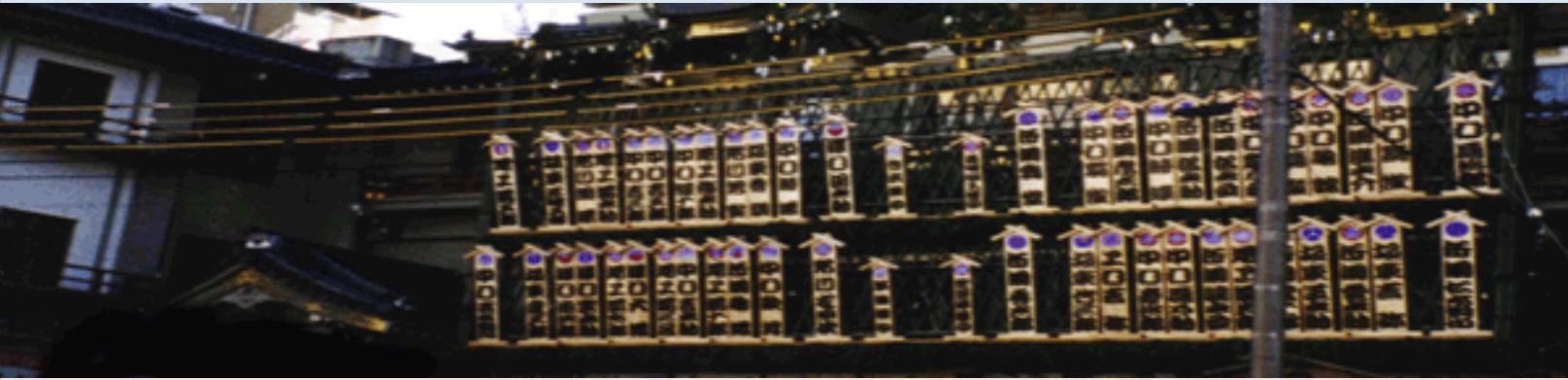




redundancy, control and collective computation



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in network dynamics

**luis m. rocha**

school of informatics & computing  
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and

instituto gulbenkian de ciência  
oeiras, portugal



**CNetS**

Cognitive  
Science  
Program

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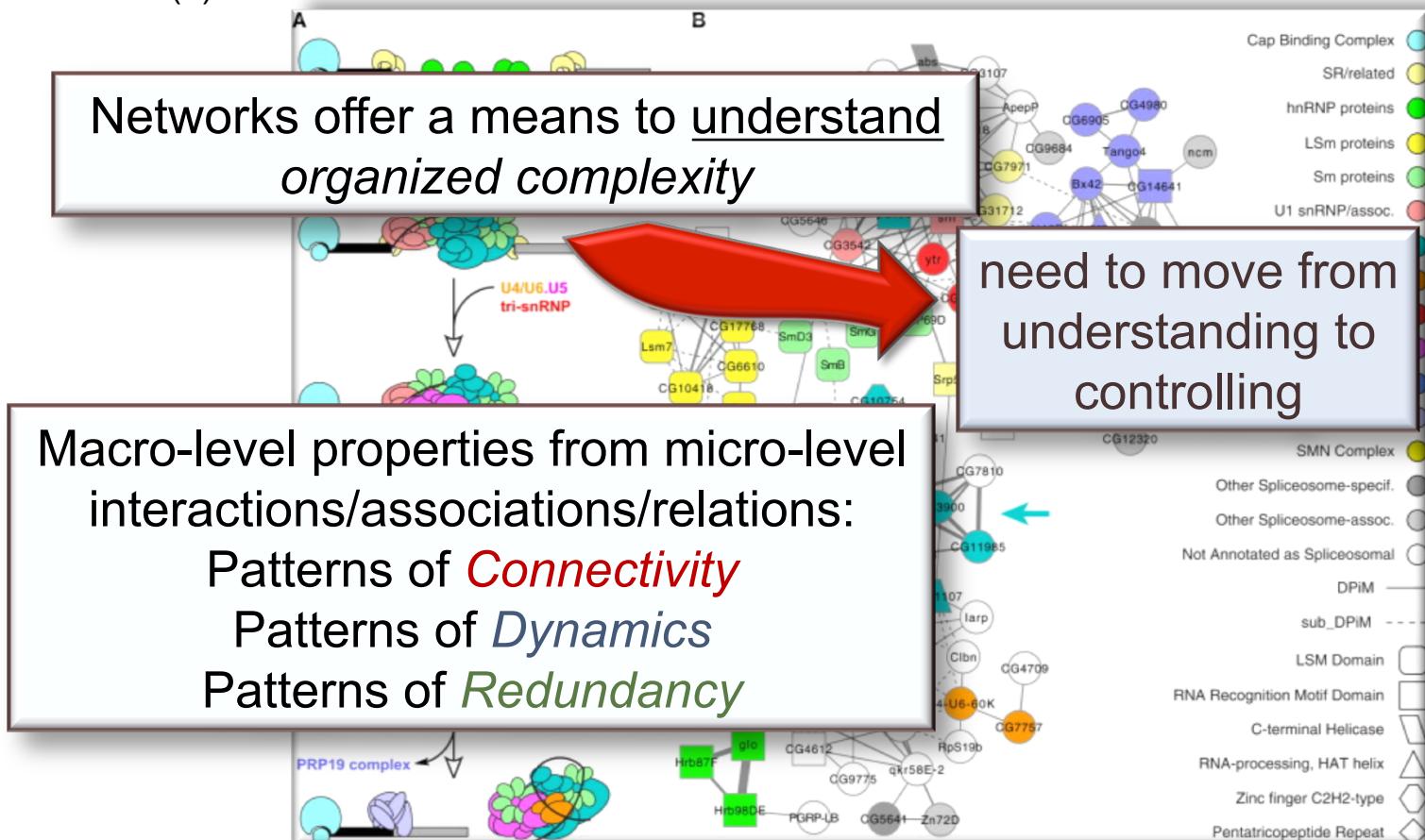


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# large-scale *drosophila* protein interaction Map (DPiM)

Guruharsha et al [2011]. "A Protein Complex Network of *Drosophila melanogaster*." *Cell.*147(3):690-703.



Modularity of the spliceosome subnetwork: 12 well-connected clusters representing interaction of snRNPs with pre-mRNA and other proteins in the process of splicing introns.





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# PATTERNS OF REDUNDANCY IN DYNAMICS

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# the drosophila segment polarity network

## an automata network model built from qualitative data



Based on the ODE model of von Dassow et al. (2000), consists of 4-cell parasegments, each cell with 15 interacting genes and proteins.

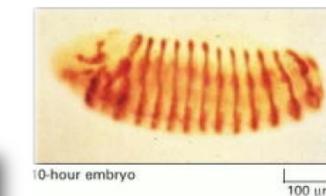
### $2^{60}$ network configurations

Reproduces wild-type and mutant gene expression patterns in development of fruit fly

2 intercellular inputs: **nhh** (*hedgehog*), **nWG** (*wingless*)

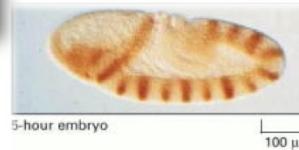
1 intracellular input: **SLP** (*sloppy paired*)

Node	State – TransitionFunction
$SLP_i^{t+1}$	$\leftarrow 0 \text{ if } i=1 \vee i=2; 1 \text{ if } i=3 \vee i=4;$
$wg_i^{t+1}$	$\leftarrow (CIA_i^t \wedge SLP_i^t \wedge \neg CIR_i^t) \vee (wg_i^t \wedge (CIA_i^t \vee SLP_i^t) \wedge \neg CIR_i^t)$
<b>Anterior</b> <b>Parasegment boundaries</b> <b>Posterior</b>	
<i>engrailed, hedgehog</i>	
<i>wingless</i>	
<i>patched</i>	
Segment boundaries	
$CI_i^{t+1}$	$\leftarrow ci_i^t$
$CIA_i^{t+1}$	$\leftarrow CI_i^t \wedge (\neg PTC_i^t \vee hh_{i-1}^t \vee hh_{i+1}^t \vee HH_{i-1}^t \vee HH_{i+1}^t)$
$CIR_i^{t+1}$	$\leftarrow CI_i^t \wedge PTC_i^t \wedge \neg hh_{i-1}^t \wedge \neg hh_{i+1}^t \wedge \neg HH_{i-1}^t \wedge \neg HH_{i+1}^t$



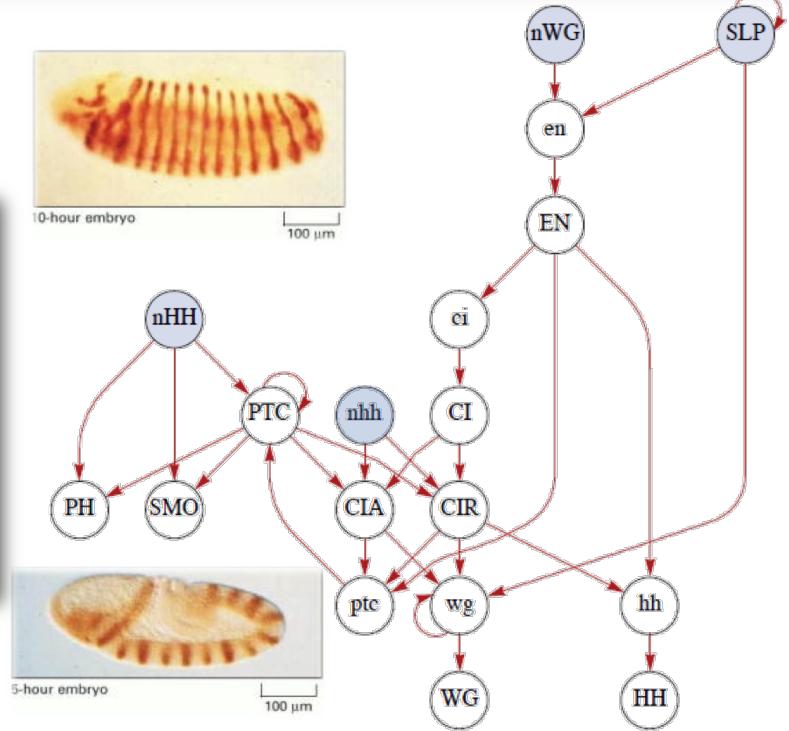
10-hour embryo

100  $\mu\text{m}$



5-hour embryo

100  $\mu\text{m}$

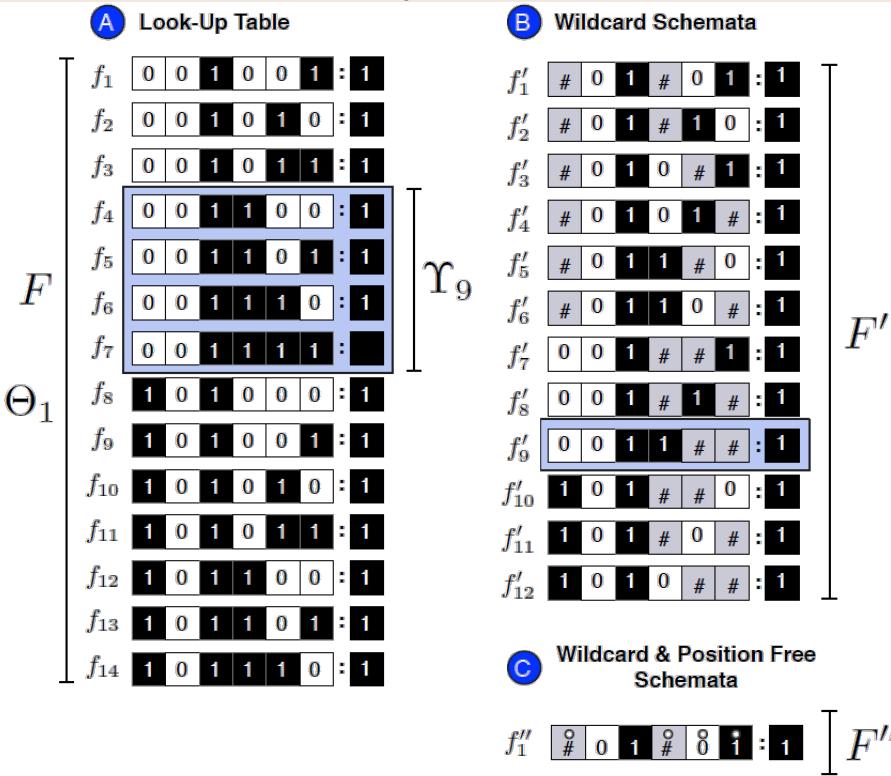




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# quantifying micro-level canalization

input redundancy, effective connectivity and input symmetry



$$k(x) = 6$$

$$F' \\ k_r(x) = \frac{\sum_{f_\alpha \in F} \max_{\theta | f_\alpha \in \Theta_\theta} (n_\theta^\#)}{2^k}$$

$$k_e(x) = k(x) - k_r(x)$$

$$F'' \\ k_s(x) = \frac{\sum_{f_\alpha \in F} \min_{\theta | f_\alpha \in \Theta_\theta} |n_\theta^o|}{2^k}$$

- Measuring two forms of *canalization*

- $K_r = 2$
- $K_e = 6 - 2 = 4$
- $K_s = 4$

Prime Implicants (Quine-McCluskey) plus group invariance



# per-node schema redescription

In biological Boolean network models

- extracting micro-level canalization
  - drosophila segment polarity genes network

node	inhibition	expression	$k$	$k_e$	$k_r$	$k_s$	$k_r^*$	$k_s^*$
$wg$	$f''_{2:1}$ $f''_{2:2}$	$f''_{2:3}$	4	1.75	2.25	2.25	0.56	0.56
PTC	$f''_{9:1}$ $f''_{9:2}$	$f''_{9:3}$ $f''_{9:4}$	4	1.56	2.44	0.75	0.61	0.19
PH	$f''_{10:1}$ $f''_{10:2}$	$f''_{10:3}$	3	1.5	1.5	0.75	0.5	0.25
SMO	$f''_{11:1}$	$f''_{11:2}$ $f''_{11:3}$	3	1.25	1.75	1.5	0.58	0.5
$ci$	$f''_{12:1}$	$f''_{12:2}$	1	1	0	0	0	0
CI	$f''_{13:1}$	$f''_{13:2}$	1	1	0	0	0	0
CIA	$f''_{14:1}$ $f''_{14:2}$	$f''_{14:3}$ $f''_{14:4}$	6	1.55	4.45	1.875	0.74	0.32
CIR	$f''_{15:1}$ $f''_{15:2}$	$f''_{15:3}$	6	1.08	4.92	5.25	0.82	0.88



