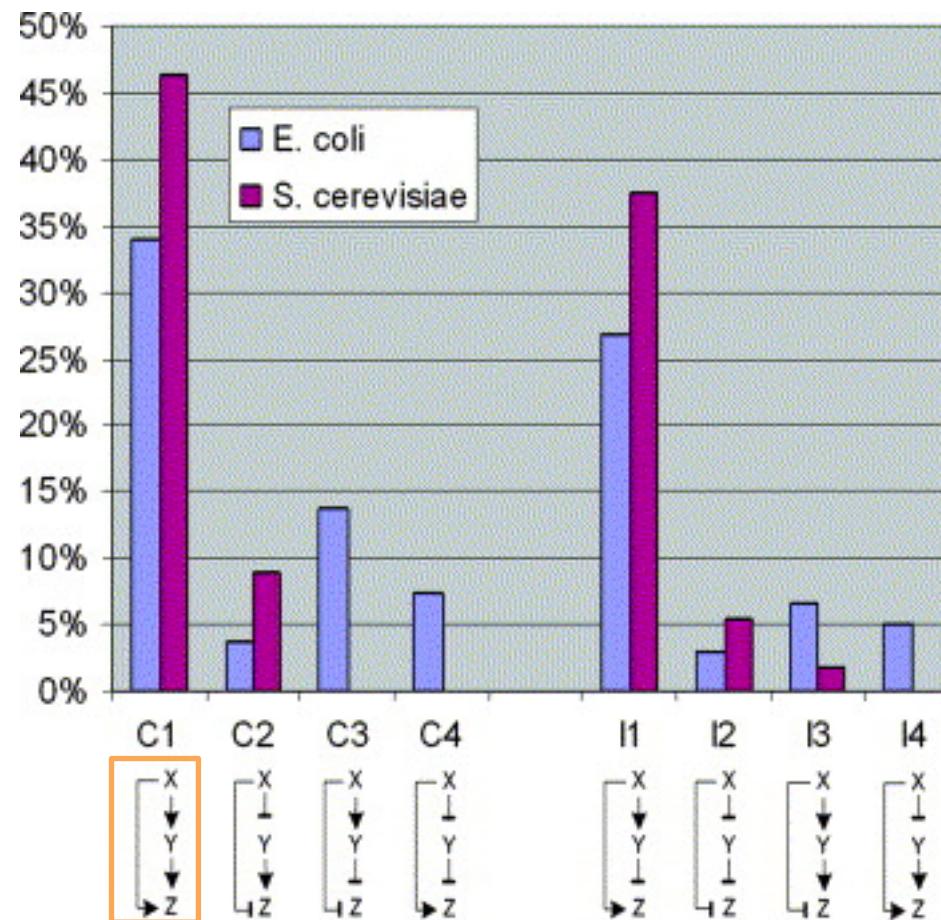
(Mangan *et al.*, JMB 356:1073-1081, 2006)

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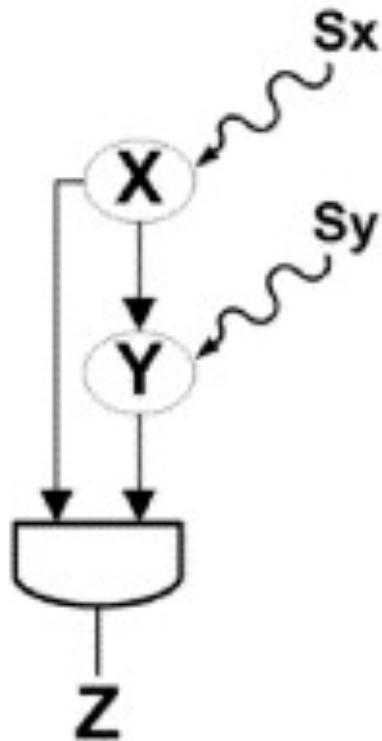
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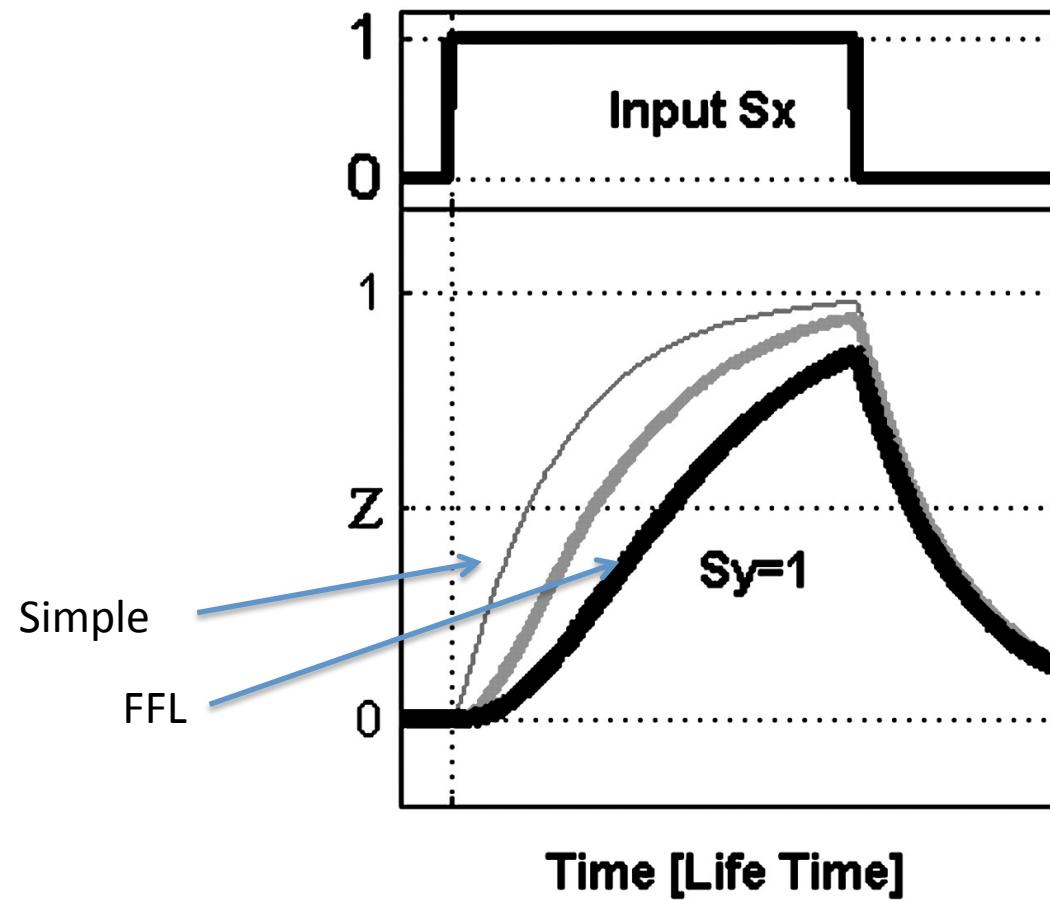
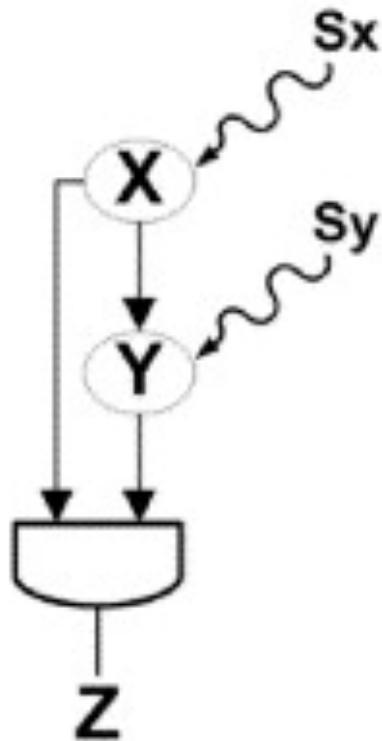
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Type 1 coherent FFLs implement delays



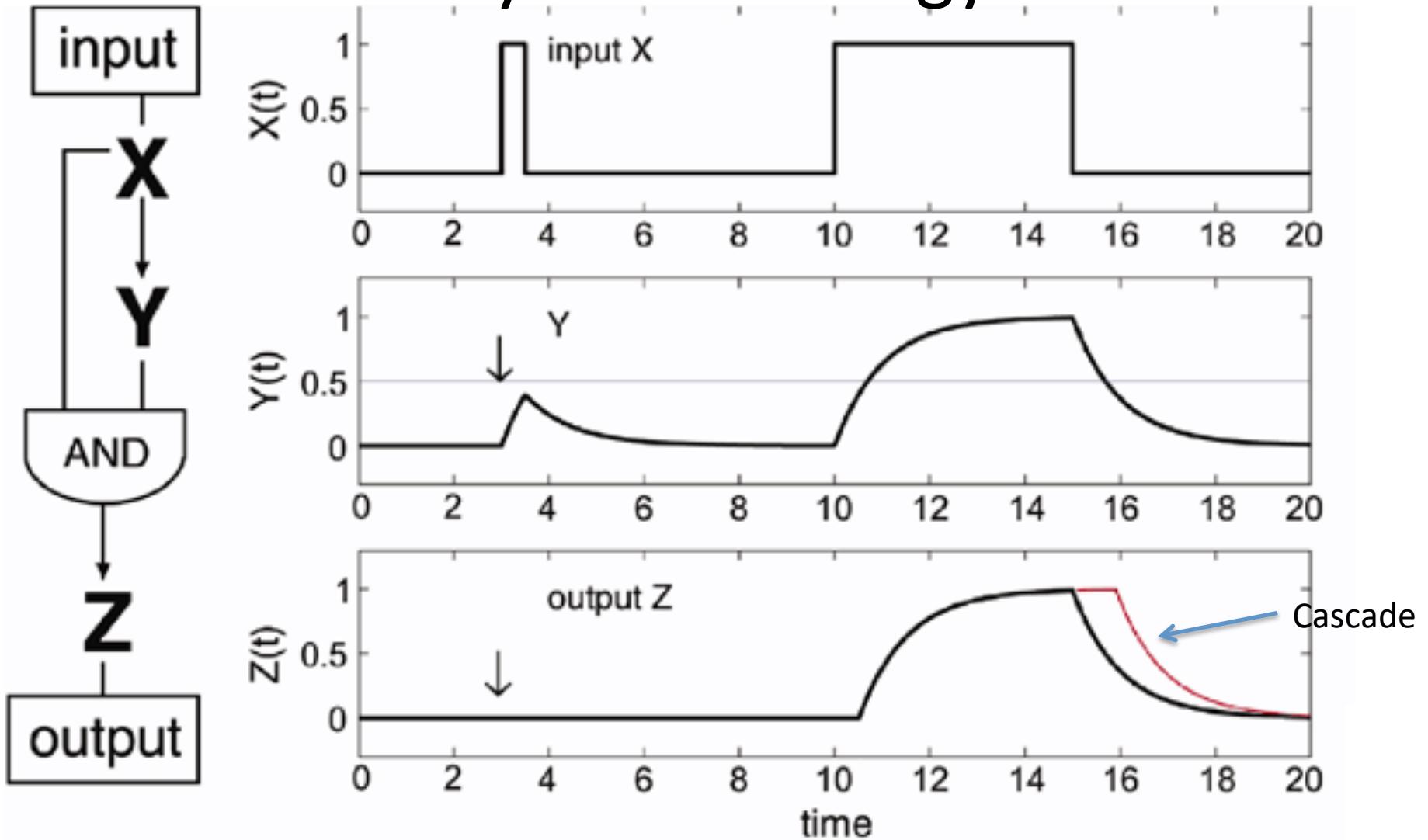
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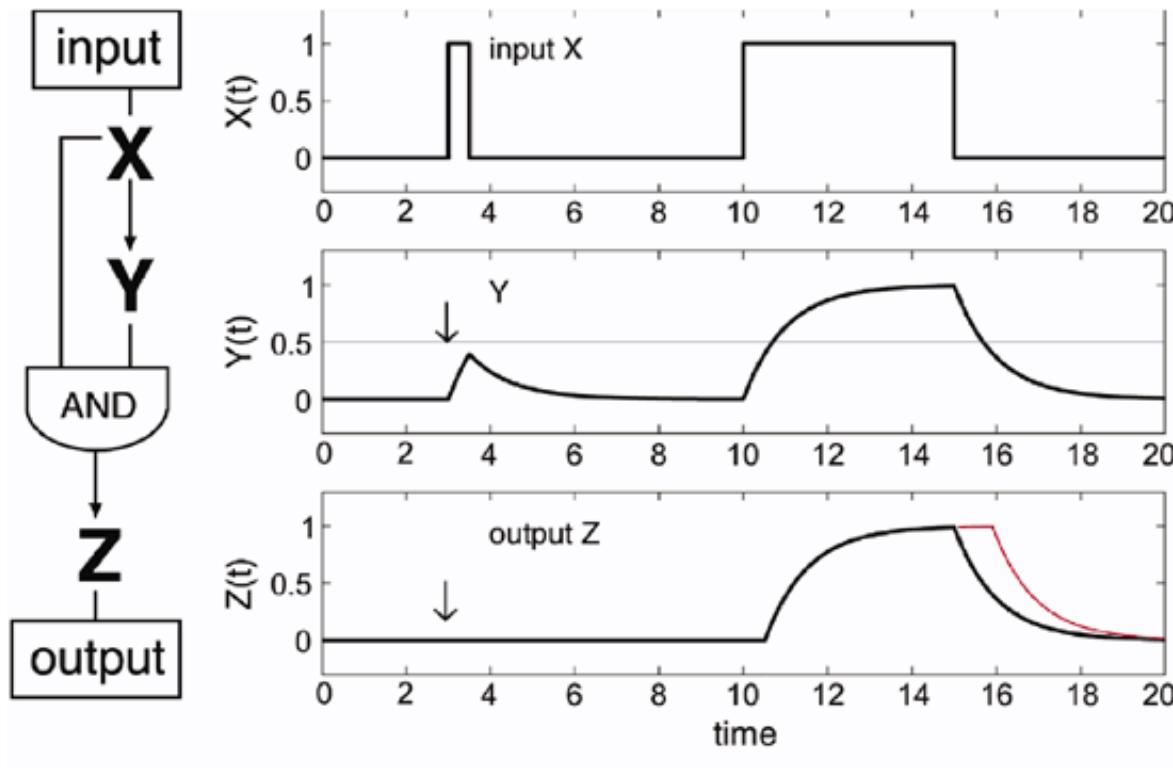
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An aside: Numerical models in systems biology



(Shen-Orr *et al.*, Nat. Gen. 2002)

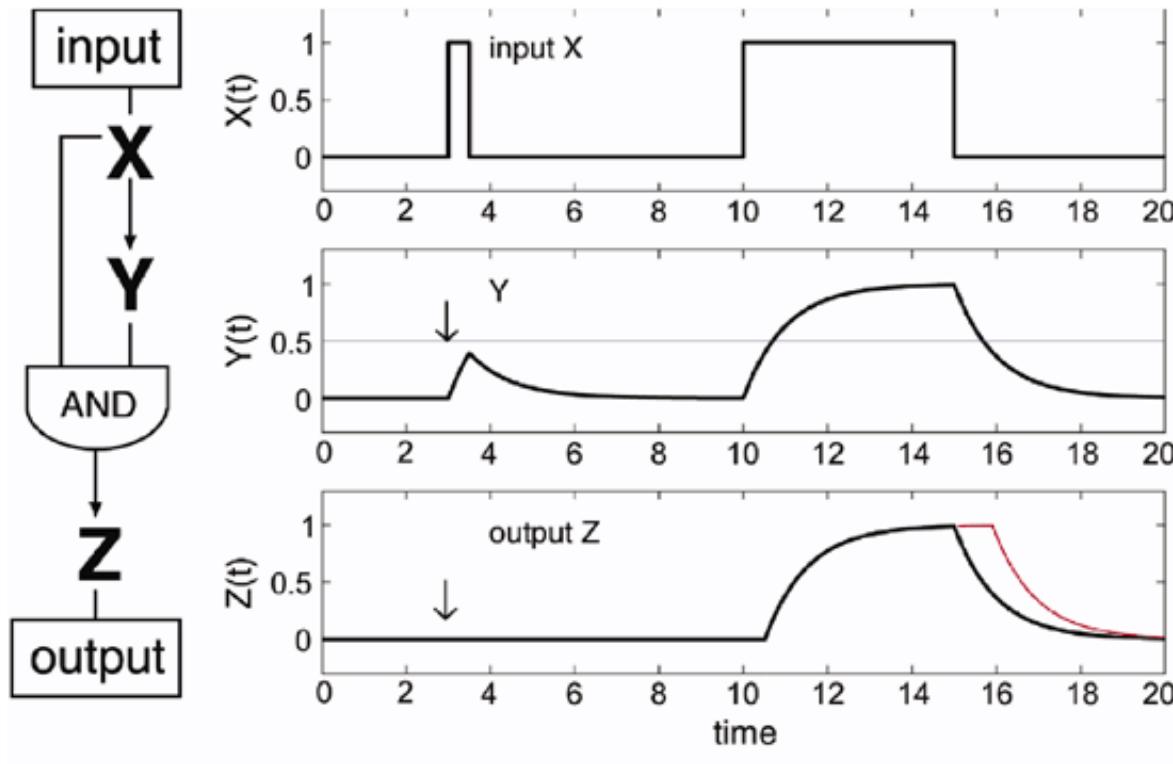
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$$\frac{dY}{dt} = F(X, T_y) - \alpha Y$$

(Shen-Orr *et al.*, Nat. Gen. 2002)

