networks in molecular biology

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networks in molecular biology

Regulatory networks:

components = gene products interactions = regulation of transcription, translation, phosphorylation...

Metabolic networks:

components = metabolites, enzymes interactions = chemical reactions

Interaction networks:

components = proteins interactions = ability to form a complex ... and so on What might people mean with the term "network"?

Representation of experimental data

a convenient way to visualize experimentally observed protein-protein interactions or correlated occurences of events

Мар

a visual tool to navigate through the world of gene products, proteins, domains, etc. Predictive Model

like an electronic circuit: a complete description of causal connections that allows to predict and engineer the behavior of a biological system, like that of a radio receiver





NY state electric power grid

Blue bars: generators, substations

Lines: transmission lines, transformers

From Strogatz, Nature 410, 268 (2001)



Molecular interaction network for mammalian cell cycle regulation



Aspects of complicatedness

- o Structural complexity (topology)
- o Evolution over time
- o Connection diversity: weights, directions, function
- O Dynamical complexity: nodes themselves can already be complicated dynamical systems
- o Node diversity

All of these complications can influence each other

Mathematical tools

- o Structural complexity: graph theory
- Dynamical complexity: calculus, theory of dynamical systems, chaos theory
- Connection diversity, node diversity : differential equations, graphical networks
- o Evolution over time: few ideas

All together: computer simulation, data analysis, very little hard results, but lots of excitement.

Simple network topologies

Regular nearest neighbour: 1d, 2d, 3d, ... All-to-all Random graph Scale free

Network topologies

regular



all-to-all

Random graph

(after "tidy" rearrangement of nodes)

Network topologies



Scale-free

(Albert/Barabasi-model)

Graphs

Graph := set of nodes + set of edges

Edges can be

- directed
- undirected
- weighted

special cases: cycles, acyclic graphs, trees

Random Edge Graphs n nodes, m edges p(i,j) = 1/m

with high probability:

m < n/2: many disconnected components

m > n/2: one giant connected component: size ~ n. (next biggest: size ~ log(n)). degrees of separation: log(n). Erdös and Rényi 1960

Some important concepts:

Small worlds Clustering Degree distribution Motifs

Small word networks

typical path length ("degrees of separation") is short

Many examples:

- Communications
- Epidemiology / infectious diseases
- Metabolic networks
- Scientific collaboration networks
- WWW
- Company ownership in Germany
- "6 degrees from Kevin Bacon"

Clustering

Clique: every node connected to everyone else

Clustering coefficient:

 $c = \frac{\text{no. edges between first-degree neighbors}}{\text{maximum possible number of such edges}}$

Random network: c=p Real networks: c » p

Degree distributions

p(k) = fraction of nodes that have k edges

Random graph: p(k) = Poisson distribution with some parameter λ ("scale")

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Many real networks: p(k) = power law,

p(k) \sim k^{-\gamma}

"scale-free"
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(WWW: Yahoo, metabolic network: ATP)

Other distributions: exponential, Gaussian

Growth models for scale free networks

Start out with one node and continously add nodes, with preferential attachment to existing nodes, with probability ~ degree of target node.

⇒ **p(k)~k**⁻³

(Simon 1955; Barabási, Albert, Jeong 1999)

Modifications to obtain $\gamma \neq 3$:

Through different rules for adding or rewiring of edges, can tune to obtain any kind of degree distribution What are the functional advantages ("evolutionary fitness") of scale free networks ?

Robustness: only a few hubs, so insensitive to the failure of most nodes However: sensitive to the failure of hubs

Real networks

- tend to have power-law scaling (truncated)
- are ,small worlds' (like random networks)
- have a high clustering coefficient independent of network size (like lattices and unlike random networks)

Network motifs

:= pattern that occurs more often than in randomized networks

Intended implications duplication: useful building blocks are reused by nature there may be evolutionary pressure for convergence of network architectures

Network motifs

- Starting point: graph with directed edges
- Scan for n-node subgraphs (n=3,4) and count number of occurence
- **Compare to randomized networks**
 - (randomization preserves in-, out- and in+out- degree of each node, and the frequencies of all (n-1)-subgraphs)

Schematic view of motif detection



All 3-node connected subgraphs





Nodes = transcription factors

Directed edge: X regulates transcription of Y

3- and 4-node motifs in transcription networks

Network	Nodes	Edges	$N_{\rm real}$	N _{rand} ± SD	Z score	$N_{\rm real}$	$N_{\rm rand} \pm SD$	Z score
Gene regulation (transcription)	on)			$\begin{array}{c} \mathbf{X} \\ \mathbf{\Psi} \\ \mathbf{Y} \\ \mathbf{\Psi} \\ \mathbf{Z} \end{array}$	Feed- forward loop	x z	Y W W	Bi-fan
E. coli	424	519	40	7 ± 3	10	2 0 3	47 ± 12	13
S. cerevisiae*	685	1, 0 52	70	11±4	14	1812	300 ± 40	41

