Information Dynamics in Complex Systems

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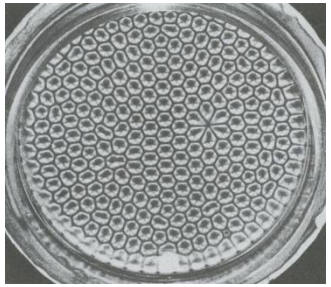
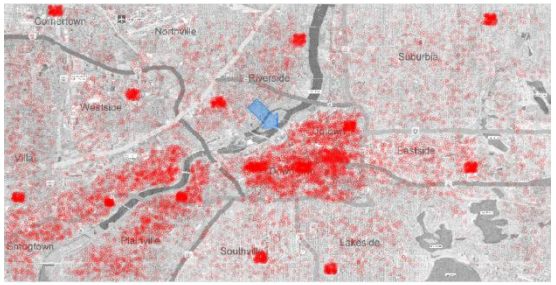
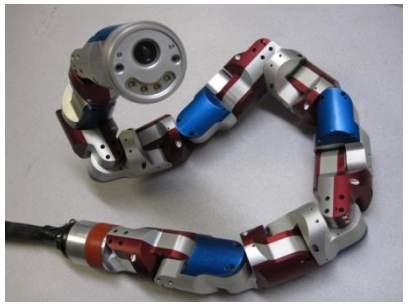
THE UNIVERSITY OF SYDNEY

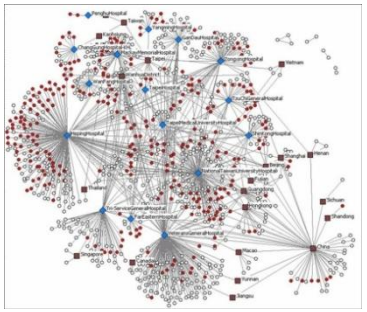
Outline

- Complexity and Self-Organisation
- Information structure:
  - artificial life
  - biological networks
- Information dynamics:
  - Cellular Automata
  - brain connectivity
  - information cascades in swarms
- Information thermodynamics
  - Random Boolean networks

Complex Systems and Self-Organisation



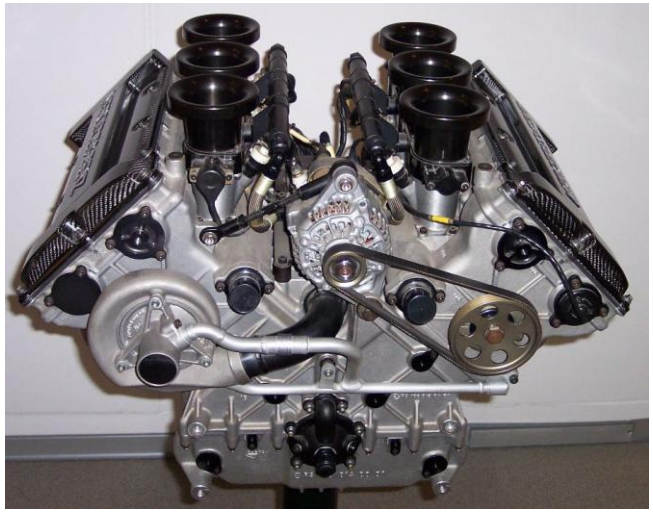


- . . . a set of dynamical mechanisms whereby structures appear at the global level of a system from interactions among its lower-level components

- The rules specifying the interactions among the system's constituent units are executed on the basis of purely local information, without reference to the global pattern, which is an emergent property of the system rather than a property imposed upon the system by an external ordering influence

  [Bonabeau et al., 1997]

Complex (“weave”) vs Complicated (“fold”)



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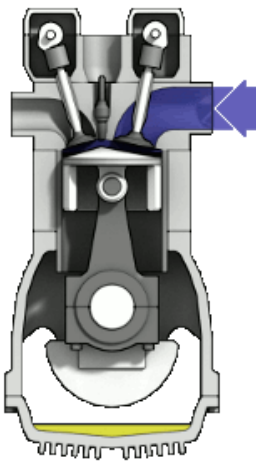


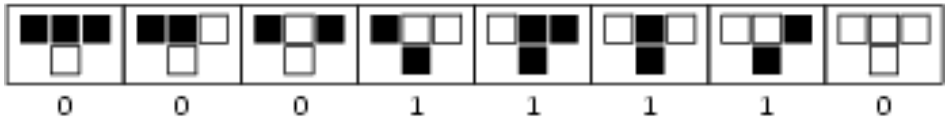
- Complex system
- Evolved adaptive response
- Emergent non-deterministic patterns
- Self-organisation: hard to predict
- Resilient to perturbations
- Interdependent networks
- Deals with information

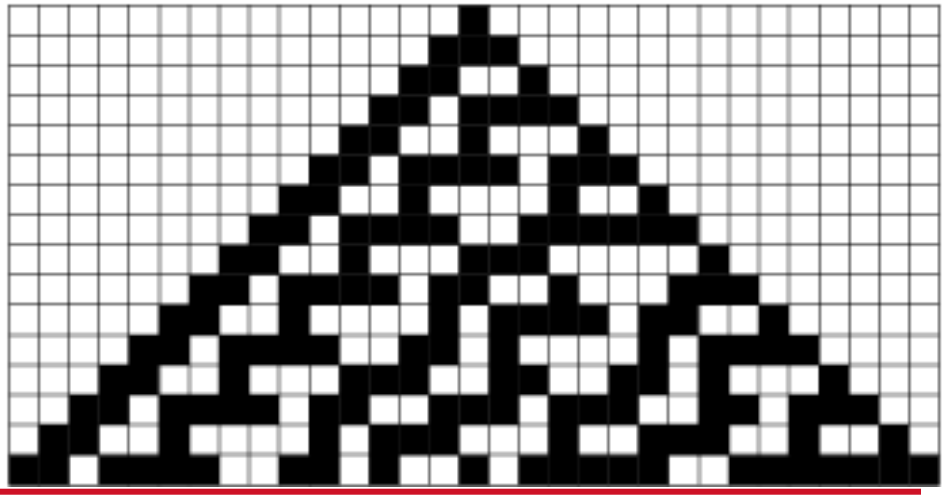
- Complicated system
- Designed for performance
- Predictable deterministic regimes
- Blueprint: verification and testing
- Brittle to malfunctions
- Centralised management
- Deals with data

Case study: complexity of Cellular Automata

- An array of cells that have a discrete value
- Future states determined by:
  - The input from the neighbourhood
  - Current state of cell
  - The rules that are applied to the input

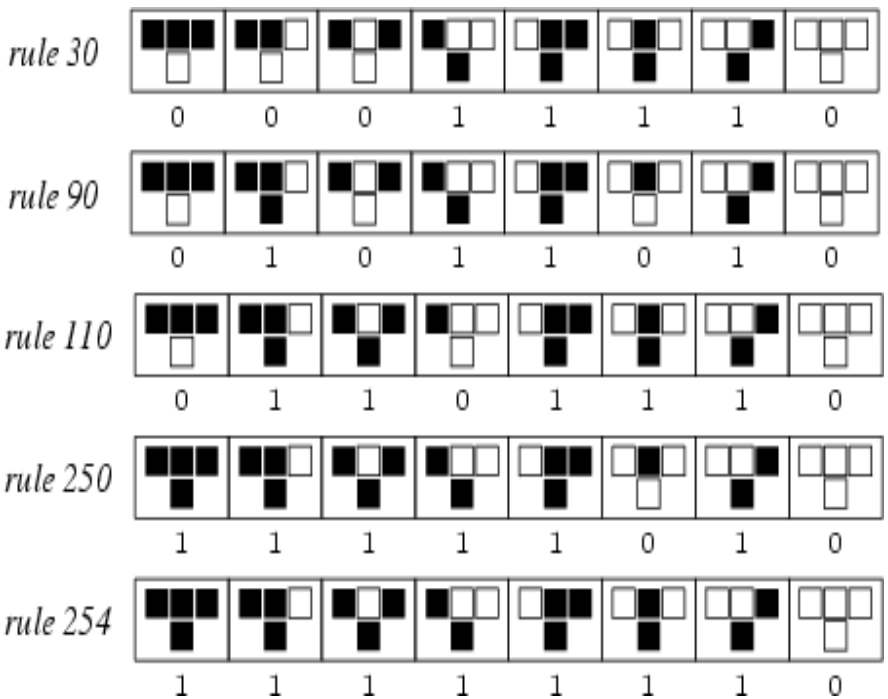
rule 30

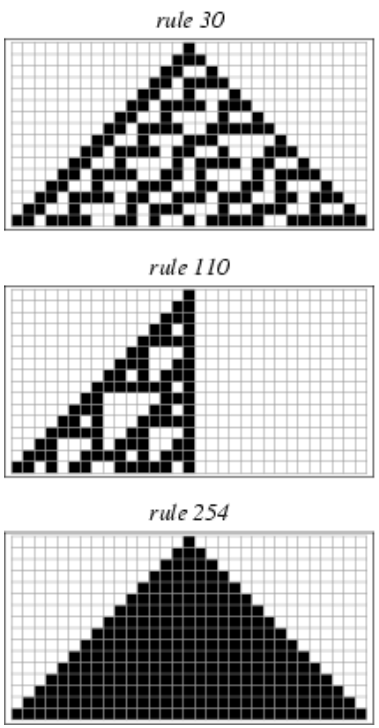


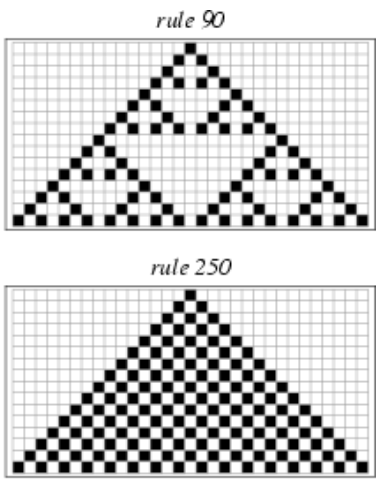


Wolfram's representation

- Binary representation of 1-dimensional rules





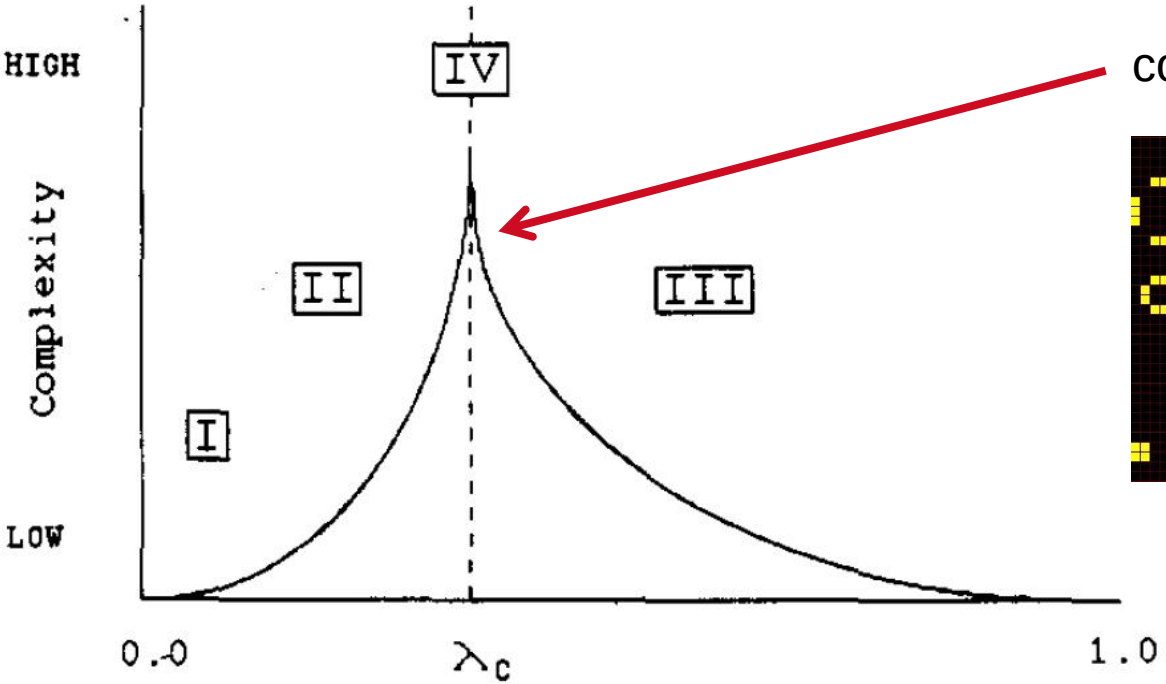


http://mathworld.wolfram.com/ElementaryCellularAutomaton.html

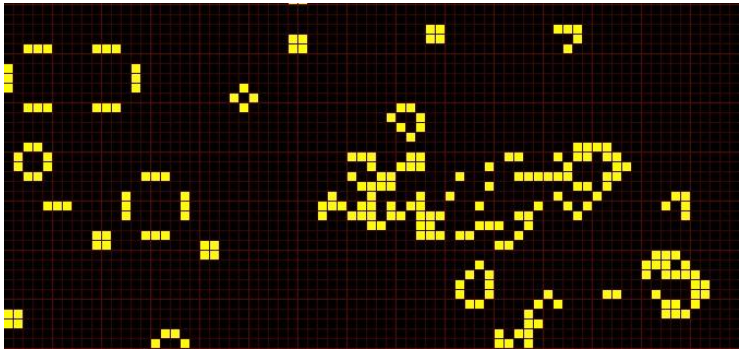
Complexity and self-organisation in CA

Chris Langton, "Computation at the edge of chaos: Phase transitions and emergent computation" (1990):

- how can emergence of computation be explained in a dynamic setting?
- how is it related to complexity of the system in point?



complex high-level structures



Information: source → receiver (Shannon)

34 *The Mathematical Theory of Communication*

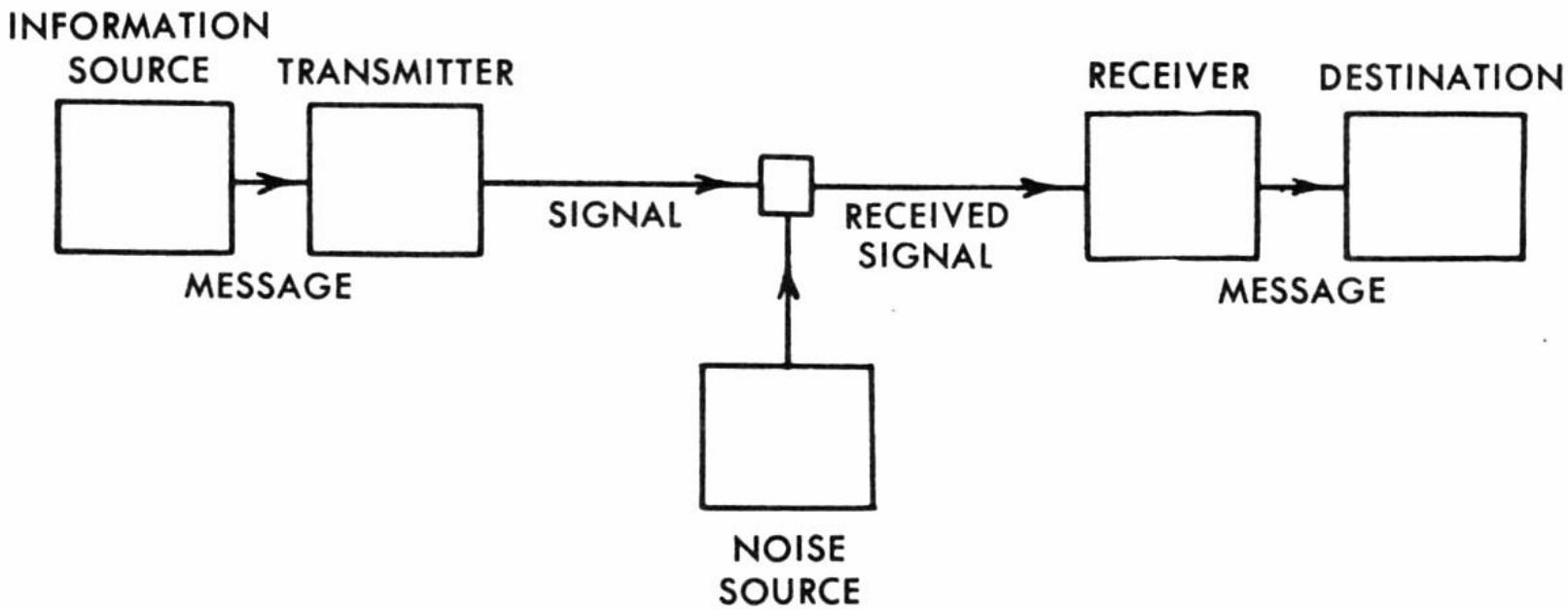


Fig. 1. — Schematic diagram of a general communication system.

Information-theoretic modelling

WILEY COMPLEXITY

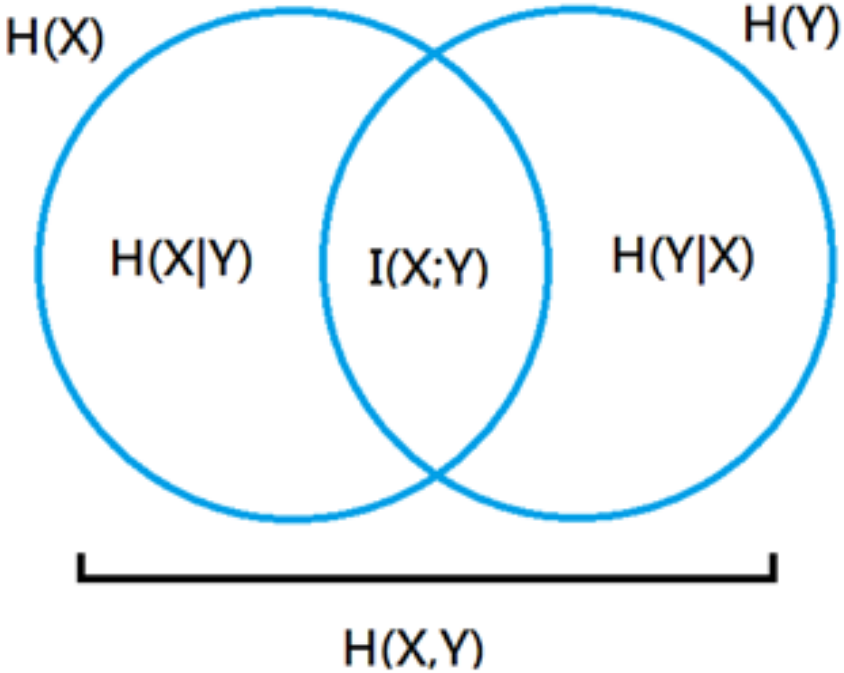
An Information-Theoretic Primer on Complexity, Self-Organization, and Emergence

$$H(X) = -\sum_{x \in \mathcal{X}} P(x) \log P(x)$$

Complex Systems Science aims to understand concepts like complexity, self-organization, emergence and adaptation, among others. The inherent fuzziness in complex systems definitions is complicated by the unclear relation among these central processes: does self-organisation emerge or does it set the preconditions for emergence? Does complexity arise by adaptation or is complexity necessary for adaptation to arise? The inevitable consequence of the current impasse is miscommunication among scientists within and across disciplines. We propose a set of concepts, together with their possible information-theoretic interpretations, which can be used to facilitate the Complex Systems Science discourse. Our hope is that the suggested information-theoretic baseline may promote consistent communications among practitioners, and provide new insights into the field. Published 2008 Wiley Periodicals, Inc. Complexity 15: 11–28, 2009