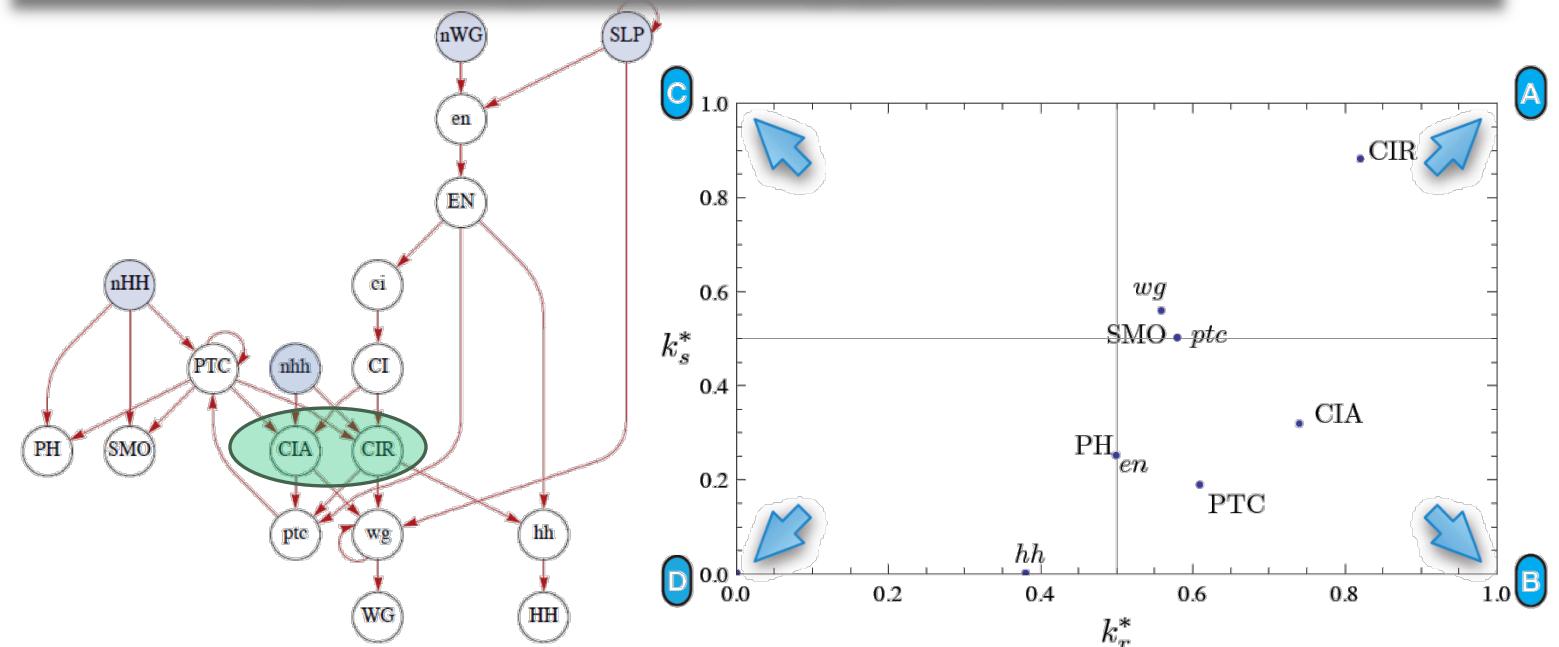
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# per-node schema redescription

## In biological Boolean network models

- extracting micro-level canalization
  - drosophila segment polarity genes network



node	inhibition	expression	$k$	$k_e$	$k_r$	$k_s$	$k_r^*$	$k_s^*$
CIA	$f''_{14:1}$ : $f''_{14:2}$ :	$f''_{14:3}$ : $f''_{14:4}$ :	6	1.55	4.45	1.875	0.74	0.32
CIR	$f''_{15:1}$ : $f''_{15:2}$ :	$f''_{15:3}$ :	6	1.08	4.92	5.25	0.82	0.88



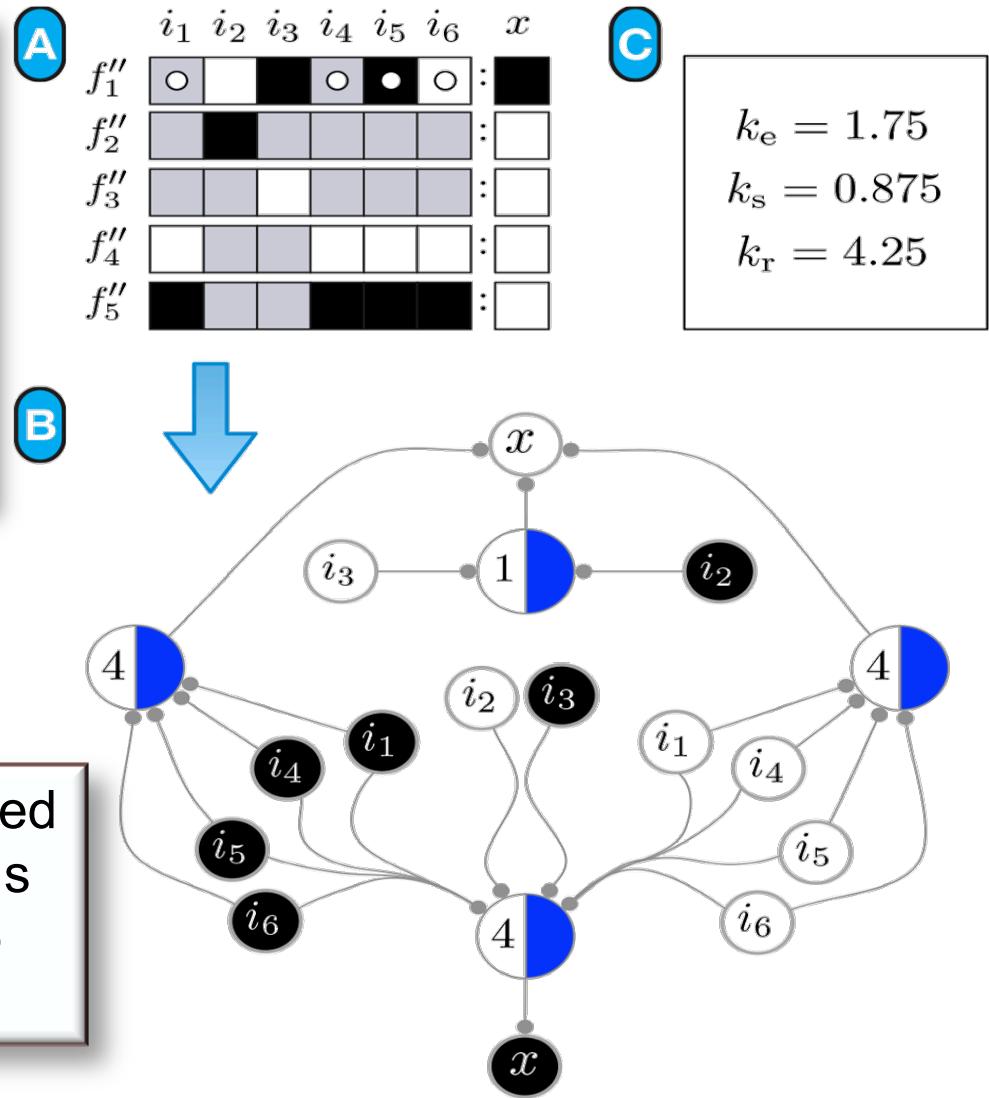
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# canalization map as minimal control two-symbol schemata as threshold networks

- understanding natural “computation”
  - How cells compute
  - minimal wiring (control) of micro-level

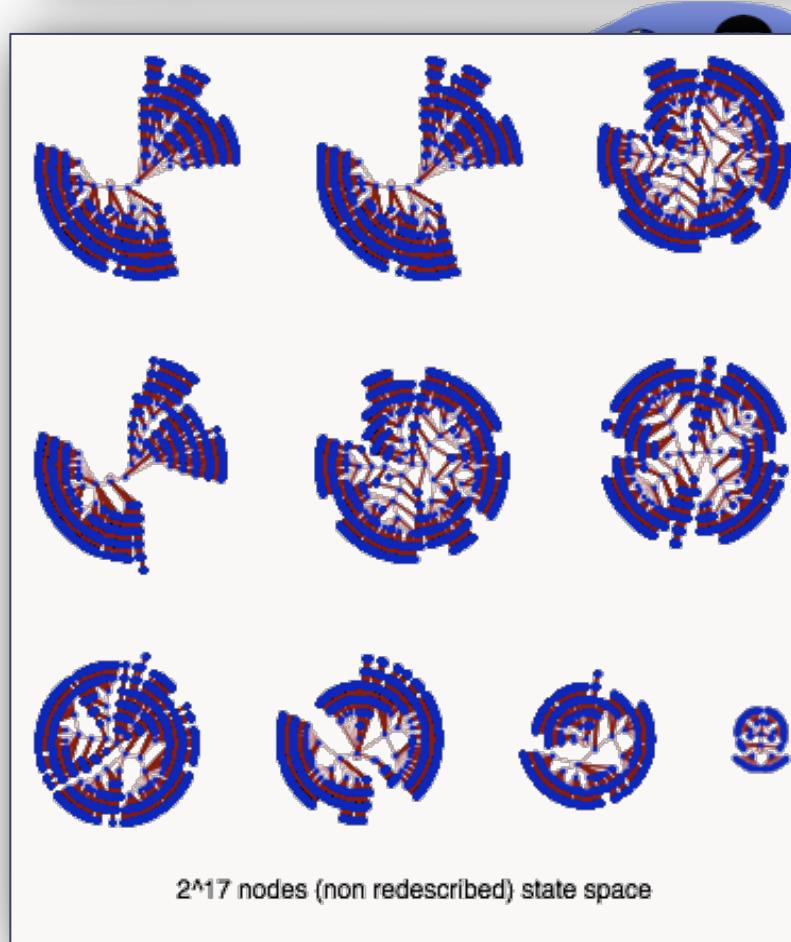
Each schema represented by conjunction of literals and symmetric group constraints



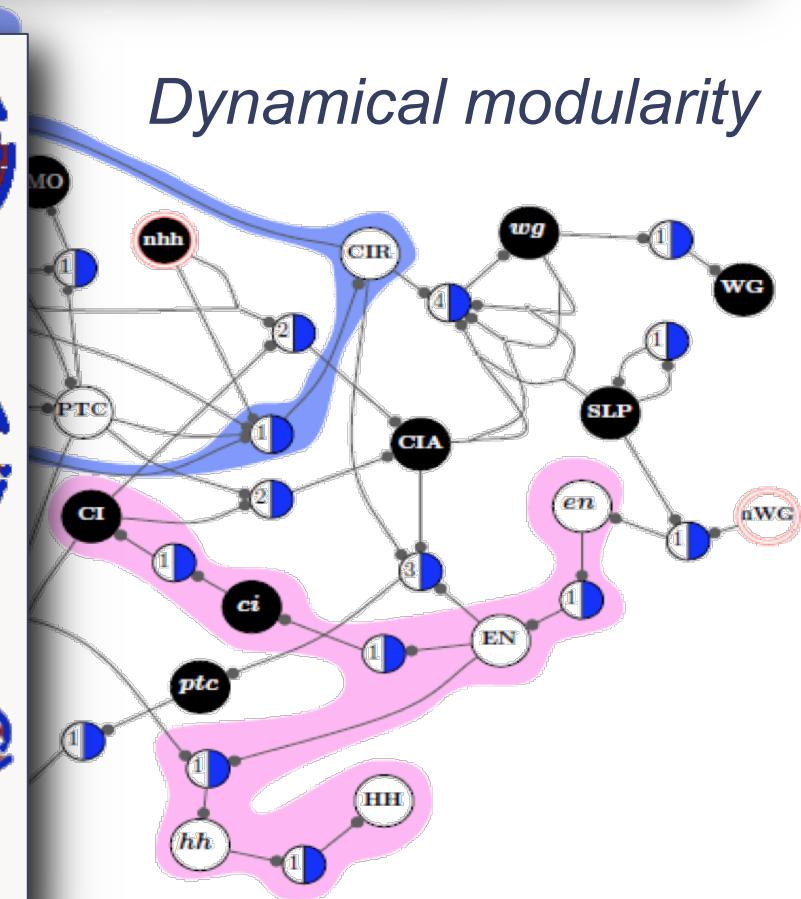


# (macro-level) dynamics canalization map from per-node schemata redescription

- Full dynamics (of single-cell model) captured by threshold network of  $2^*N+M$  nodes