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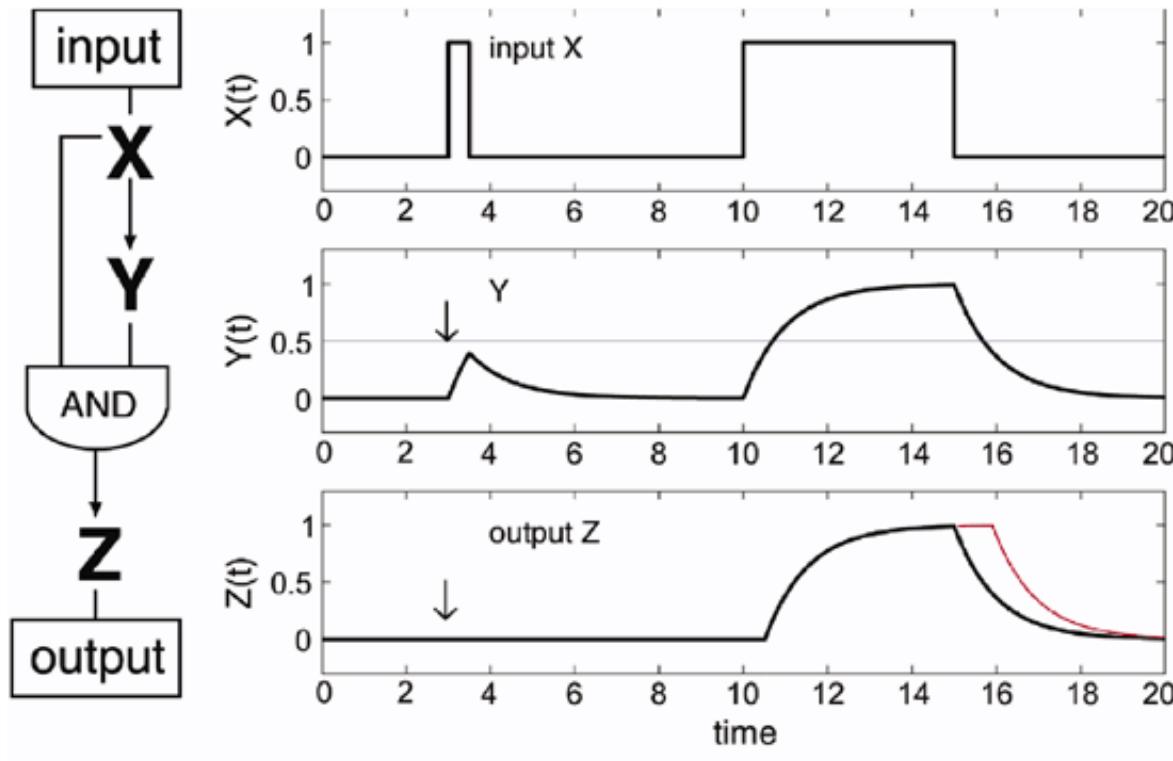


$$\frac{dY}{dt} = F(X, T_y) - \alpha Y$$

Rate of change in [Y] $\frac{dY}{dt}$ $F(X, T_y)$ αY
Threshold on X value Degradation rate of Y

(Shen-Orr *et al.*, Nat. Gen. 2002)

An aside: Numerical models in systems biology

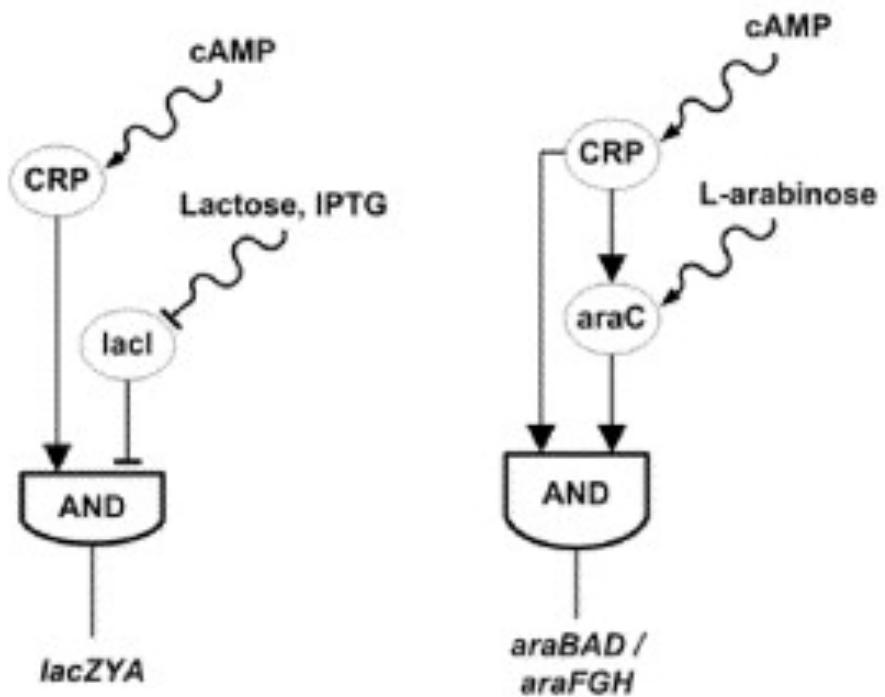


$$\frac{dY}{dt} = F(X, T_y) - \alpha Y$$

$$\frac{dZ}{dt} = F(X, T_y)F(Y, T_z) - \alpha Z$$

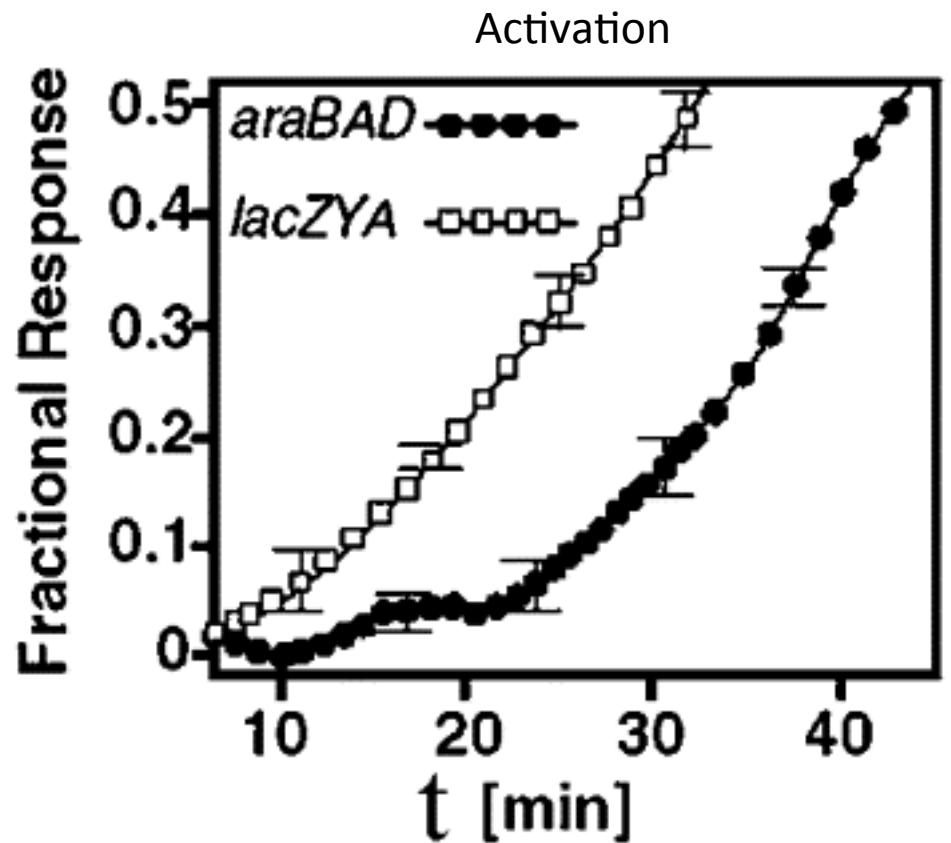
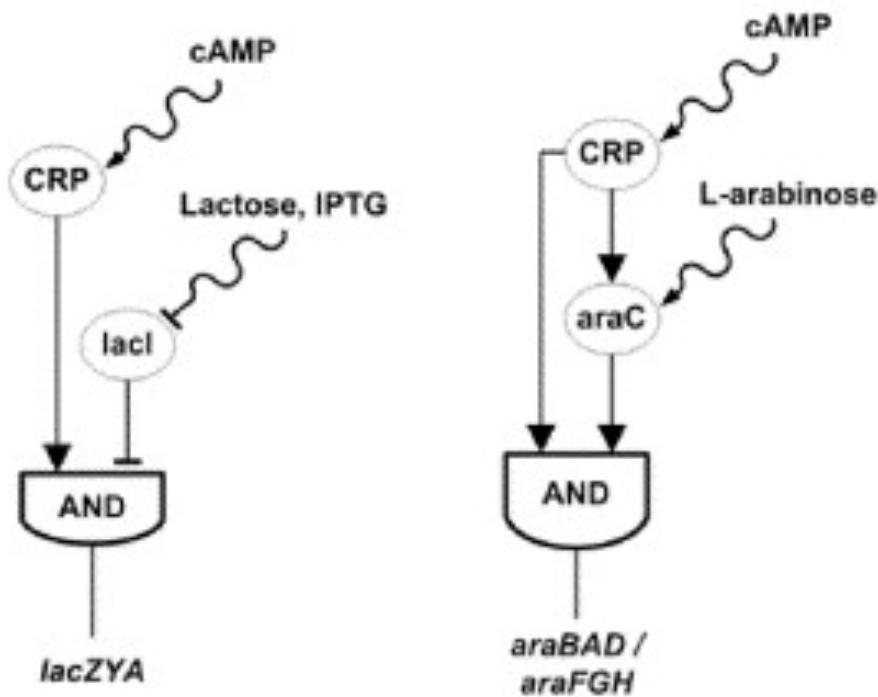
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Type 1 coherent FFLs in a real regulatory network



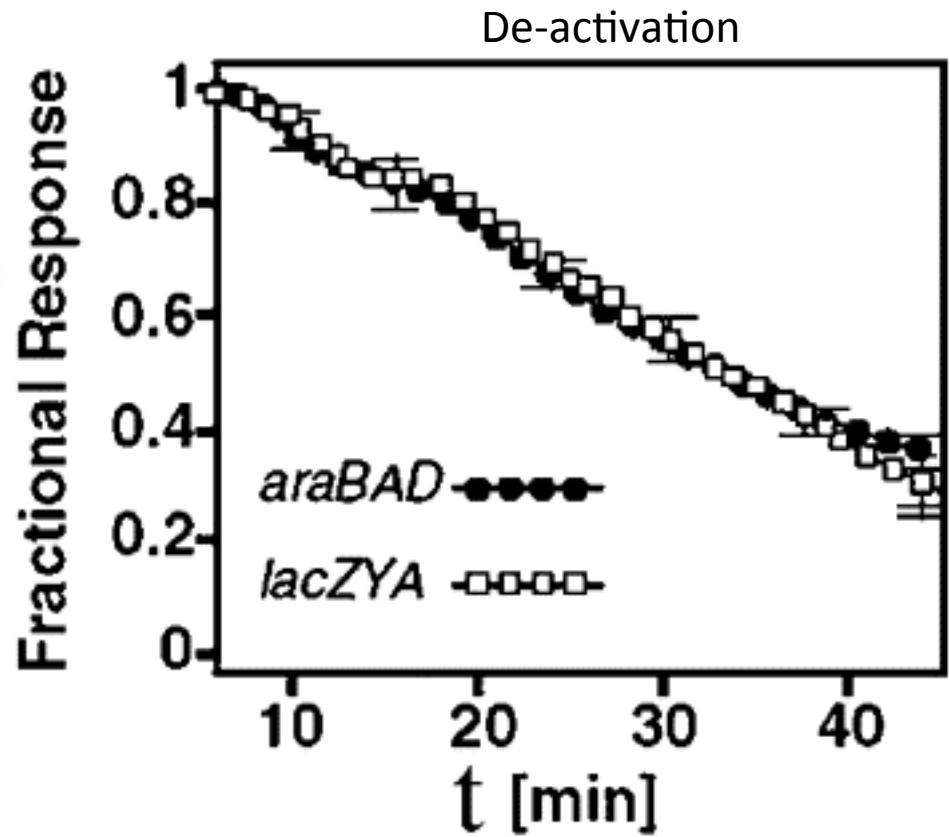
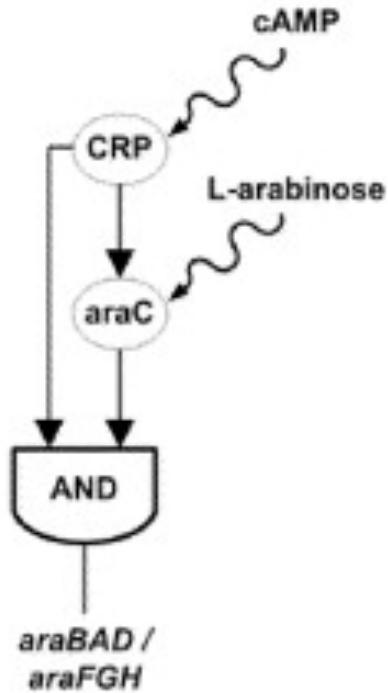
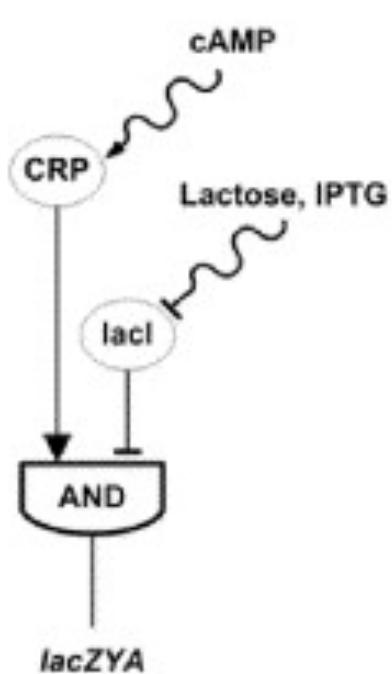
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Type 1 coherent FFLs in a real regulatory network



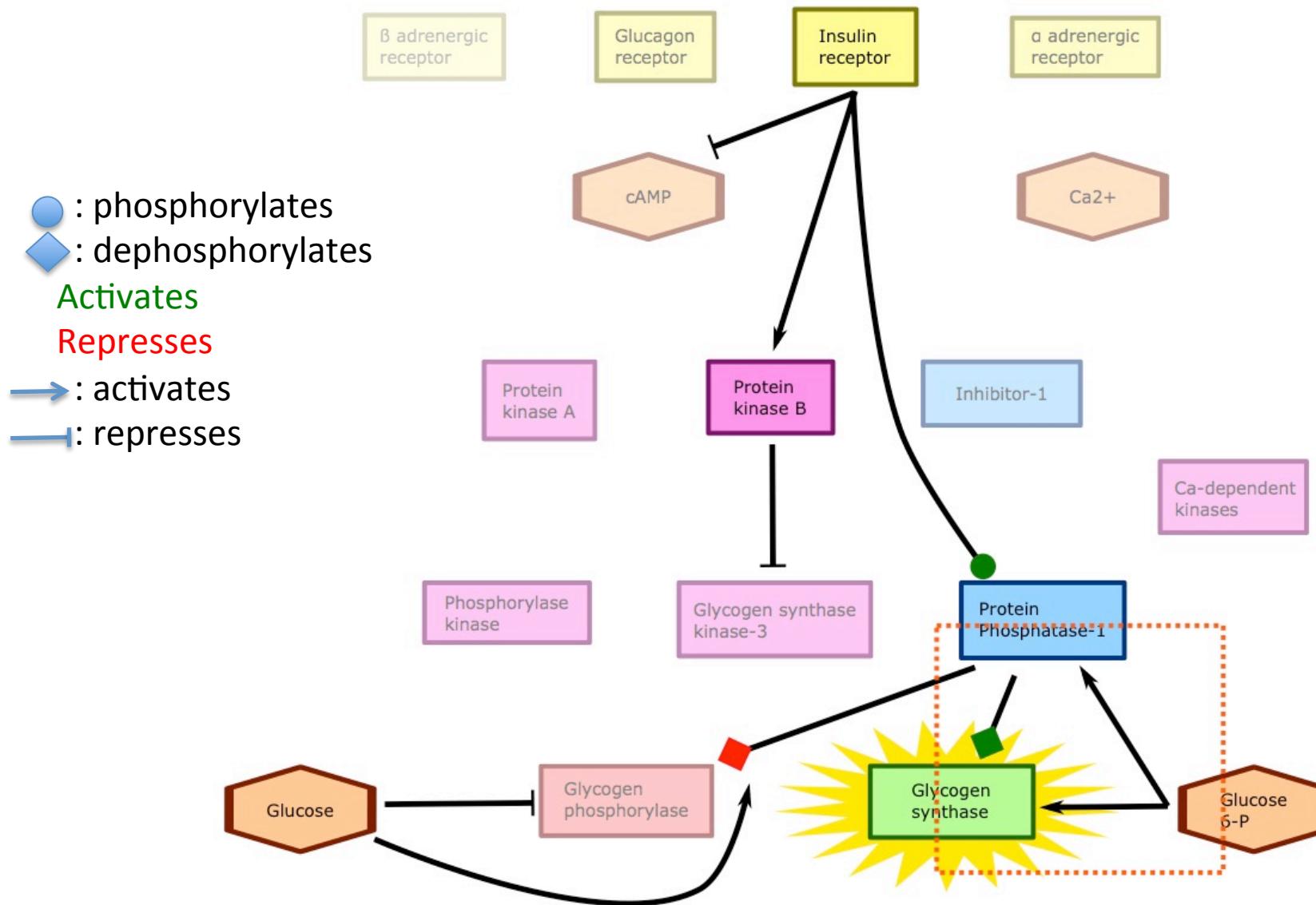
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Type 1 coherent FFLs in a real regulatory network

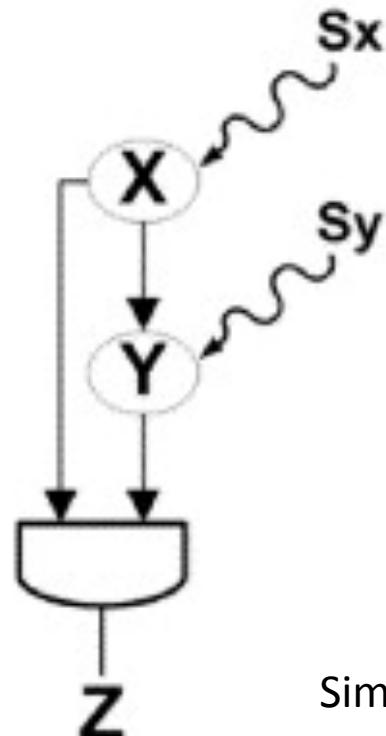


(Mangan *et al.*, JMB 2006)