MIKHAIL PROKOPENKO, FABIO BOSCHETTI, AND ALEX J. RYAN

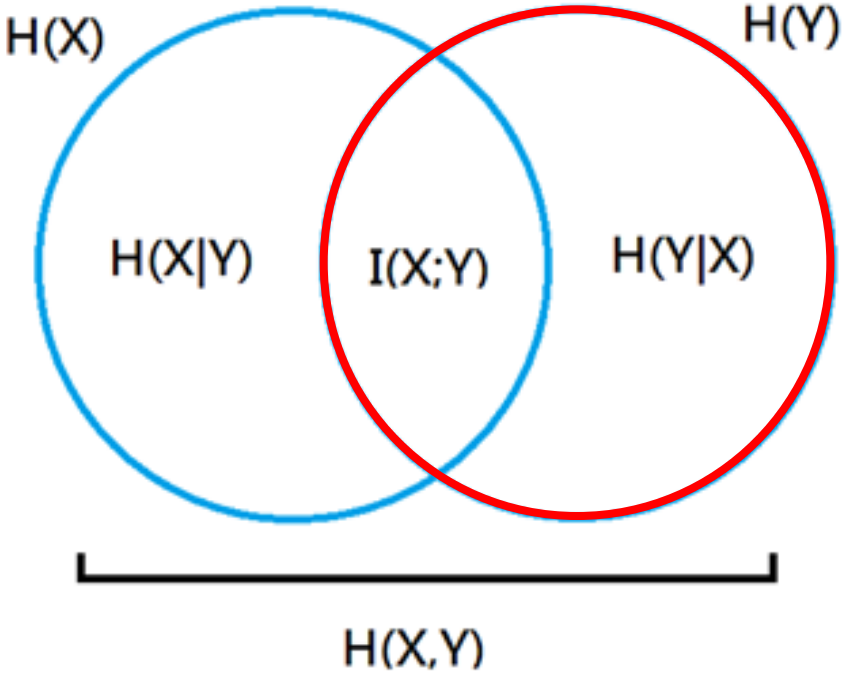
Towards task-independence: Entropy and information



$$H(X) = -\sum_{x \in \mathcal{X}} P(x) \log P(x)$$

$$I(X;Y) = H(X) + H(Y) - H(X,Y) = H(Y) - H(Y|X)$$

Entropy and information



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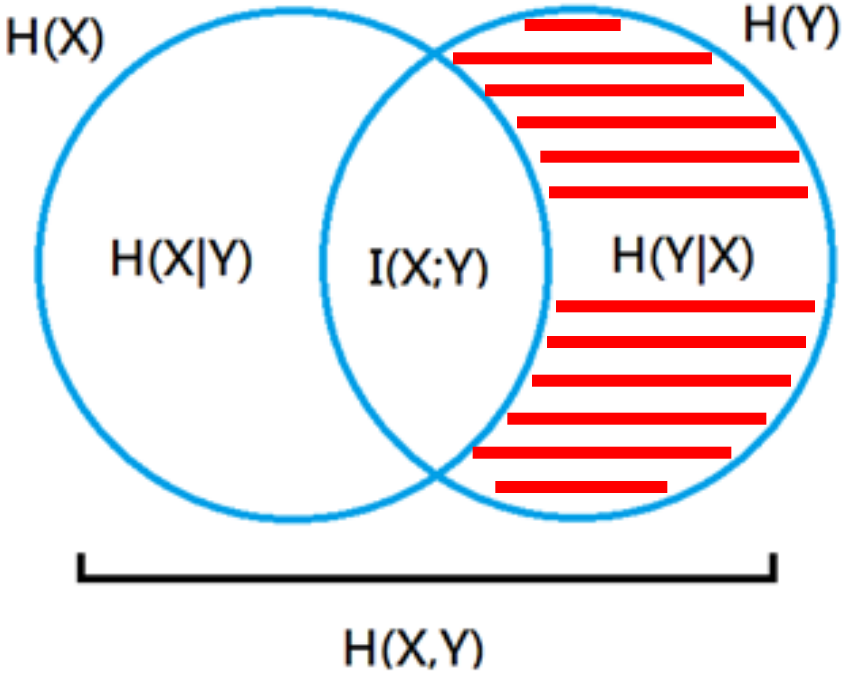
receiver's diversity

Entropy and information

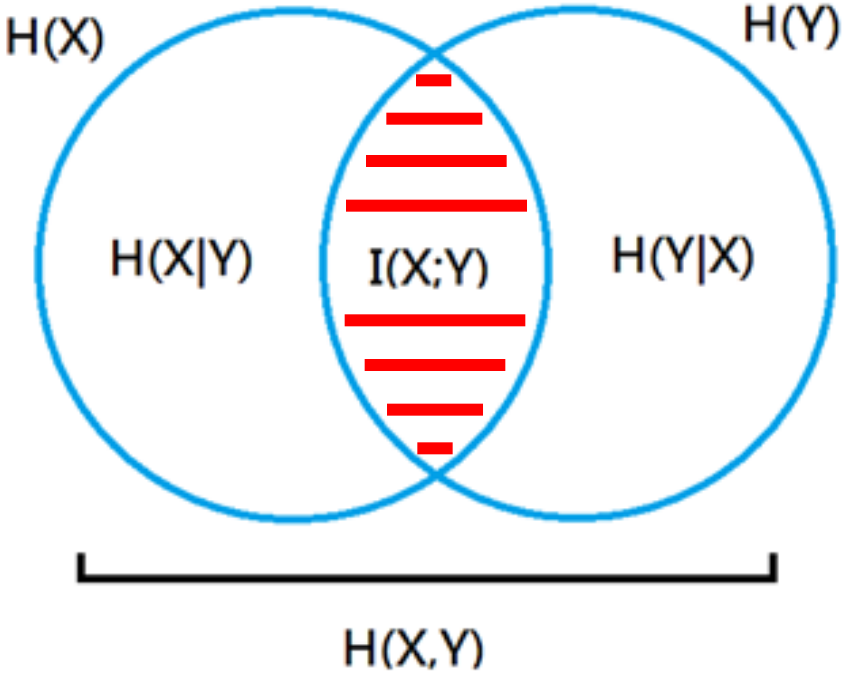


$$H(X) = -\sum_{x \in \mathcal{X}} P(x) \log P(x)$$

$$I(X;Y) = H(X) + H(Y) - H(X,Y) = H(Y) - H(Y|X)$$

equivocation of receiver about source

The “magic” formula



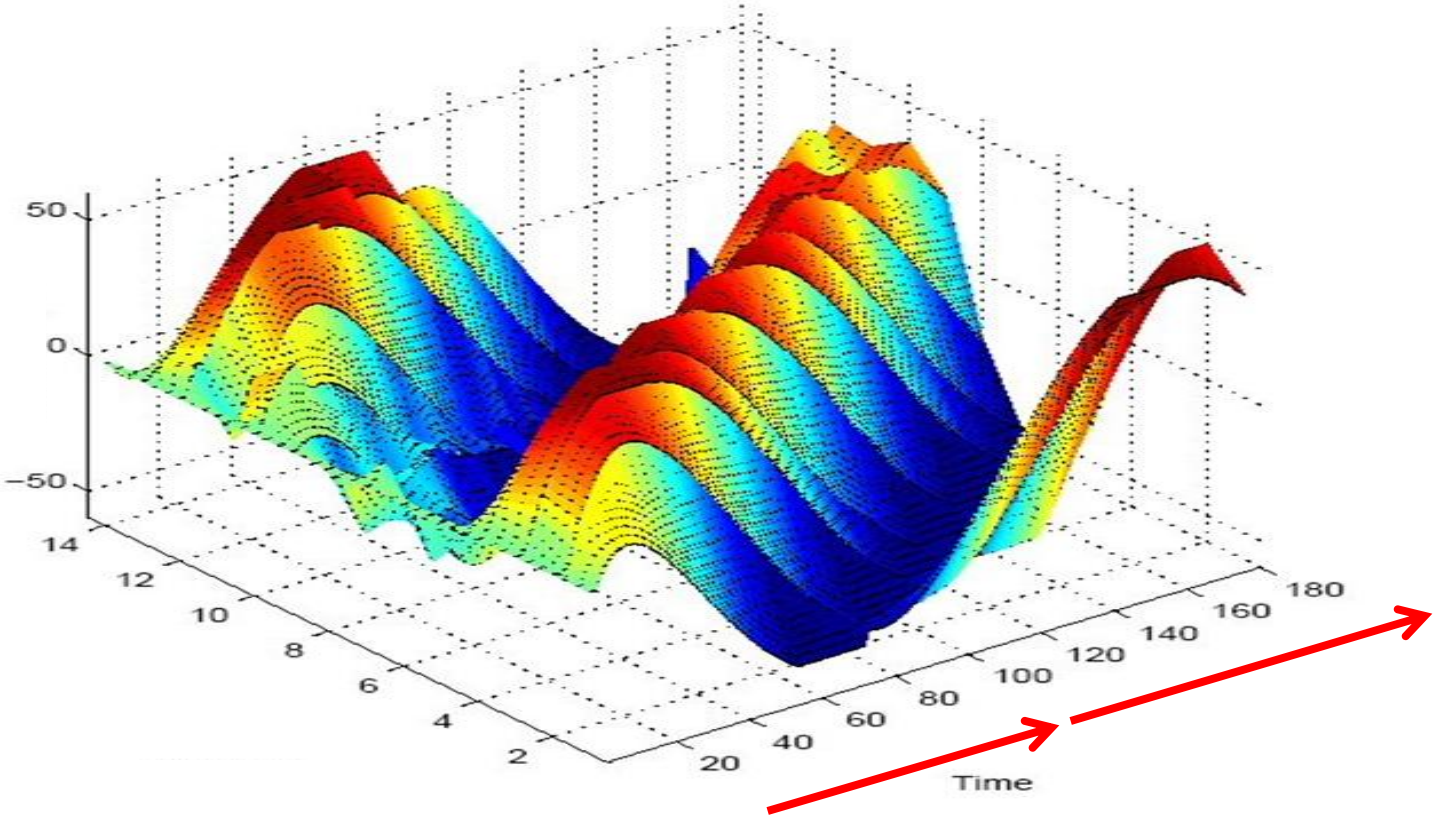
$$H(X) = -\sum_{x \in \mathcal{X}} P(x) \log P(x)$$

$$I(X;Y) = H(X) + H(Y) - H(X,Y) = H(Y) - H(Y|X)$$

Mutual information =

receiver’s diversity – equivocation of receiver about source

Pred



$$I_{pred}(T, T') = H(T') - H(T'|T)$$

predictive information = total uncertainty about the future −

uncertainty about the future, given the past

Case study: coordination in modular robots

Evolving Spatiotemporal Coordination in a Modular Robotic System

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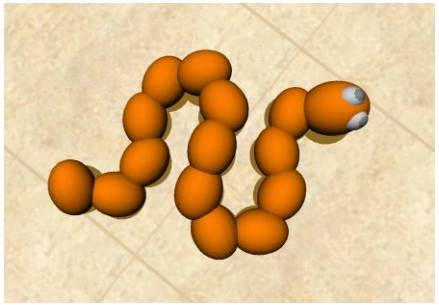
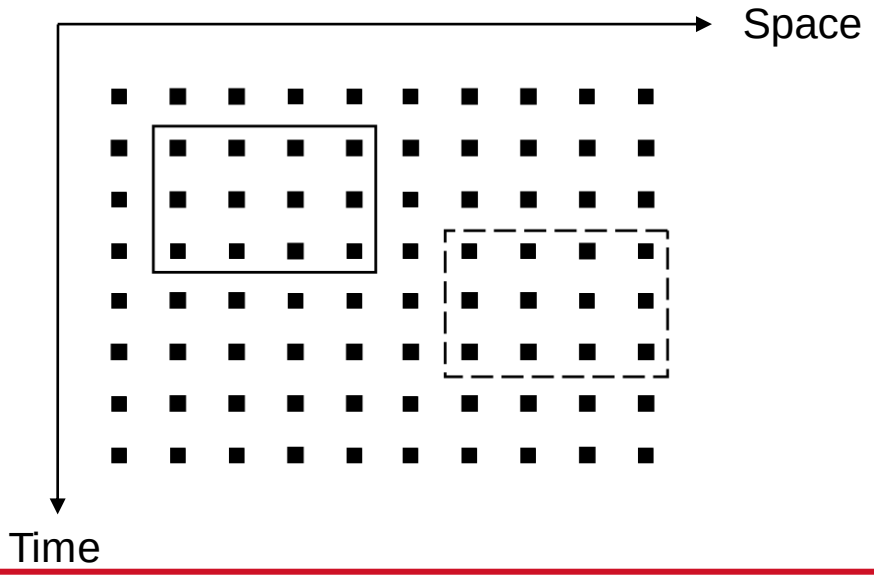
[2]Department of Information Systems Design, Doshisha University, 1-3 Miyakodani, Tatara, Kyotanabe, Kyoto 610-0321, Japan
mikhail.prokopenko@csiro.au

Abstract. In this paper we present a novel information-theoretic measure of spatiotemporal coordination in a modular robotic system, and use it as a fitness function in evolving the system. This approach exemplifies a new methodology formalizing co-evolution in multi-agent adaptive systems: information-driven evolutionary design. The methodology attempts to link together different aspects of information transfer involved in adaptive systems, and suggests to approximate direct task-specific fitness functions with intrinsic selection pressures. In particular, the information-theoretic measure of coordination employed in this work estimates the generalized correlation entropy K_2 and the generalized excess entropy E_2 computed over a multivariate time series of actuators' states. The simulated modular robotic system evolved according to the new measure exhibits regular locomotion and performs well in challenging terrains.



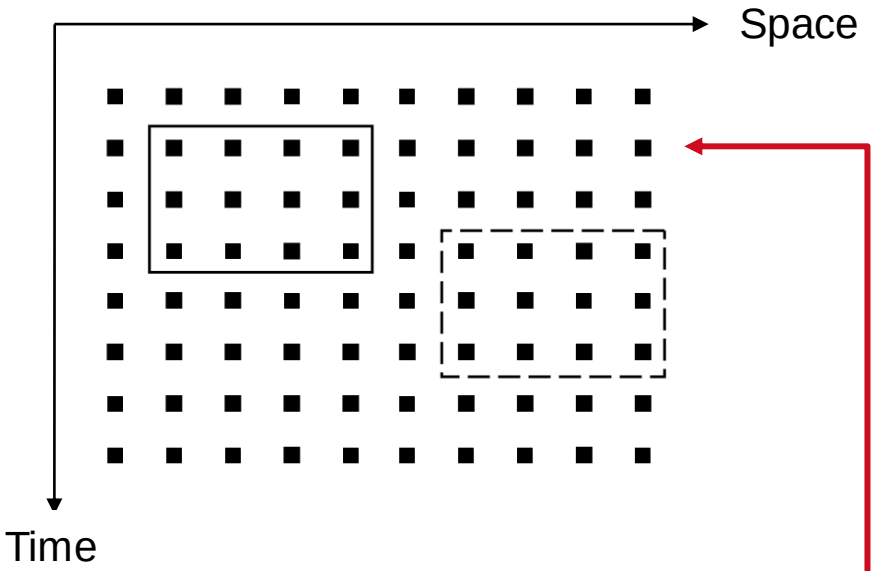
Richness / complexity of structure

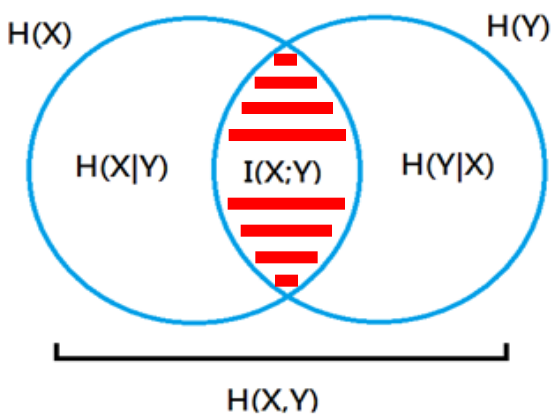
- Objective:
  - evolve snakebots for robust locomotion
- Conjecture:
  - robust locomotion needs coordinated actuators
- Technical questions:
  - how to estimate “irregularity” of multivariate time series in space & time?
  - how to quantify “structure” within the series?

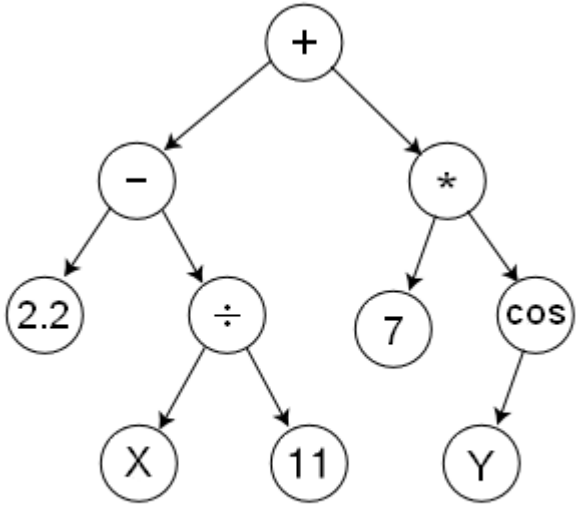


Maximising excess entropy

rich structure → high excess entropy = fitness function (*max*)







$$\left(2.2 - \left(\frac{X}{11}\right)\right) + \left(7 * \cos(Y)\right)$$

Results: actual angles

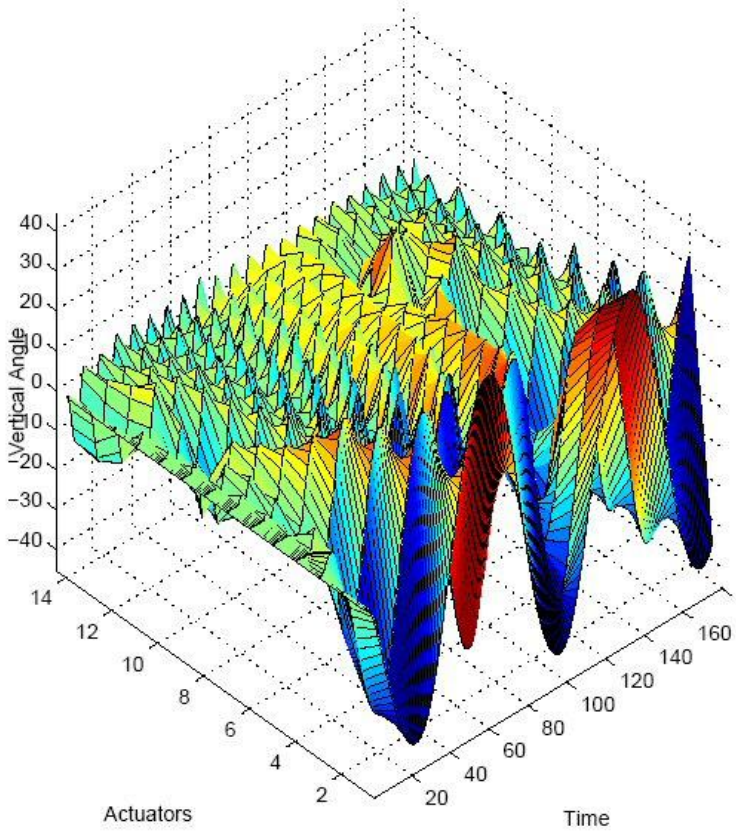


Fig. 3: First offspring: actuator angles.

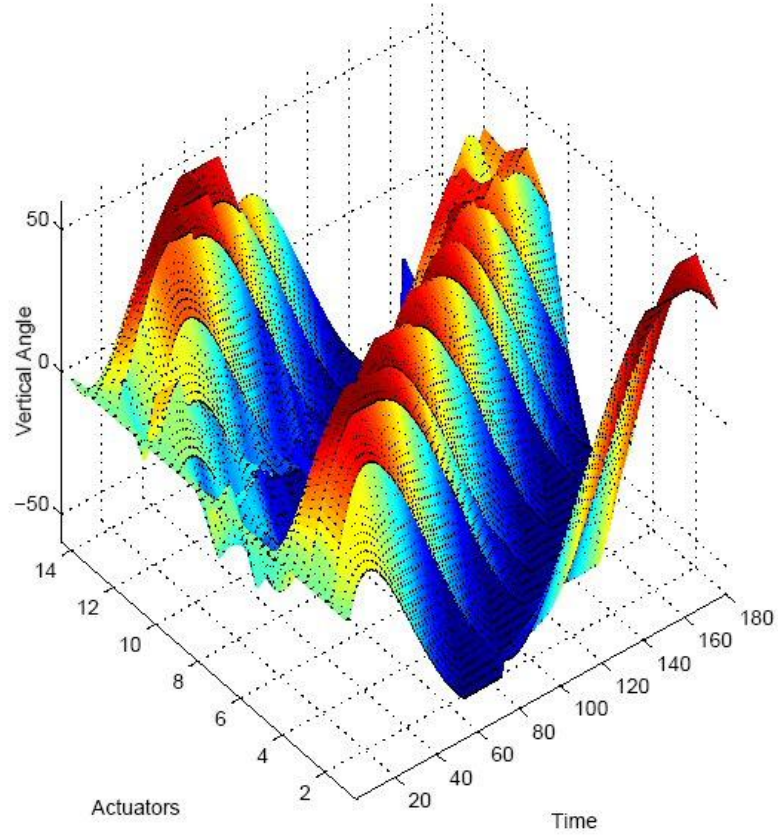
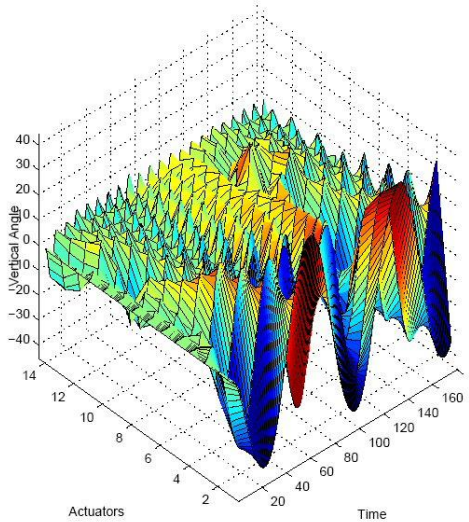


Fig. 4: Evolved solution: actuator angles.