*Dynamical modularity*





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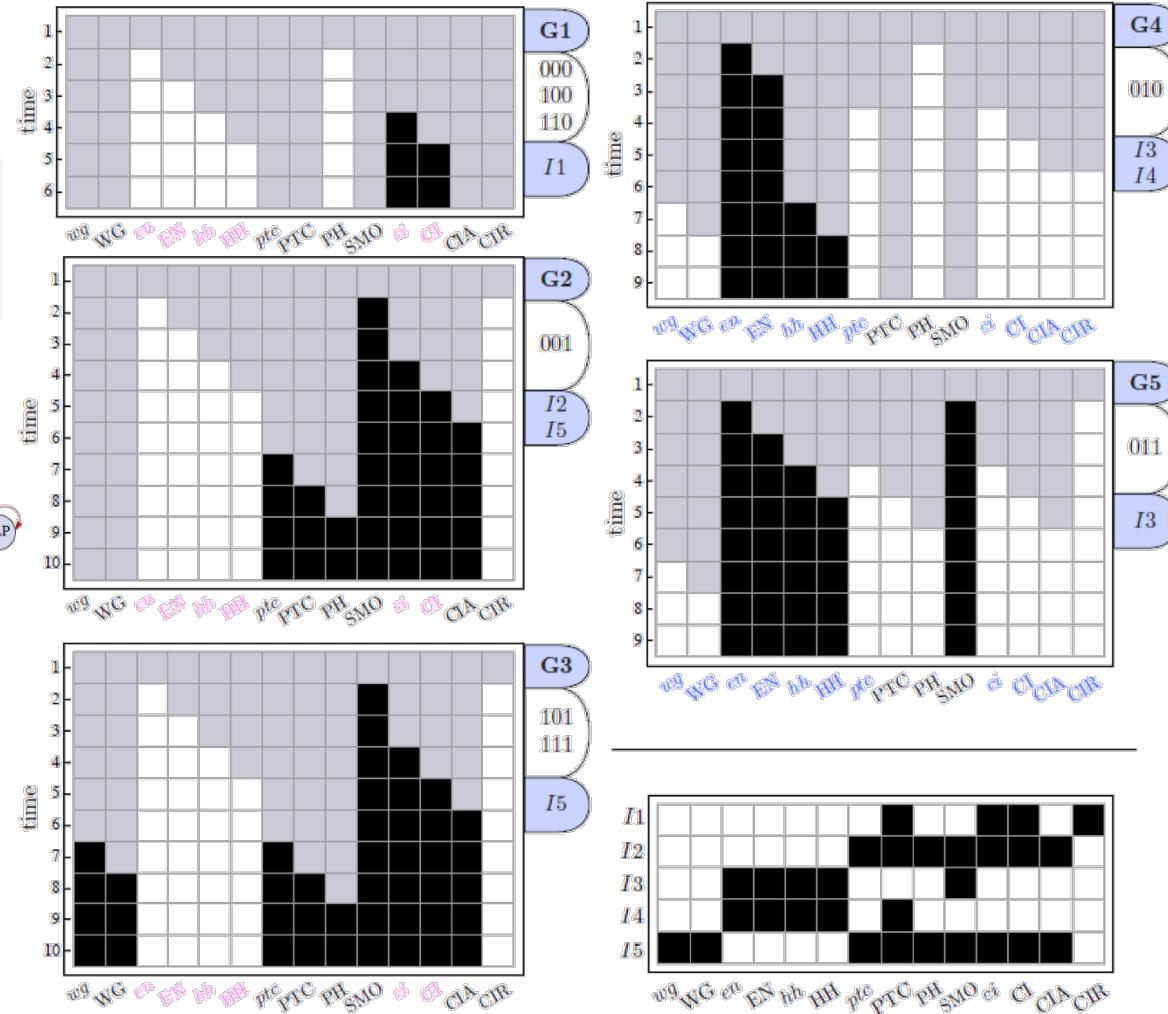
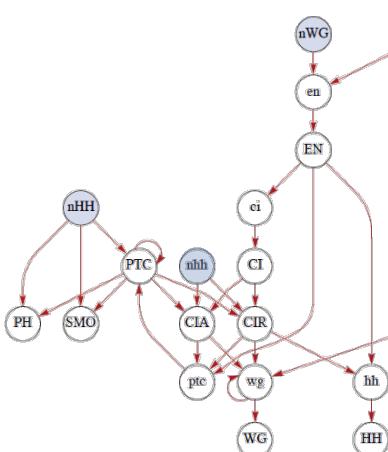
# CONTROL FROM PATTERNS OF REDUNDANCY IN DYNAMICS

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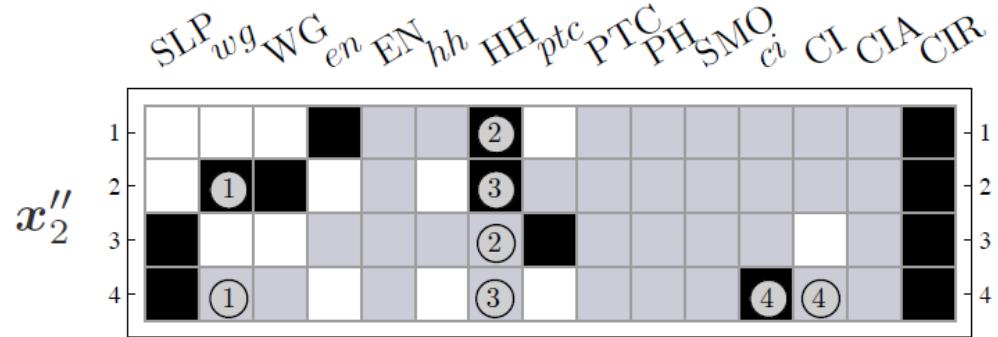
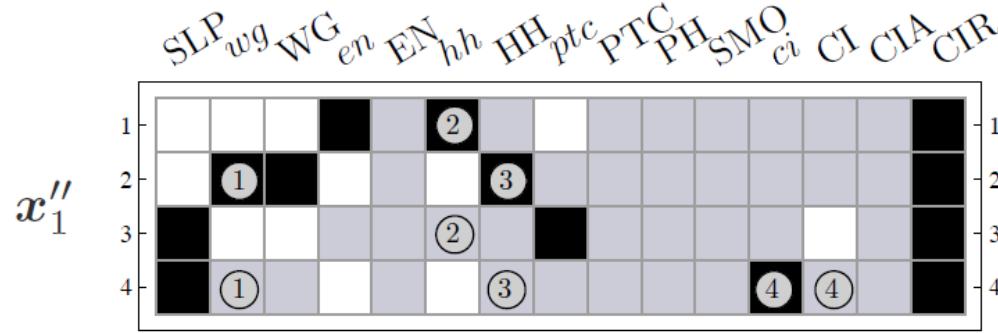
## Dynamical unfolding from partial information

- inputs in drosophila segment polarity net: SLP, nWG, nhh

How much control certain nodes have on network dynamics.



## minimal conditions (“pre-patterns”) for wild-type attractor



Less than half of the nodes are needed to ensure convergence to **wt**, which is very **robust** and **larger** than previously thought.

But losing one essential input (enputs) leads to a “unspecific” attractor. In this case could go to wt, wt (ptc mutant) or no segmentation.



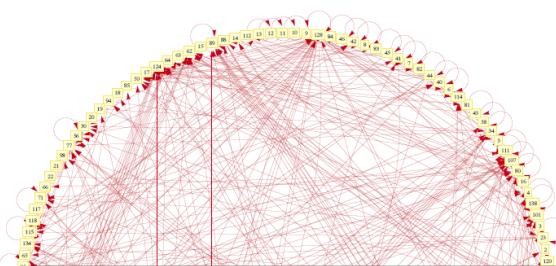


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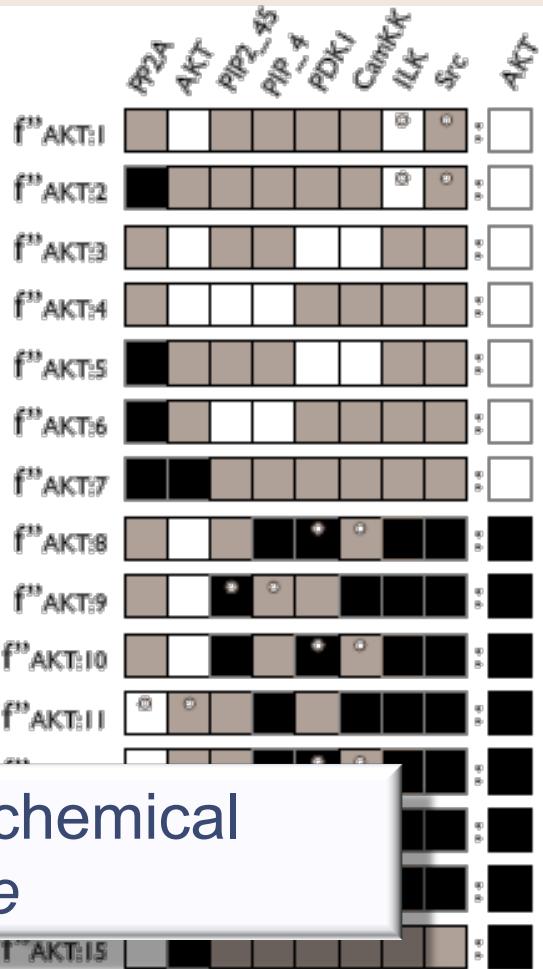
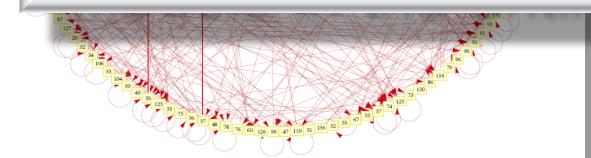
# redundancy in intracellular signaling networks

## canalization

- Activation of AKT in generic fibroblasts (130 node BN)
  - LUT of  $2^8=256$  entries redescribed by only 15 schemata
    - Large amount of canalization
  - Very few actual inputs need to be known to determine state-transition



Upcoming work: analysis of biochemical models in the entire *cell collective*





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# PATTERNS OF DYNAMICS

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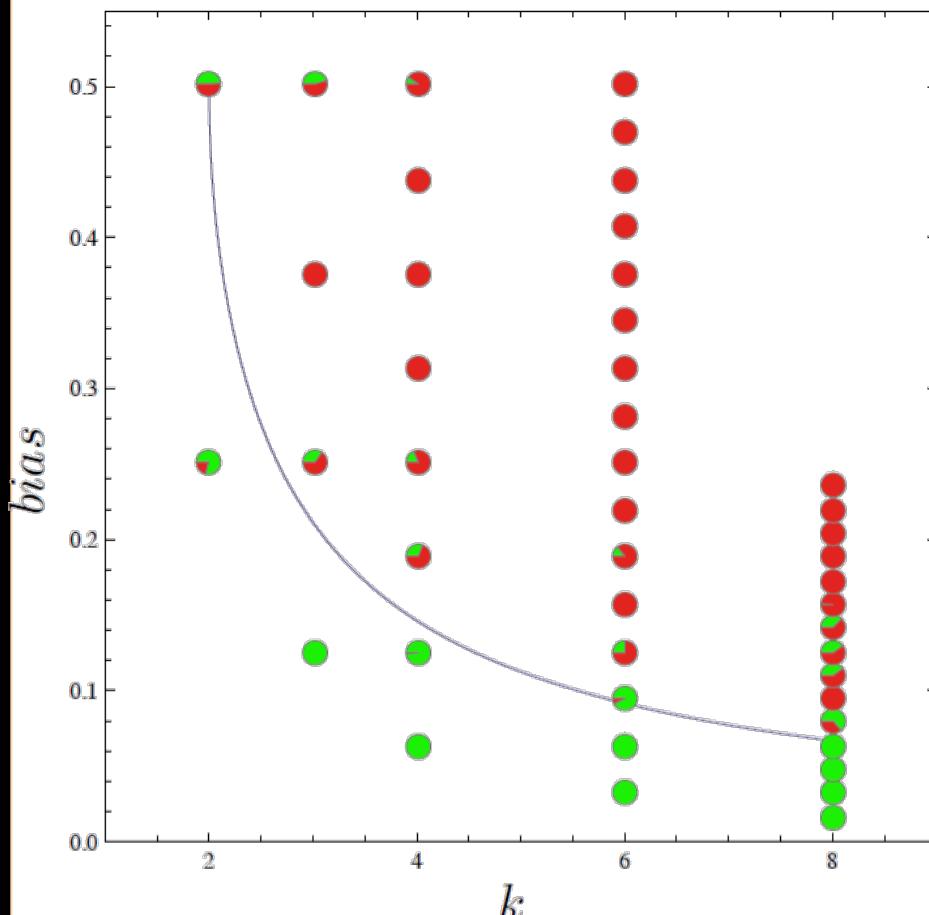


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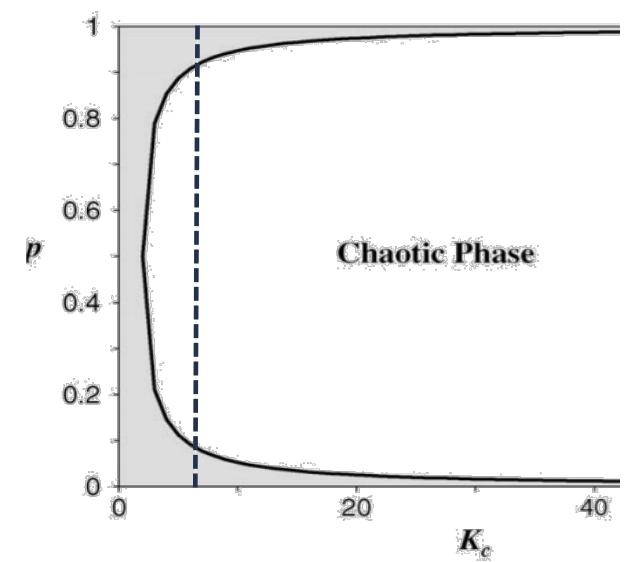
# Criticality in Boolean Networks

## Current theory



$$p = \frac{1}{2} \left( 1 - \sqrt{1 - \frac{2}{k}} \right)$$

Aldana, M. [2003]. *Physica D*. **185**: 45–66



Marques-Pita, Manicka, Teuscher & Rocha, [2014]. Submitted

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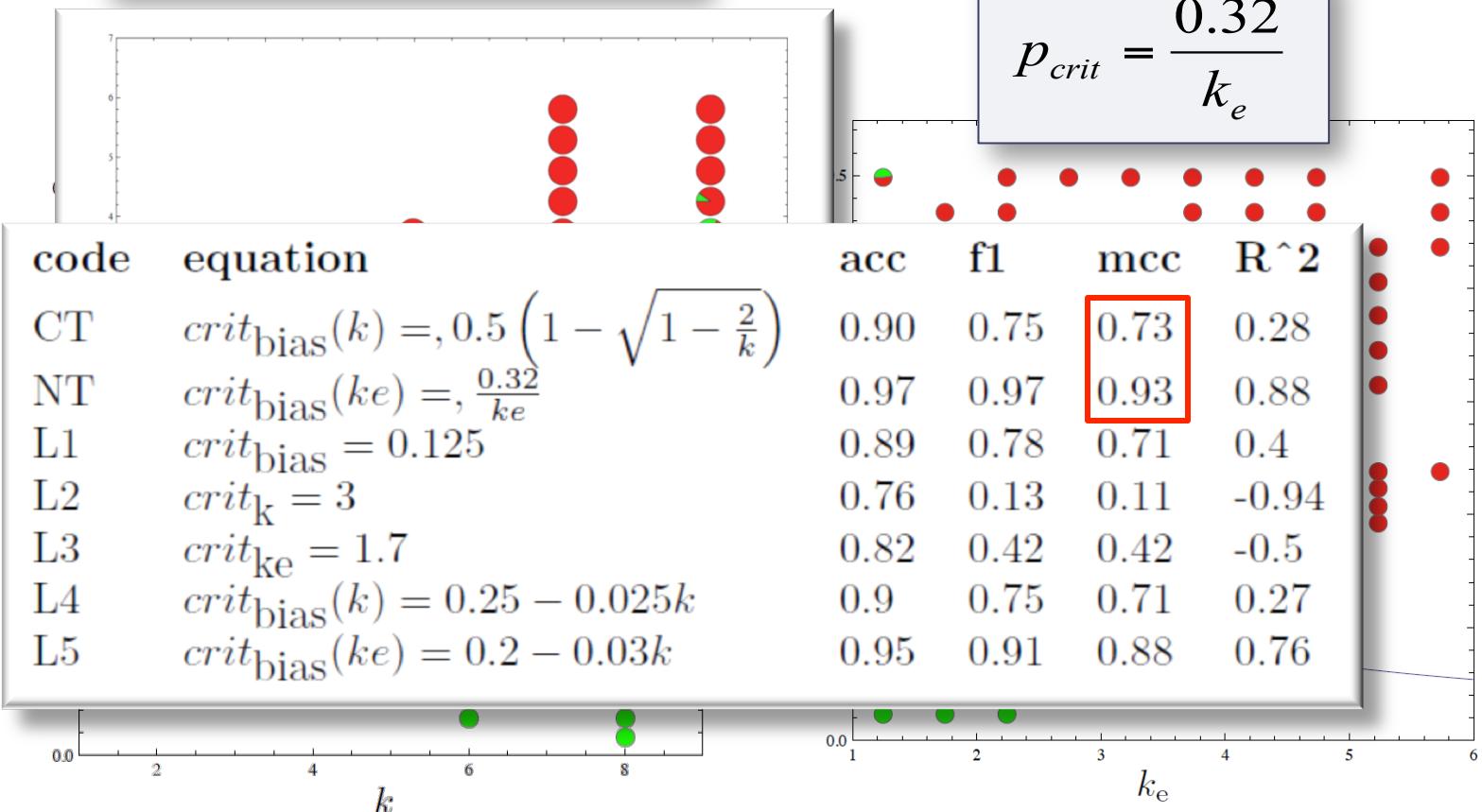