Network	Nodes	Edges	N_{teal}	N _{tand} ±SE) Z scote	N_{teal}	$N_{tand} \pm SD$	Z scote	N_{teal}	N _{tand} ±SI	⊃ Zscote
Gene regulation		X Feed		X	X	Bi-fan					
(transcriptio	n)			V	forward						
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E. coli	424	519	40	7 ± 3	10	203	47 ± 12	13			
S. cerevisitie*	685	1,052	70	11 ± 4	14	1812	300 ± 40	41			
Neurons				X	Feed -	X	X	Bi-fan	<i>¹</i> ²	K N	Bi-
				¥	forward		\leq		-	1	parallel
				¥ V	loop	Z	-34V W		Y A	V^2	
			⊳	z						W	
C. ele gans†	252	509	125	90 ± 10	3.7	127	55 ± 13	5.3	227	35 ± 10	20
Food webs				X	Three	, x		Bi-			
				¥.	chain		*	parallel			
				Ϋ́.		4	¥2				
				ż		w	ŕ				
Little Rock	92	984	3219	3120±50	2.1	7295	2220 ± 210	25	1		
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	30	82 ± 4	NS	26	5 ± 2	8			
Coachella	29	243	279	235 ± 12	3.6	181	80 ± 20	5			
Skipwith B. Breed	25	189	184	150±7	5.5	397	80±25 30±2	13			
Electronic di	20	104	101	130±7	L.4	207	V 10 1	52 Ristain		×	Ri.
(forward logic	cuns chins)			Ŵ	forward	Ń	À.	DI-IAII	K.	. 7	parallel
(101 1111 128	c cutps)			Y.	loop	VZ	SW .		Y N	vz	Puttier
			6	V	-	z	W		,	w ^r	
				Z							
s15850	10,383	14,240	424	2 ± 2	285	1040	1±1	1200	480	2±1	335
s38417	20,717	34,204	612	10±3	400	2404	0±2	300	531	9±2	320
s9234	5,844	8,197	211	2 ± 1	140	754	1±1 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 ci	rcuits		X	ζ.	Three-	x	Y	Bi-fan	X-	$\rightarrow \gamma$	Four-
(digital fractional multipliers)		pliers)	1	1	node		Λ				node
			· .	1	feedback	VZ	24			. ⊻	feedback.
			¥<	— z	loop	z	W		Z ≤	—w	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		P	X	Feed back	x		Fully	X	•	Uplinked	
				¥	with two	Z	1	connected	/	1	mutual
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				ż	a yaas						
nd.eda§	325,729	1.46e6	1.1e5	$2e3 \pm 1e2$	800	6.8e6	5e4±4e2	15,000	1.2e6	1e4 ± 2e	2 5000

System-size dependence

Extensive variable: proportional to system size.
E.g. mass, diameter, number of molecules
Intensive variable: independent of system size.
E.g. temperature, pressure, density, concentration

"Vanishing variable": decreases with system size. E.g. Heat loss through radiation; in a city, probability to bump into one particular person

Alon et al.: In real networks, number of occurences of a motif is extensive. In randomized networks, it is non-extensive.

Examples

Yeast-2-Hybrid Rosetta compendium Regulatory networks

TAP: Tandem-Affinity-Purification

Two-hybrid screen



Idea:

"Make potential pairs of interacting proteins a transcription factor for a reporter gene"



Two-hybrid arrays



Current Opinion in Chemical Biology

Colony array: each colony expresses a defined pair of proteins

Table 2.

Two-hybrid array screens discussed in this paper.									
Organism	Project	Proteins*	Assays*	Interactions*	Refs				
Drosophila	Cell cycle proteins	13	45	19	[7]				
C. elegans	Vulva development	29	841	8 [†]	[9]				
Mouse	Whole-genome pilot	~3500	~12×10⁵	145	[15]				
HCV	Whole genome	10	~100	0/3*	[16]				
Vaccinia	Whole genome	266	~64 000	37	[17]				
Yeast	One by one array	192	~1 150 000	281	[18"]				
Yeast	Pool by pool	~6000	~36 000 000	4549/841 [‡]	[19,20"]				
Yeast	Cell polarity	68	~408 000	191*	[10]				
Yeast	Proteasome	31	~186 000	55	[12]				

Sensitivity, specificity and reproducibility

Specificity – false positives: the experiment reports an interaction even though is really none

Sensitivity – false negatives: the experiment reports no interaction even though is really one

Problem: what is the objective definition of an interaction?

(Un)reproducibility: the experiment reports different results when it is repeated

"The molecular reasons for that are not really understood..." (Uetz 2001)

Reproducibility



Rosetta compendium

568 transcript levels



Transcriptional regulatory networks from "genome-wide location analysis"



regulator:= a transcription factor (TF) or a ligand of a TFtag:c-myc epitope

106 microarrays

samples:enriched (tagged-regulator + DNA-promoter)probes:cDNA of all promoter regionsspot intensity ~ affinity of a promotor to a certain regulator

Transcriptional regulatory networks bipartite graph

106 regulators (TFs)







promoters

Network motifs



Network motifs



Literature

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