Results: excess entropy (generalized)



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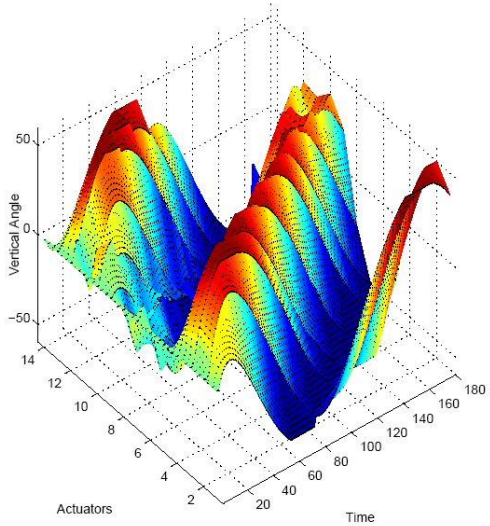

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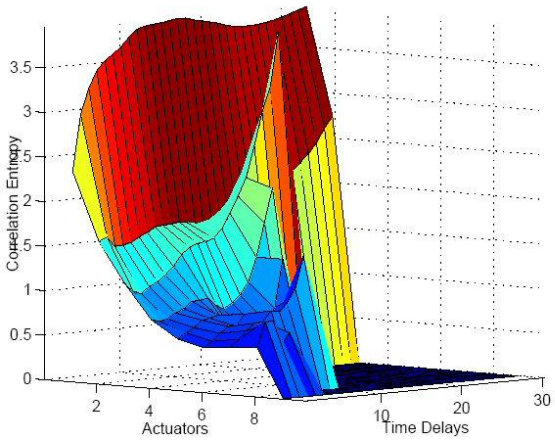


Fig. 5: First offspring: correlation entropy.

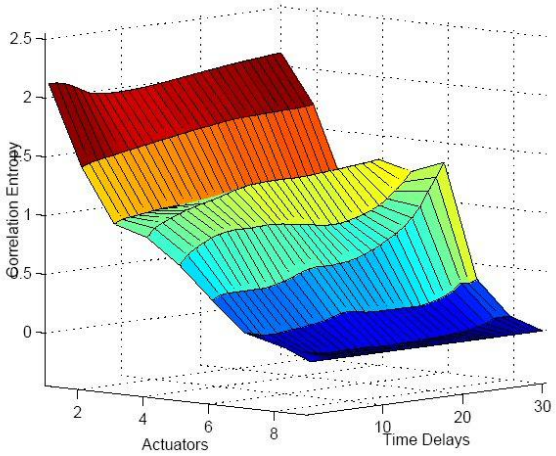
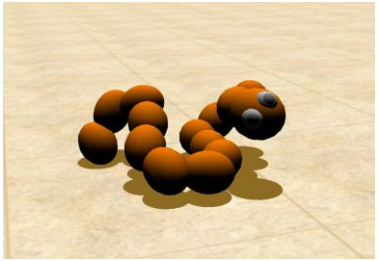
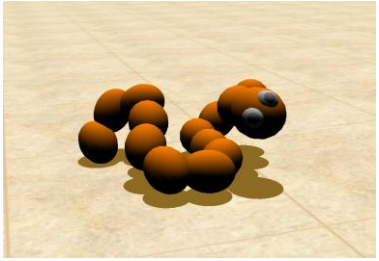


Fig. 6: Evolved solution: correlation entropy.





Complex networks (Sole & Valverde)

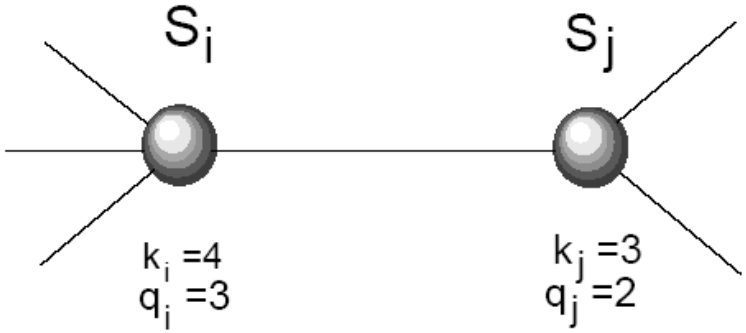


FIG. 4 Computing correlations in a network. Here two given, connected nodes s_i, s_j are shown, displaying different degrees k_i, k_j. Since we are interested in the remaining degrees, a different value needs to be considered (here indicated as q_i, q_j).

$$I(q) = H(q) - H(q|q')$$

Information "transfer" within the network =

diversity in the network – assortative noise in the network

Complex networks (Sole & Valverde)

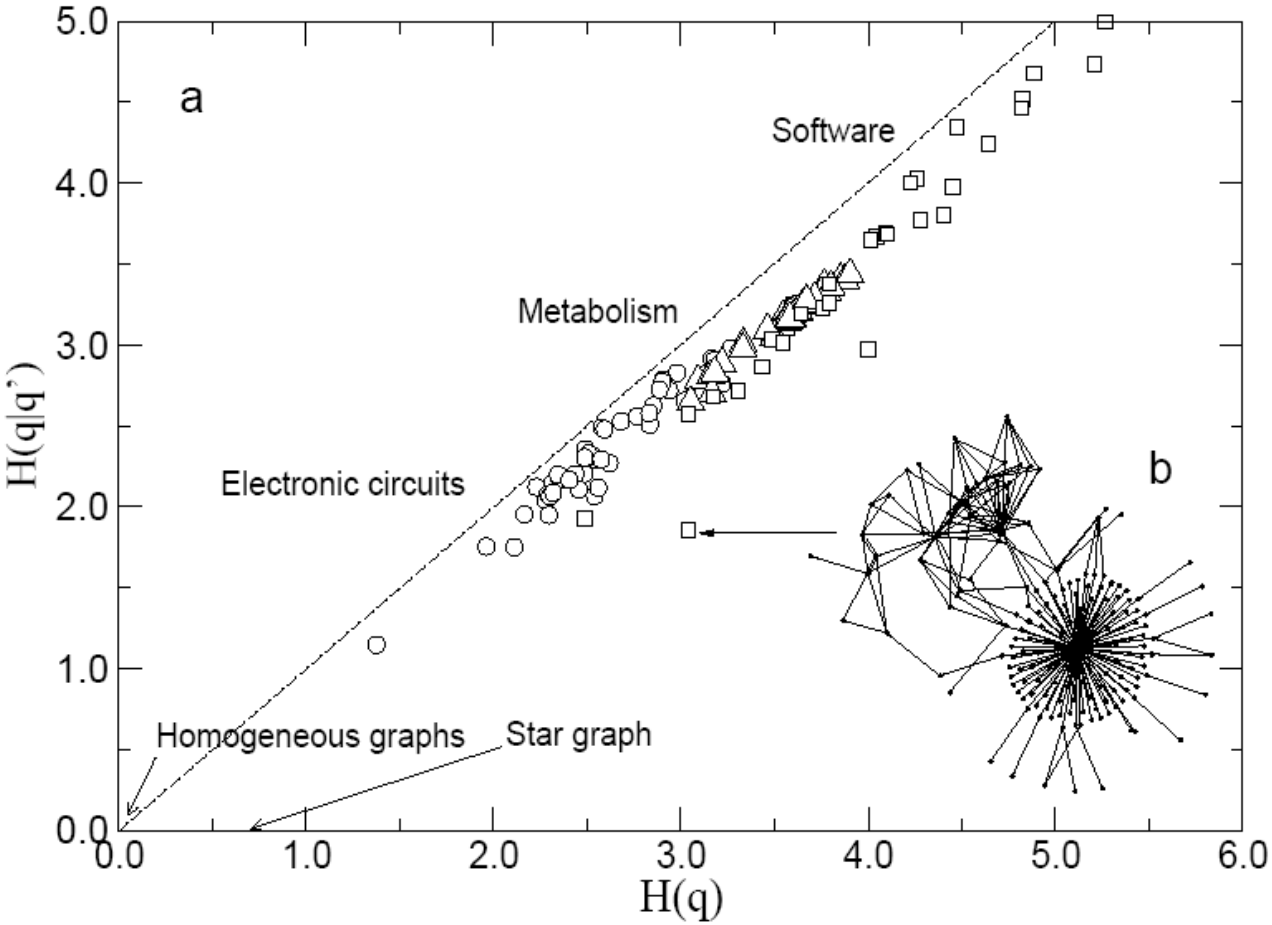


FIG. 8 Noise-entropy plot for different real networks, both natural and artificial. Here electronic circuits (open circles), metabolic (triangles) and software maps (squares) are shown to be close to the zero-information line, i. e. when entropy equals to noise. An example of a software graph that significantly deviates from the $H = H_c$. The network is small and has a rather particular shape, involving a large hub plus another cluster of connected classes.

Information content in directed networks

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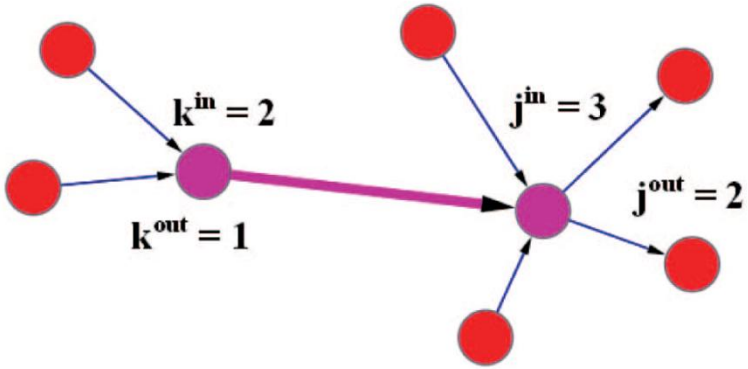
Assortative Mixing in Directed Biological Networks

Mahendra Piraveenan, Mikhail Prokopenko, and Albert Zomaya

Abstract—We analyze assortative mixing patterns of biological networks which are typically directed. We develop a theoretical background for analyzing mixing patterns in directed networks before applying them to specific biological networks. Two new quantities are introduced, namely the in-assortativity and the out-assortativity, which are shown to be useful in quantifying assortative mixing in directed networks. We also introduce the local (node level) assortativity quantities for in- and out-assortativity. Local assortativity profiles are the distributions of these local quantities over node degrees and can be used to analyze both canonical and real-world directed biological networks. Many biological networks, which have been previously classified as disassortative, are shown to be assortative with respect to these new measures. Finally, we demonstrate the use of local assortativity profiles in analyzing the functionalities of particular nodes and groups of nodes in real-world biological networks.



Information content in directed networks

Network	Size N	r		r_d		r_{out}		r_{in}	
			$I(r)$		$I(r_d)$		$I(r_{out})$		$I(r_{in})$
Neural networks									
C. elegans	297	-0.15	0.42	-0.23	0.46	0.1	1.01	-0.09	0.35
GRNs									
rat (R. norvegicus)	819	0.86	1.65	0.31	0.95	0.64	2.24	0.59	0.75
human (H. sapiens)	1452	-0.03	1.08	-0.03	0.61	0.2	1.41	-0.01	0.48
mouse (M. musculus)	981	0.66	1.92	0.2	0.75	0.53	1.98	0.49	0.62
C. elegans	581	-0.09	0.94	-0.12	0.68	0.36	1.06	0.01	0.38
A. thaliana	395	-0.04	1.07	-0.12	0.61	0.16	1.31	0.03	0.52
Transcription nets									
E. coli	1147	-0.26	0.96	0.06	0.36	0.17	1.26	0.03	0.11
C. glucamitum	539	-0.37	0.84	-0.04	0.31	0.09	0.22	-0.01	0.13
C. jeikeium	52	-1	1	undefined	0	-1	0	-1	0
C. efficiens	50	-0.64	0.86	undefined	0	-1	0	-1	0

"Regulators" **"Regulatees"**

Information content in directed networks

Cortical networks									
human	994	0.17	0.19	0.13	0.19	0.17	0.19	0.17	0.19
Macaque monkey	71	0.02	0.97	-0.01	0.41	0.06	0.4	-0.01	0.39
Macaque sensory motor cortex	47	0.01	0.68	-0.02	0.4	0.03	0.45	-0.02	0.5
Cat cortex	65	0.01	0.52	-0.05	0.32	-0.03	0.37	0.09	0.4
Foodwebs									
Chesapeake Lower	170	-0.39	0.64	-0.45	0.57	0.21	0.7	-0.06	0.49
Chesapeake Upper	193	-0.33	0.38	-0.38	0.58	0.1	1.61	-0.12	0.49
Chrystal river c	106	-0.33	0.49	-0.48	0.63	0.08	1.38	-0.14	0.47
Chrystal river d	90	-0.46	0.45	-0.54	0.65	0.06	1.18	-0.18	0.34
Bay wet	2216	-0.12	0.39	-0.23	0.71	0.02	2.71	0.24	0.7
Bay dry	2248	-0.11	0.39	-0.23	0.75	0.03	2.78	0.25	0.74

“Regulators” **“Regulatees”**

Adaptation and evolution (Adami)

Adaptation = increase in the mutual information between the system and the environment.

"Evolution increases the amount of information a population harbors about its niche" (Adami)

$$I(X,Z) = H_{max} - H(X|Z) \tag{15}$$

where H_{max} is the entropy in the absence of selection, i.e. the unconditional entropy of a population of sequences, and $H(X|Z)$ is the conditional entropy of X given Z, i.e. the diversity tolerated by selection in the given environment. When selection does not act, no sequence has an advantage over any other, and all sequences are equally probable in ensemble X. Hence, H_{max} is equal to the sequence length.

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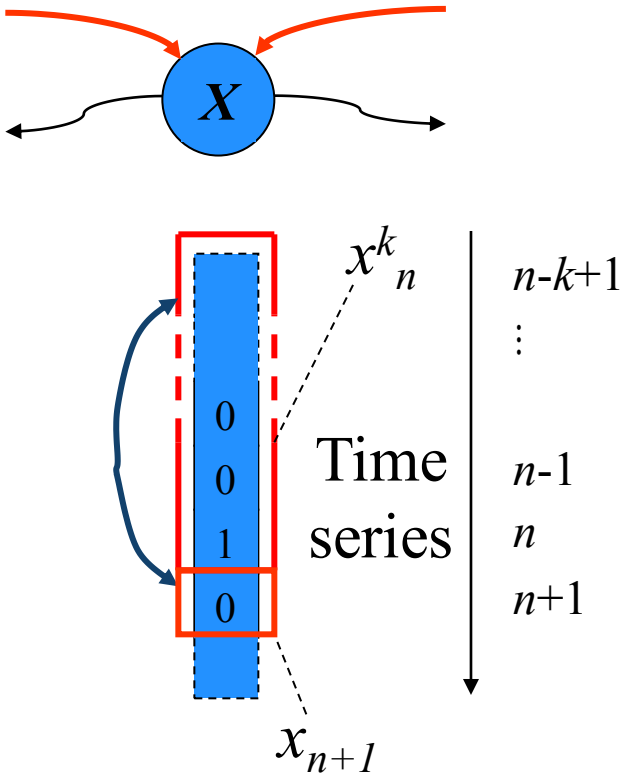
physical complexity = how much data can be stored –
how much data irrelevant to environment is stored

Mutual information = diversity – equivocation (assortative noise, conflicts)

The magic formula

Structure = diversity – assortative noise

Active Information Storage (AIS): “memory”

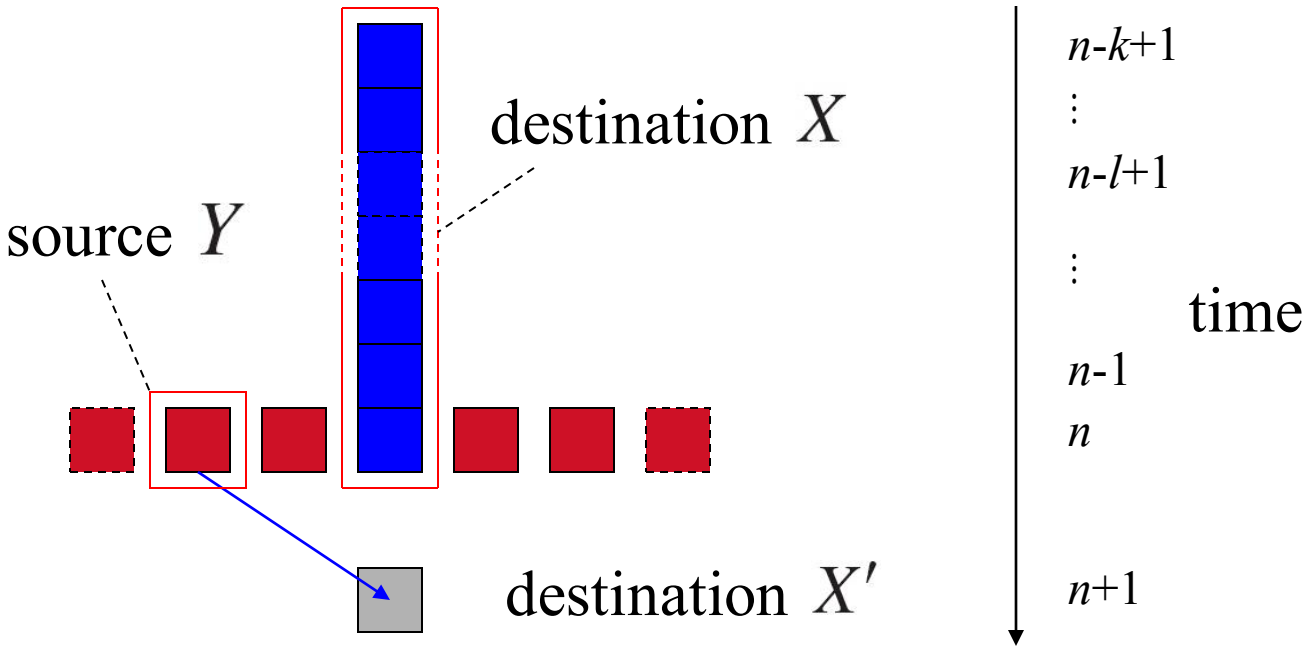


- Information storage: info in past of an agent relevant to predicting its future
- Active info storage = mutual info between past and next step:

$$A_X(k) = I(X^{(k)}; X')$$

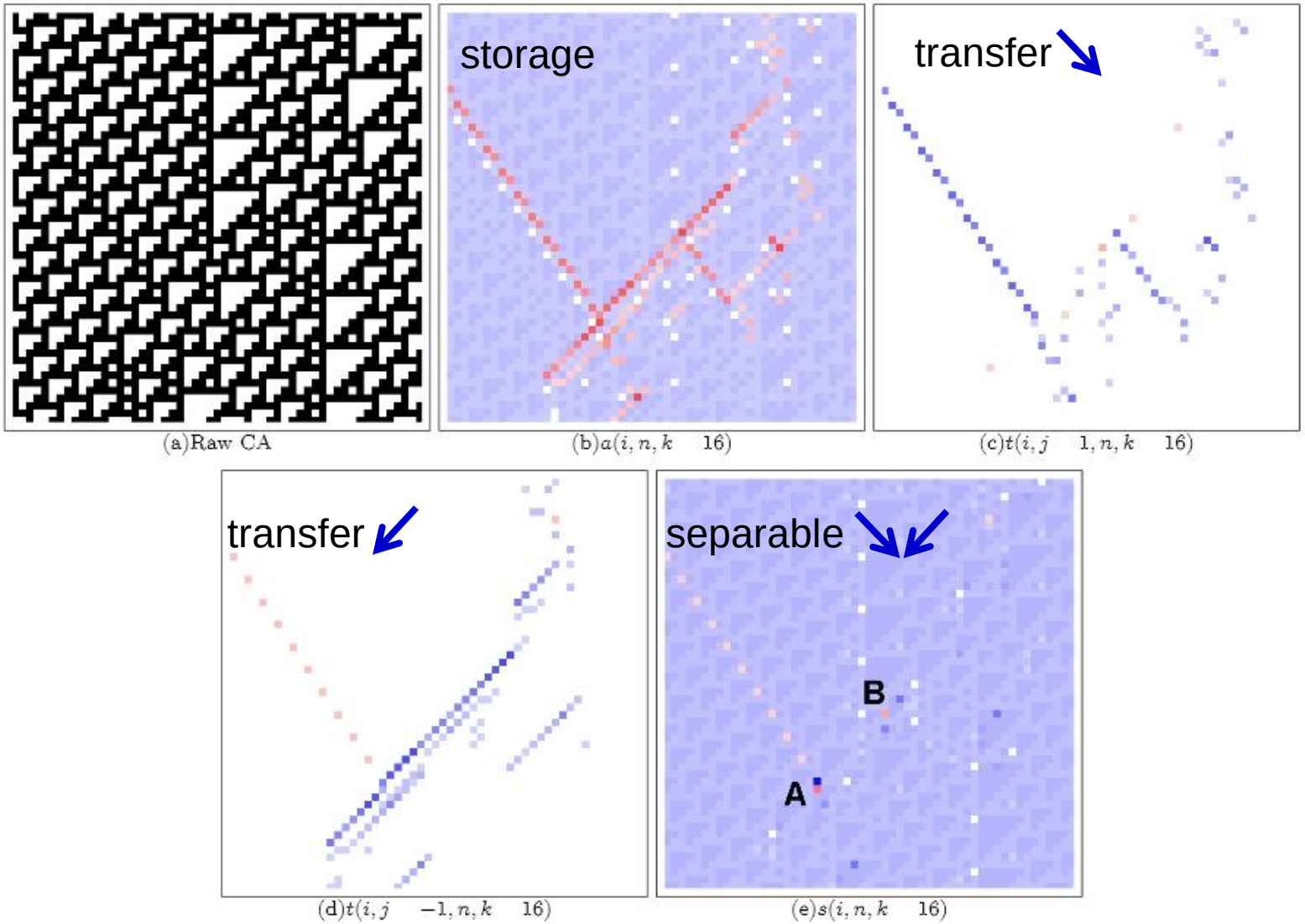
Transfer Entropy (TE): “communications”

$$T_{Y\to X'} = I(Y;X'|X) = H(X'|X) - H(X'|X,Y)$$



$$T_{Y\to X} = \frac{1}{N}\sum_{n=1}^{N} \log_2 \frac{p(x_{n+1}|x_n^{(k)}, y_n^{(l)})}{p(x_{n+1}|x_n^{(k)})}$$