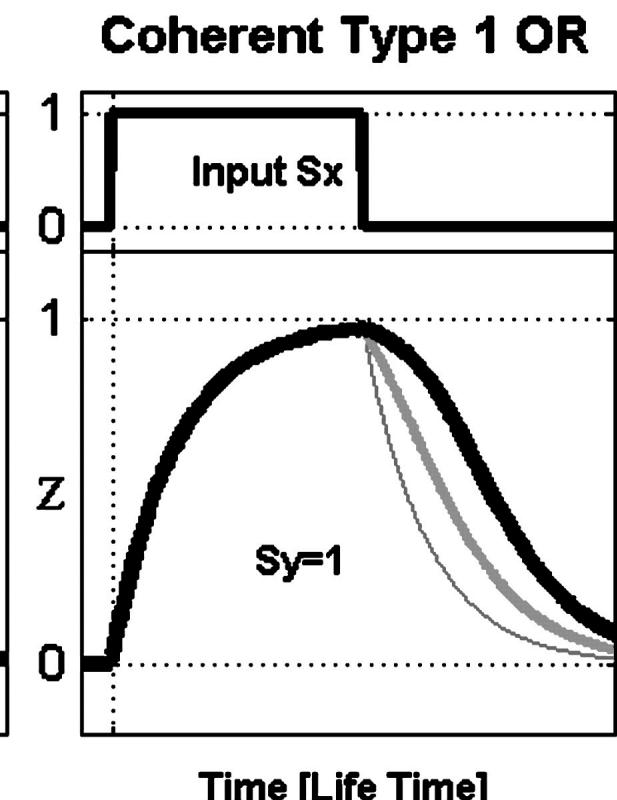
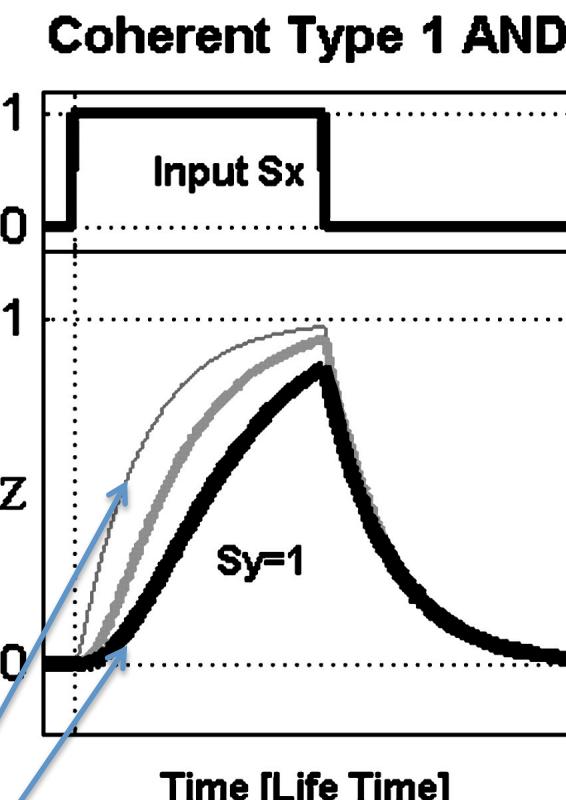
FFLs in regulation of glycogen synthesis



Changing the logic at the promoter alters behavior

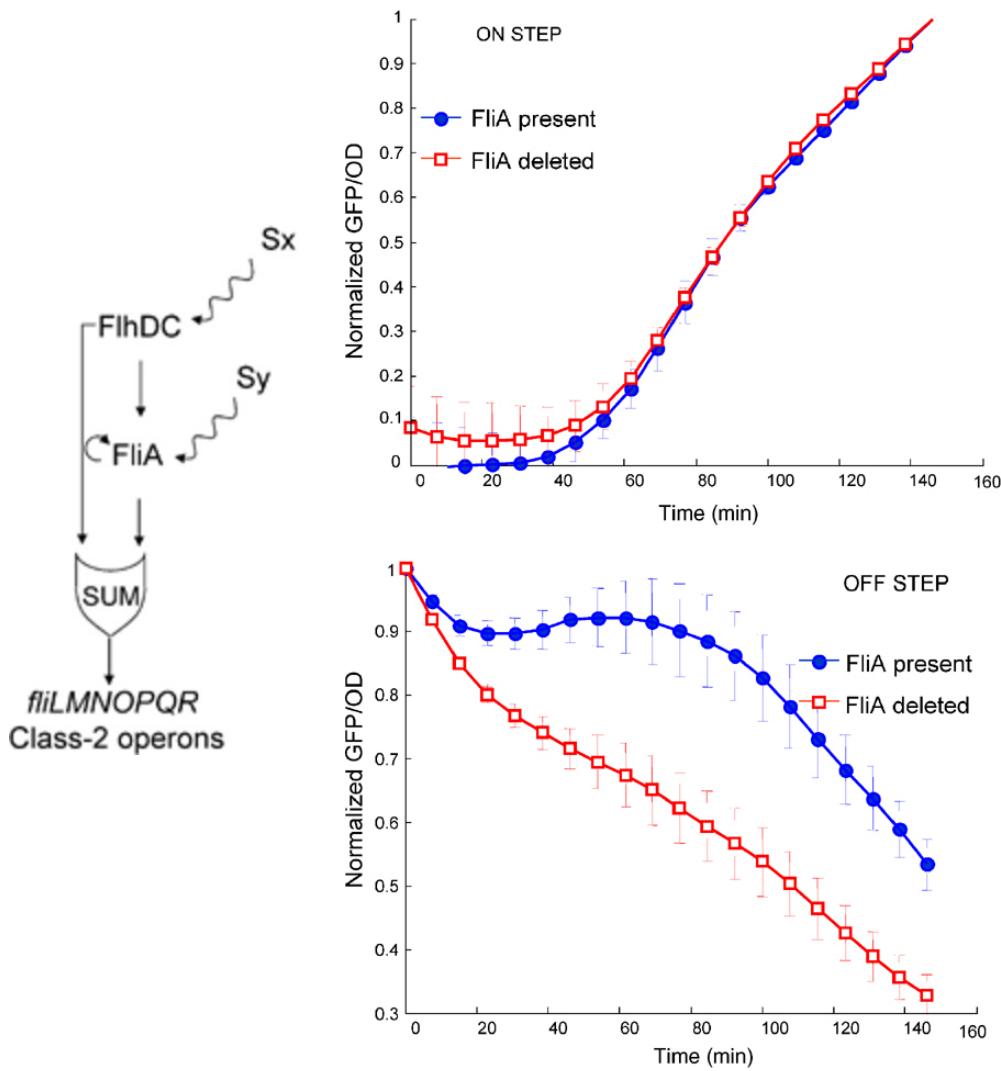


Simple
FFL



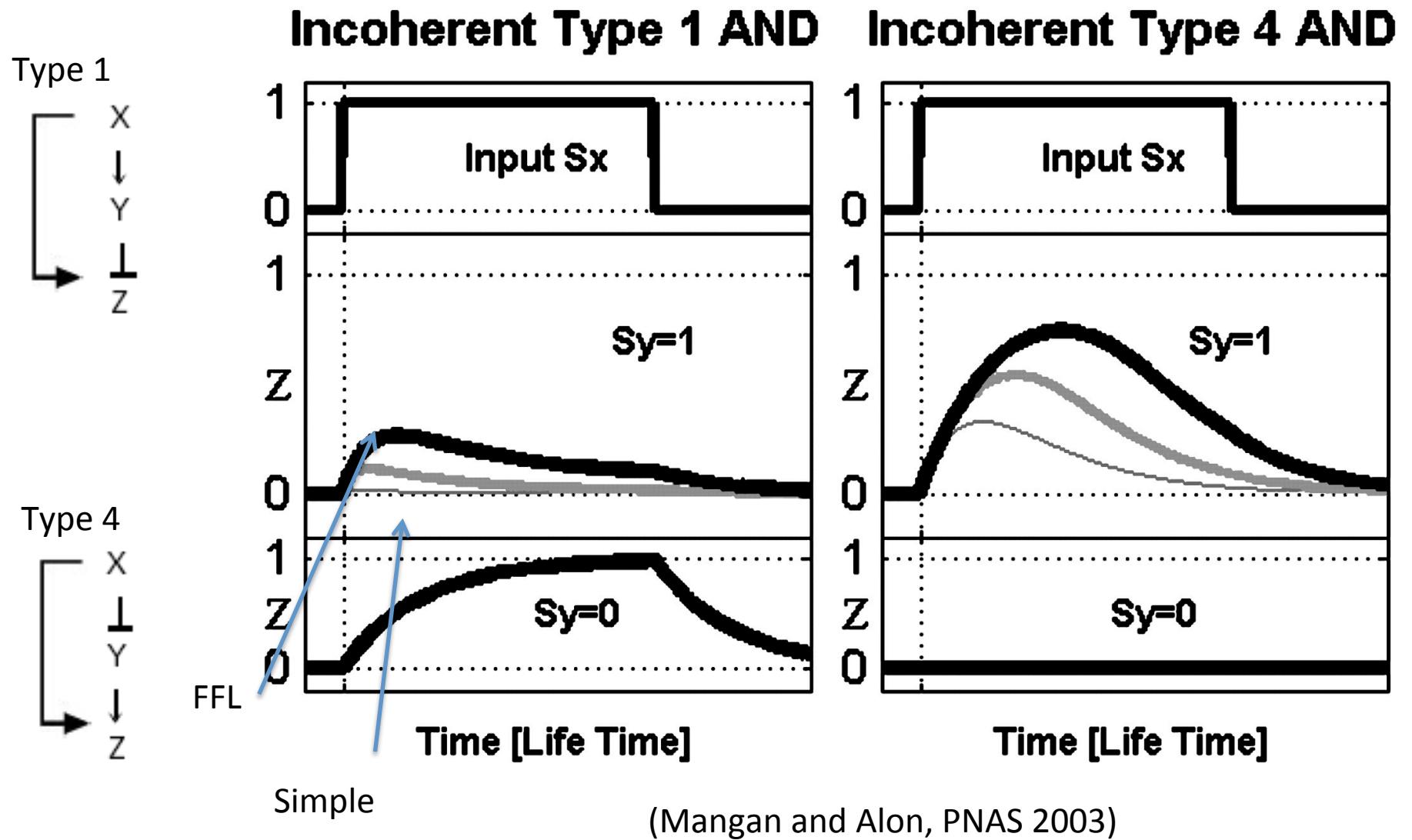
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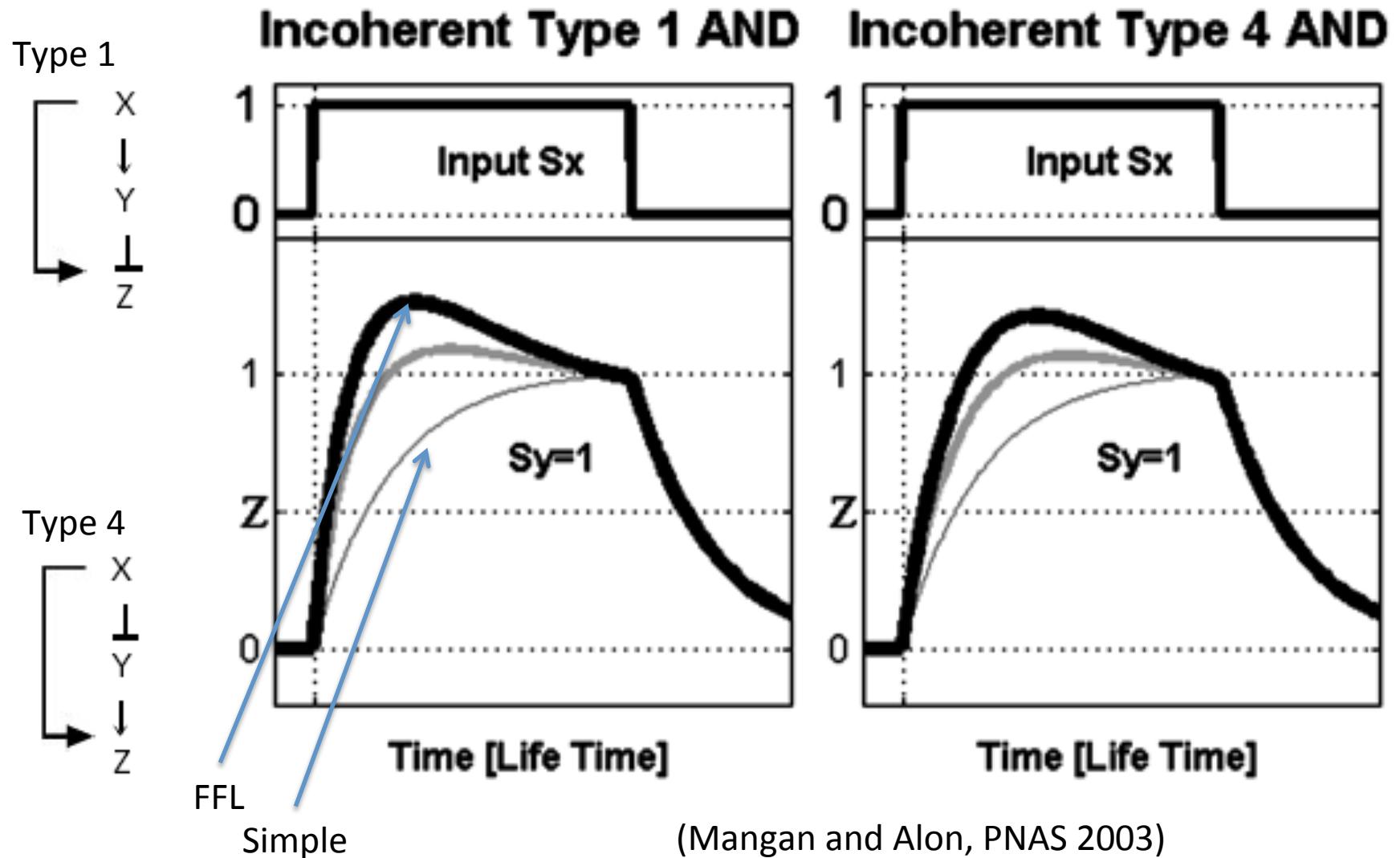


(Kalir *et al.*,
Mol. Sys. Bio. 2005)

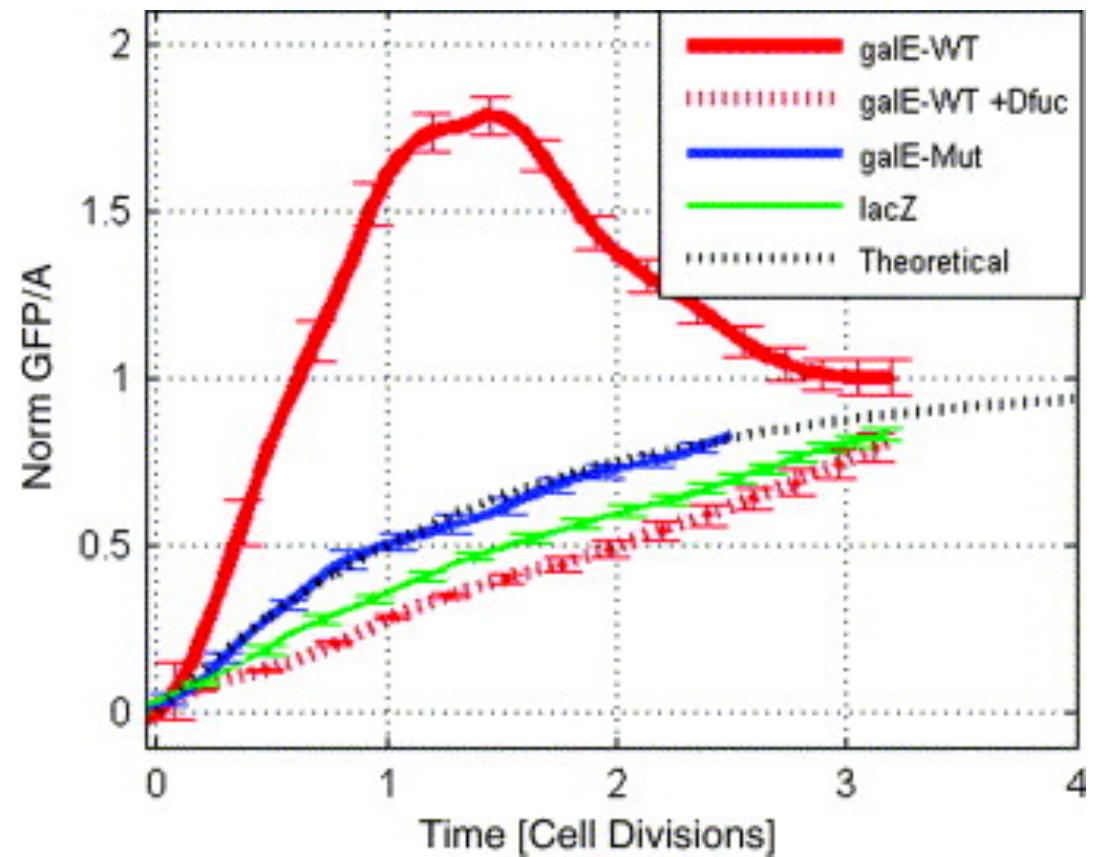
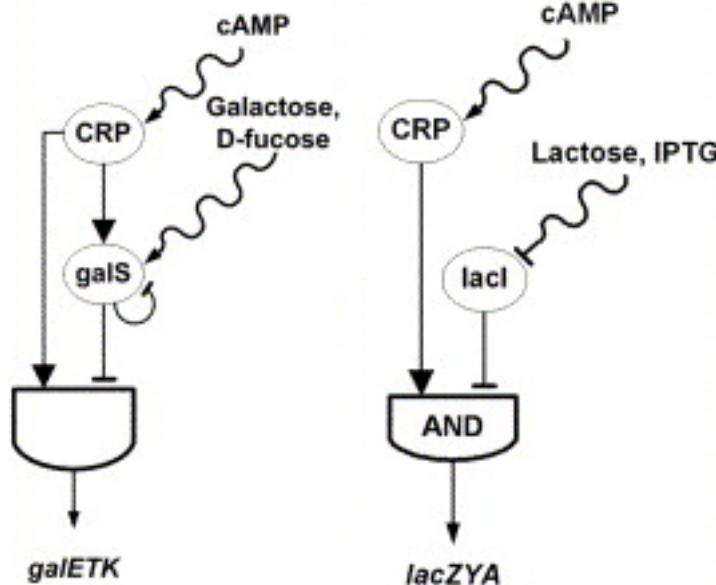
Incoherent FFLs allow rapid response or transient bursts