# criticality in the presence of canalization

## input redundancy, effective connectivity

$$k_r(x) = \frac{\sum_{f_\alpha \in F} \max_{\theta | f_\alpha \in \Theta_\theta} (n_\theta^\#)}{2^k}$$

$$k_e(x) = k(x) - k_r(x)$$





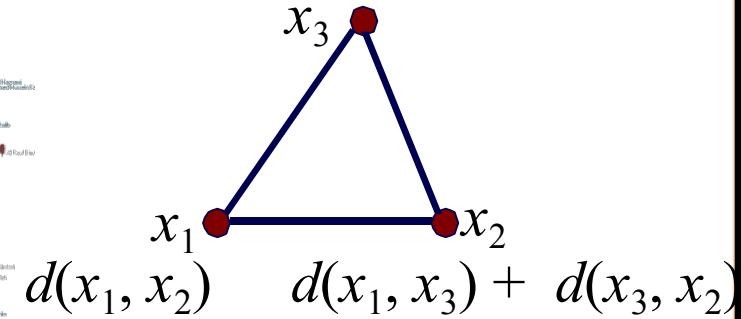
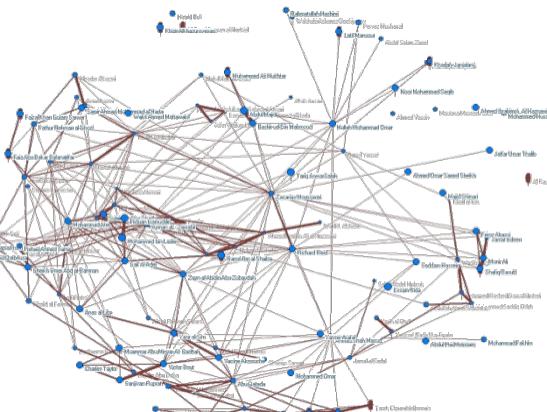
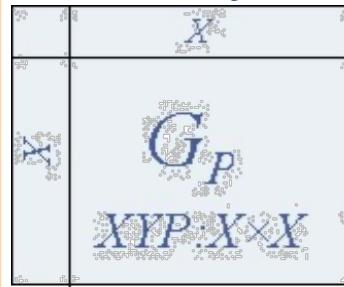
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# PATTERNS OF CONNECTIVITY

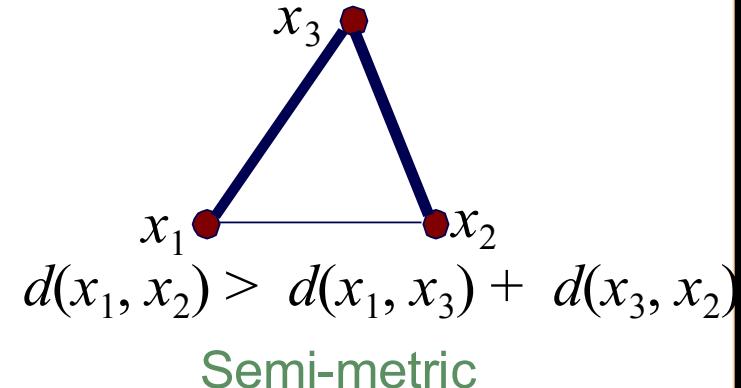
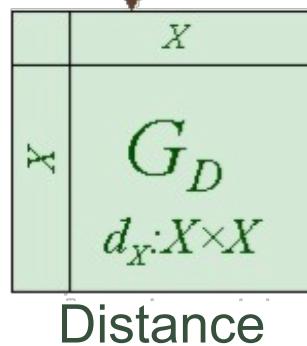
from weighted graphs

## Proximity



$$\varphi : d_X(x_i, x_j) = \frac{1}{XYP(x_i, x_j)} - 1$$

$\phi$  is a nonlinear **distance function**: nonnegative, symmetric, antireflexive ( $d(x, x) = 0$ )



Rocha & Bollen [2001] In: *SFI Series*. Segel & Cohen (Eds.), 305-334.

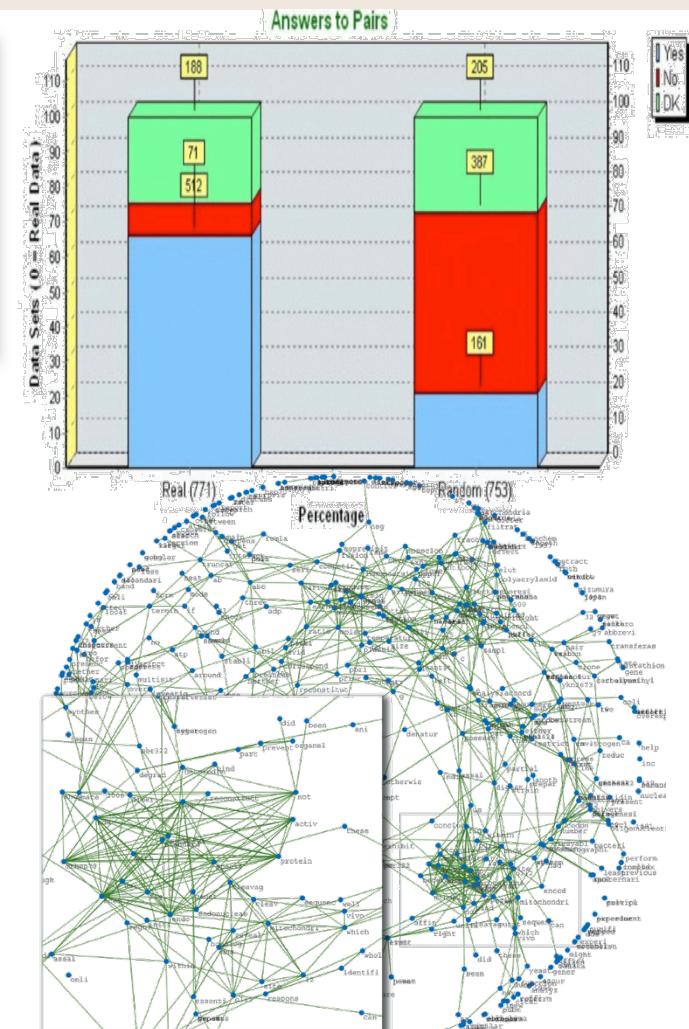
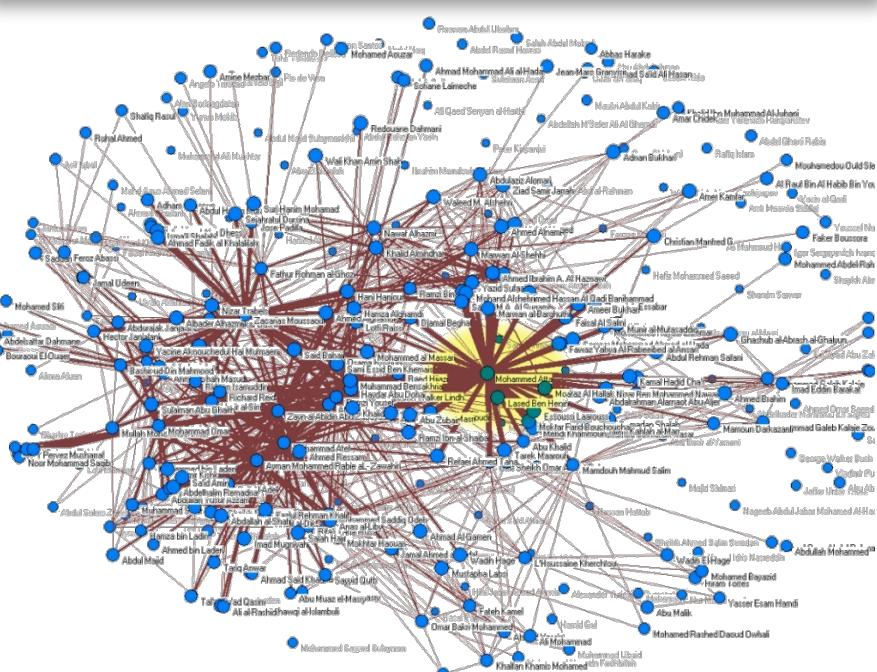
Rocha, L.M. [2002]. In: *Soft Computing Agents*: 137-163.

Rocha, L.M. et al [2005]. *IEEE Web Intelligence* (WI'05): 565-571.



## latent associations in data

- indirectly connected items
  - Higher chance of future strength
- Applications
  - Recommender systems
  - Social biochemical networks



Rocha, L.M. et al [2005]. *IEEE Web Intelligence* (WI'05): 565-571.

Simas & Rocha [2012]. *IEEE Web Intelligence* (WI'12). 175-179.

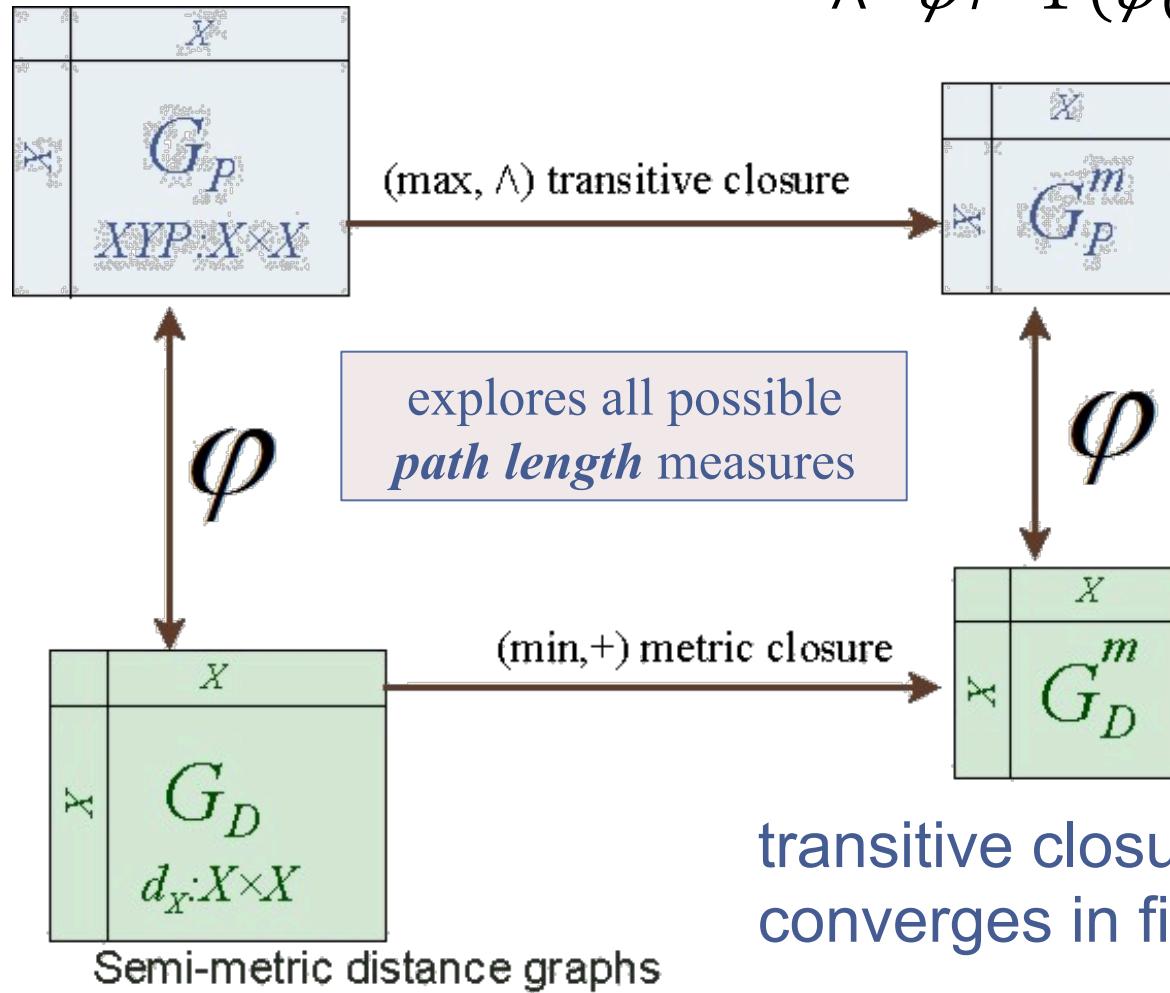
Abi-Haidar, A et al. [2008] *Genome Biology* 9(Suppl 2):S11.



shortest-path closures ( $\vee$ =maximum)