Information Dynamics of Cellular Automata



(a)Raw CA (b)$a(i, n, k \quad 16)$ (c)$t(i, j \quad 1, n, k \quad 16)$

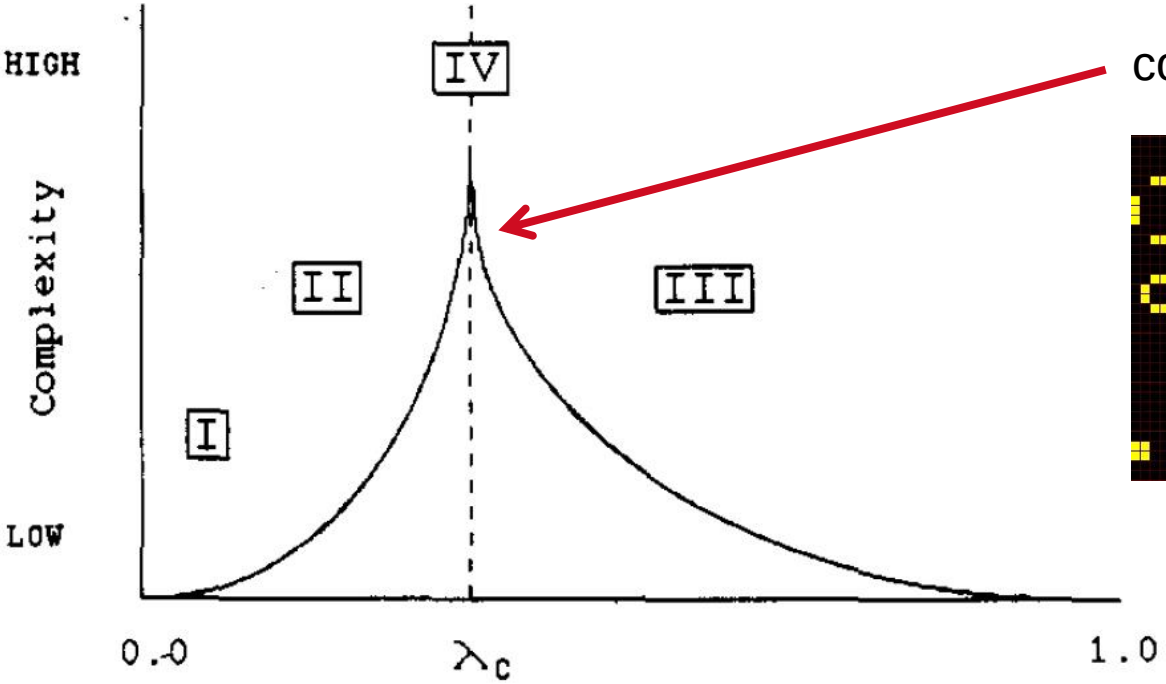
(d)$t(i, j \quad -1, n, k \quad 16)$ (e)$s(i, n, k \quad 16)$

Java Information Dynamics Toolkit (Joseph Lizier): http://code.google.com/p/information-dynamics-toolkit/

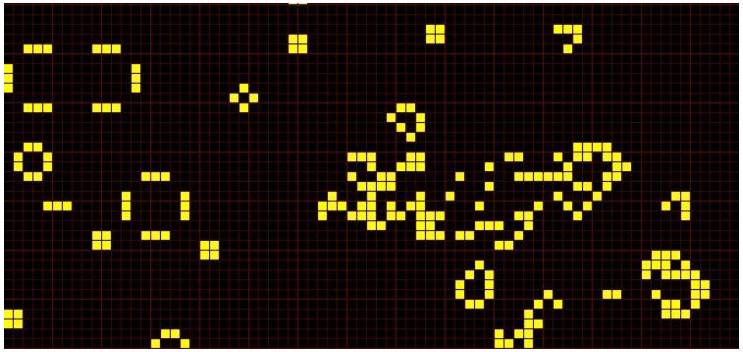
Revisiting our motivating questions…

Chris Langton, "Computation at the edge of chaos: Phase transitions and emergent computation" (1990):

- how can emergence of computation be explained in a dynamic setting?
- how is it related to complexity of the system in point?

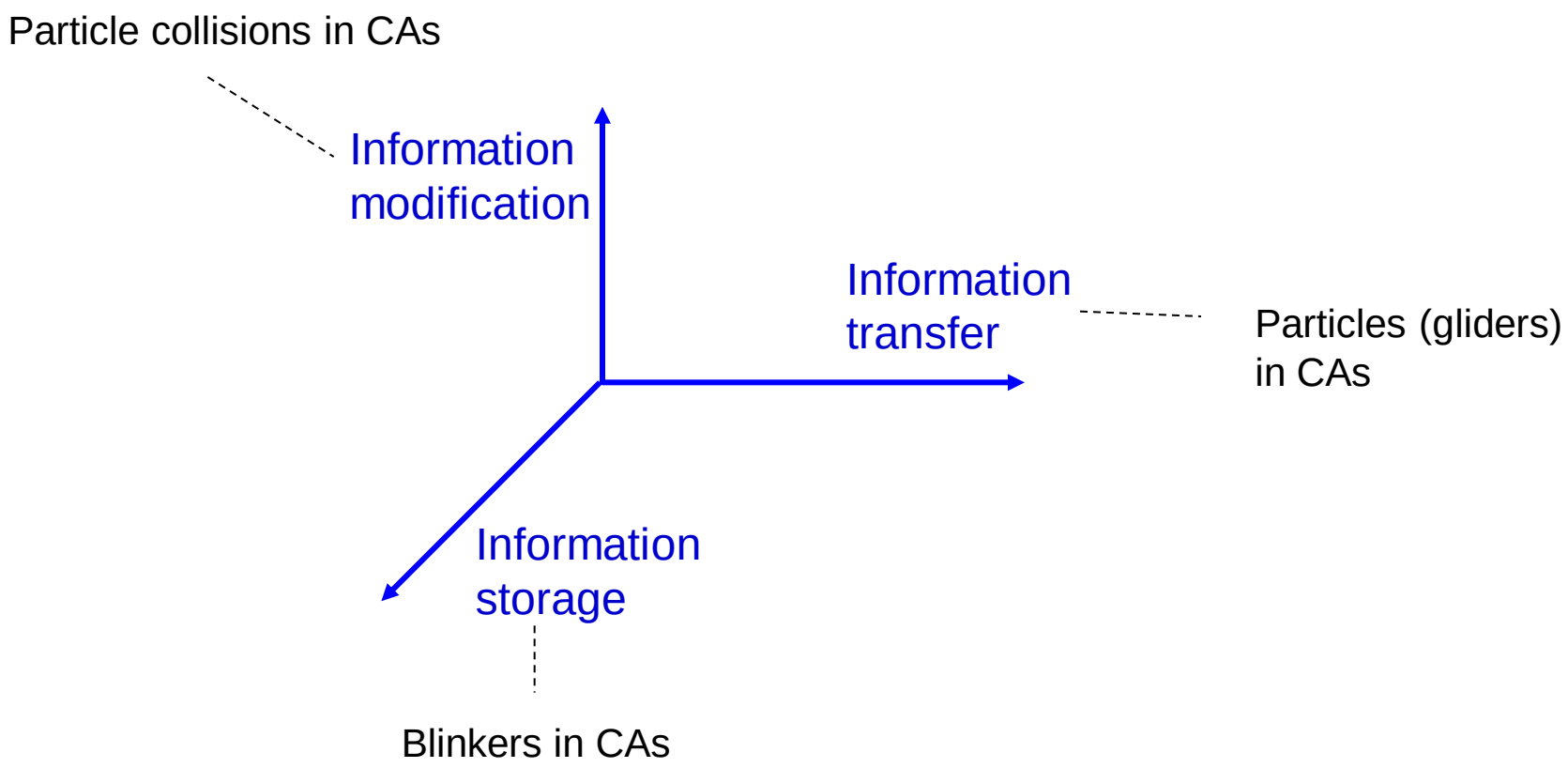


complex high-level structures



Information dynamics: axis of complexity

Information dynamics of distributed computation in terms of 3 components of Turing universal computation:



Local Information Dynamics

PHYSICAL REVIEW E **77**, 026110 (2008)

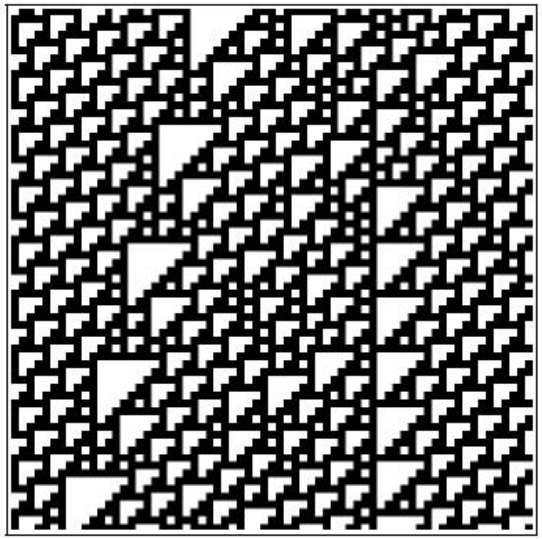
Local information transfer as a spatiotemporal filter for complex systems

Joseph T. Lizier,[1,2,*] Mikhail Prokopenko,[1] and Albert Y. Zomaya[2]
[1]*CSIRO Information and Communications Technology Centre, Locked Bag 17, North Ryde, NSW 1670, Australia*
[2]*School of Information Technologies, The University of Sydney, NSW 2006, Australia*
(Received 17 January 2007; revised manuscript received 15 August 2007; published 15 February 2008)

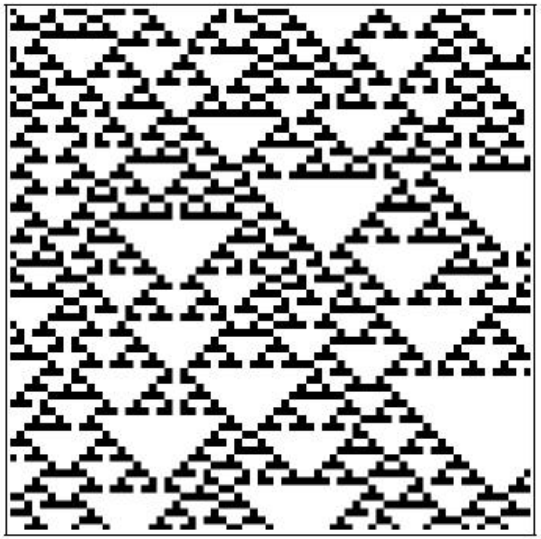
We present a measure of local information transfer, derived from an existing averaged information-theoretical measure, namely, transfer entropy. Local transfer entropy is used to produce profiles of the information transfer into each spatiotemporal point in a complex system. These spatiotemporal profiles are useful not only as an analytical tool, but also allow explicit investigation of different parameter settings and forms of the transfer entropy metric itself. As an example, local transfer entropy is applied to cellular automata, where it is demonstrated to be a useful method of filtering for coherent structure. More importantly, local transfer entropy provides the first quantitative evidence for the long-held conjecture that the emergent traveling coherent structures known as particles (both gliders and domain walls, which have analogs in many physical processes) are the dominant information transfer agents in cellular automata.

DOI: 10.1103/PhysRevE.77.026110 PACS number(s): 89.75.Fb, 89.75.Kd, 89.70.Cf, 05.65.+b

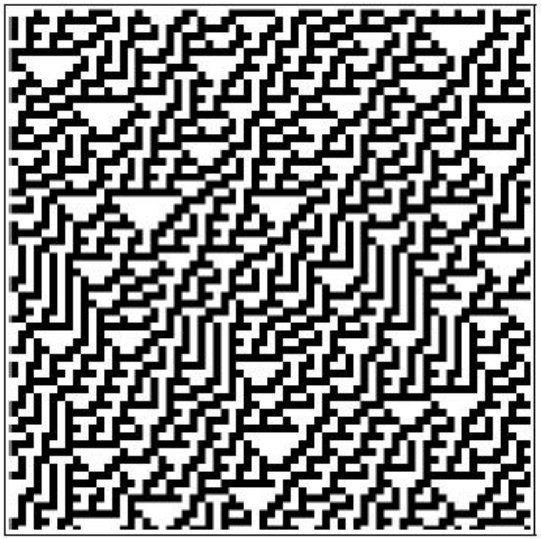
Coherent computation: can it be used for GSO?



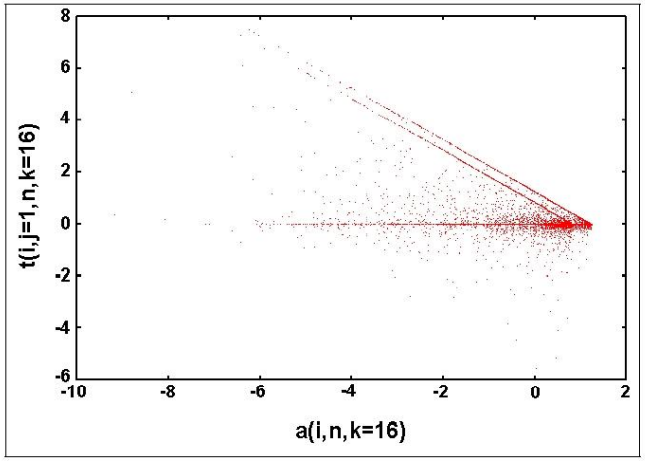
(a) 110: raw states



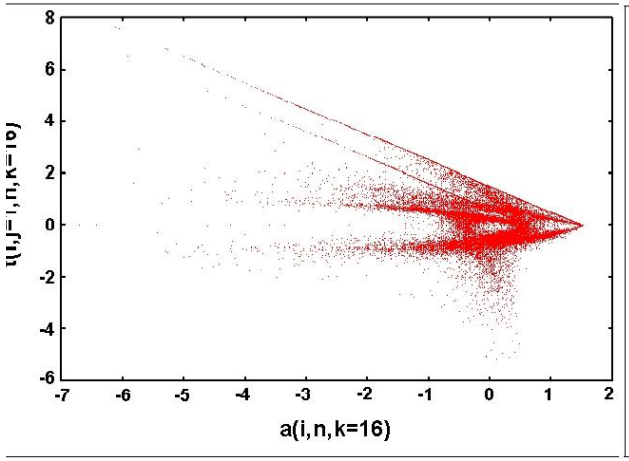
(b) 22: raw states



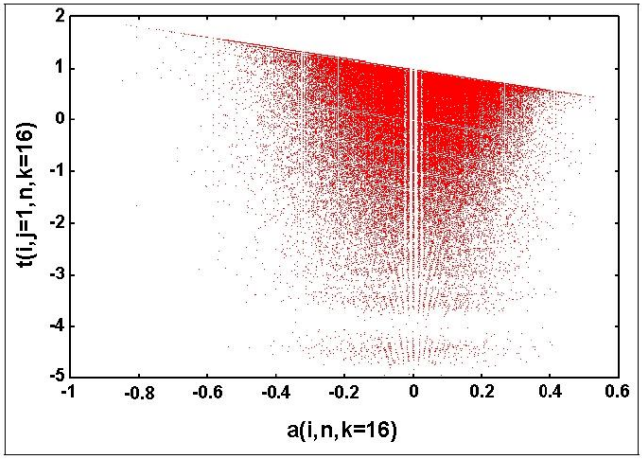
(c) 30: raw states



(a) rule 110: $t(i, j = 1, n, k = 16)$ vs $a(i, n, k = 16)$



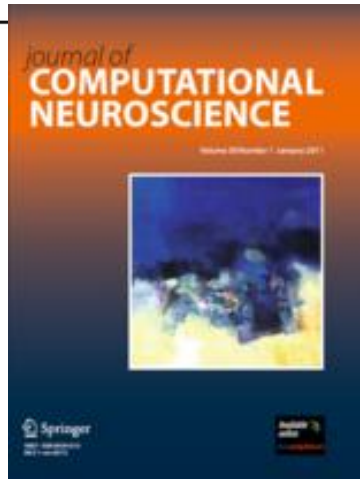
(c) rule 22: $t(i, j = 1, n, k = 16)$ vs $a(i, n, k = 16)$



(b) rule 30: $t(i, j = 1, n, k = 16)$ vs $a(i, n, k = 16)$

Case study: computational neuroscience

J Comput Neurosci (2011) 30:85–107
DOI 10.1007/s10827-010-0271-2



Multivariate information-theoretic measures reveal directed information structure and task relevant changes in fMRI connectivity

Joseph T. Lizier · Jakob Heinzle · Annette Horstmann · John-Dylan Haynes · Mikhail Prokopenko

Received: 2 January 2010 / Revised: 17 June 2010 / Accepted: 12 August 2010 / Published online: 27 August 2010
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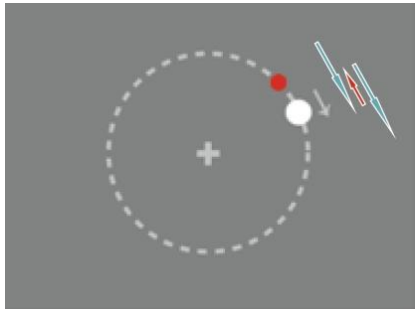
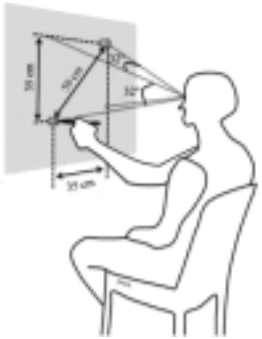
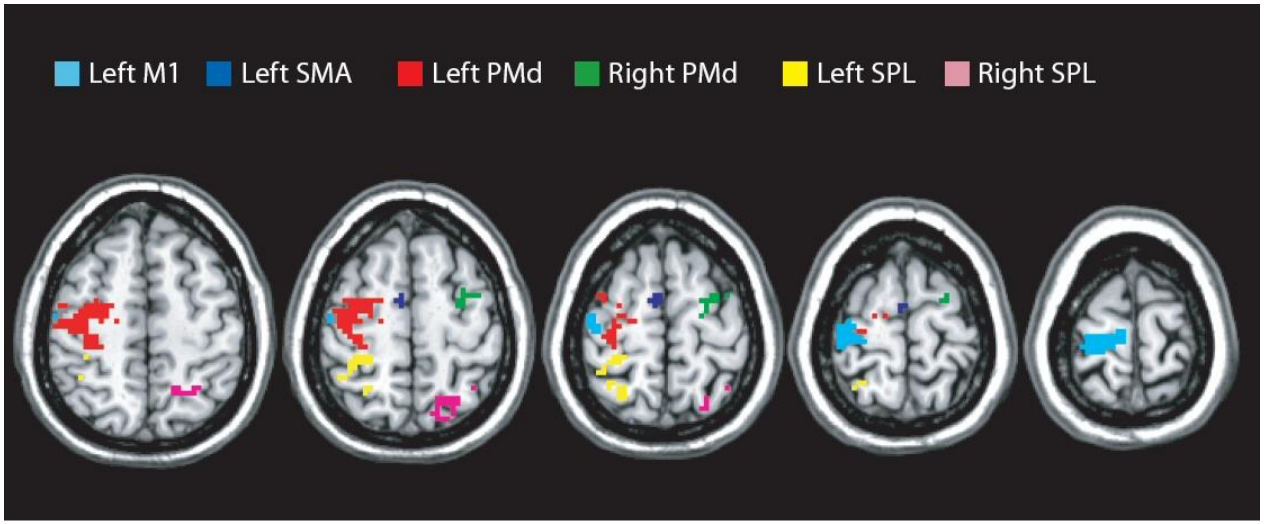
Abstract The human brain undertakes highly sophisticated information processing facilitated by the interaction between its sub-regions. We present a novel method for interregional connectivity analysis, using multivariate extensions to the mutual information and transfer entropy. The method allows us to identify the underlying directed information structure between brain regions, and how that structure changes according to behavioral conditions. This method is distinguished in using asymmetric, multivariate, information-theoretical analysis, which captures not only directional and non-linear relationships, but also collective interactions. Importantly, the method is able to estimate multivariate information measures with only relatively little data. We demonstrate the method to analyze functional magnetic resonance imaging time series to establish the directed information structure between brain regions involved in a visuo-motor tracking task.