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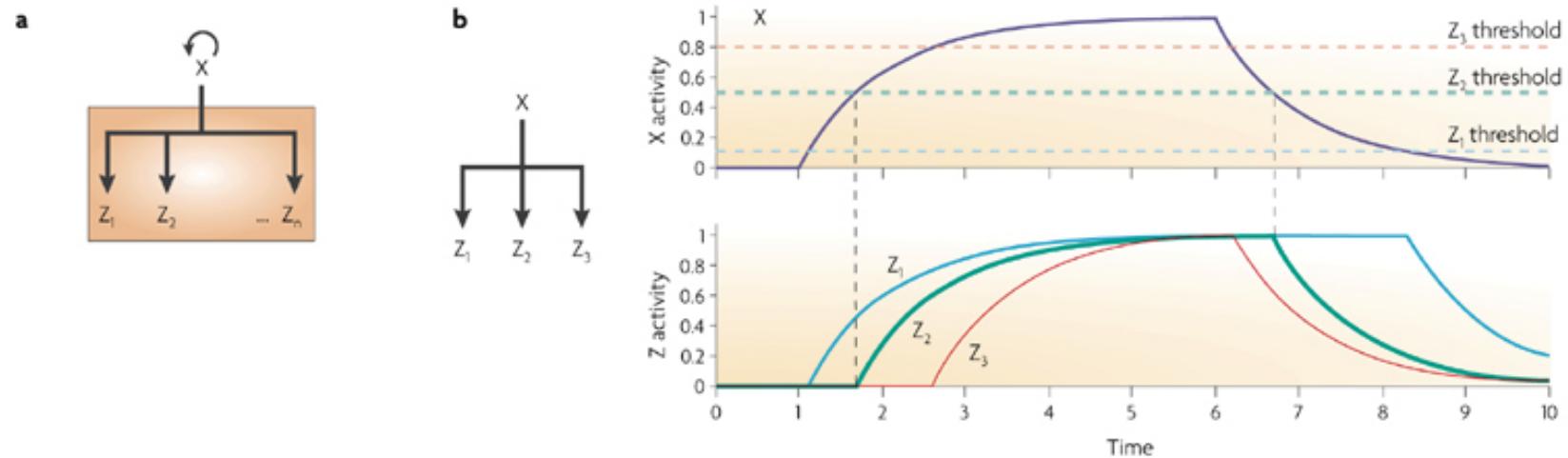


FFL-accelerated response in biological context



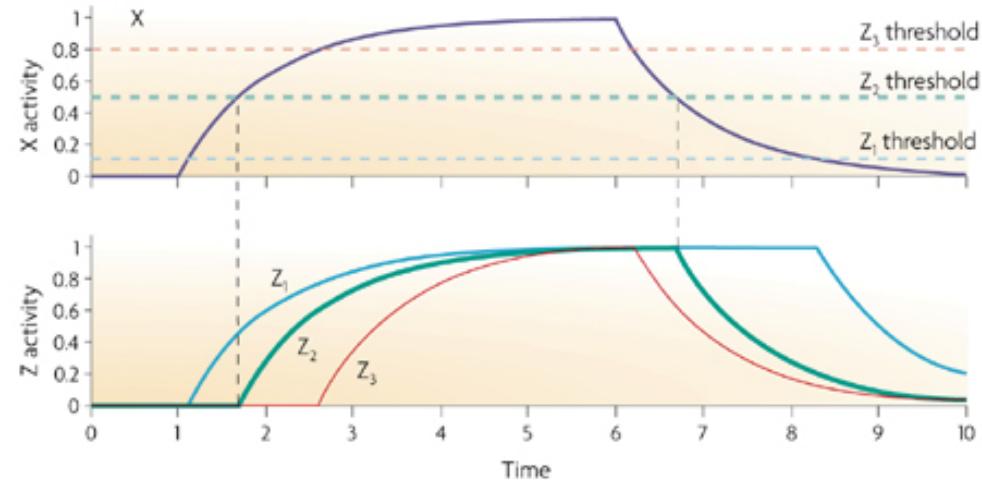
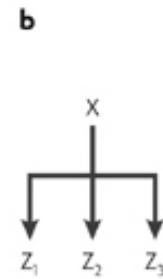
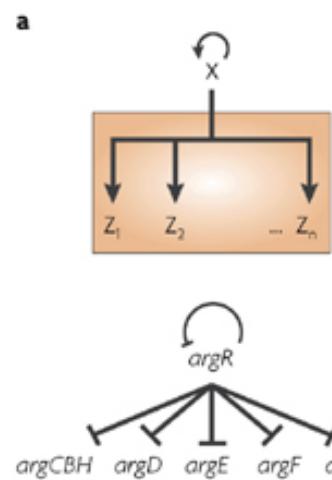
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Single-input modules (SIMs) allow coordination of large regulons



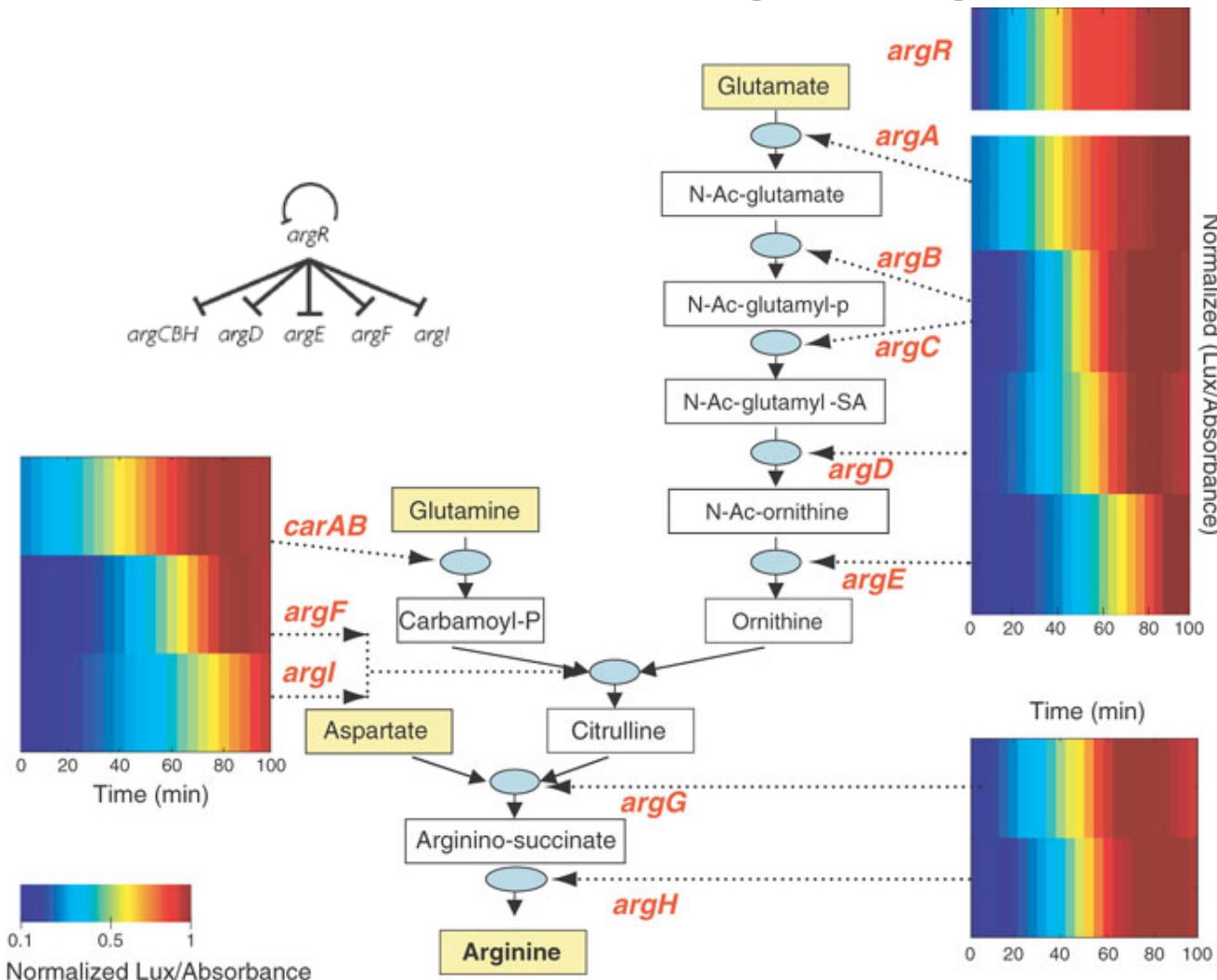
(Alon, Nat. Rev. Genet. 2007)

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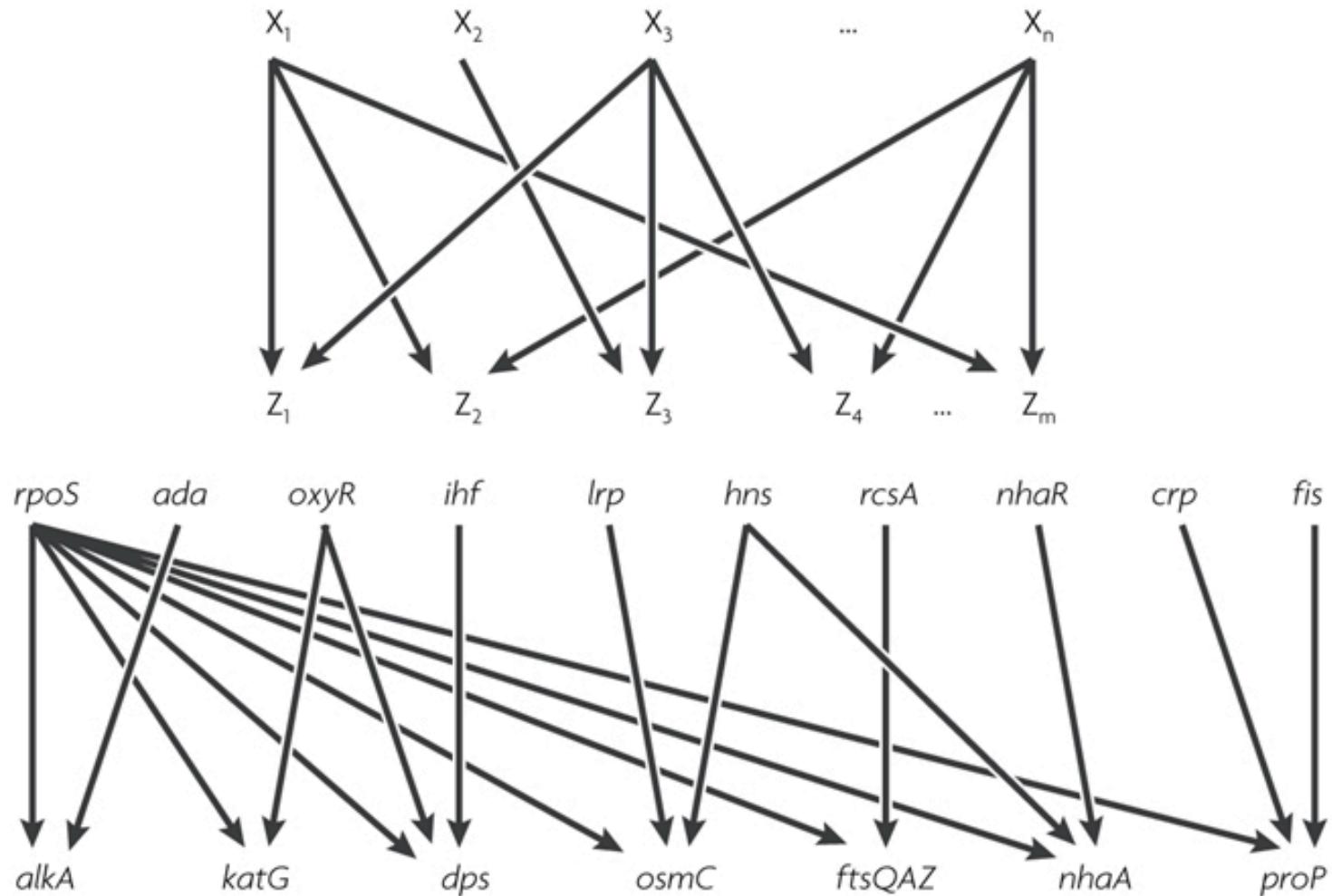
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Single-input modules (SIMs) allow coordination of large regulons



(Zaslaver *et al.*, Nat. Genet. 2004)

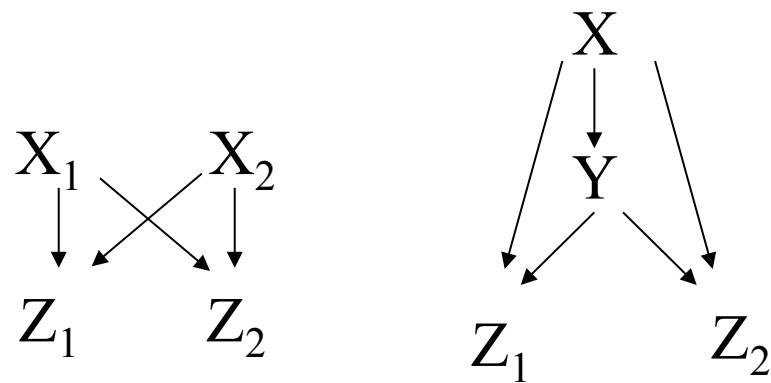
Dense overlapping regulons enable combinatorial control



(Alon, Nat. Rev. Genetics 2007)

Nature Reviews | Genetics

Dense overlapping regulons enable combinatorial control

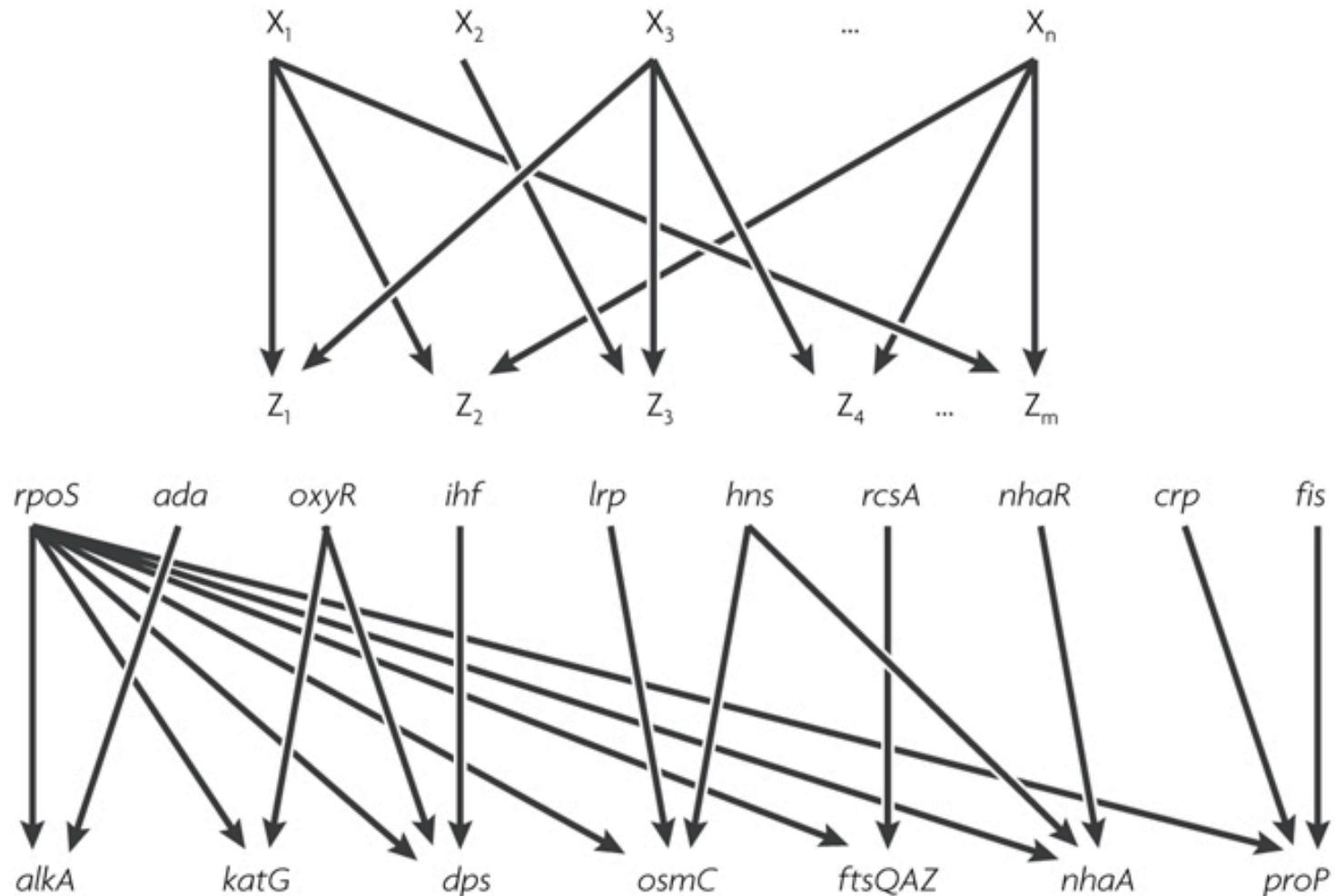


Bifan

Two-output
Feed-forward loop

(U. Alon, *An Introduction to Systems Biology*)