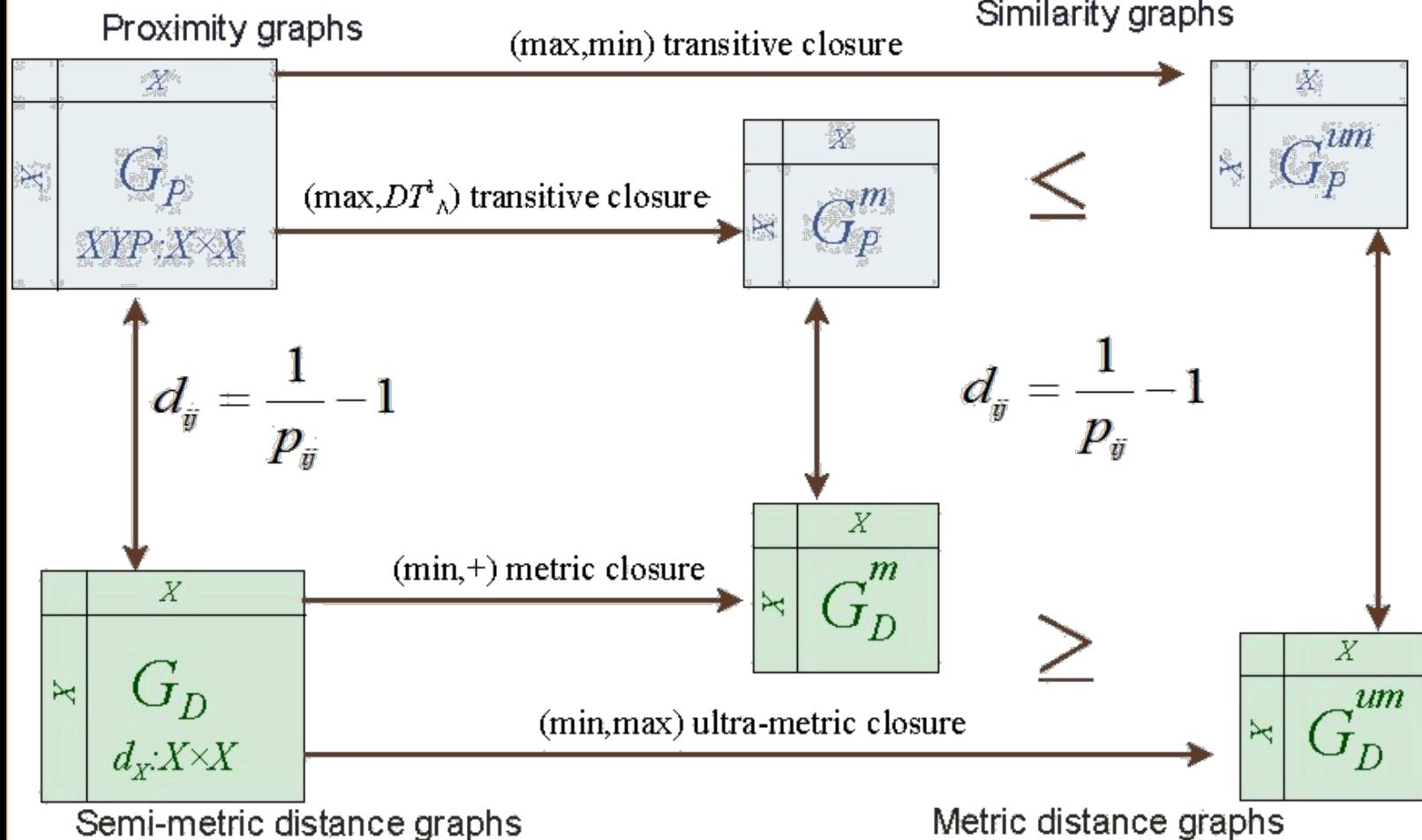
## generalized distance closure with APSP (Dijkstra)

$$\wedge = \varphi^{\uparrow-1} (\varphi(a) + \varphi(b))$$



most aggressive

shortest-path where *path length* is weakest link





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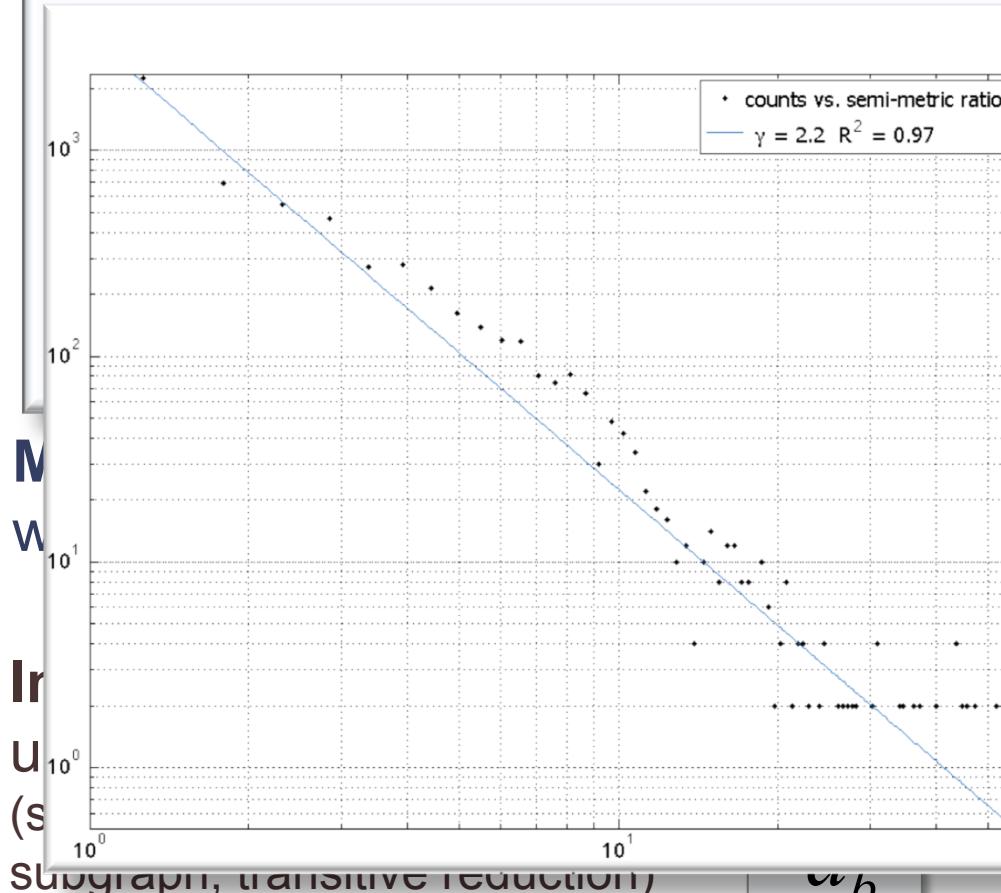
# PATTERNS OF REDUNDANCY



# semi-metric (semi-triangular) behavior and structure of weighted complex networks

## ■ Semi-metric (semi-triangular) edges:

- Redundant for shortest-path computation (distance closure)
- Null edge betweenness centrality
- Varying semi-metric distortion



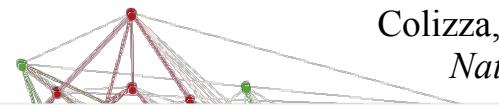
ity

$$s \downarrow i,j = d \downarrow i,j$$

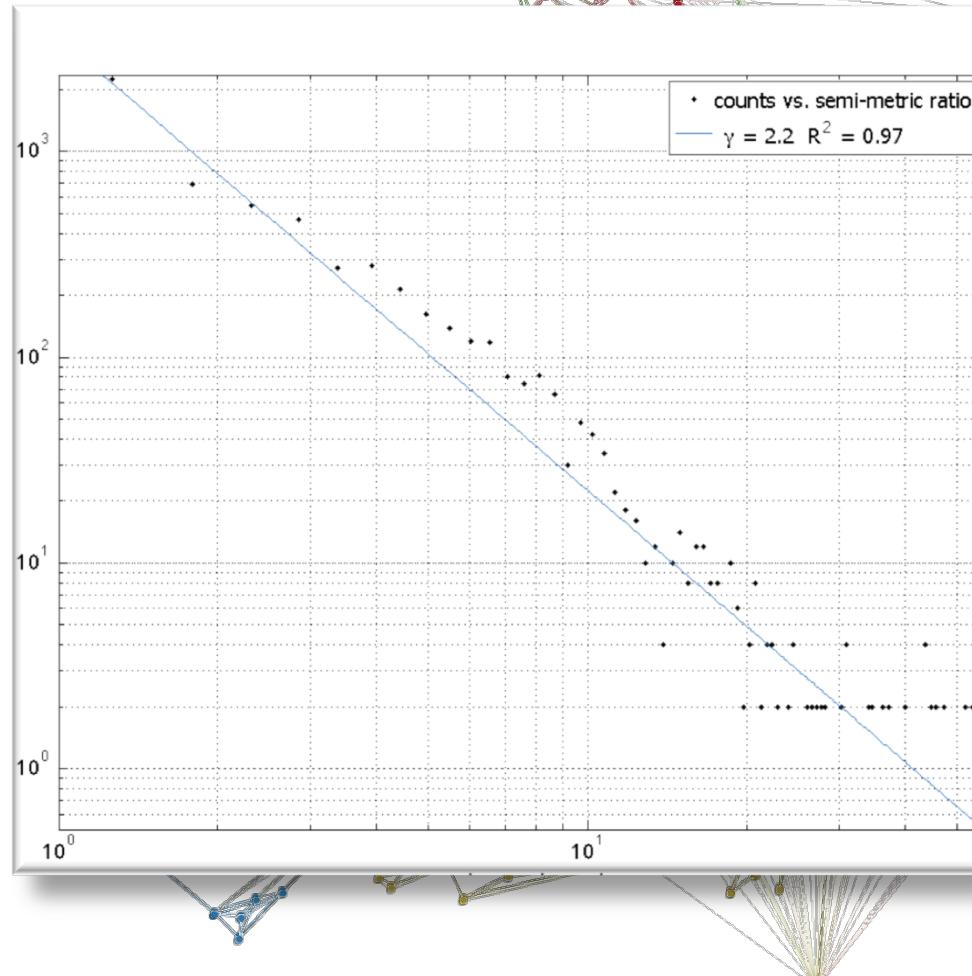
b-graph for

$$d^{mc}$$

## US airport Network



Colizza,, Pastor-Satorras,, Vespignani [2007].  
*Nature Physics* 3, 276-282.;



Available airplane seats between US cities

5% (83%) of edges are semi-metric (semi-ultra-metric) and removed from backbone

Simas, T. [2012]. *PhD Thesis*. Indiana University.

Simas, Ciampaglia, Sporns & Rocha [2014]. In Preparation.



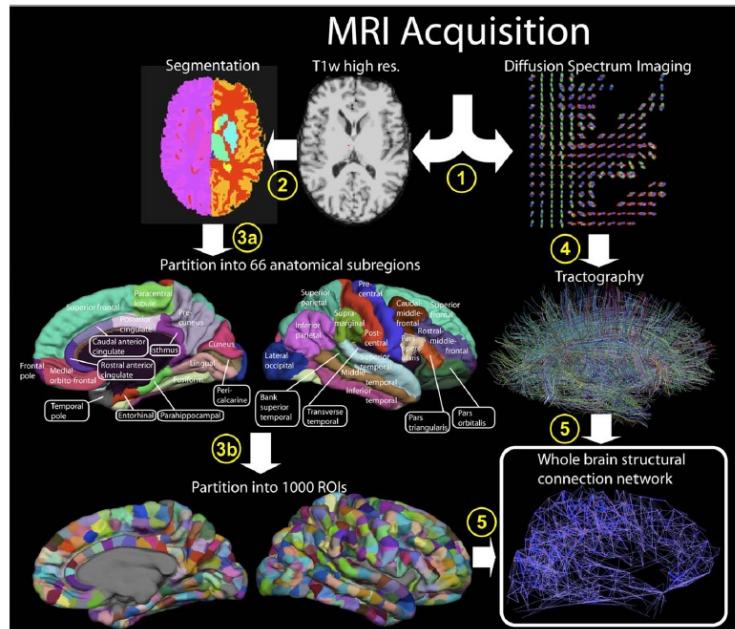


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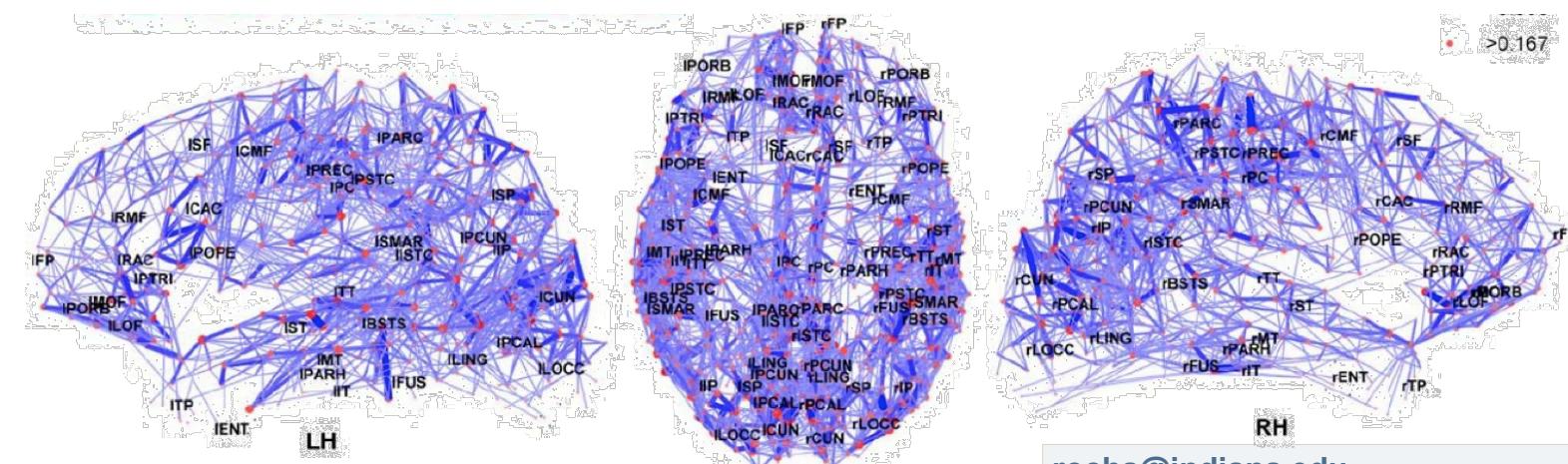
## Full network



## Human Cerebral Cortex Network

# cortico-cortical axonal pathways from diffusion spectrum Imaging (DSI)

## Nodes: functionally specialized regions



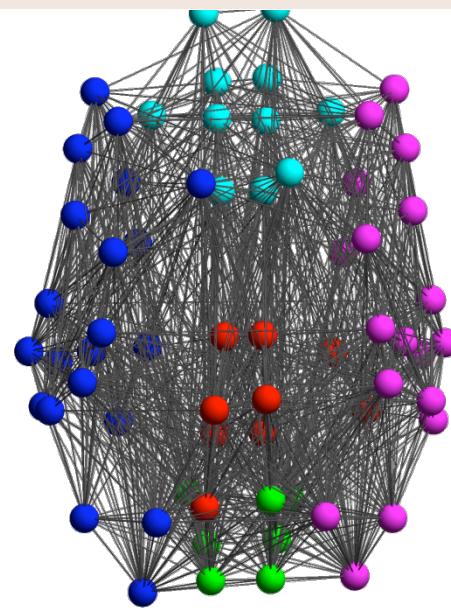
Hagmann et al. [2008]. *PLoS Biol* 6(7): e159.