Computational neuroscience: visuo-motor task







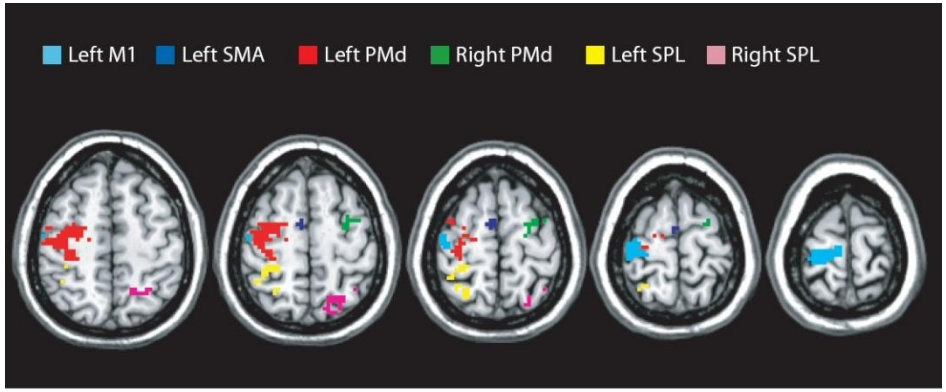
- *extremely complex pathways*
- *limited data resolution*
- *very sparse data*
- *multiple (concurrent) information flows*
- *experimental constraints*

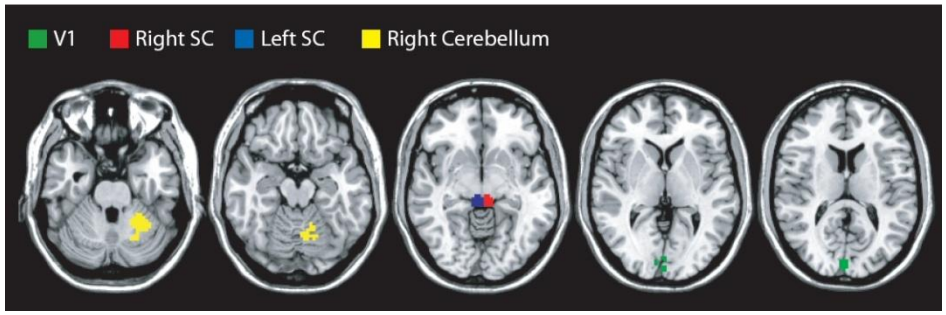
Experiment (BCCN, Berlin, Germany)

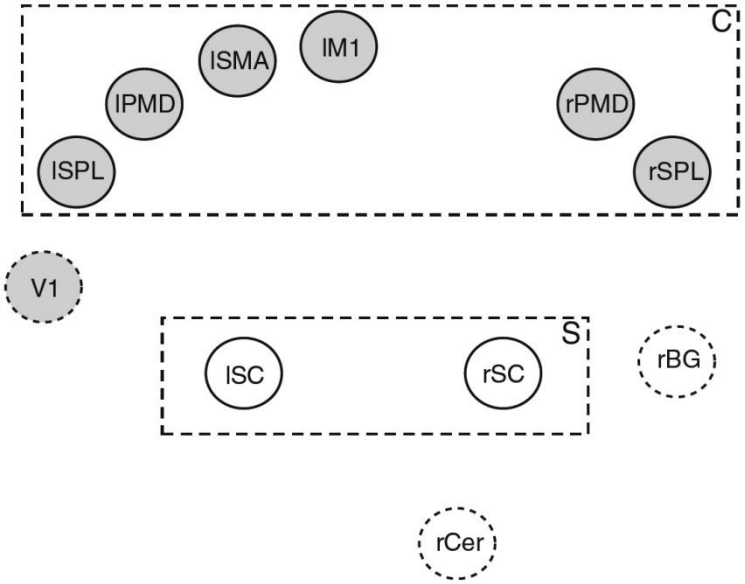
- Cognitive task: visuo-motor tracking
  - control a mouse with right hand to track a moving target on a computer screen
  - 4 levels of difficulty
  - 8 subjects
  - functional Magnetic Resonance Imaging (fMRI) measurements
  - brain activity in 16 localized regions
  - resolution: typically, hundreds of voxels in each regions

- Research aim: information flow
  - underlying *directed* interaction structure between region pairs
  - changes in the structure as a function of the tracking difficulty

Objectives



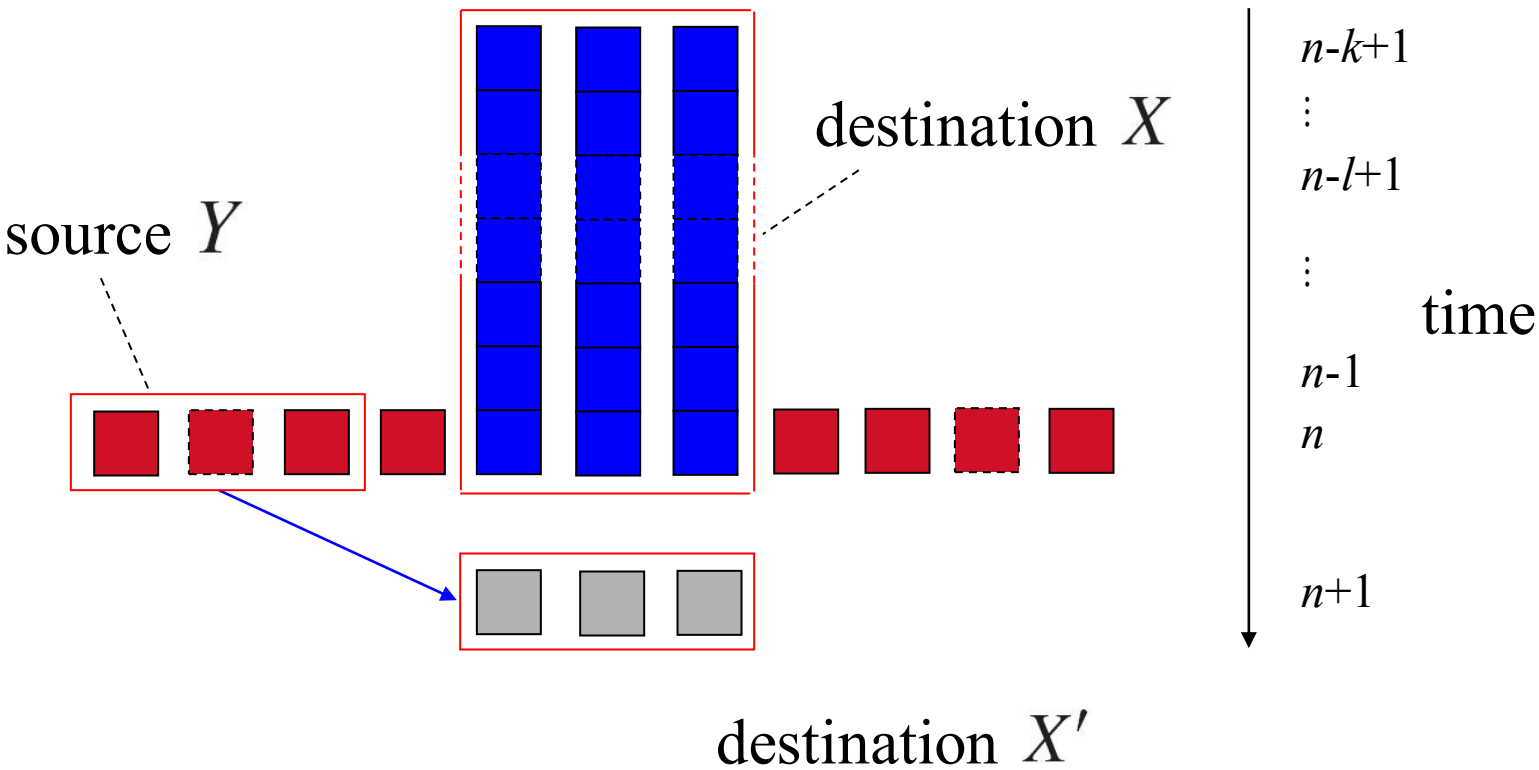




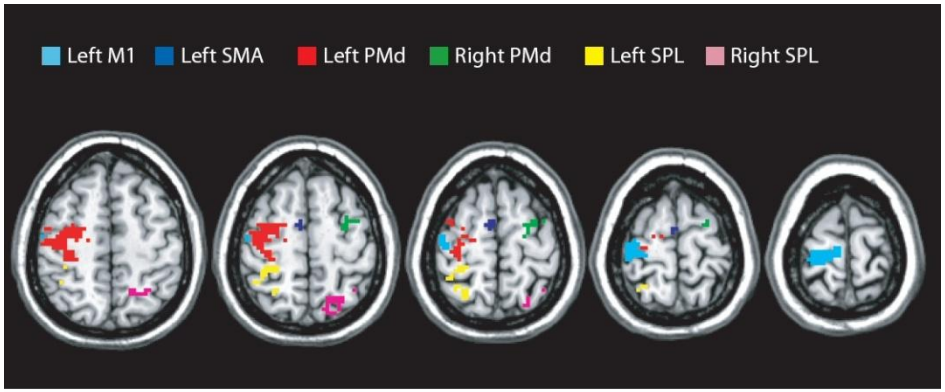
- *How to build a network?*
- *What is the information flow?*

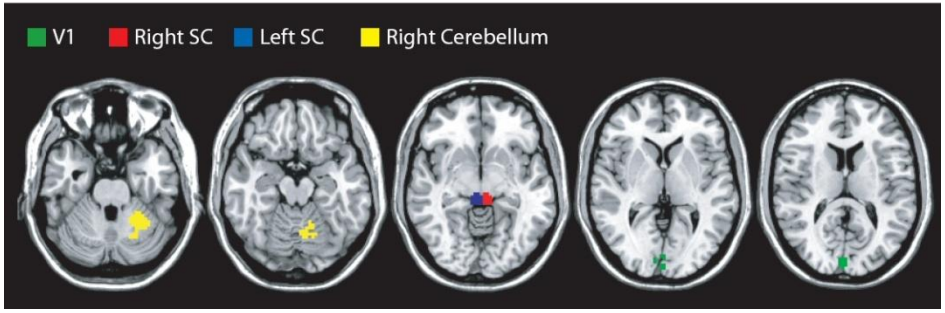
Multivariate Information Transfer

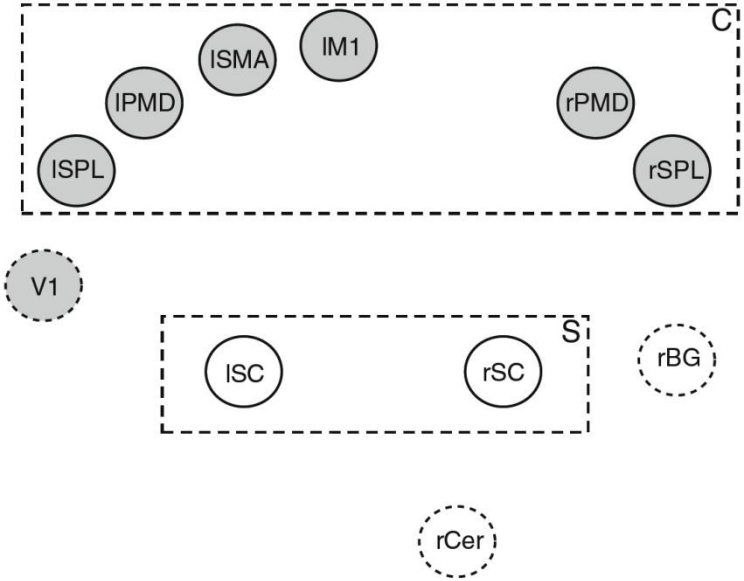
$$T_{Y \to X'} = I(Y;X'|X) = H(X'|X) - H(X'|X,Y)$$



Approach



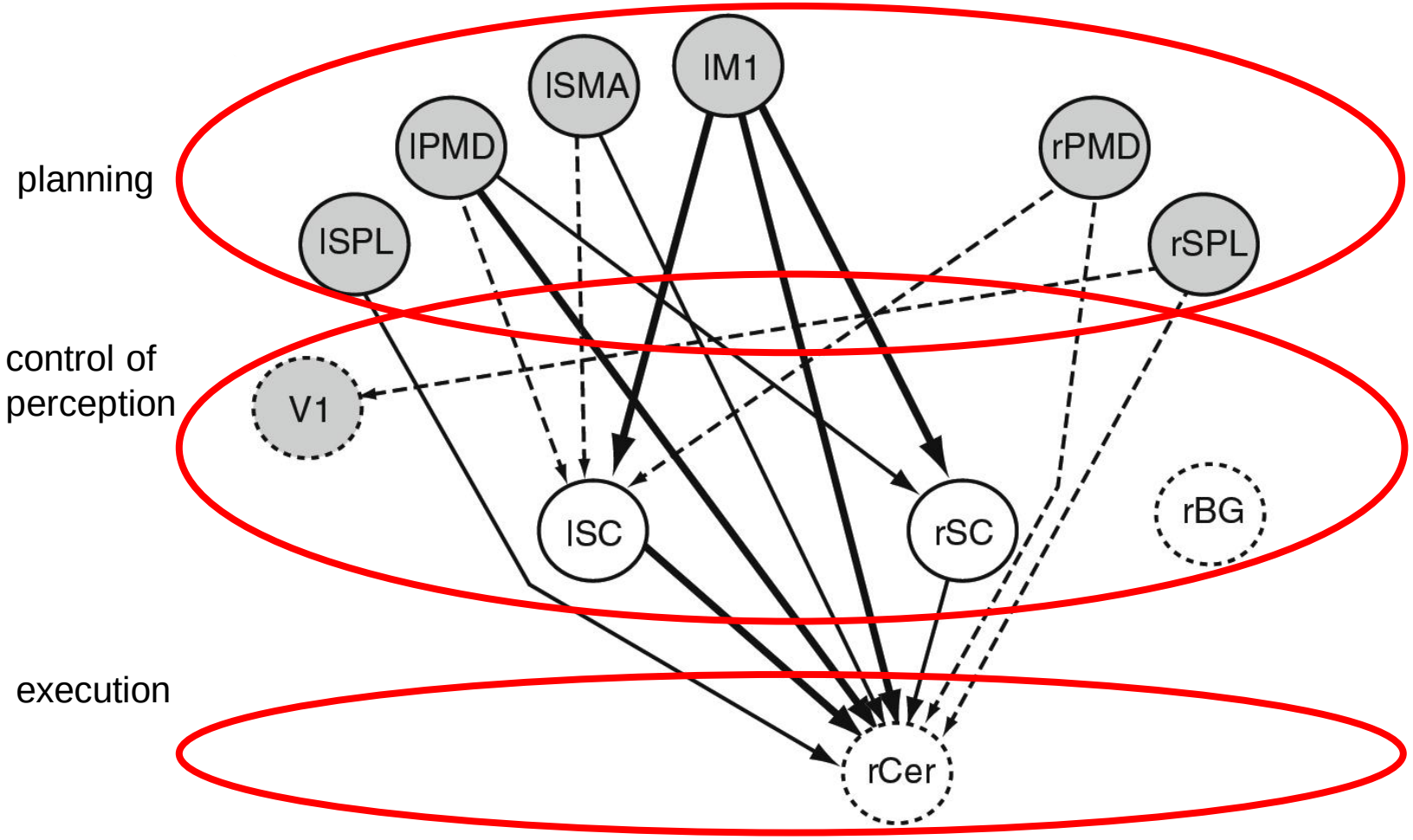




- *How to build a network?*
- *What is the information flow?*

→ *add links if information transfer is significant*

Directed information structure



Statistical significance of the information transfer against the null hypothesis of having no temporal relationship within a region pair

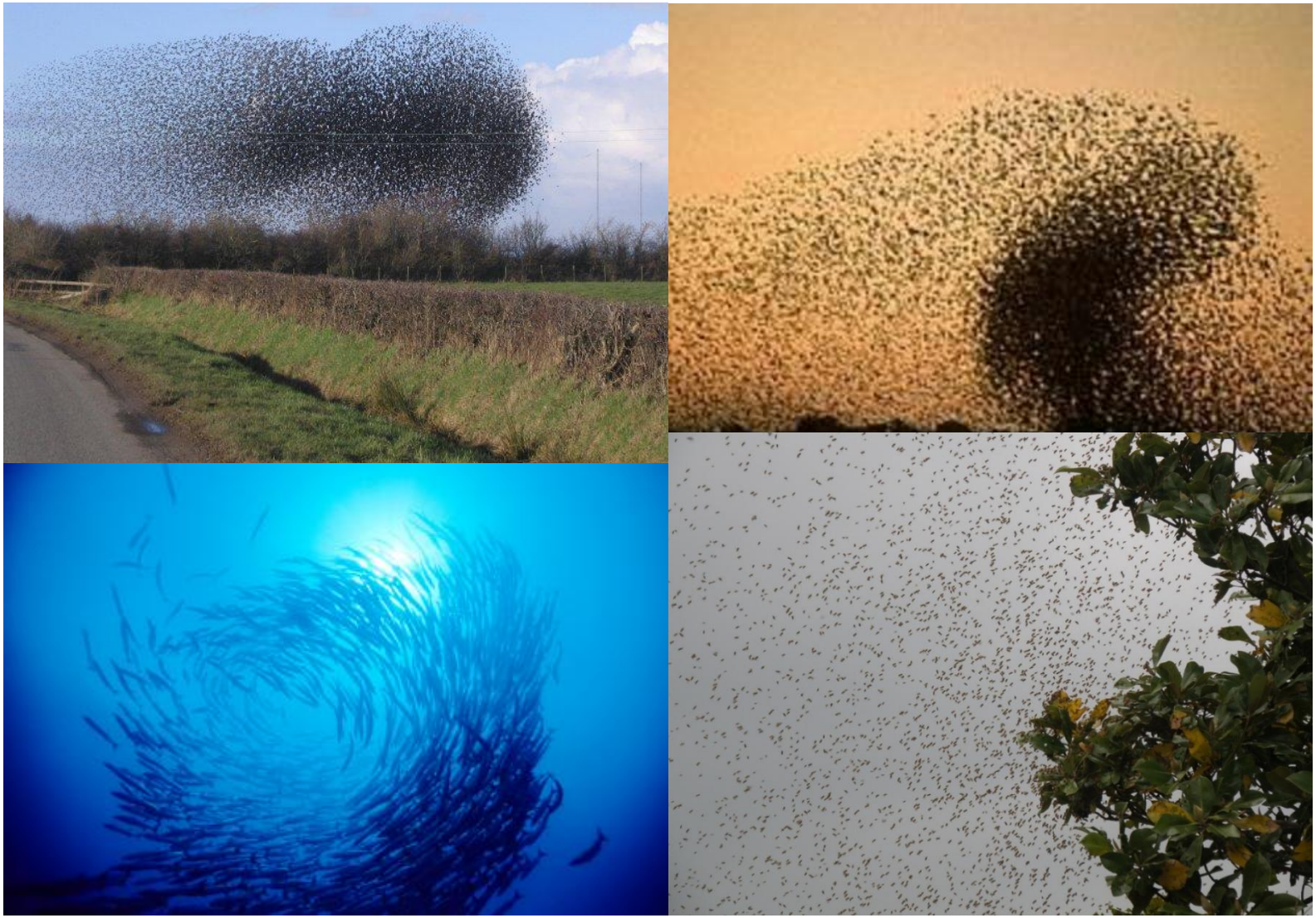
Thickness of lines indicates the number of subjects which had a statistically significant connection

Visuo-motor task: results

- 3-tier inter-regional structure
  - movement planning
  - sensor (visual) processing and control of eye movement
  - motor (movement) execution

- as task becomes more difficult, there is an increased coupling between regions involved in
  - (a) <u>movement planning</u> (left SMA and left PMd) and
  - (b) <u>execution</u>:
    - right cerebellum for hand movements
    - right SC for eye movement