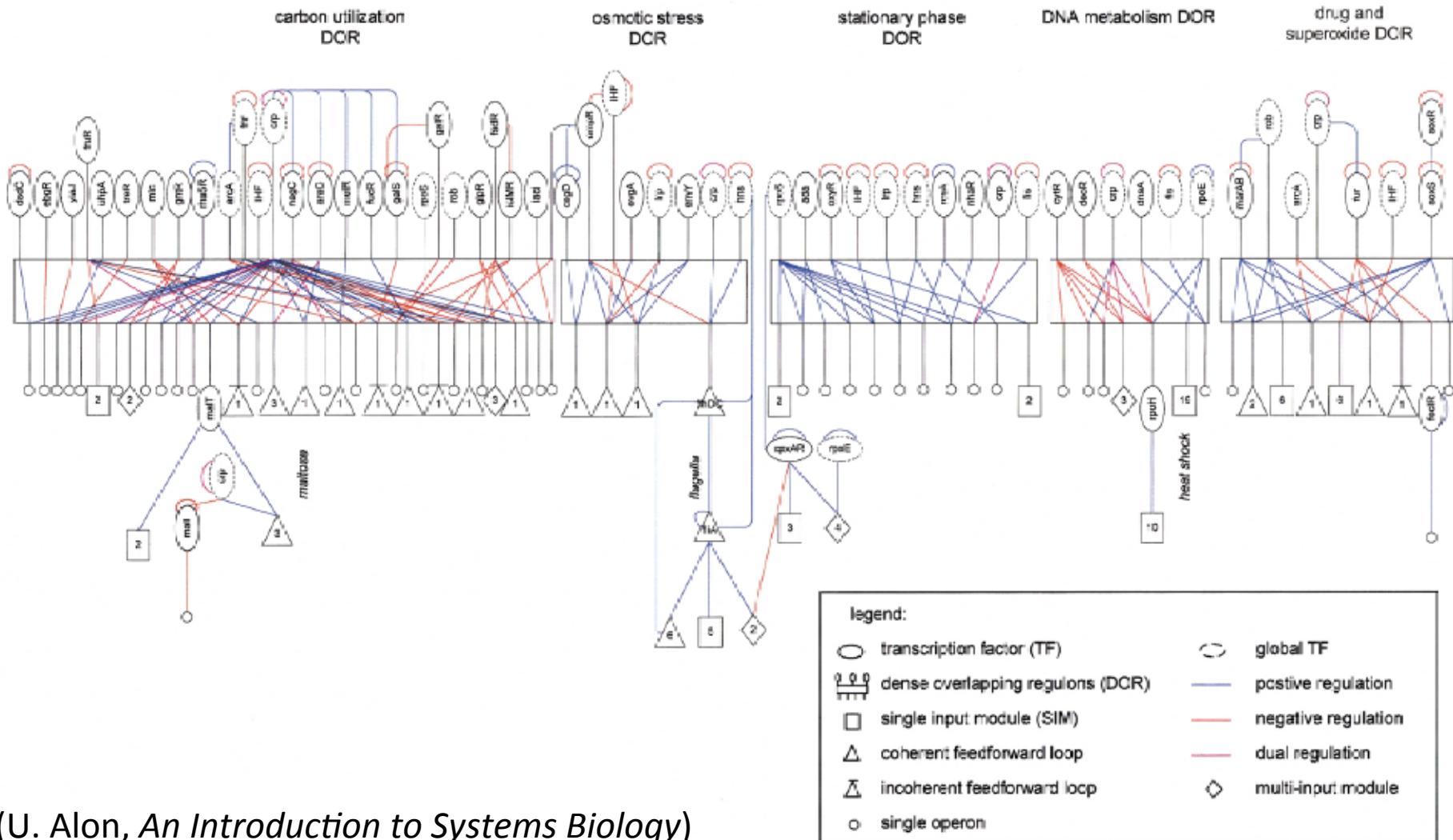
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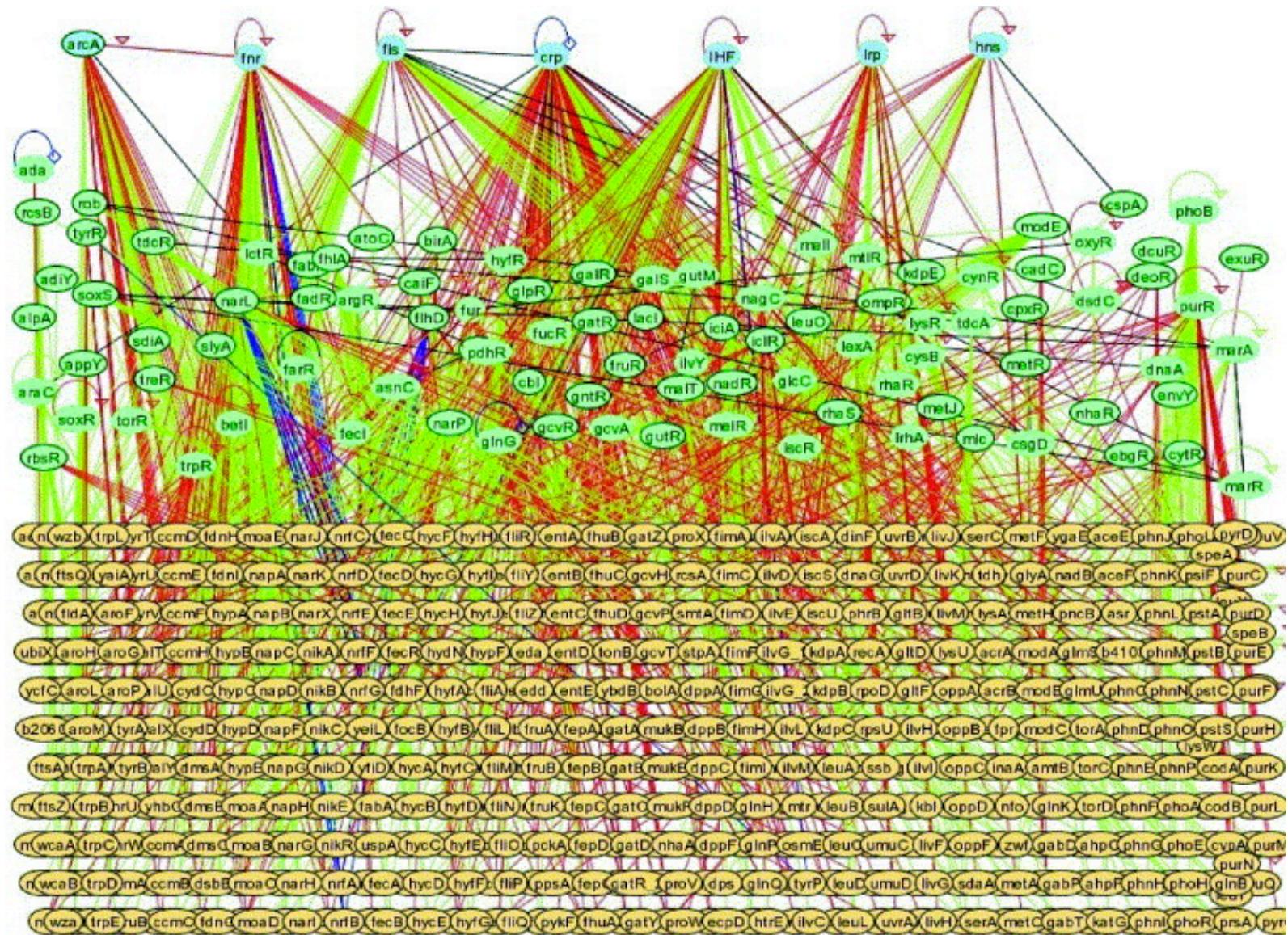
Nature Reviews | Genetics

Circuit diagram of the *E. coli* transcriptional regulatory network



(U. Alon, *An Introduction to Systems Biology*)

Standard display of the same network



(Martinez-Antonio and Collado-Vides, 2003)

Current Opinion in Microbiology

Network motifs in other biological networks

Sensory transcriptional regulatory networks:

- Coherent and incoherent FFLs
- Single-input module
- Dense overlapping regulons

Network motifs in other biological networks

Sensory transcriptional regulatory networks:

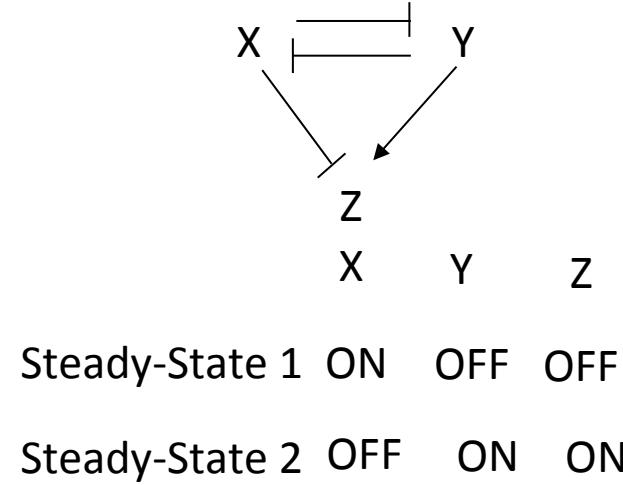
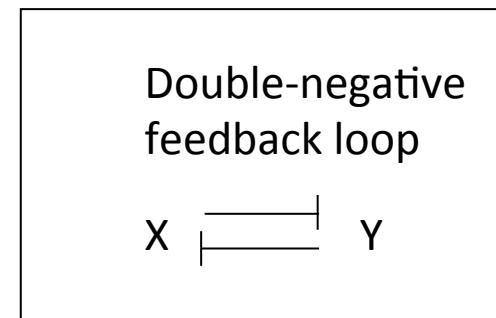
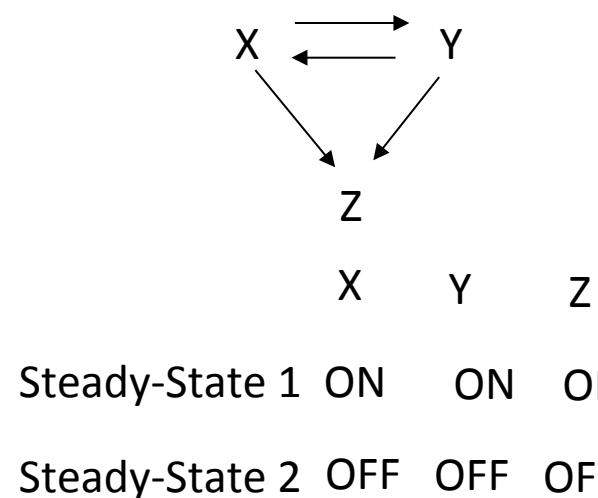
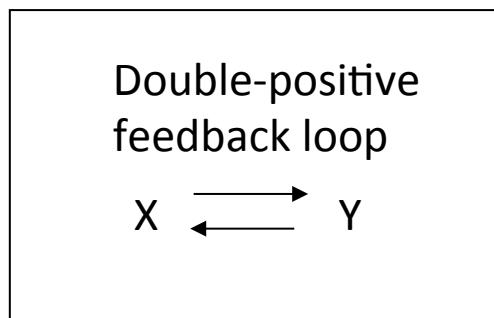
- Coherent and incoherent FFLs
- Single-input module
- Dense overlapping regulons

Additional motifs in other network types:

- Feedback loops
- Long signaling cascades
- Multi-input FFLs

Network motifs in other biological networks

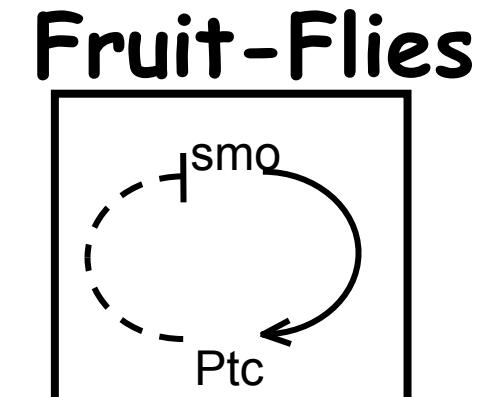
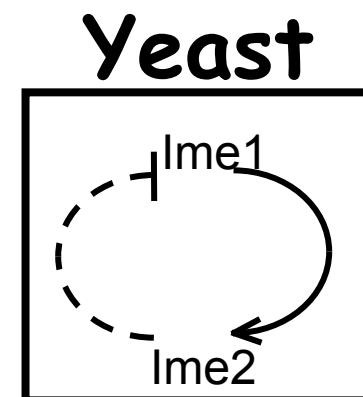
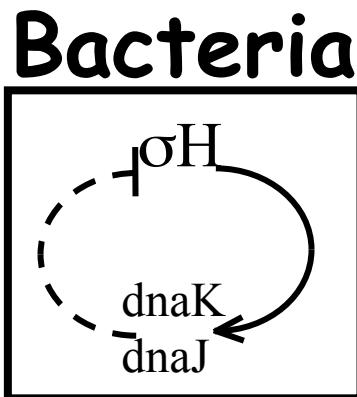
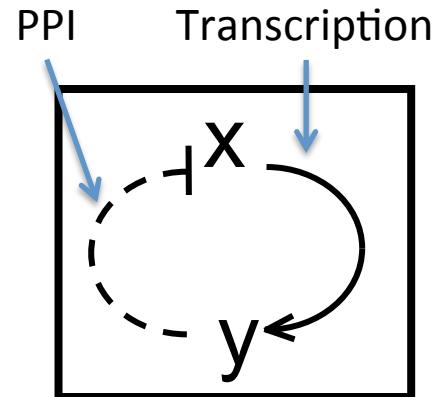
Feedback loops



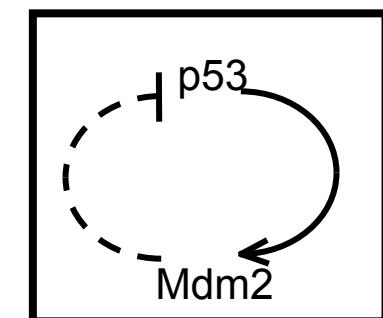
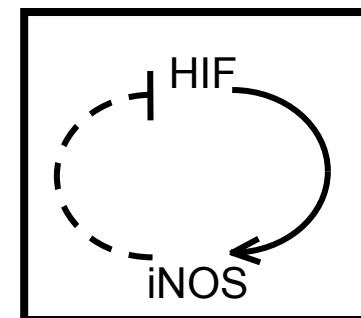
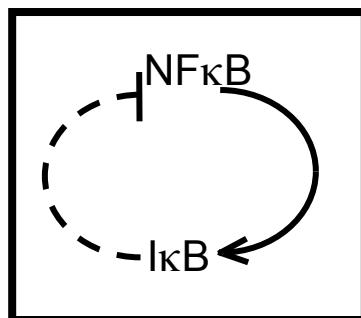
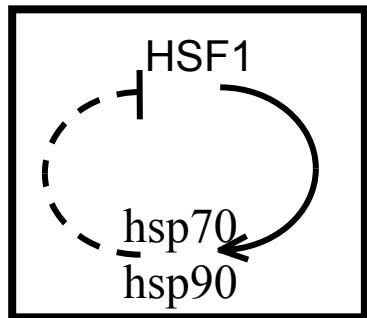
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Network motifs in other biological networks

Feedback loops



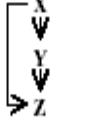
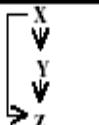
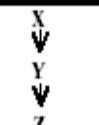
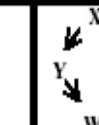
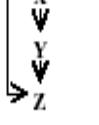
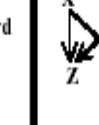
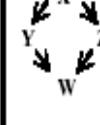
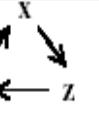
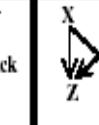
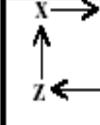
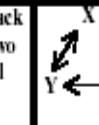
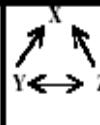
Mammals



(U. Alon, *An Introduction to Systems Biology*)

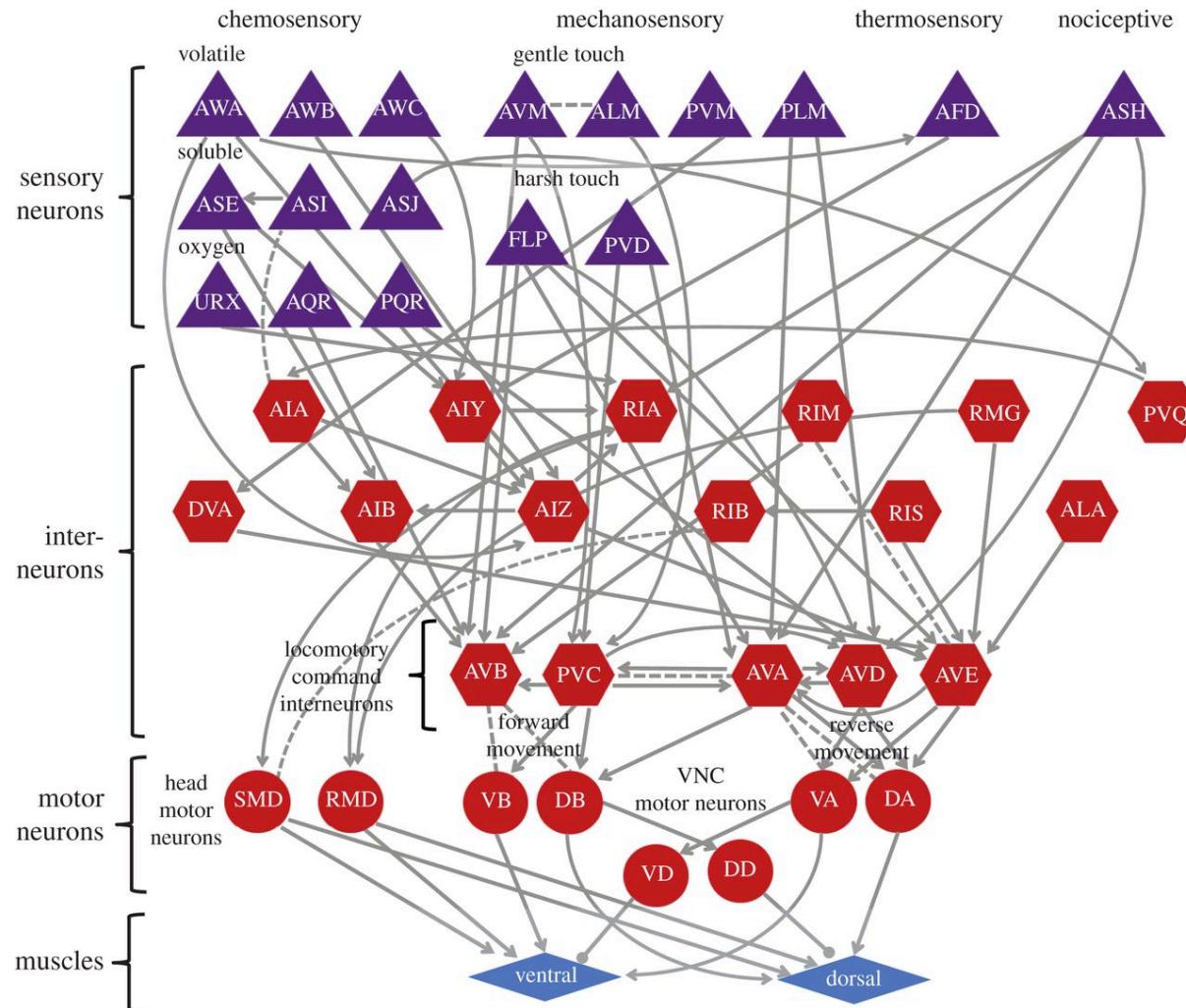
Network motifs in other biological networks

(U. Alon, *An Introduction to Systems Biology*)