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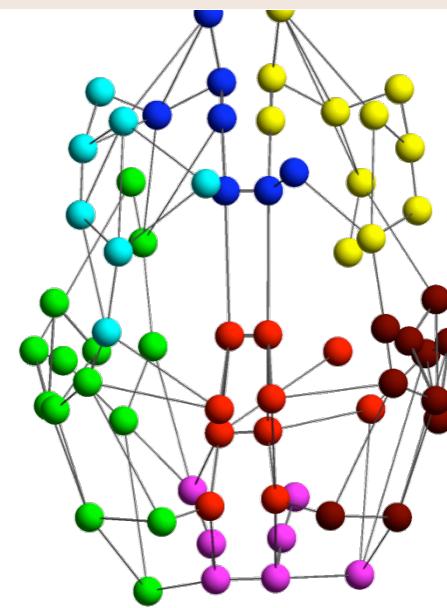
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## Human Cerebral Cortex Network



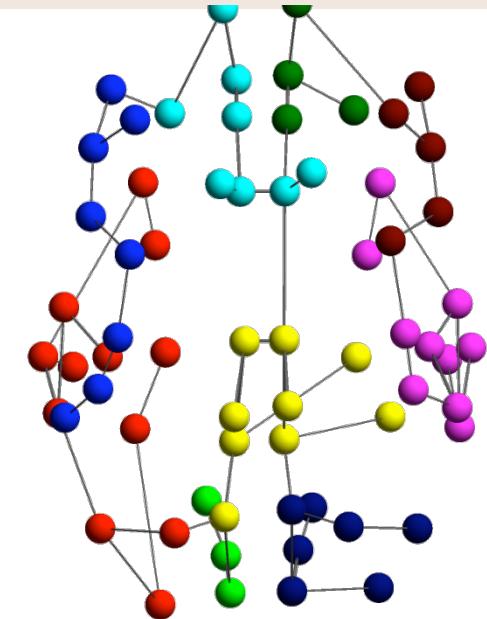
Original

cortico-cortical  
axonal pathways from  
diffusion spectrum  
Imaging (DSI)



Metric Backbone

distance backbone



Ultra-Metric  
Backbone

91% of edges are semi-metric  
(removed from backbone)!!!

94% of edges are semi-ultra-metric

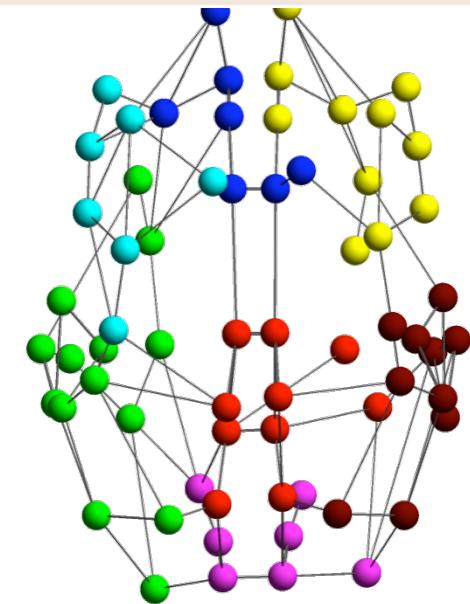
Simas, T. [2012]. *PhD Thesis*. Indiana University.

Simas, Ciampaglia, Sporns & Rocha [2014]. In Preparation.

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## Semi-metricity and modularity

#id	Network	# Nodes	SM	USM
1	USN	500	75%	83%
2	HCN	66	91%	94%
3	HBFN	116	85%	98%
4	C-Elegans	297	31%	45%
5	BKF	58	85%	91%
6	ARP-IPP	1,702	71%	88%
7	ARP-PIP	382	73%	93%
8	ARP-Keywords	500	96%	99%
9	WordNet	150	85%	93%
10	SCN	12,722	9%	28%
11	APN	14,845	20%	48%
12	HEN	5,835	13%	34%



## Metric Backbone

Ta net coi net net	USN	HCN	HBFN	C-Elegans	BKF	ARP-IPP	ARP-PIP
NET	0.6175	0.7165	1	0.1691	0.7474	0.7374	0.6265
MB	0.2335	0.1318	0.4783	0.1261	0.2482	0.2832	0.2866
UMB	0.2335	0.0	0.0	0.1115	0.1412	0.1359	0.0913

ARP-Keywords	WordNet	SCN	APN	HEN
0.9925	0.4247	0.6517	0.6696	0.5062
0.1950	0.1269	0.6165	0.6077	0.4600
0.0093	0.0214	0.6165	0.6077	0.4600

work; APN - LANL co-citation  
citation scientific collaboration

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<http://informatics.indiana.edu/rocha>



# automatic fact checking: can machines determine truth? from data in Wikipedia



Giovanni Luca  
Ciampaglia



4.0 million “things” with  
470 million “facts”.

Using *metric closure*, predicts democrat from republican politician with very high accuracy (also decent for geography, capitals director, academy awards)



Johan Bollen

Fil Menczer

Alessandro  
Flammini

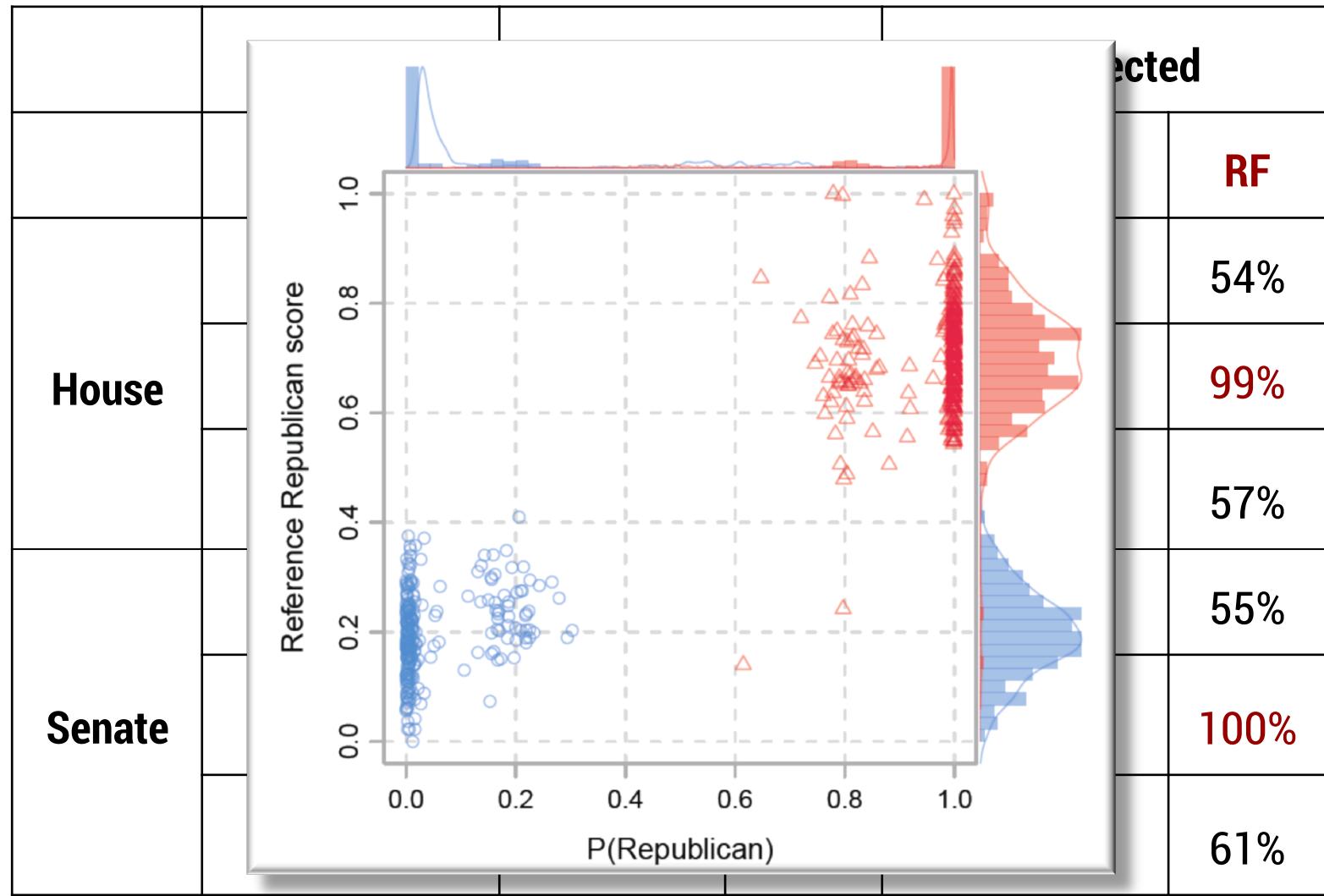
Massive graph ( $V = 3.14M$ ;  $E = 23M$ )  
is extremely semimetric (98%)



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AUC



**Baseline:** original graph  
with no closure

## CASCI Team

and computational intelligence @ indiana university,  
<http://casci.informatics.indiana.edu>



**luis m. rocha (PI)**



"Let the whole outside world consist of a long paper tape". —John von Neumann, 1948

- computation as a general principle for generating open-ended complexity (in embodied systems)
  - Turing/Von Neumann principle of universal computation/ self-replication is most fundamental principle of life: evolution via genetic variation and selection.
- general questions deriving from this evolutionary principle
  - How do cells and collectives of cells compute?
  - How can artificial systems evolve?
  - How does external language extend cognition?
  - Can we understand and control collective intelligence via external language? Does it evolve?
- projects focus on language and information on networks
  - dynamics in complex networks, automata dynamics, network topology, text mining for translational biomedicine, computational biology, agent-based modeling, artificial life, evolutionary systems, collective intelligence



and computational biology  
@ instituto gulbenkian de ciéncia, portugal



selected projects – text, literature, and social media mining

## Content Extraction and Event Detection:

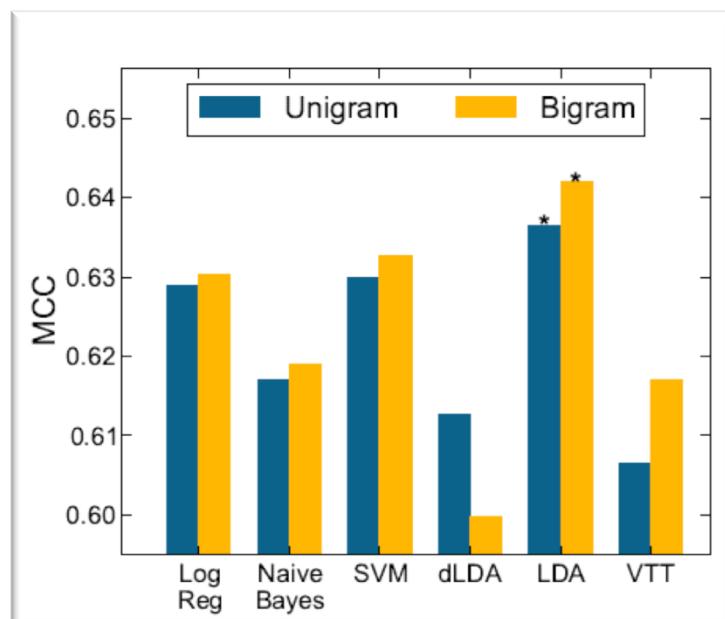
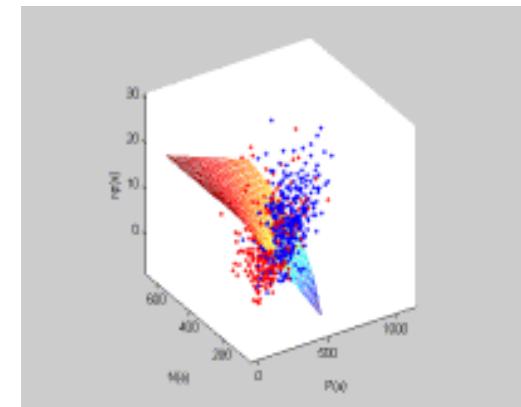
Protein-Protein Interaction, Drug-Drug-interaction, Drug Pharmacokinetics, Numerical Parameter, Event Prediction from Twitter data, Protein Structure Prediction, etc. Among top performing teams in BioCreative PPI tasks

Wu et al [2013]. *BMC Bioinformatics*, 14:35.

Wang, et al [2009]. *J. Biomedical Informatics*. 42 (4): 726-735.

Abi Haidar, A et al. [2008] *Genome Biology* 9(Suppl 2):S11.

Verspoor, K., et al [2005]. *BMC Bioinformatics*, 6(Suppl 1):S20.



## Text Classification: Retrieval of relevant documents, tweets, profiles, etc.

Lourenco, et al [2011]. *BMC Bioinformatics*. 2(Suppl 8):S12

Abi-Haidar & L.M. Rocha [2011]. *Evol. Intel.* 4(2):69-80.

Kolchinsky, et al [2010]. *Trans. Comp. Bio. Bioinf.*, 7(3):400-411

Kolchinsky et al [2013]. PSB 18:409-420.

Kolchinsky et al [2014]. *PLoS One*. In Press.