Motivating example: information cascades in swarms



Information cascades in swarms

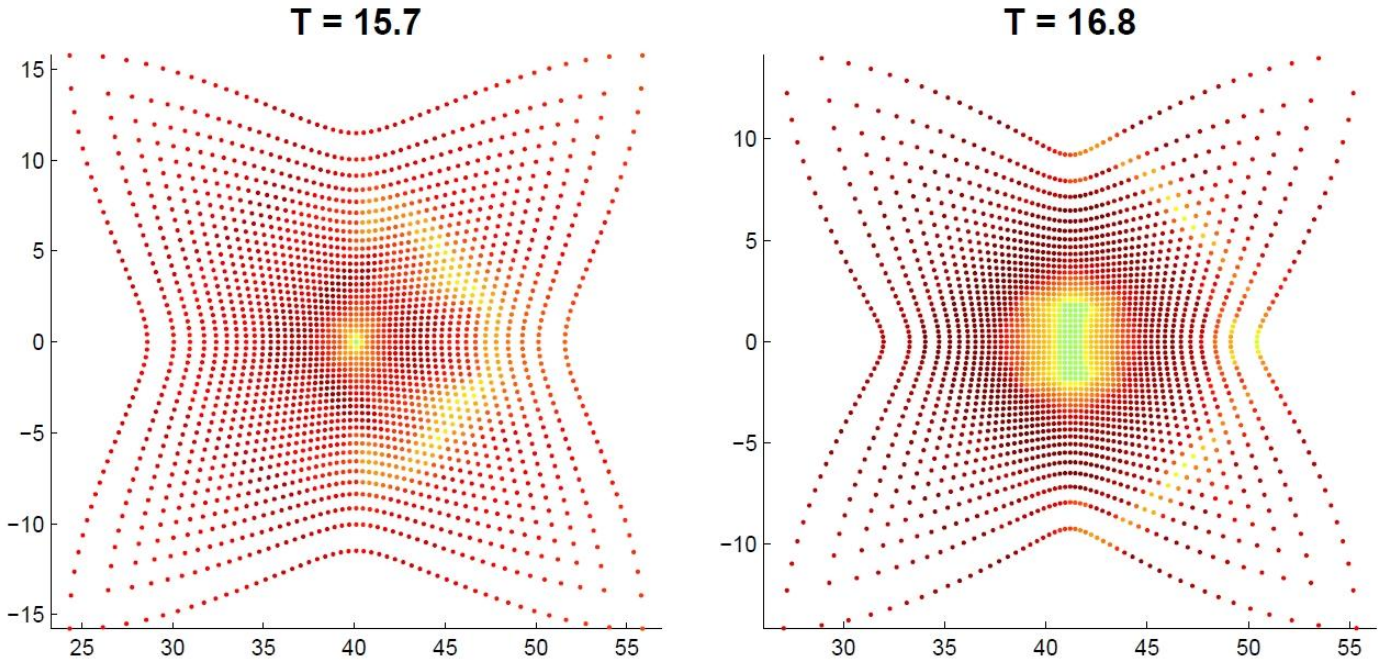
OPEN ACCESS Freely available online

PLoS one

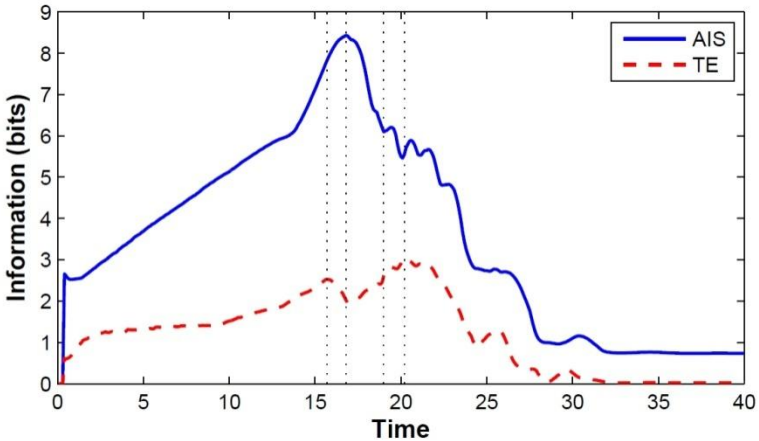
Quantifying and Tracing Information Cascades in Swarms

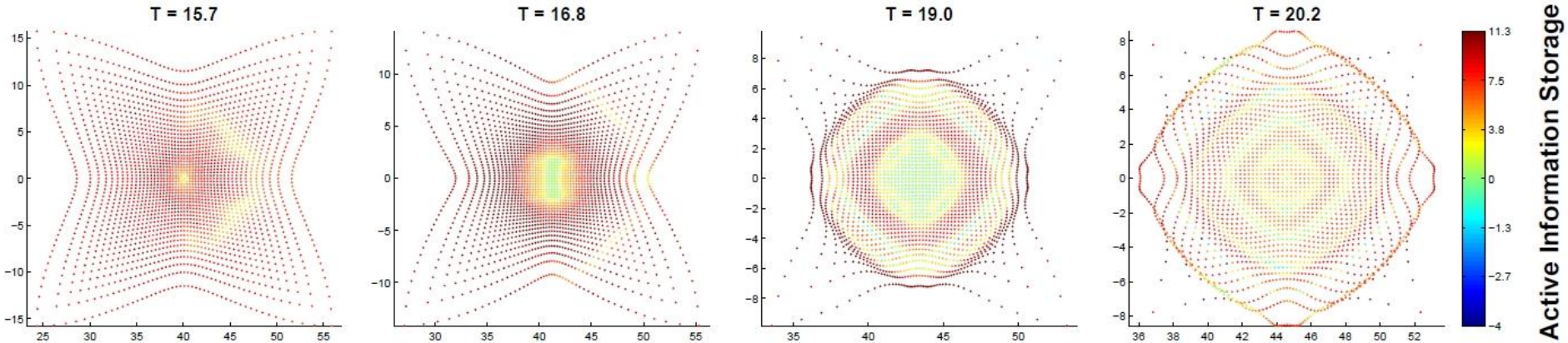
X. Rosalind Wang[1]*, Jennifer M. Miller[2], Joseph T. Lizier[1,3], Mikhail Prokopenko[1], Louis F. Rossi[2]

1 CSIRO Information and Communication Technologies Centre, Marsfield, New South Wales, Australia, **2** Department of Mathematical Sciences, University of Delaware, Newark, Delaware, United States of America, **3** Max Planck Institute for Mathematics in the Sciences, Leipzig, Germany

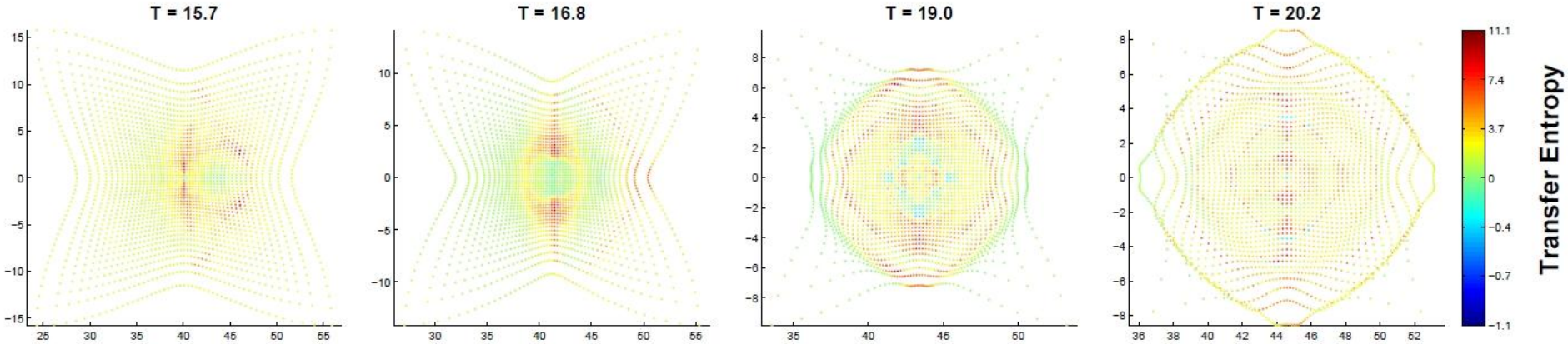


Results – experiment 1

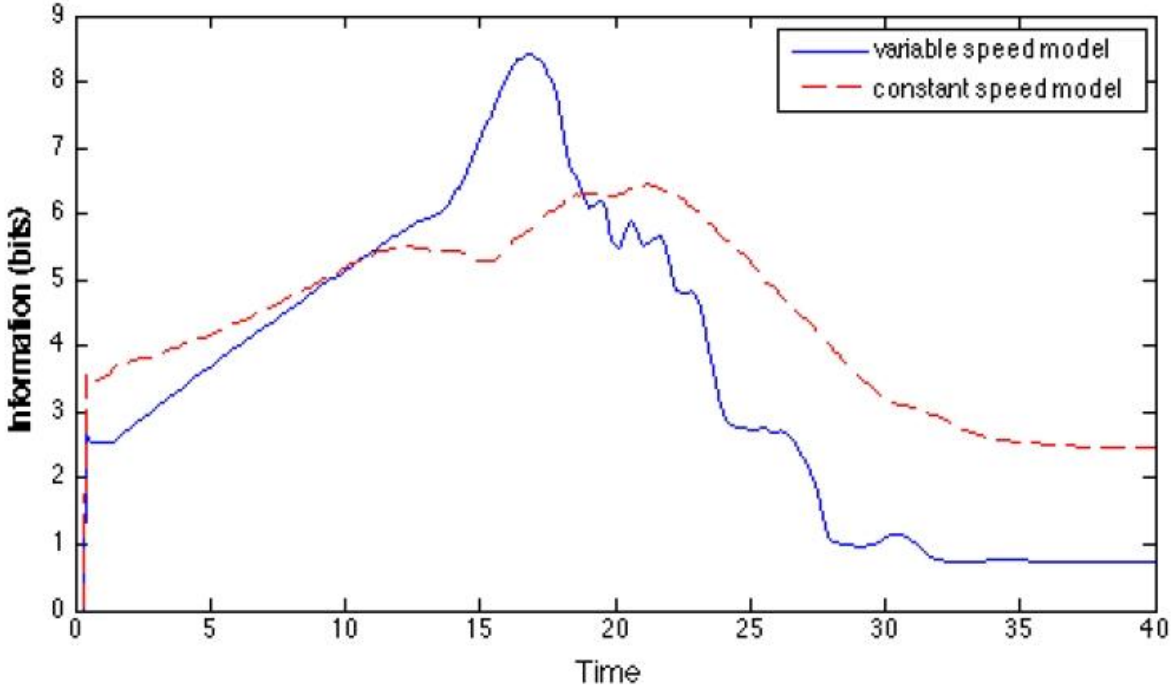




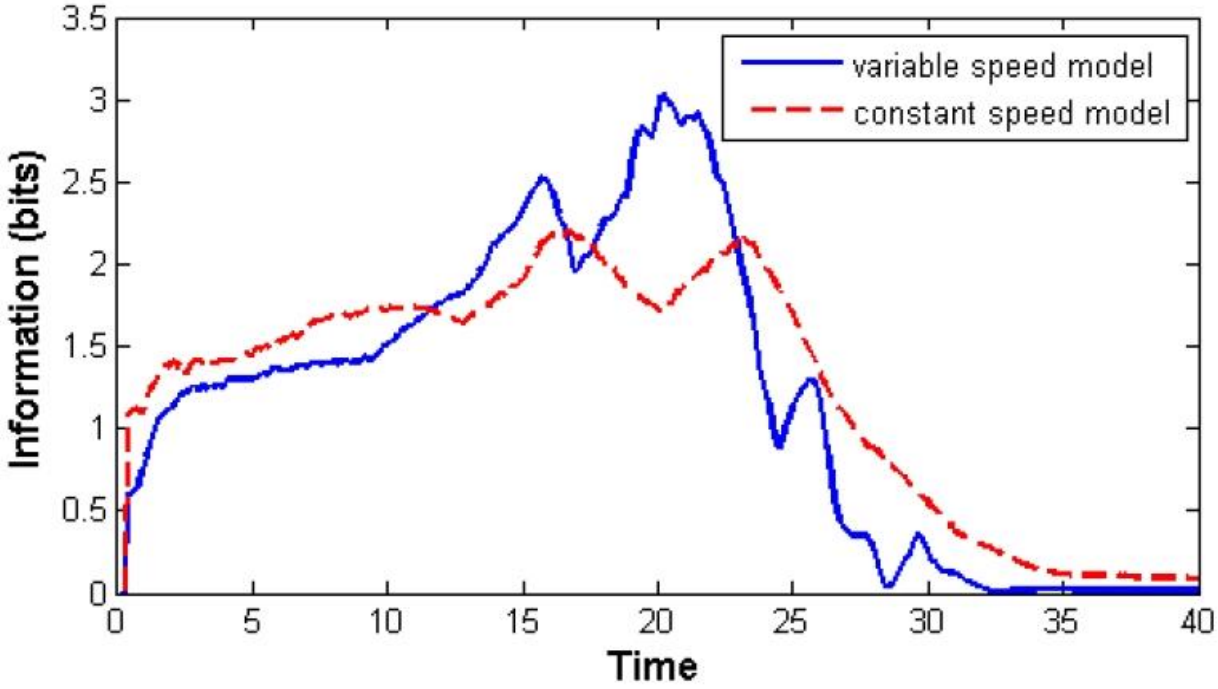
(b) (c) (d) (e)



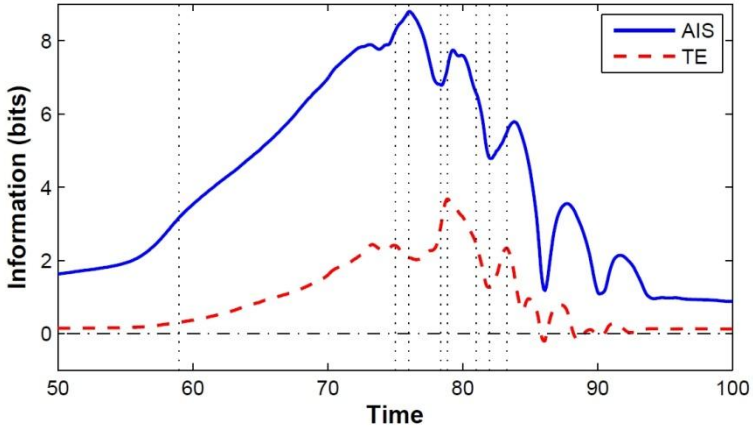
Results (AIS): constrained model (single swarm)

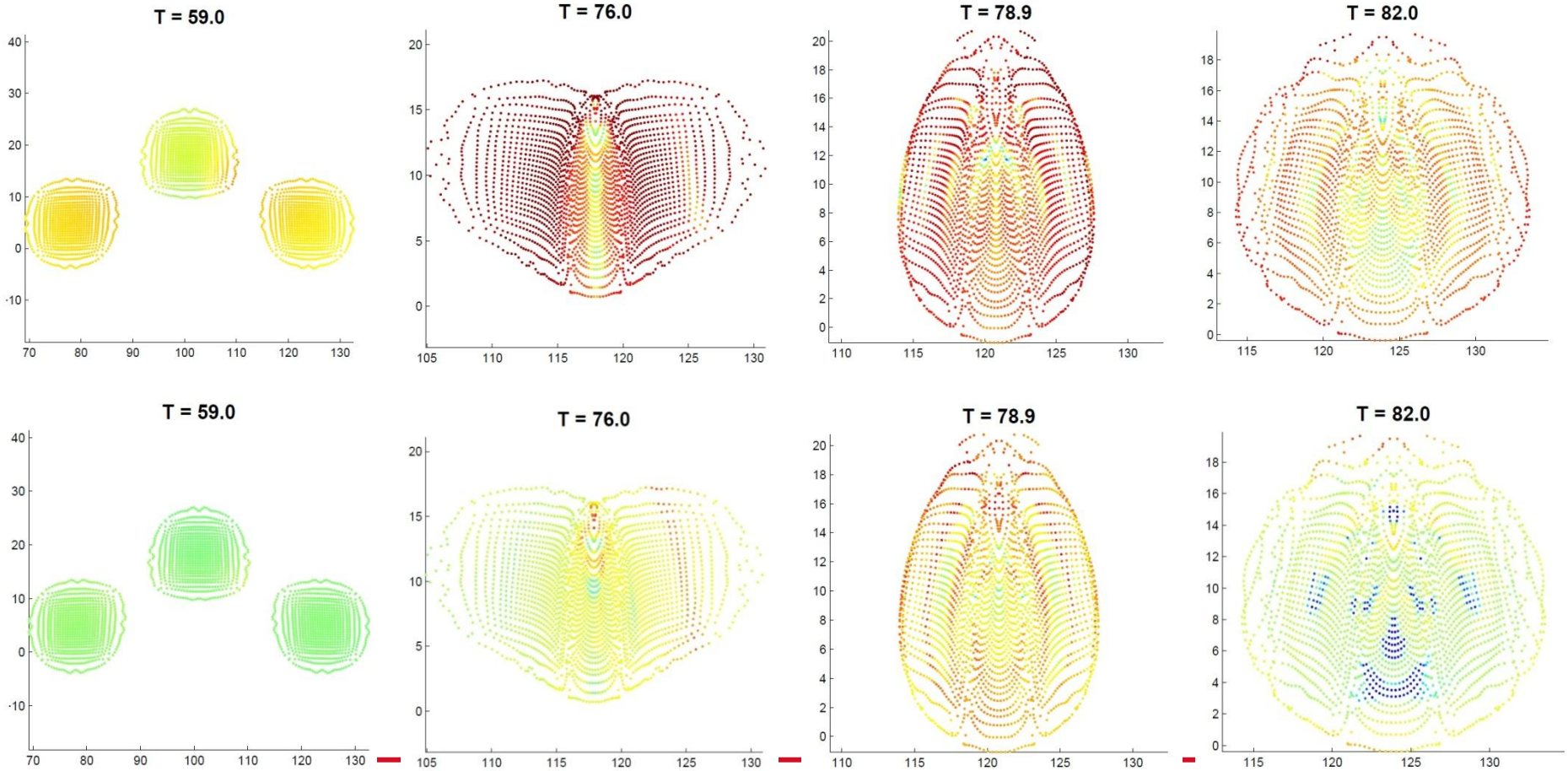


Results (TE): constrained model (single swarm)

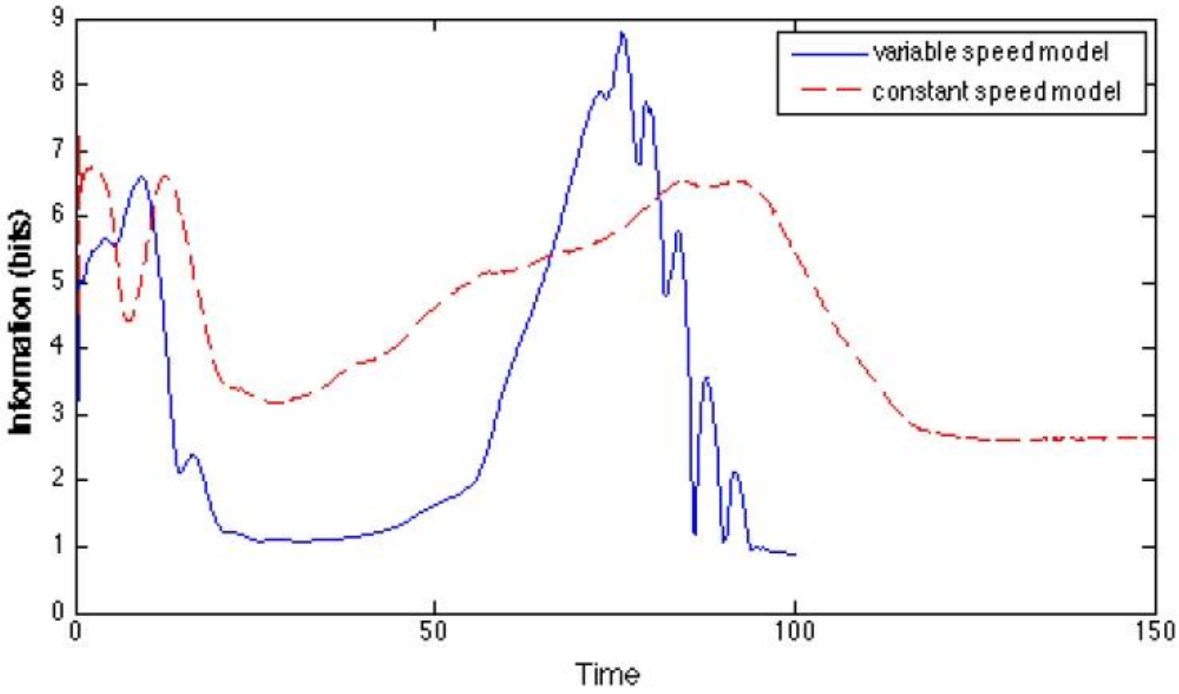


Results – experiment 2

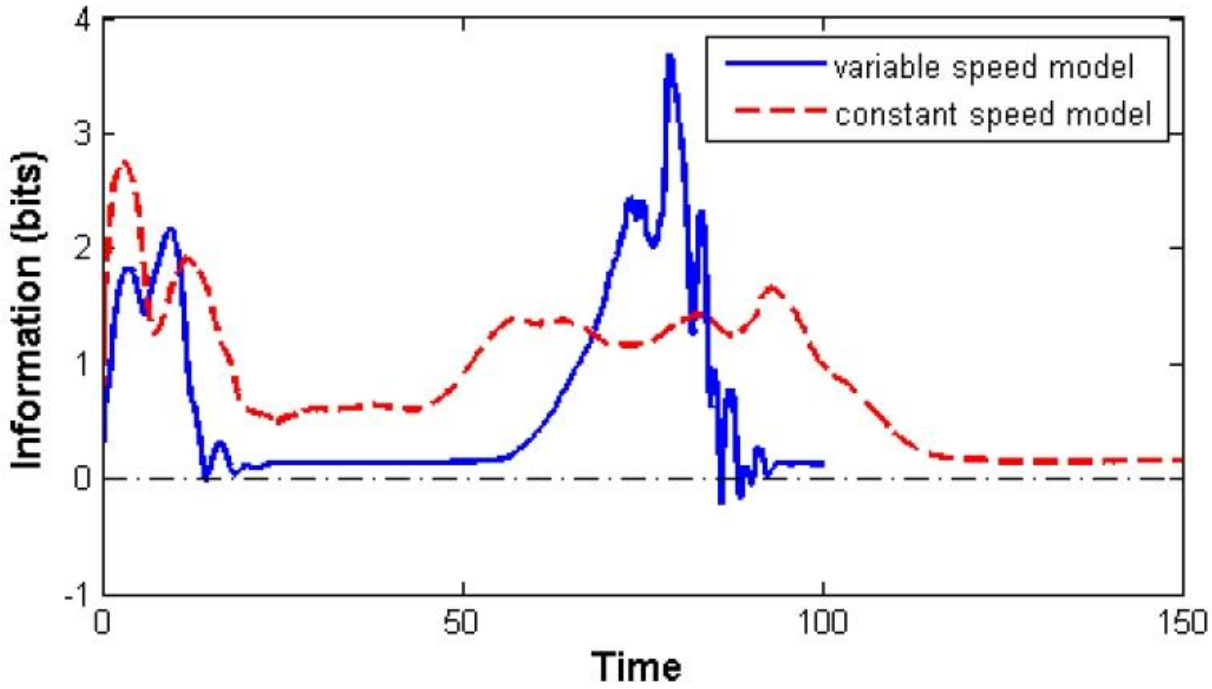




Results (AIS): constrained model (three swarms)