Network	Nodes	Edges	N_{real}	$N_{\text{rand}} \pm \text{SD}$	Z score	N_{real}	$N_{\text{rand}} \pm \text{SD}$	Z score	N_{real}	$N_{\text{rand}} \pm \text{SD}$	Z score
Gene regulation (transcription)				Feed-forward loop			Bi-fan				
<i>E. coli</i>	424	519	40	7 ± 3	10	203	47 ± 12	13			
<i>S. cerevisiae*</i>	685	1,052	70	11 ± 4	14	1812	300 ± 40	41			
Neurons				Feed-forward loop			Bi-fan		Bi-parallel		
<i>C. elegans†</i>	252	509	125	90 ± 10	3.7	127	55 ± 13	5.3	227	35 ± 10	20
Food webs				Three chain			Bi-parallel				
Little Rock	92	984	3219	3120 ± 50	2.1	7295	2220 ± 210	25			
Ythan	83	391	1182	1020 ± 20	7.2	1357	230 ± 50	23			
St. Martin	42	205	469	450 ± 10	NS	382	130 ± 20	12			
Chesapeake	31	67	80	82 ± 4	NS	26	5 ± 2	8			
Coachella	29	243	279	235 ± 12	3.6	181	80 ± 20	5			
Skipwith	25	189	184	150 ± 7	5.5	397	80 ± 25	13			
B. Brock	25	104	181	130 ± 7	7.4	267	30 ± 7	32			
Electronic circuits (forward logic chips)				Feed-forward loop			Bi-fan		Bi-parallel		
s15850	10,383	14,240	424	2 ± 2	285	1040	1 ± 1	1200	480	2 ± 1	335
s38584	20,717	34,204	413	10 ± 3	120	1739	6 ± 2	800	711	9 ± 2	320
s38417	23,843	33,661	612	3 ± 2	400	2404	1 ± 1	2550	531	2 ± 2	340
s9234	5,844	8,197	211	2 ± 1	140	754	1 ± 1	1050	209	1 ± 1	200
s13207	8,651	11,831	403	2 ± 1	225	4445	1 ± 1	4950	264	2 ± 1	200
Electronic circuits (digital fractional multipliers)				Three-node feedback loop			Bi-fan		Four-node feedback loop		
s208	122	189	10	1 ± 1	9	4	1 ± 1	3.8	5	1 ± 1	5
s420	252	399	20	1 ± 1	18	10	1 ± 1	10	11	1 ± 1	11
s838†	512	819	40	1 ± 1	38	22	1 ± 1	20	23	1 ± 1	25
World Wide Web				Feedback with two mutual dyads			Fully connected triad		Up-linked mutual dyad		
nd.edu§	325,729	1.46×10^6	1.1×10^5	$2e3 \pm 1e2$	800	6.8×10^6	$5e4 \pm 4e2$	15,000	1.2×10^6	$1e4 \pm 2e2$	5000

Network motifs in other biological networks

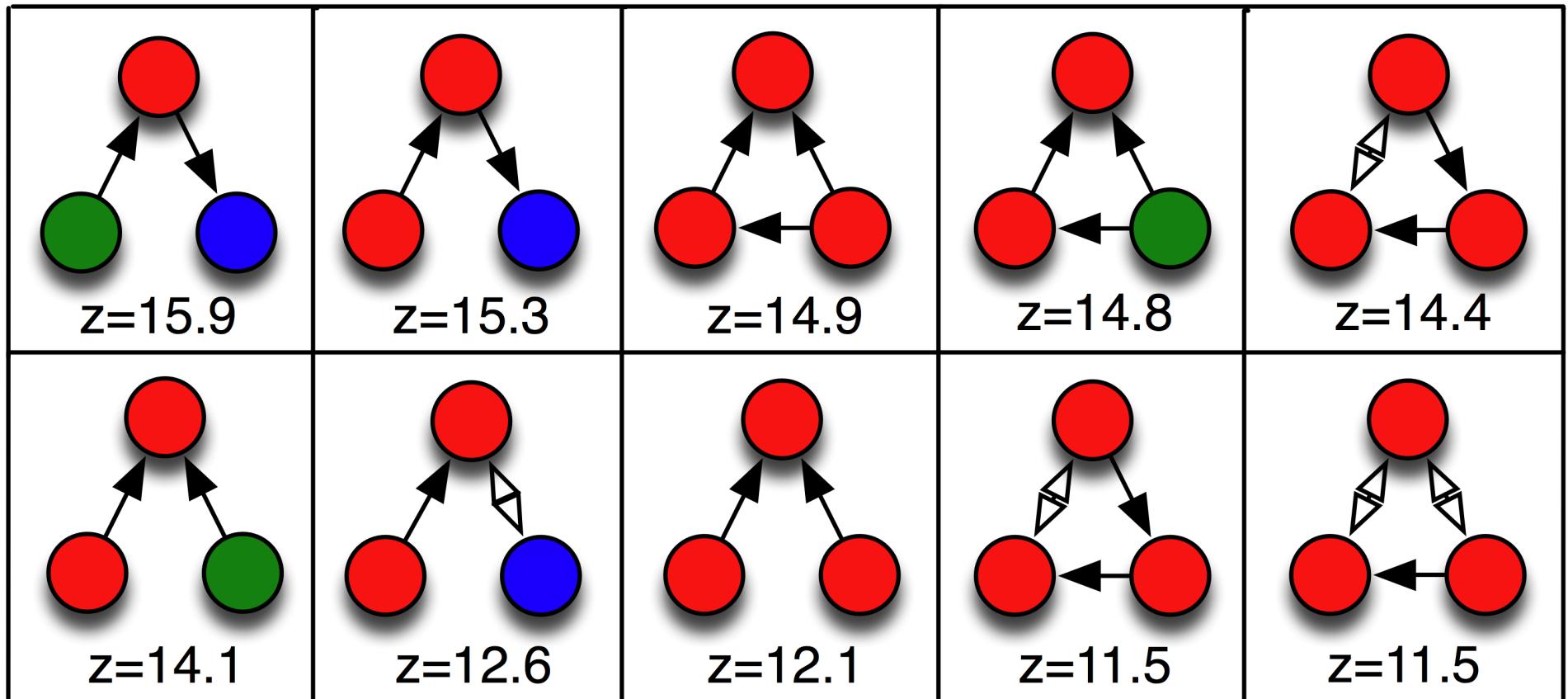
C. elegans somatic nervous system



(Fang-Yen et al., Phil. Trans. Royal Soc. B 2015)

Network motifs in other biological networks

C. elegans somatic nervous system

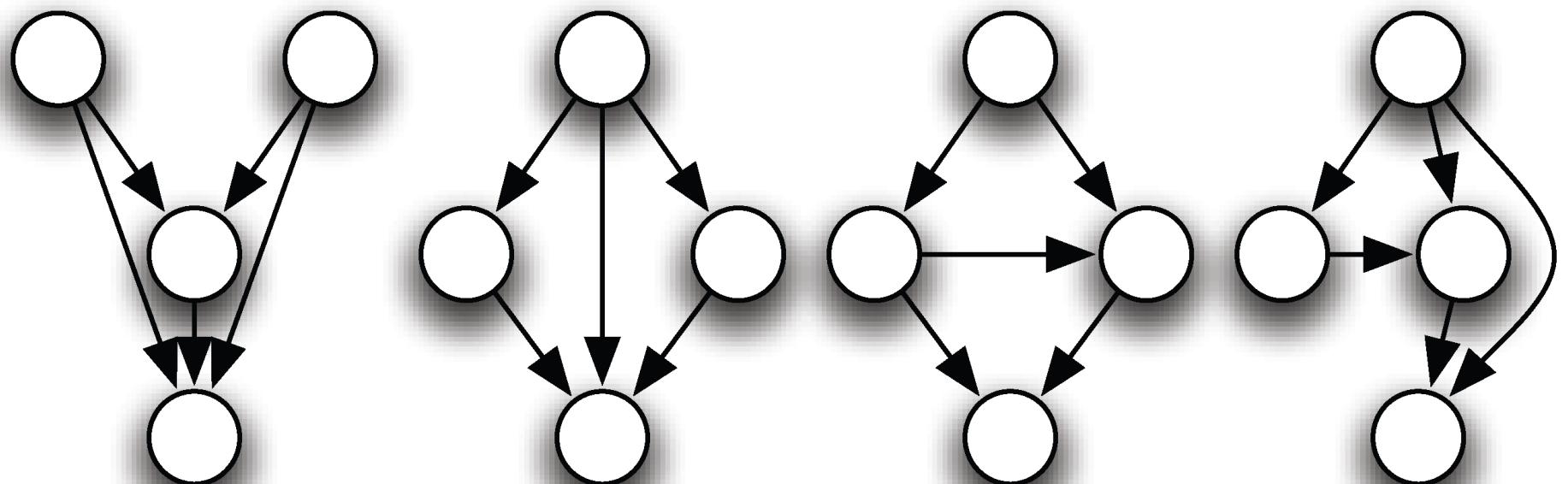


(Qian et al., PLoS One 2011)

Sensory neuron
Interneuron
Motor neuron

Network motifs in other biological networks

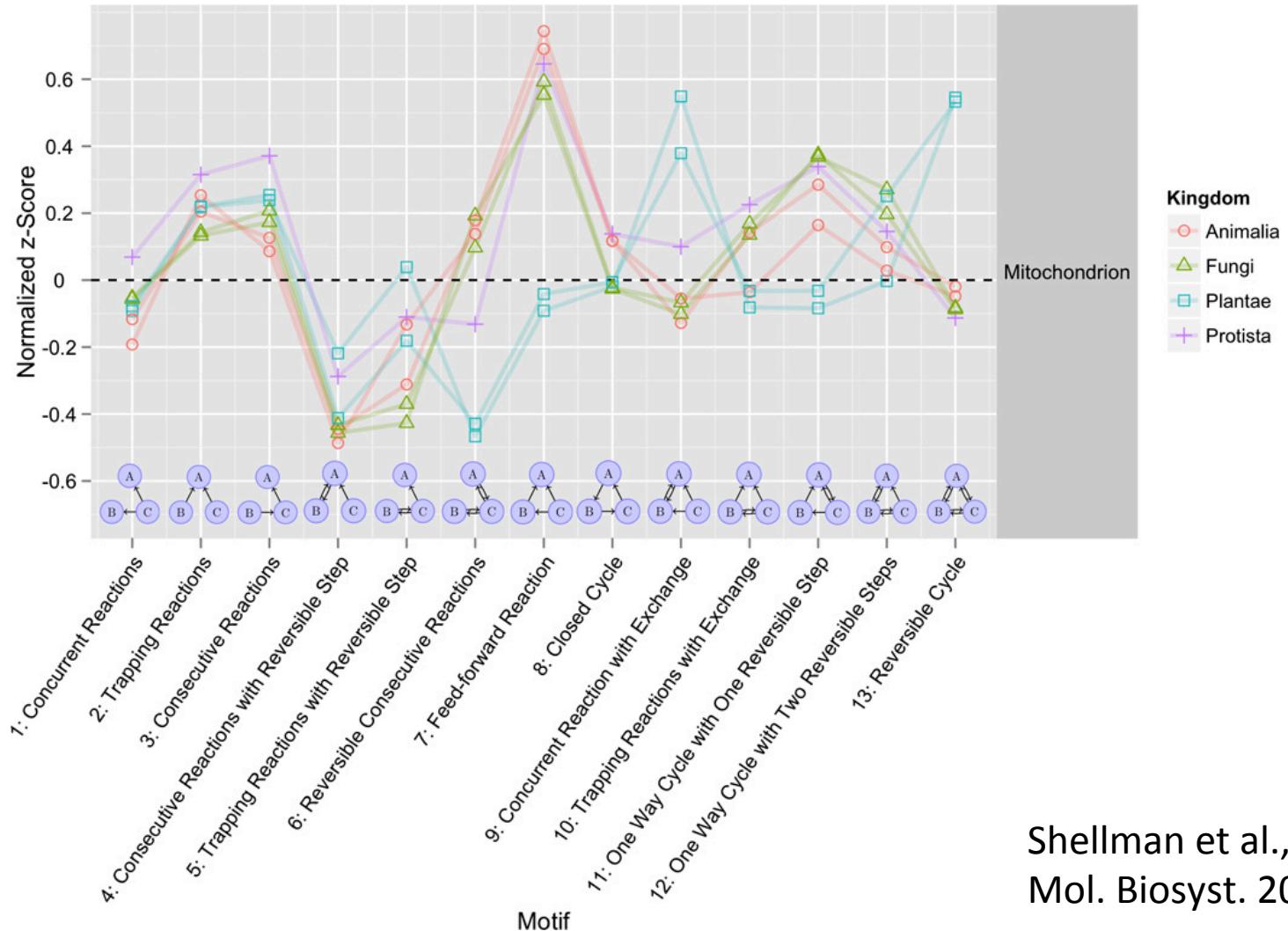
C. elegans somatic nervous system



(Qian et al., PLoS One 2011)

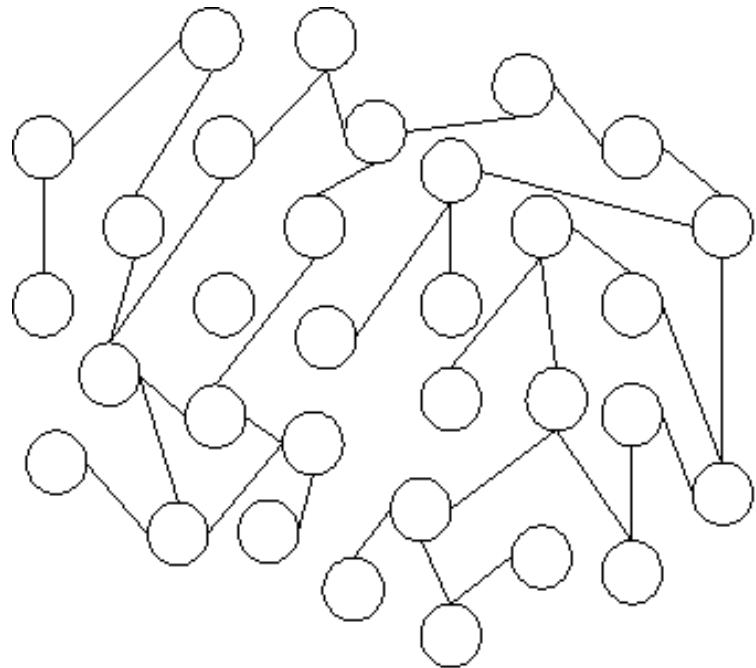
Network motifs in other biological networks

Mitochondrial metabolic networks from various eukaryotes

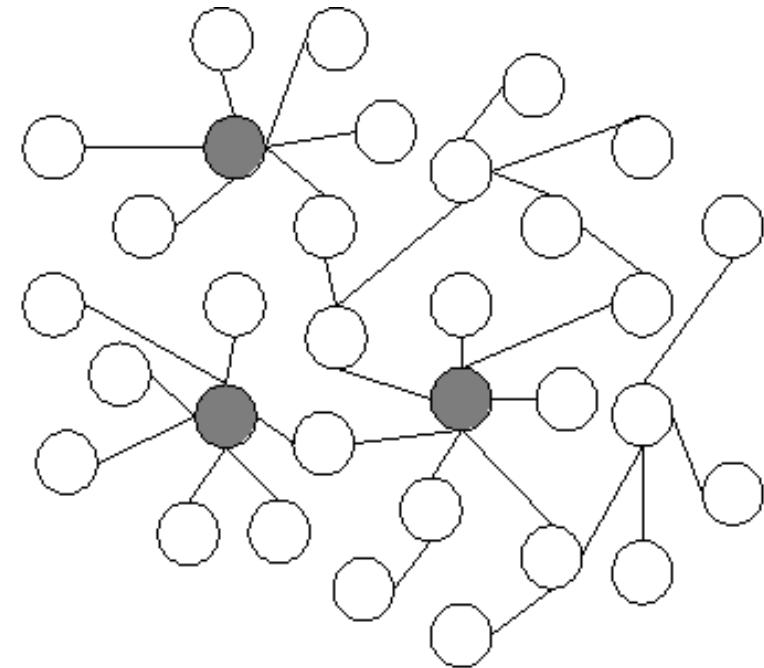


Shellman et al.,
Mol. Biosyst. 2013

Many biological networks show scale-free organization



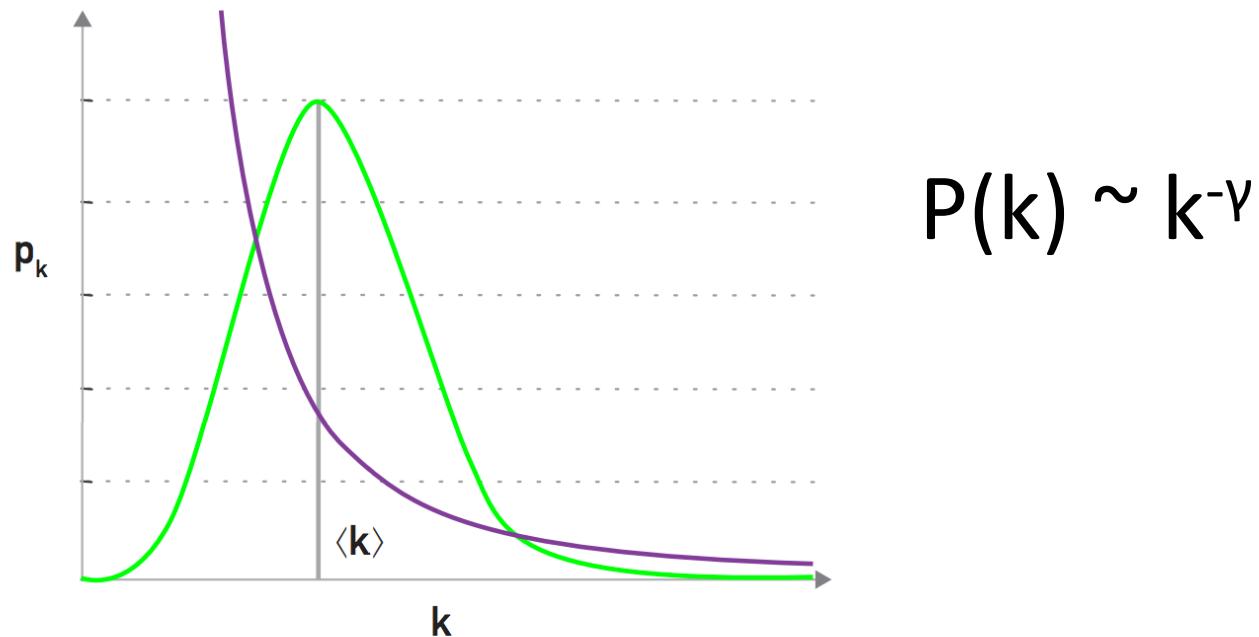
(a) Random network



(b) Scale-free network

(Image from Carlos Castillo)