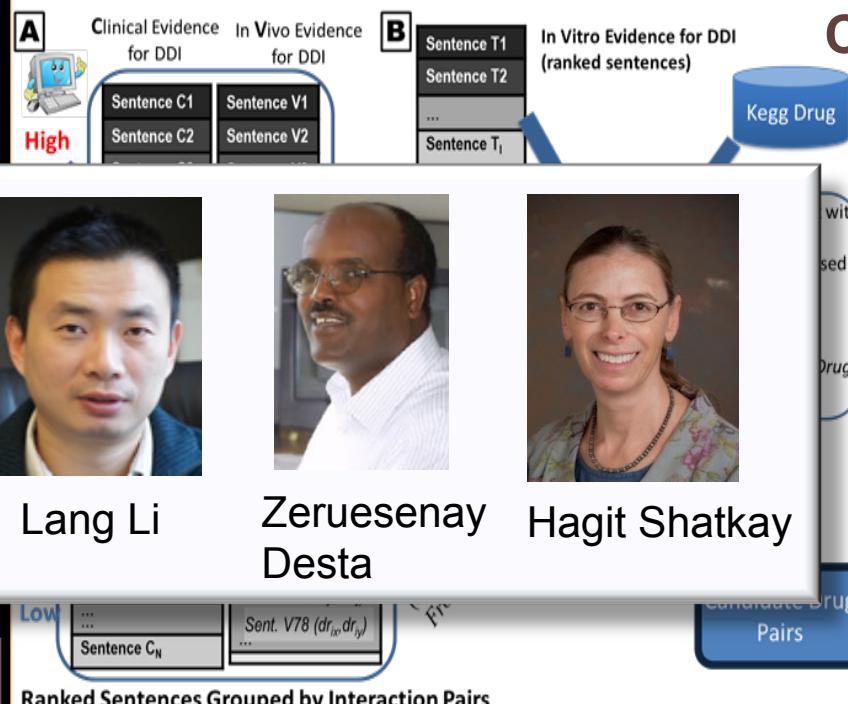
classification and extraction of evidence from the Bibliome

**threat to public health:** drug-drug interaction (DDI) is major cause of *adverse drug reaction* (ADR).  $\approx 195K/\text{year}$  hospitalizations and  $74K/\text{year}$  emergency room visits in US. Expected to increase with *polypharmacy*.



**DDI experimental evidence:** *in vitro*, molecular interactions within cell; *in vivo*, whether molecular interaction impacts drug exposure in humans; *clinical*, whether DDI changes human response to drugs (efficacy, ADR).

**Knowledge gaps:** missing evidence of any of the three types. **Need to link evidence** of molecular to clinical DDI, at collective intelligence level



**Corpora development and Text Classification of evidence:** abstracts and sentences with evidence of DDI of one type to fill **knowledge gaps**

Kolchinsky et al [2013]. *PSB* 18:409-420.

Wu et al [2013]. *BMC Bioinformatics*, 14:35.  
DOI:10.1186/1471-2105-14-35.

Kolchinsky et al [2014]. *PLOS One*. In Press.

Wu et al [2014]. *J. Biomed. Informatics*, Submitted.



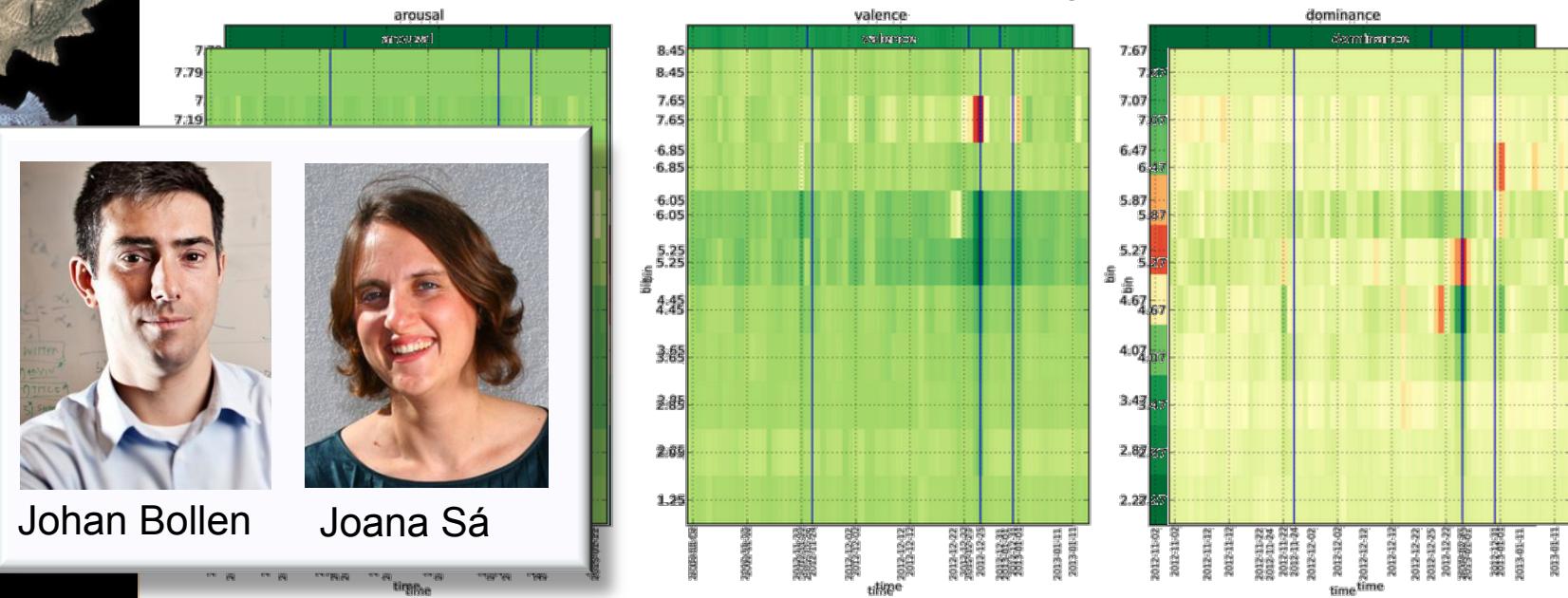
# studying collective behavior

eigenmoods from text records on social media

- text as external component of collective behavior
  - patterns of text used by collectives
    - rather than individual brains and genes
  - e.g. Collective mood behavior on Twitter
    - Sex search data
    - Situations with divergent collective moods

ANEW Twitter measurements 2012

Reconstructed matrix after first singular vector removed



Johan Bollen

Joana Sá

Wood et al [2014]. *In Preparation.*

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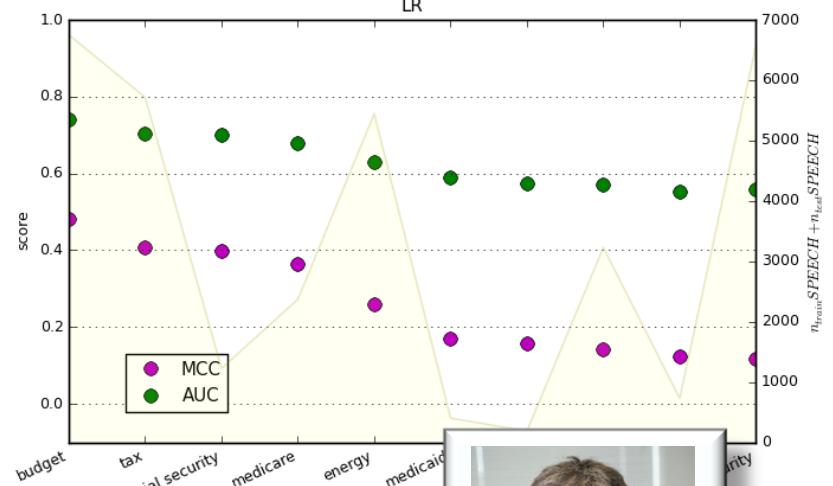
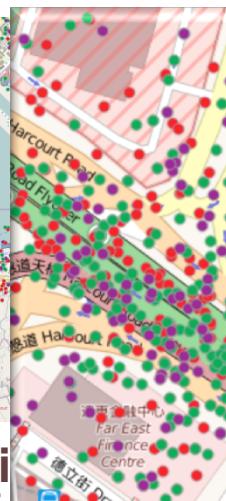


## Selected projects

### Political activity: social unrest via Instagram and polarization in congress



Norbert Chan

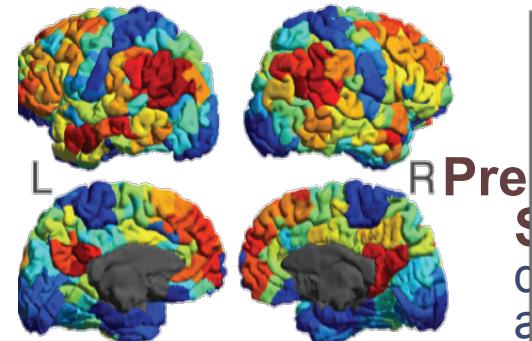


### Time-series Classification Classification, RNA E

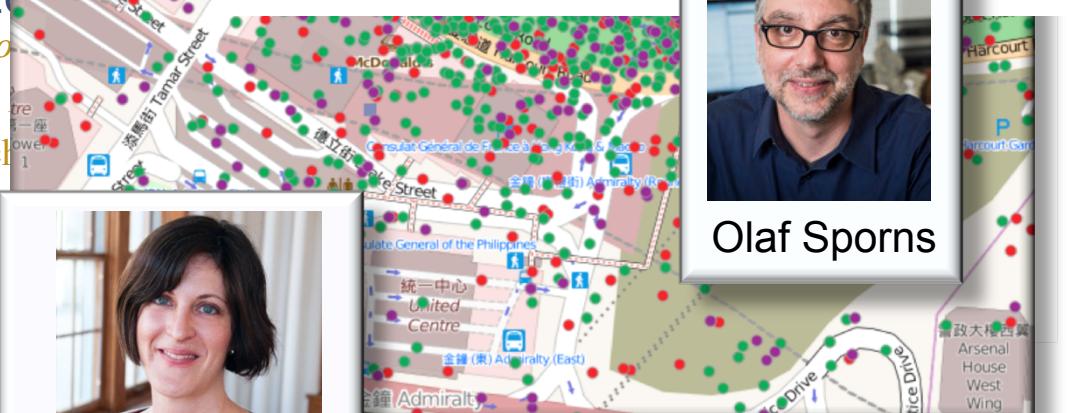
Huang, C-F, et al [2007]. *Evolution*

Abi-Haidar & Rocha [2011]. *Evol.*

Francisco, Wood, Sabanovic & Rocha



Selma Sabanovic



Olaf Sporns

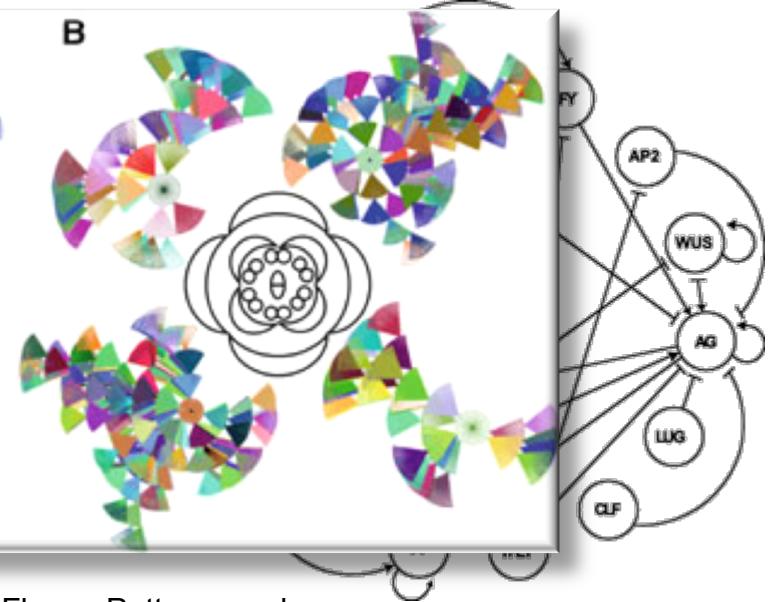
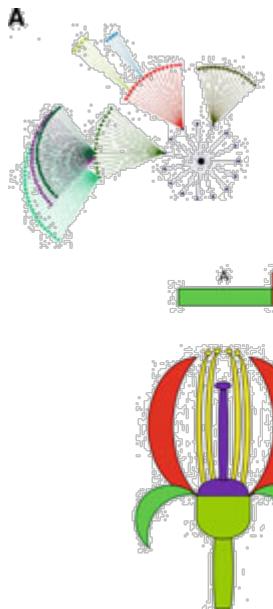
Kolchinsky et al [2014]. *Frontiers in Psychology* 5:166.  
Kolchinsky & Rocha [2011]. *ECAL 2011*: 423-430.



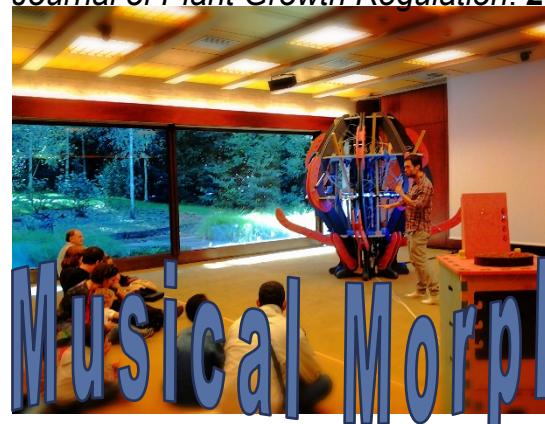
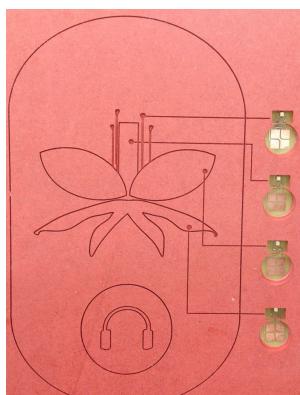


# self-organization and the cybernetics of life

## Boolean networks, sound, art, and education



Chaos et al [2006]. "From Genes to Flower Patterns and Evolution: Dynamic Models of Gene Regulatory Networks". *Journal of Plant Growth Regulation*. 25(4): 278-289.