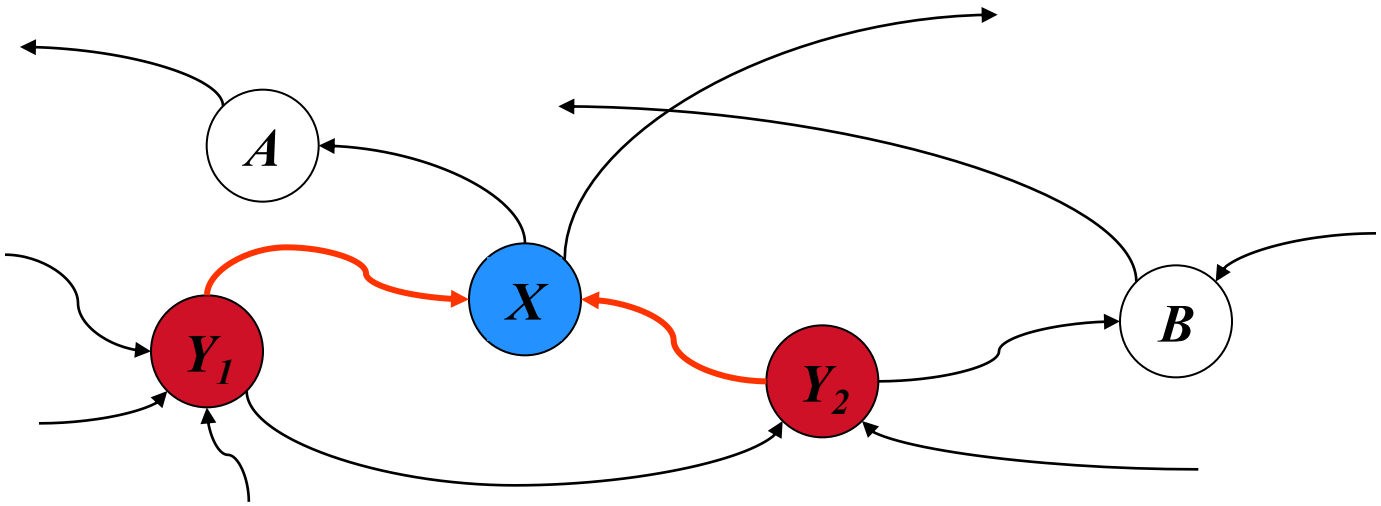
Results (TE): constrained model (three swarms)



Swarms: lessons

- information cascades occur in waves rippling through the swarm
- swarm's collective memory: active information storage (AIS)
- swarm's collective communications: transfer entropy (TE)
- ambiguous external stimuli: positive and negative local TE
- *guidance*: fixed velocity affects *coherence*

Case study: Random Boolean Networks (RBNs)



RBNs have:

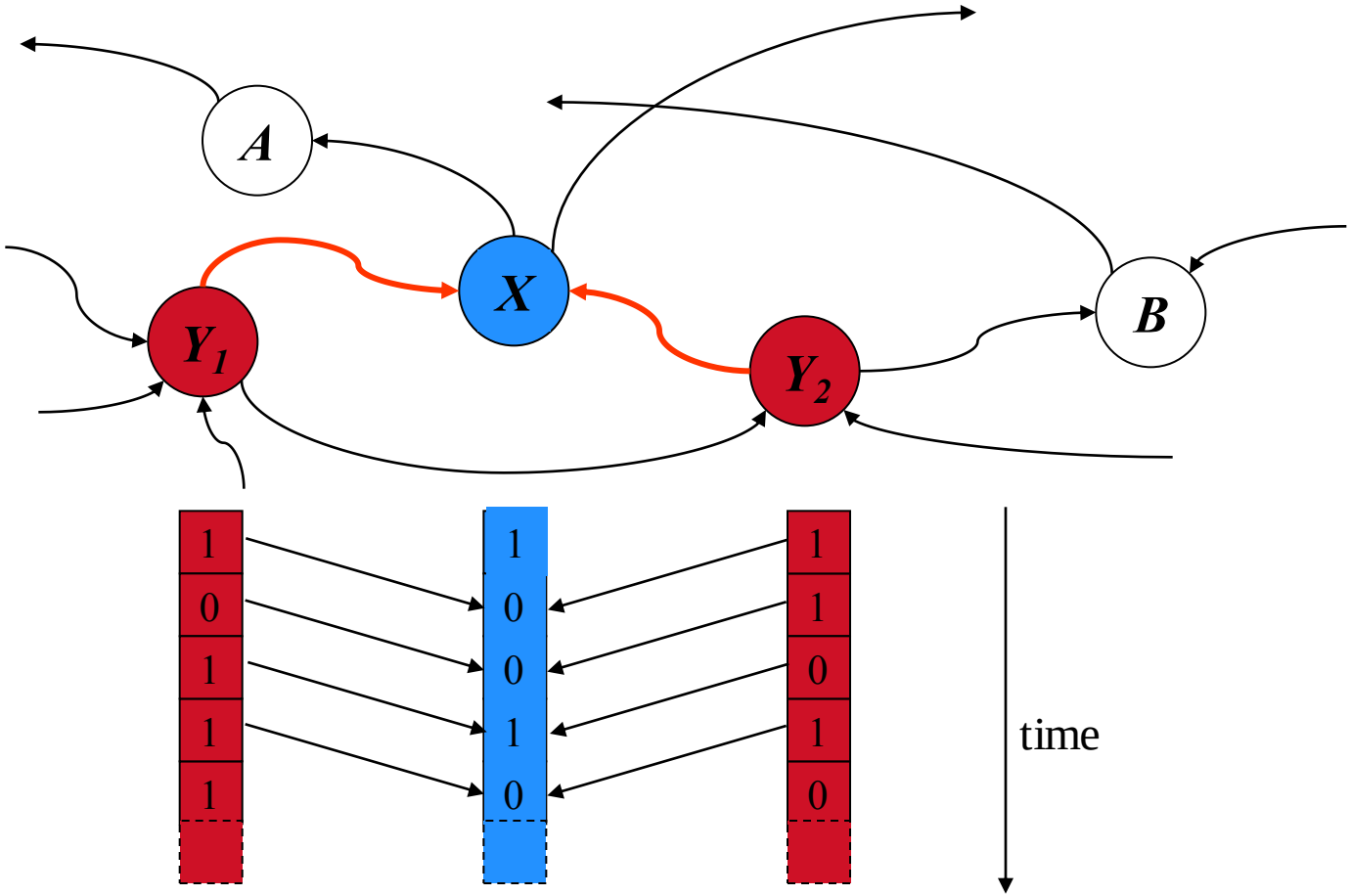
- N nodes in a directed structure
- which is determined at random from an average in-degree

$$\overline{K}$$

Each node has:

- Boolean states updated synchronously in discrete time
- update table determined at random, with some bias r

Dynamics in RBN



Y_1	Y_2	X
0	0	1
0	1	0
1	0	0
1	1	1

Random Boolean Networks – phases of dynamics

- Ordered
  - Low connectivity (small *K*) or activity (*r* close to 0 or 1)
  - High regularity of states and strong convergence of similar global states in state space

- Chaotic
  - High connectivity and activity
  - Low regularity of states and divergence of similar global states

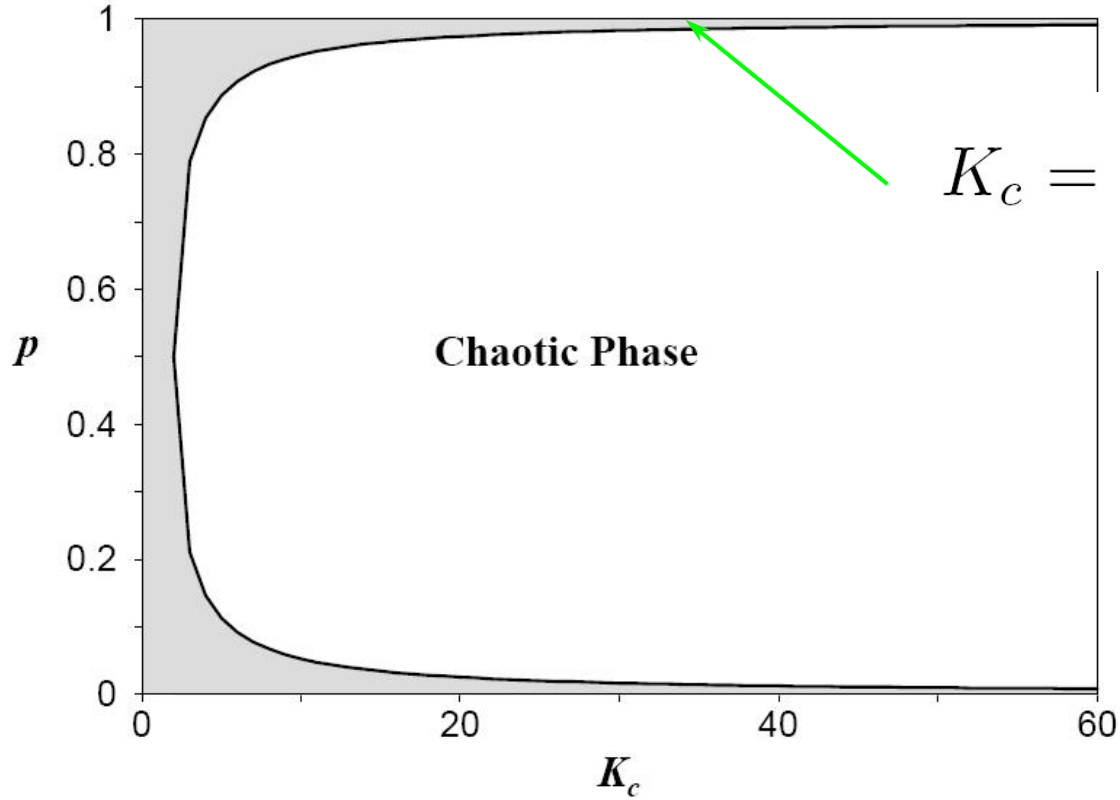
- Critical
  - The “edge of chaos”, separating ordered and chaotic phases
  - Change at a node in the network spreads marginally
  - Compromise between “stability” and “evolvability”
  - Given bias *r*, can calculate *K*

$$K_c = \frac{1}{2r(1-r)}$$

Phase transitions in RBNs

Connectivity	**Low** $\overline{K} < 2$	**Intermediate** $\overline{K} \approx 2$	**High** $\overline{K} > 2$
Phase	Ordered	Critical	Chaotic
Sensitivity to initial conditions	Low $\delta < 0$	Critical $\delta \approx 0$	High $\delta > 0$
Convergence of similar macro states	Strong	Uncertain	Highly divergent

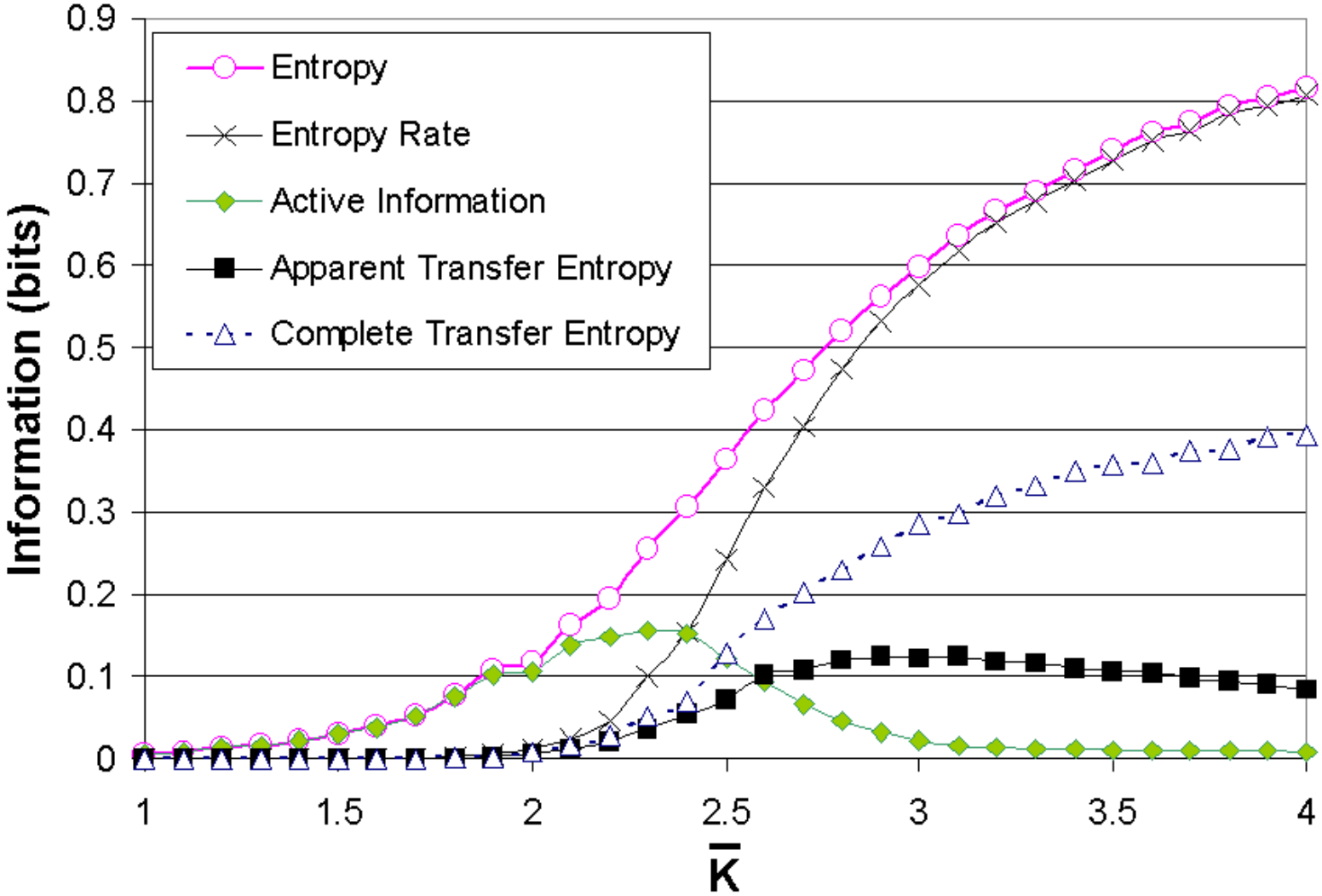
Phase diagram



$$K_c = \frac{1}{2r(1-r)}$$

FIG. 1: Phase diagram for the standard N-K model. The solid curve is the critical connectivity K_c as a function of p. The shaded area represents the ordered phase ($K < K_c$) whereas the white area represents the chaotic phase ($K > K_c$).

Information transfer in RBNs?



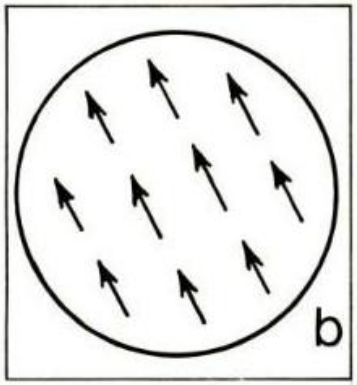
Information dynamics during phase transitions

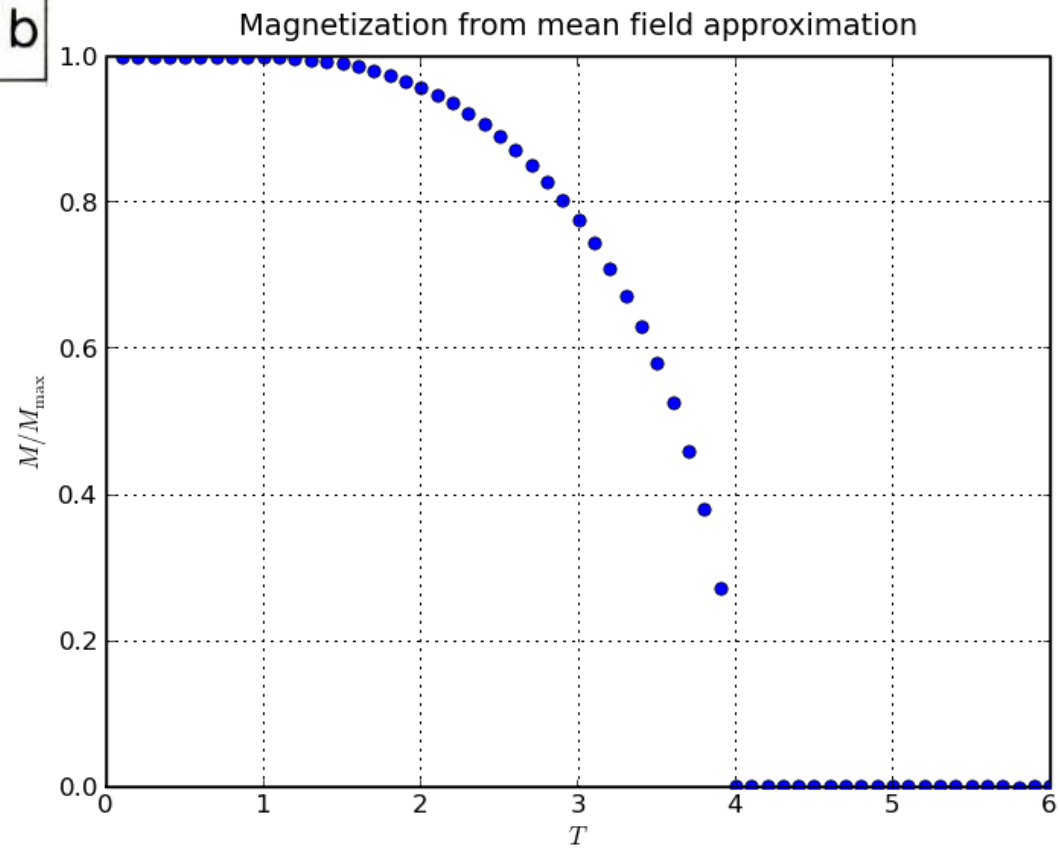
- order parameter sharply changes in response to a change in control parameter

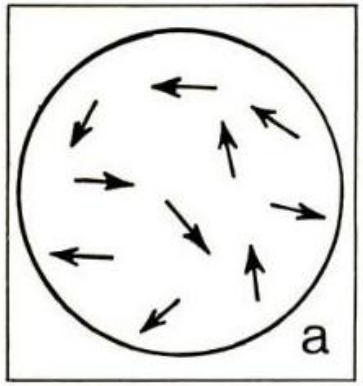
- what is the best generic (information) measure of
  - order parameter?
  - the rate of change in the order parameter?

- specific questions:
  - what is the order parameter for RBNs?
  - what is the derivative of RBN's order parameter?