Many biological networks show scale-free organization



Random Network

Randomly chosen node: $k = \langle k \rangle \pm \langle k \rangle^{1/2}$

Scale: $\langle k \rangle$

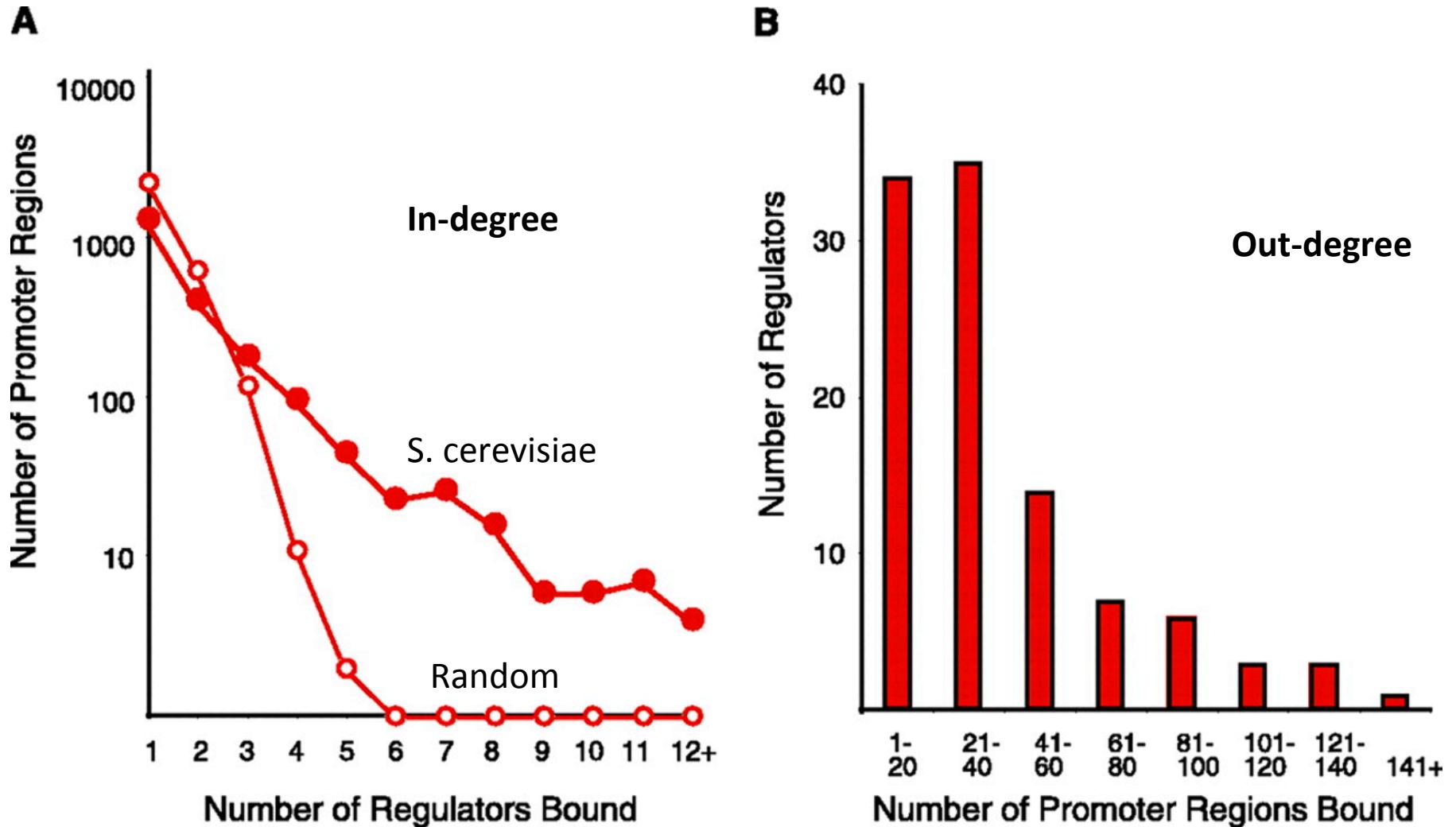
Scale-Free Network

Randomly chosen node: $k = \langle k \rangle \pm \infty$

Scale: none

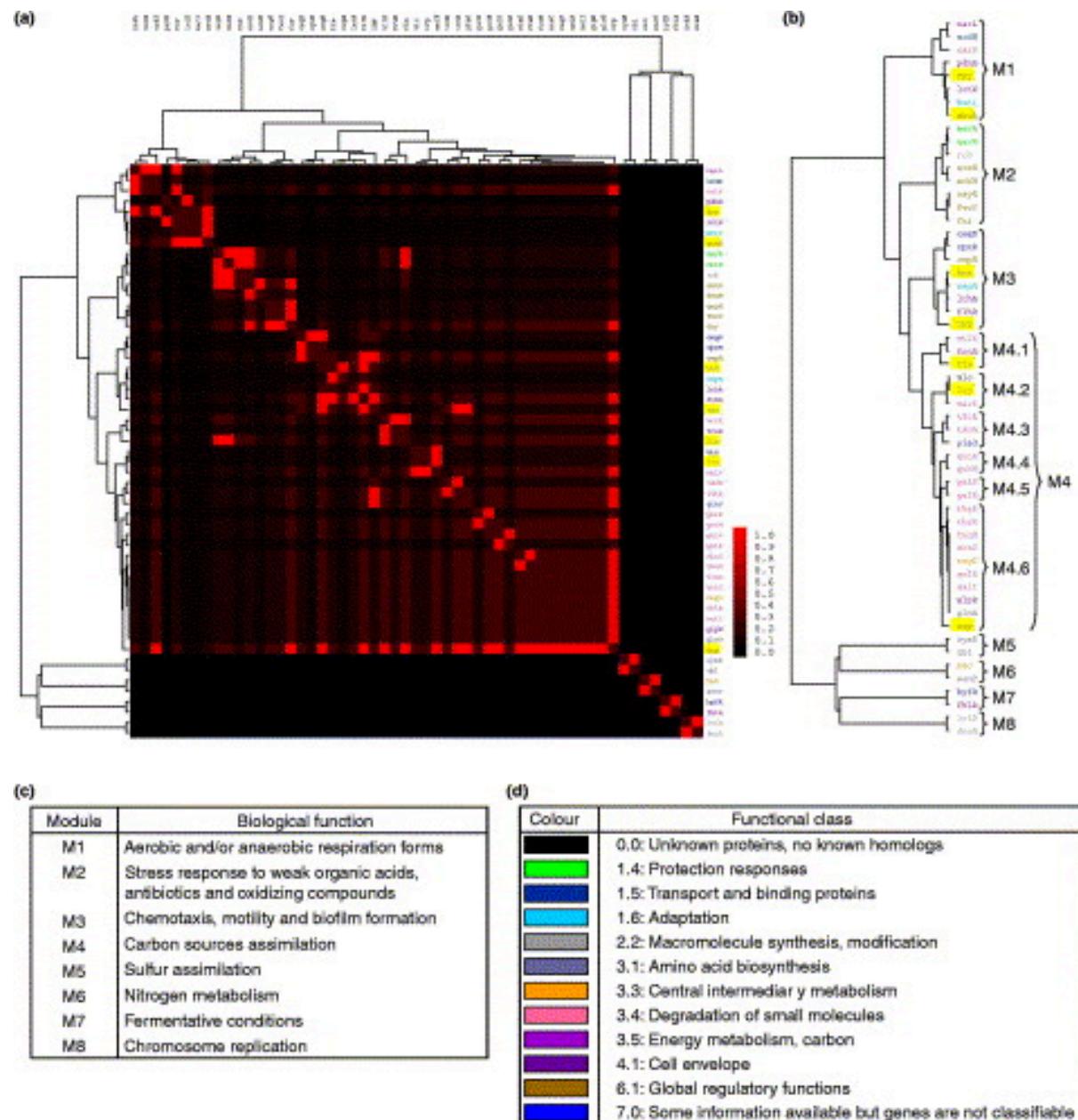
(Albert Barabasi,
Network Science)

Many biological networks show scale-free organization



(Lee et al., Science 2002)

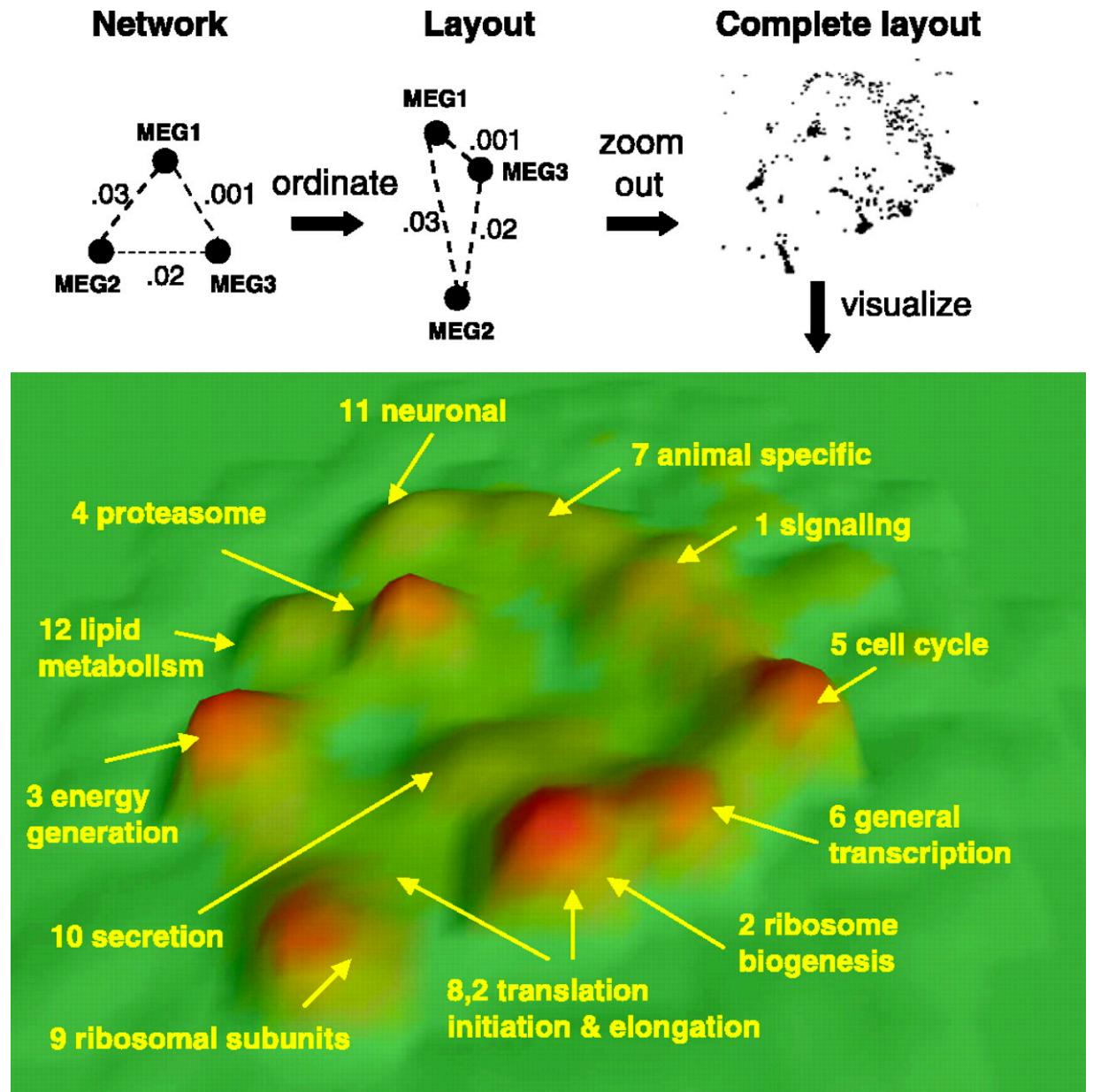
Biological networks are often modular



(Resendes-Antonio et al.,
Trend. Genet. 2005)

Biological networks are often modular

(Stuart et al.,
Science 2003)



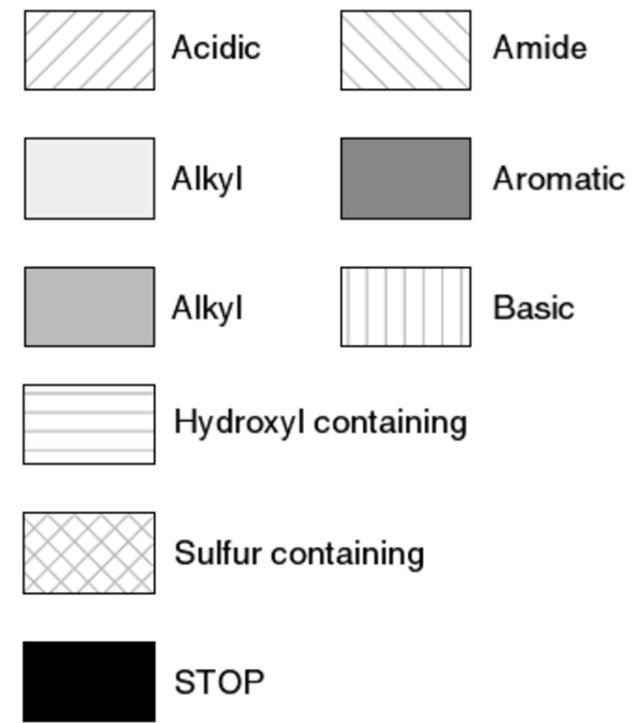
Biological networks are **robust**

“A biological system is robust if it continues to function in the face of perturbation”

--Andreas Wagner, *Robustness and Evolvability in Living Systems*

Biological networks are robust

	U		C		A		G	
U	UUU	Phe	UCU	Ser	UAU	Tyr	UGU	Cys
	UUC	Phe	UCC	Ser	UAC	Tyr	UGC	Cys
	UUA	Leu	UCA	Ser	UAA	TER	UGA	TER
	UUG	Leu	UCG	Ser	UAG	TER	UCG	Trp
C	CUU	Leu	CCU	Pro	CAU	His	CGU	Arg
	CUC	Leu	CCC	Pro	CAC	His	CGC	Arg
	CUA	Leu	CCA	Pro	CAA	Gln	CGA	Arg
	CUG	Leu	CCG	Pro	CAG	Gln	CGG	Arg
A	AUU	Ile	ACU	Thr	AAU	Asn	AGU	Ser
	AUC	Ile	ACC	Thr	AAC	Asn	AGC	Ser
	AUA	Ile	ACA	Thr	AAA	Lys	AGA	Arg
	AUG	Met	ACG	Thr	AAG	Lys	AGG	Arg
G	GUU	Val	GCU	Ala	GAU	Asp	GGU	Gly
	GUC	Val	GCC	Ala	GAC	Asp	GGC	Gly
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	GUG	Val	GCG	Ala	GAG	Glu	GGG	Gly

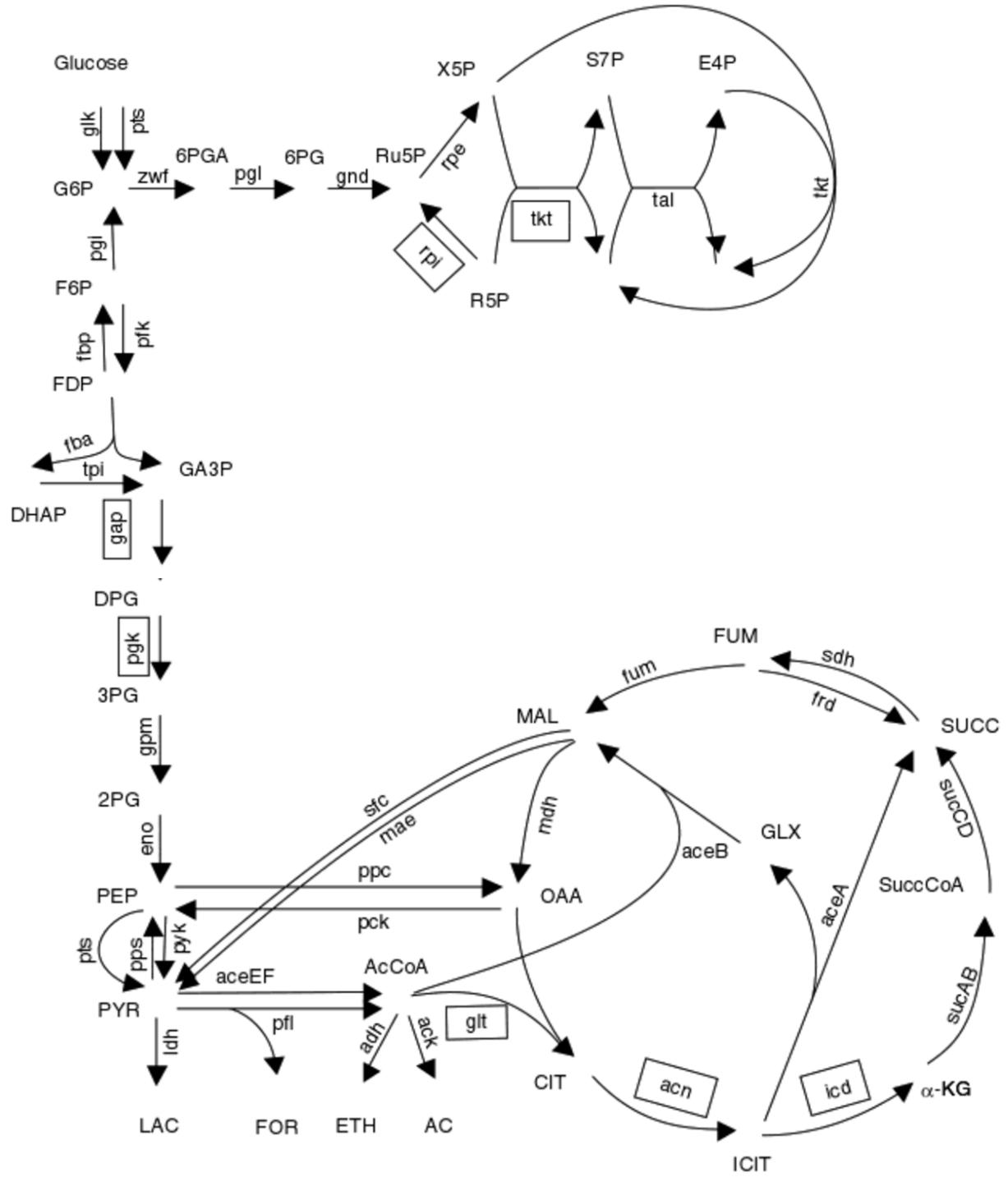


(A. Wagner, *Robustness and Evolvability in Living Systems*)