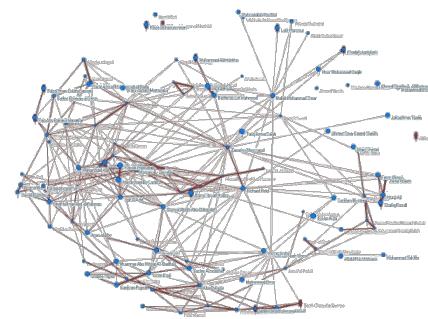
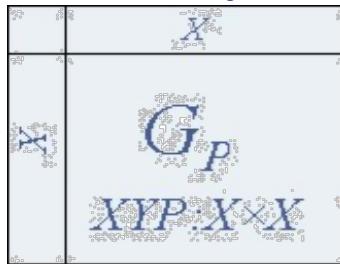


# Musical Morphogenesis

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## metric closure – APSP (Dijkstra)

## Proximity

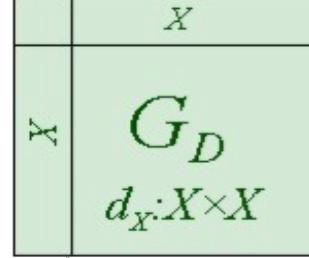


Rocha, Luis M. [2002]. In: *Soft Computing Agents*. V. Loia (Ed.):137-163.

Rocha, L.M. et al [2005]. *IEEE Web Intelligence* (WI'05): 565-571.

shortest-path where *path length* is sum of edges

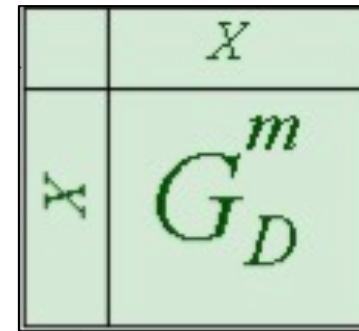
$$d_X(x_i, x_j) = \frac{1}{XYP(x_i, x_j)} - 1$$



Distance

Metric Closure  
(min/+)

= metric  
> semi-metric



(Shortest Path)

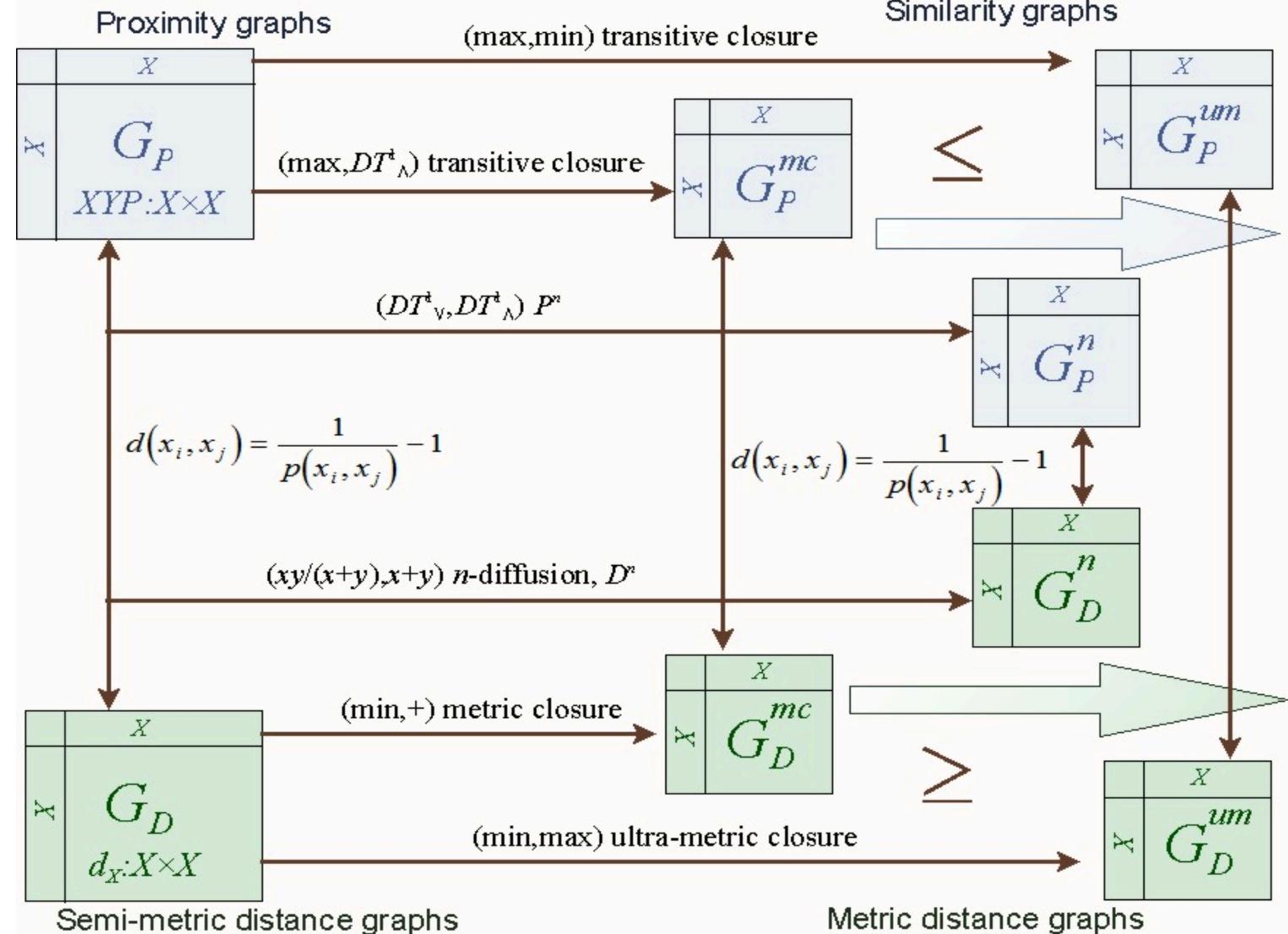
$$b \downarrow i,j = d \downarrow i,j$$

$$s \downarrow i,j = d \downarrow i,j$$

Measures of semi-metric behavior



## all cases



## intuition about latent associations



close to metric

more semi-metric





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intuition



ultra-metric closure

weak weakest link



strong weakest link



Tends to link items very strongly  
Greater distortion of original graph  
Worse for inference

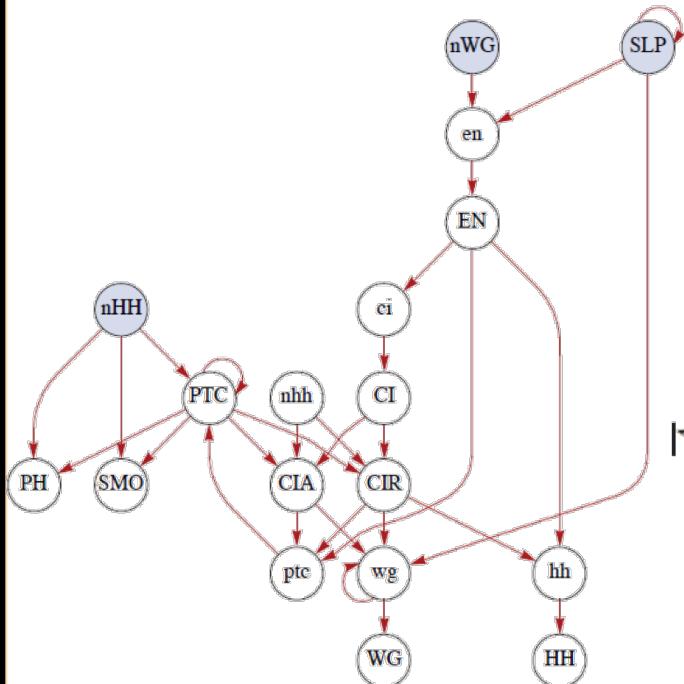
rocha@indiana.edu  
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# Can structural controlability uncover control?

## Drosophila model (Albert et al)

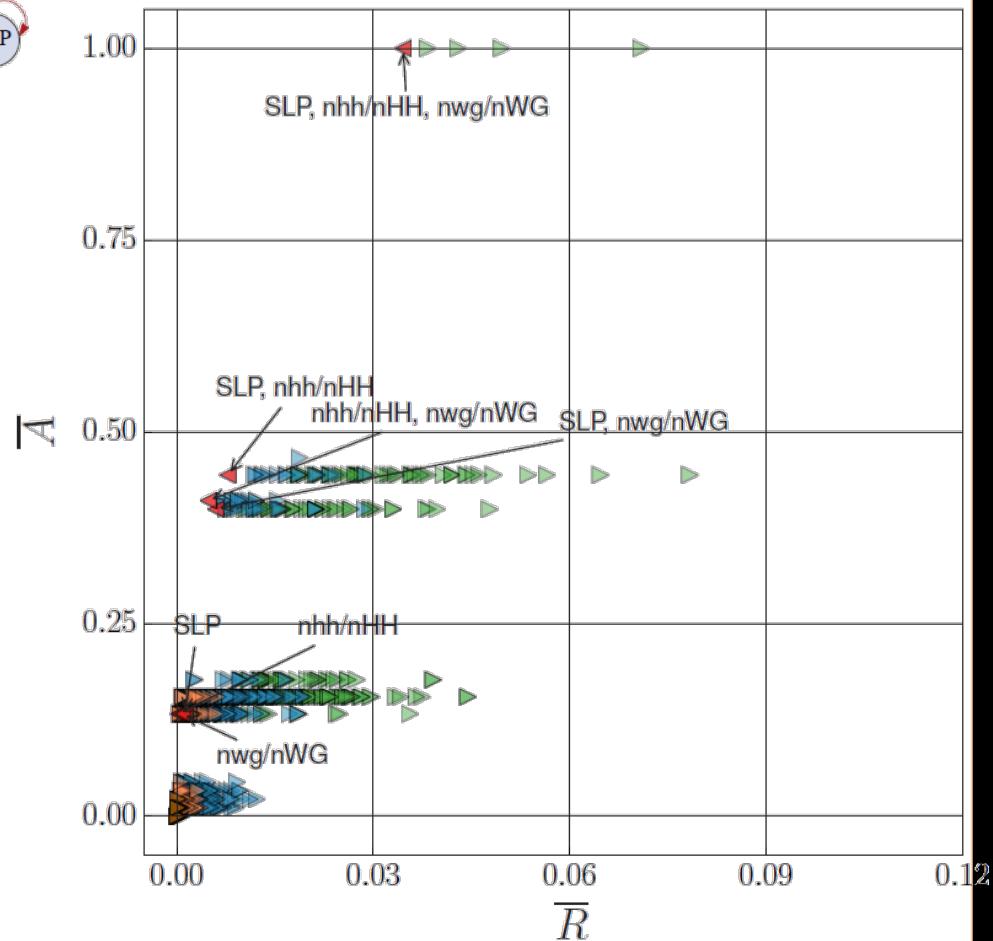


4 nodes predicted by structural control:

- {*SLP, nWG, nhh/nHH, PH*},
- {*SLP, nWG, nhh/nHH, SMO*},
- {*SLP, nWG, nhh/nHH, CIR*},
- {*SLP, nWG, nhh/nHH, CIA*}

Gates & Rocha [2014]. *ALIFE 2014*: 429-430.

Gates & Rocha [2014]. *In preparation..*



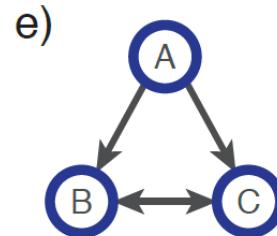
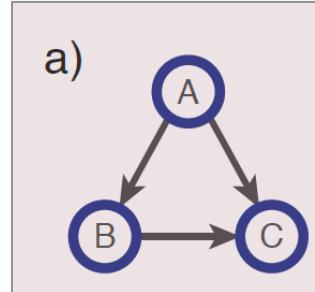
rocha@indiana.edu  
<http://informatics.indiana.edu/rocha>



# Can structural controllability uncover control?

In presence of dynamics

Consider small network motifs:



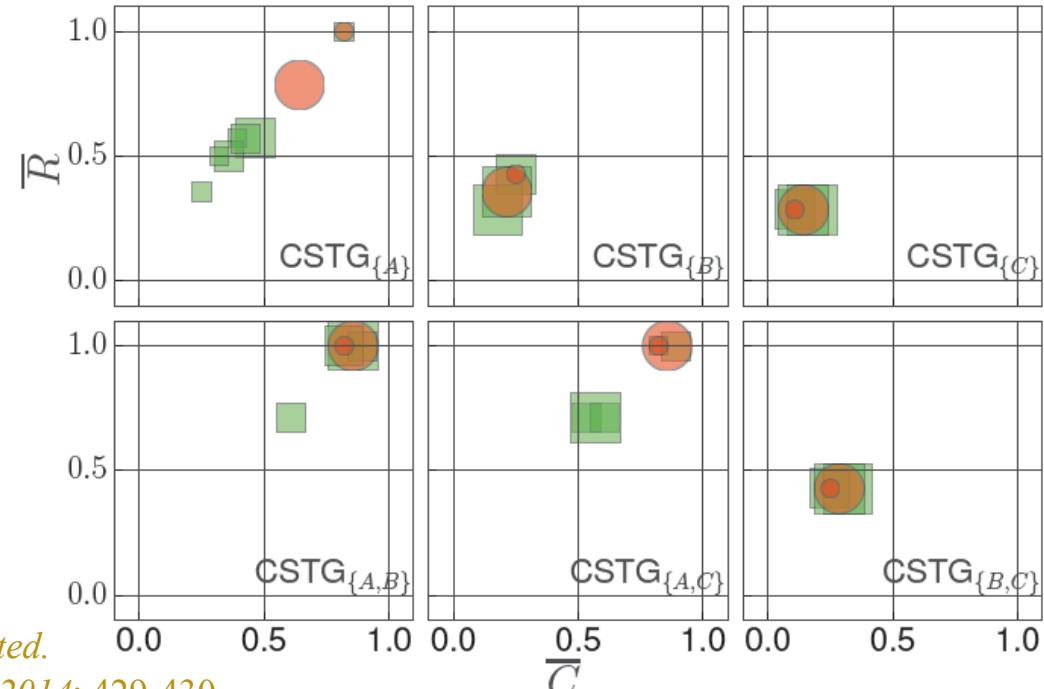
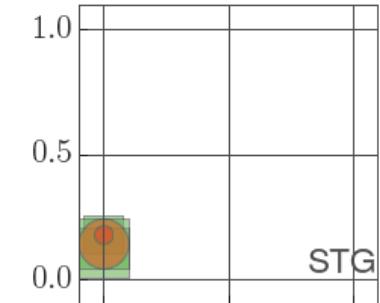
The larger the  
**canalization**, the less  
predictable is  
structural control

Full Ensemble

1	8	16
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Non-trivial Subset

1	8	16
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Gates & Rocha [2014]. Submitted.

Gates & Rocha [2014]. ALIFE 2014: 429-430.