Example: Central carbon metabolism of *E. coli*

Of 48 reactions, only 7 essential;
2/3 give less than 5% growth defect

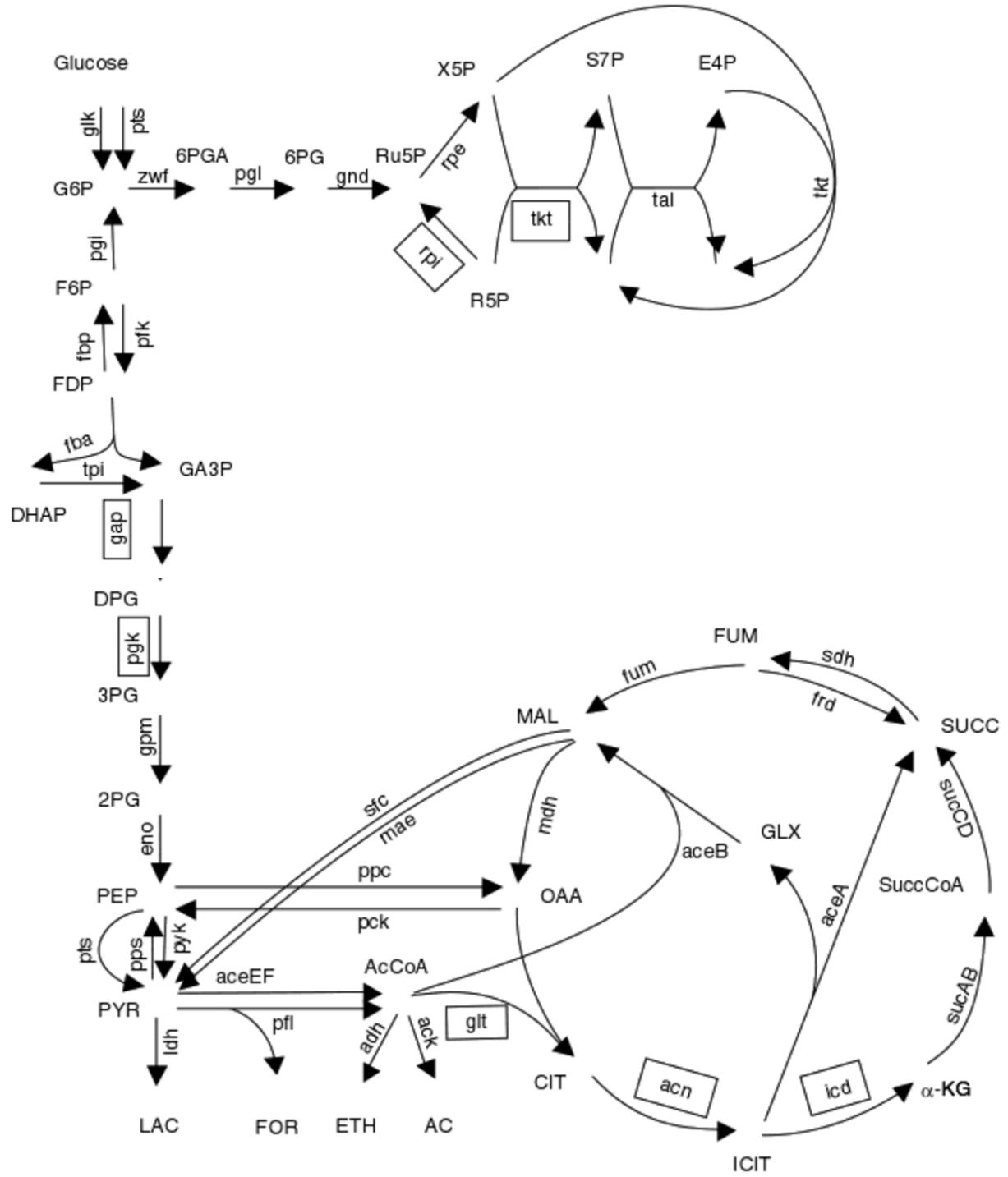
(A. Wagner, *Robustness and Evolvability in Living Systems*)



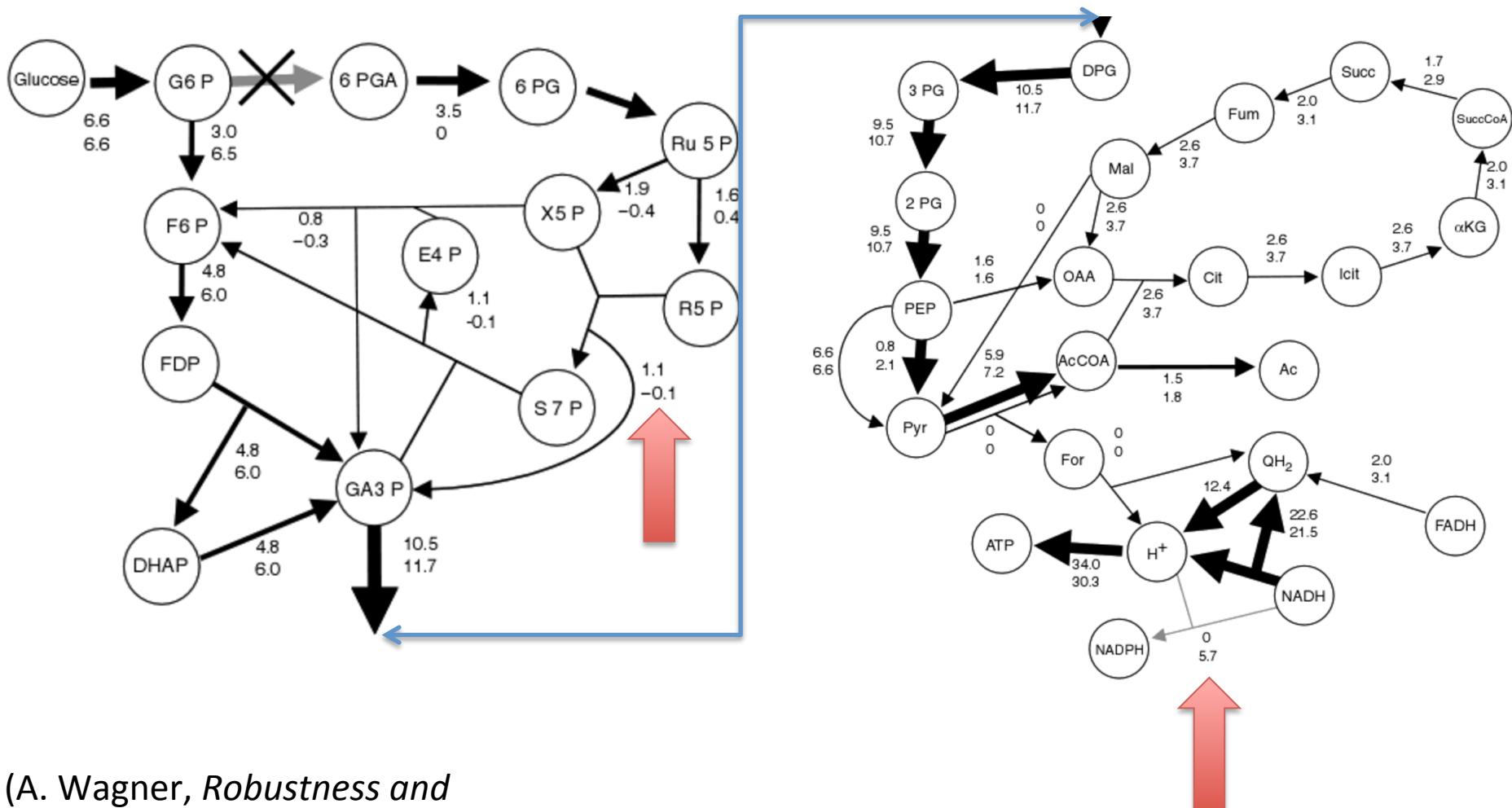
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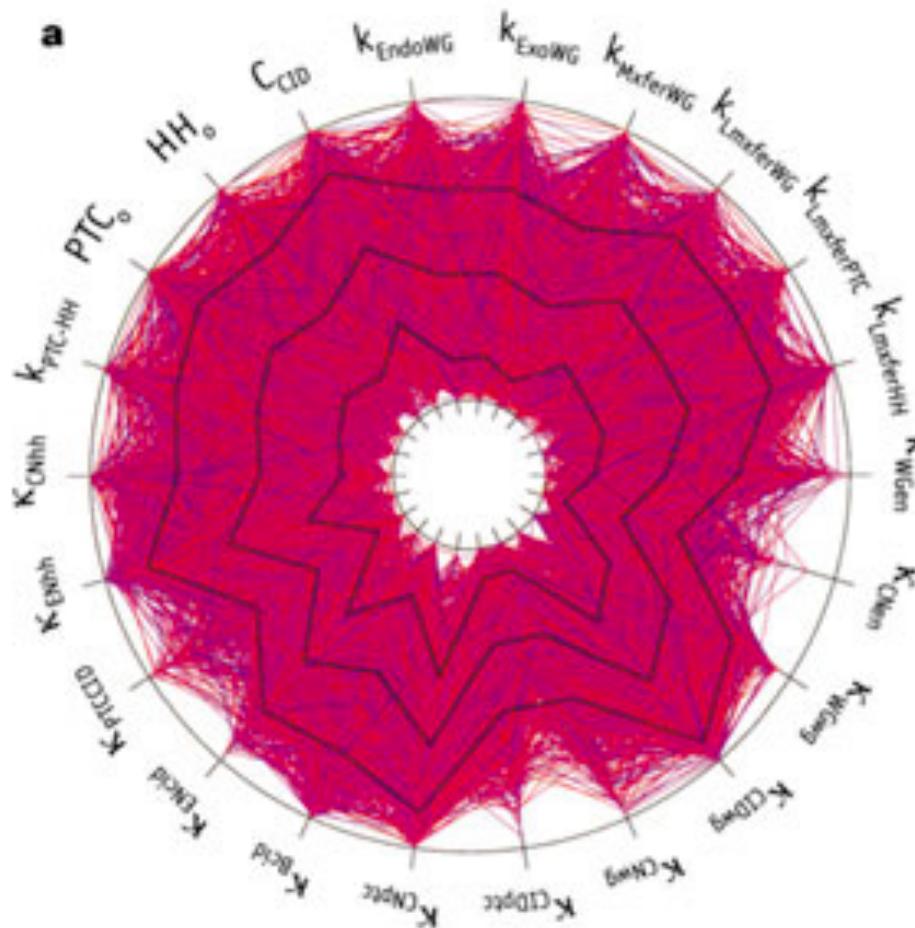


Example: Central carbon metabolism of *E. coli*



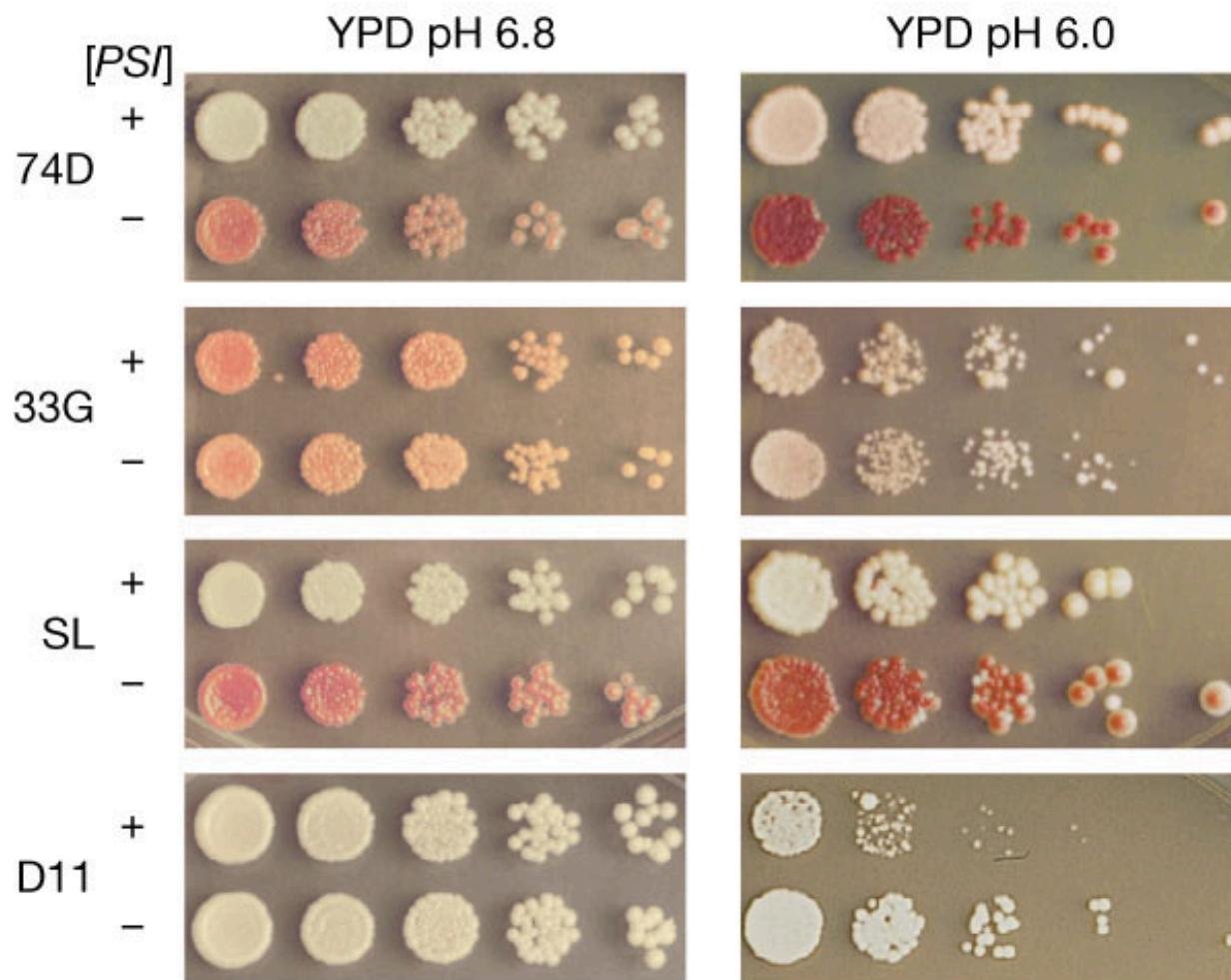
(A. Wagner, *Robustness and Evolvability in Living Systems*)

Robustness enables evolutionary capacitance



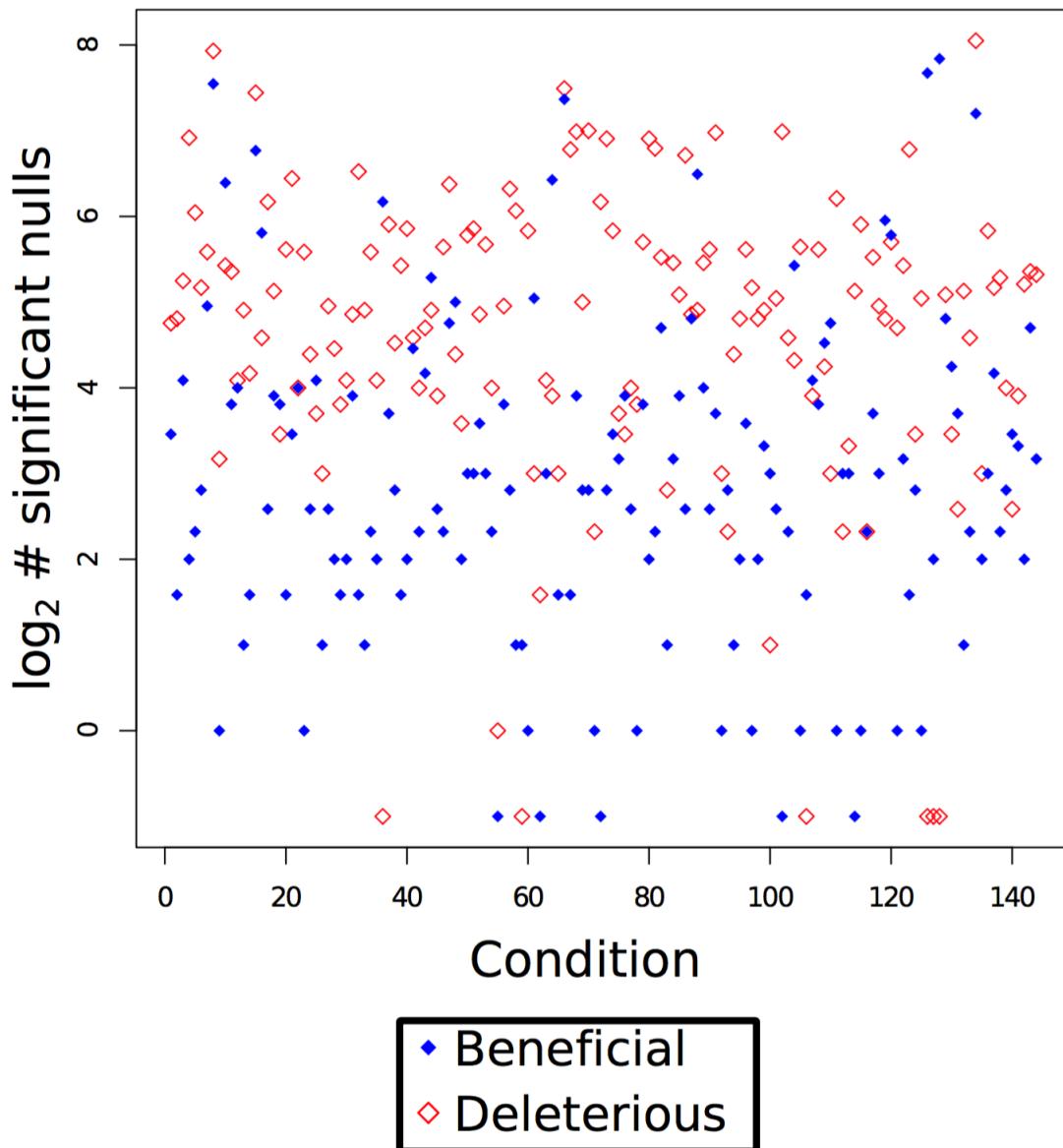
(Von Dassow *et al.*, Nature, 2000)

Robustness enables evolutionary capacitance



(True and Lindquist, Nature, 2000)

Robustness facilitates rapid evolution



Data drawn from 144 non-redundant conditions across 7 studies

Average of 19 beneficial null mutations and 42 deleterious null mutations per condition

(Hottes et al.,
PLoS Genetics 2013)

Biological networks...

- Show enriched functional motifs
- Are highly modular
- Often have scale-free organization
- Are robust to internal and external perturbation

... and we can use our understanding of the behavior of network components to understand the behavior of the whole

Additional reading

- *An Introduction to Systems Biology* – Uri Alon
- *Robustness and Evolvability in Living Systems* – Andreas Wagner
- *Physical Biology of the Cell* -- Jane Kondev, Julie Theriot, and Rob Phillips