Phase transitions and order parameters

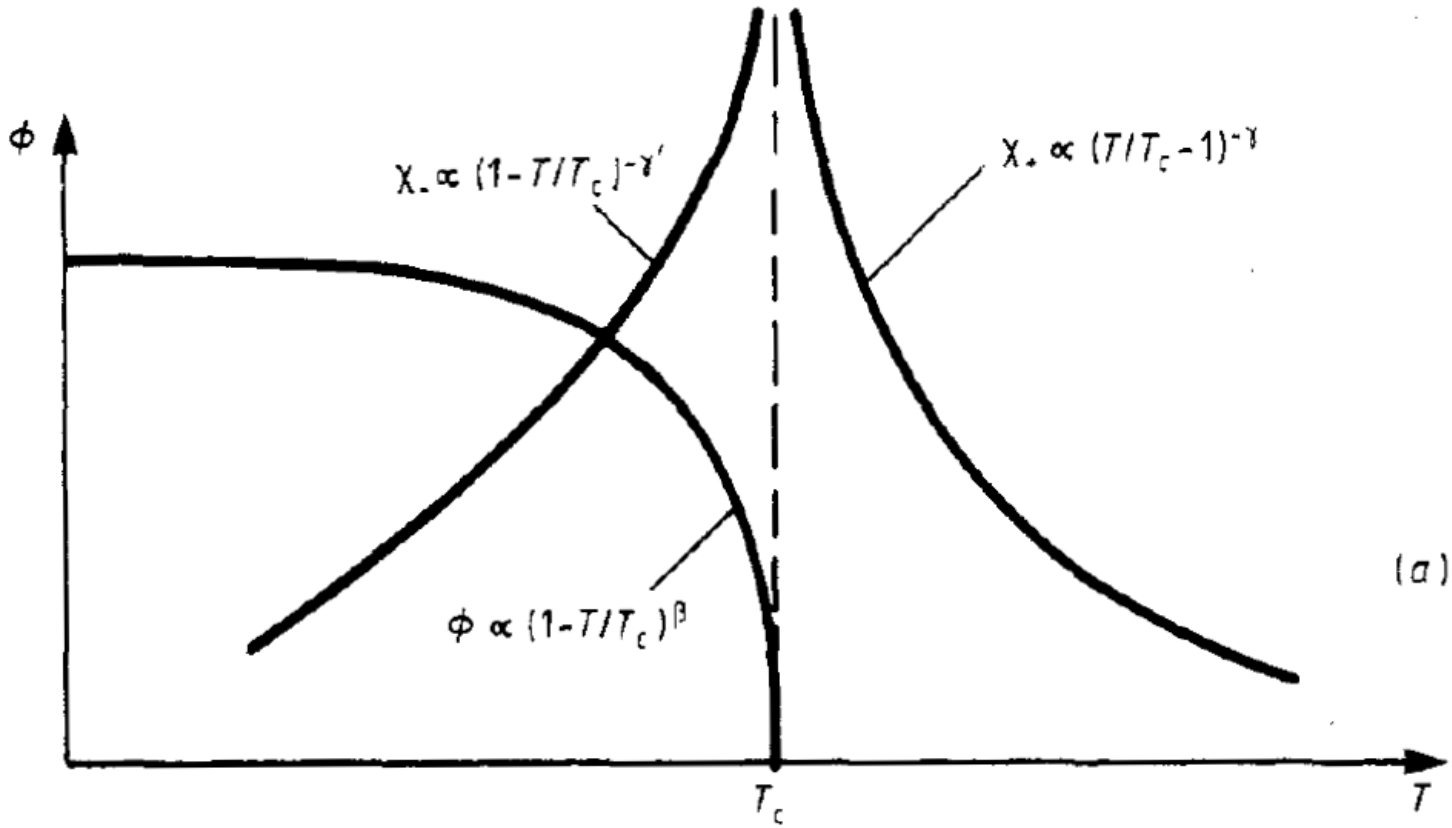






Derivative of order parameter (divergence)

K Binder (1987)



RBNs: searching for divergence at critical point…

RIBEIRO *et al.* (2008)

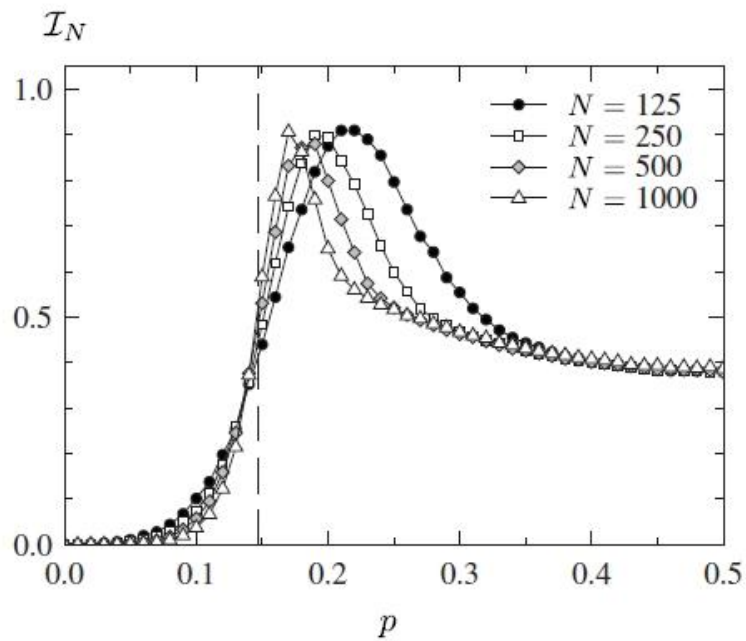


FIG. 6. $\mathcal{I}_N$ as a function of p for several different system sizes. For these calculations we use 10^4 networks with 40 runs from different initial states per network and a discarded transient of length 10^4. (For some data points far into the disordered regime, good convergence was obtained for discarded transients of length 10^3.) The sequences of states were recorded for a sample of $10N$ pairs of nodes in each network. The vertical dashed line indicates the critical value of p.

RBNs: searching for divergence at critical point…

Wang *et al.* (2011)

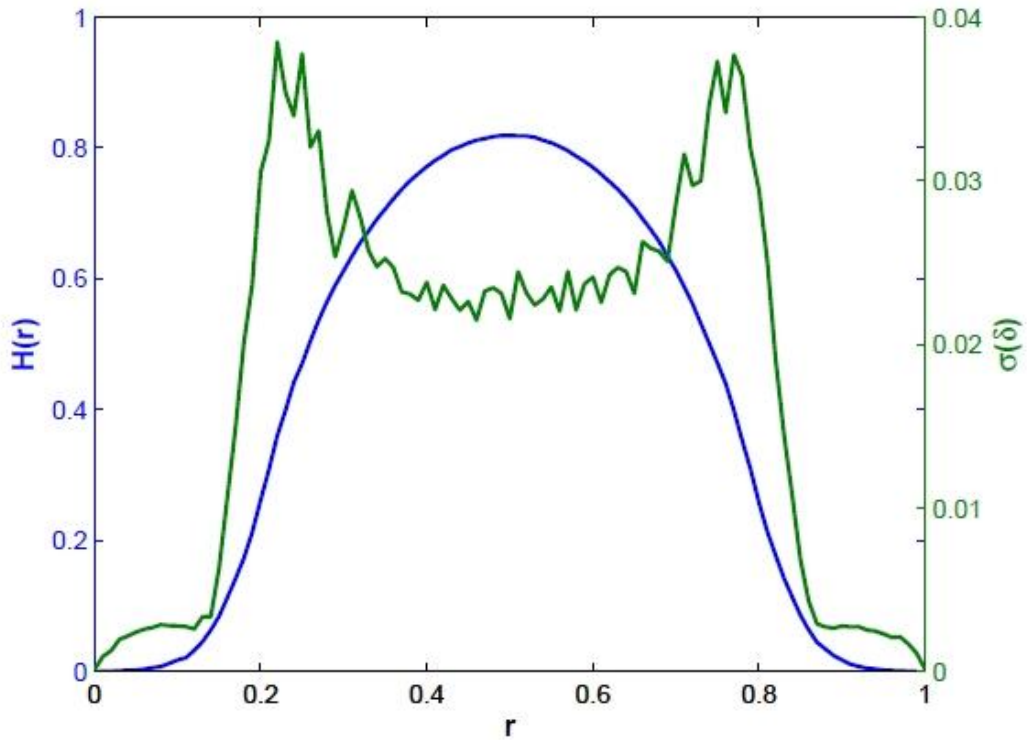


Figure 1: (blue) Average Shannon information $H(r)$ and (green) standard deviation of the convergence/divergence parameter δ versus the bias of the network r. The RBNs here have network size $N = 250$, and average network connectivity $\bar{K} = 4.0$.

Fisher Information

A way of measuring the amount of information that an observable random variable X has about an unknown parameter θ

$$F(\theta) = \int_x \left(\frac{\partial \ln(p(x|\theta))}{\partial \theta} \right)^2 p(x|\theta) dx$$

Fisher information is not a function of a particular observation, since the random variable X is averaged out

...connection to thermodynamics

PHYSICAL REVIEW E **84**, 041116 (2011)

Relating Fisher information to order parameters

Mikhail Prokopenko,[1,*] Joseph T. Lizier,[2] Oliver Obst,[1] and X. Rosalind Wang[1]
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[2]*Max Planck Institute for Mathematics in the Sciences, Inselstraße 22, D-04103 Leipzig, Germany*
(Received 8 July 2011; published 13 October 2011)

We study phase transitions and relevant order parameters via statistical estimation theory using the Fisher information matrix. The assumptions that we make limit our analysis to order parameters representable as a negative derivative of thermodynamic potential over some thermodynamic variable. Nevertheless, the resulting representation is sufficiently general and explicitly relates elements of the Fisher information matrix to the rate of change in the corresponding order parameters. The obtained relationships allow us to identify, in particular, second-order phase transitions via divergences of individual elements of the Fisher information matrix. A computational study of random Boolean networks supports the derived relationships, illustrating that Fisher information of the magnetization bias (that is, activity level) is peaked in finite-size networks at the critical points, and the maxima increase with the network size. The framework presented here reveals the basic thermodynamic reasons behind similar empirical observations reported previously. The study highlights the generality of Fisher information as a measure that can be applied to a broad range of systems, particularly those where the determination of order parameters is cumbersome.

DOI: 10.1103/PhysRevE.84.041116 PACS number(s): 05.70.Fh, 64.60.Bd, 64.60.De, 02.50.−r

Physical Review E
statistical, nonlinear, and soft matter physics

$$F(\theta) = \int_x \left(\frac{\partial \ln(p(x|\theta))}{\partial \theta} \right)^2 p(x|\theta) dx$$

Fisher Information and order parameters

$$F_{ij}(\theta) = \beta \frac{\partial \phi^i}{\partial \theta^j}$$

Fisher information matrix

Rate of change of the order parameter !

Fisher Information for RBN

The discrete form of Fisher information is:

$$F(\theta) = \sum_{x_j} p_{x_j} \left(\frac{\Delta \ln(p_{x_j})}{\Delta \theta} \right)^2$$

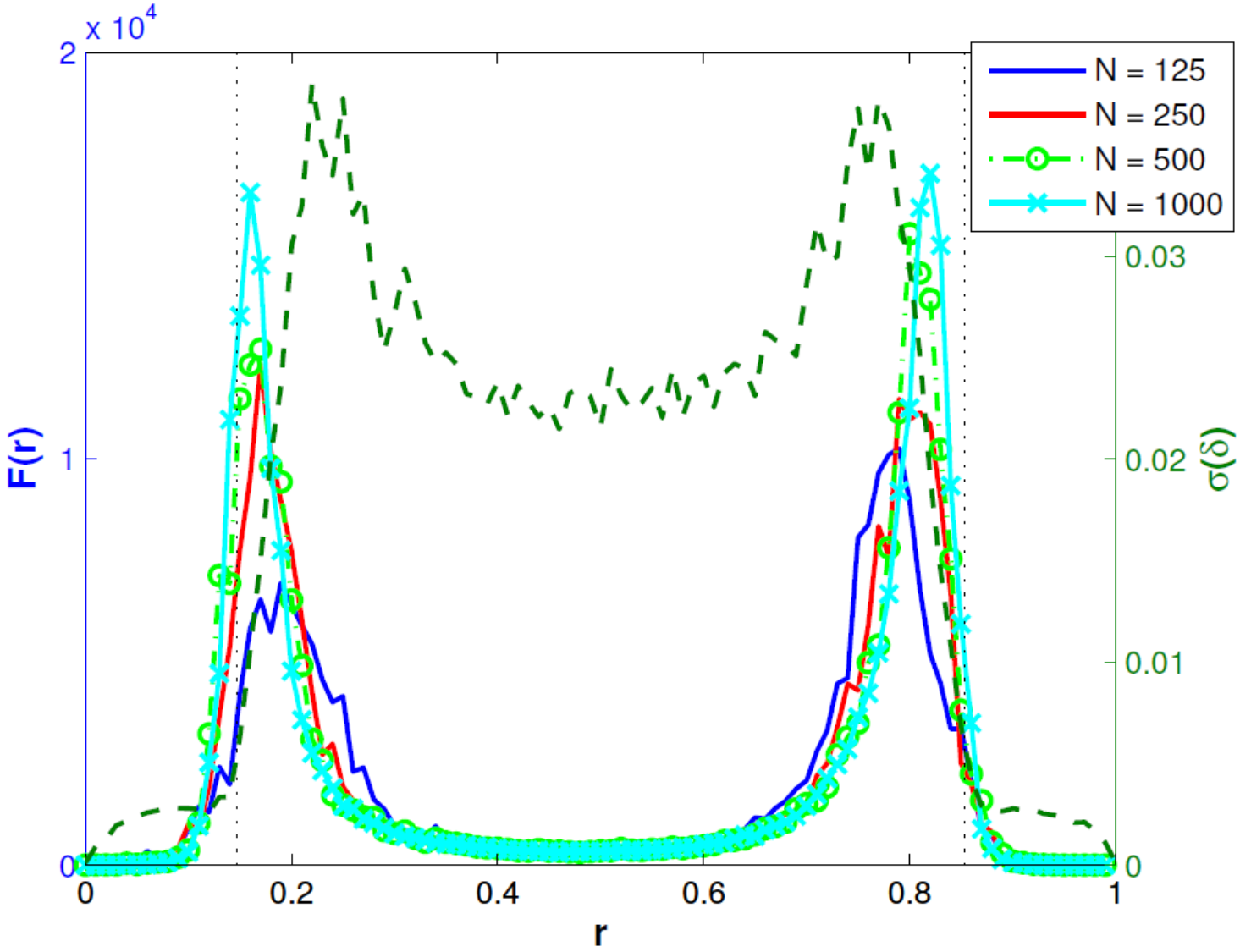
where

$$\Delta \ln(p_{x_j}) = \ln(p'_{x_j}) - \ln(p_{x_j})$$
$$p_{x_j} = p(x_j|\theta)$$
$$p'_{x_j} = p(x_j|\theta + \Delta\theta)$$

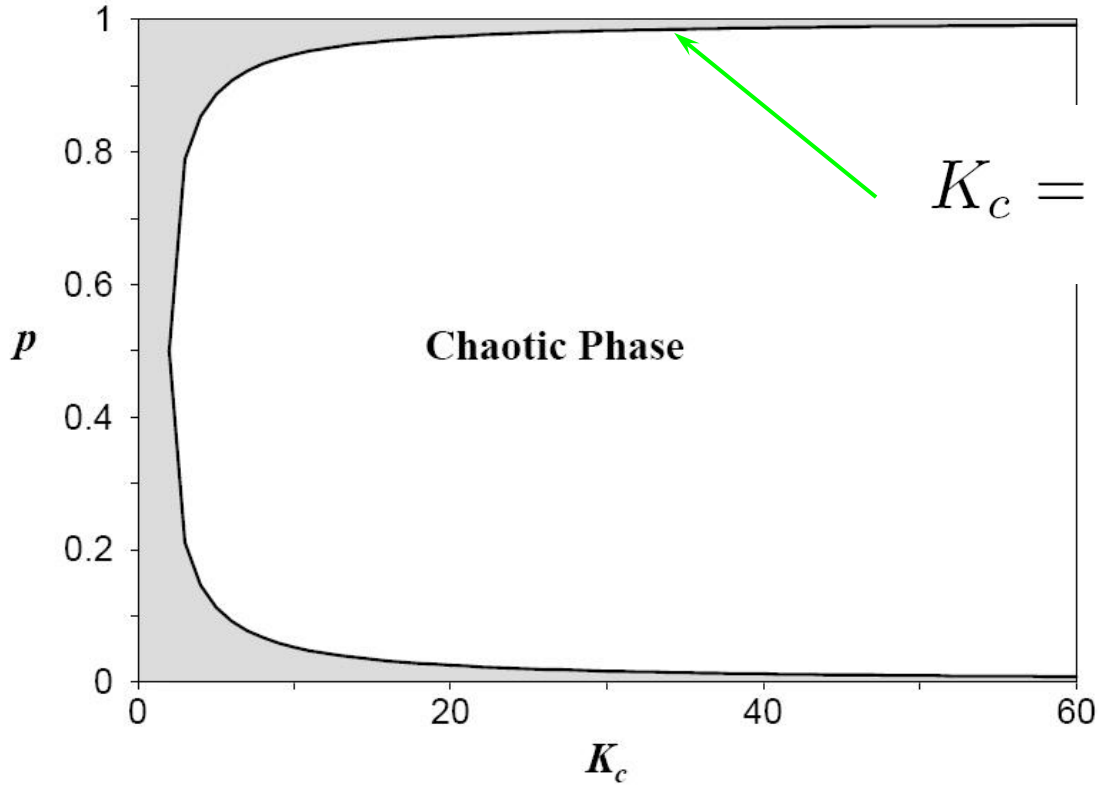
The average Fisher information of the individual node, i:

$$F(r)_{RBN} \triangleq \langle F_i(r) \rangle$$

Fisher Information – finite-size RBNs



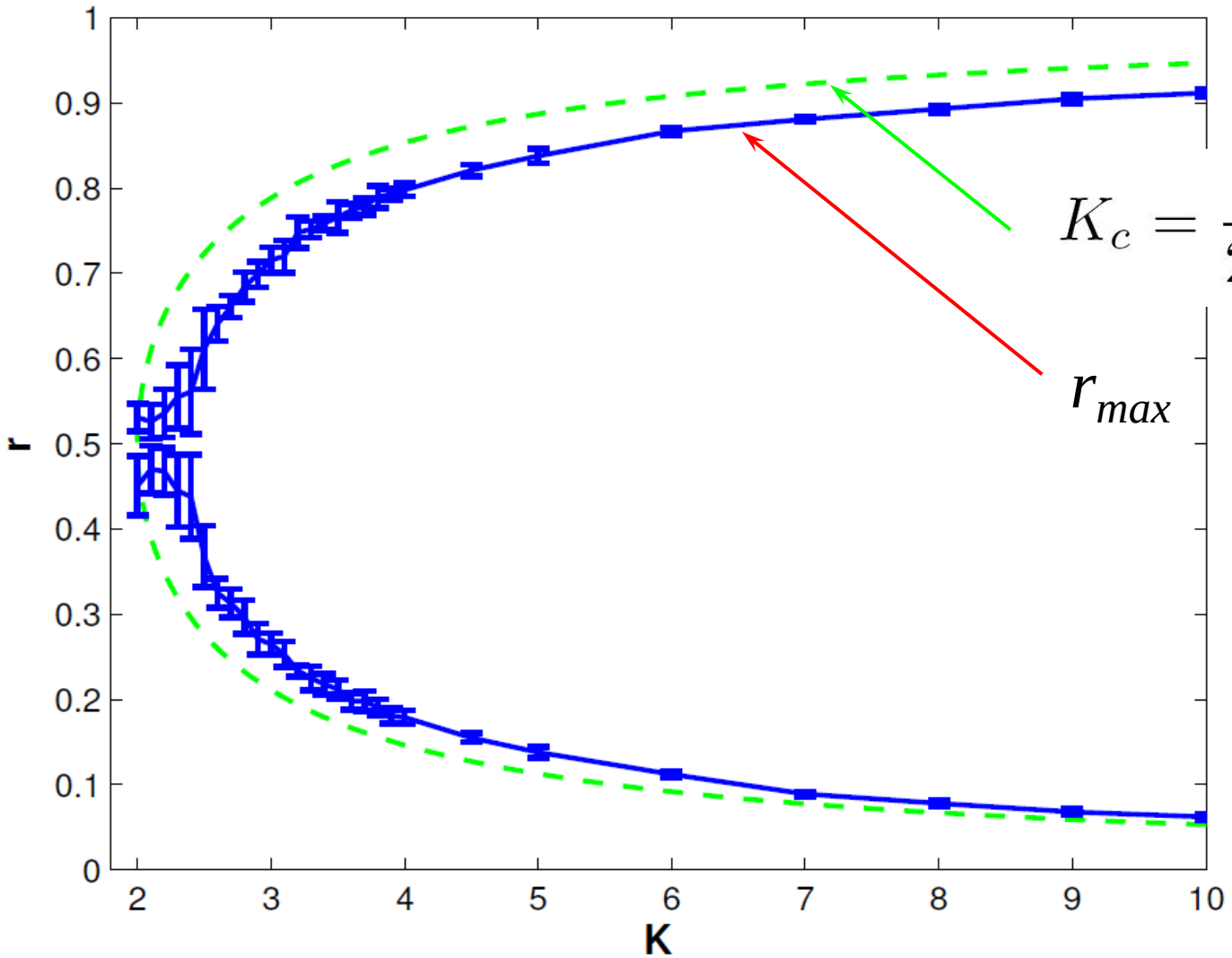
Phase diagram – revisited



$$K_c = \frac{1}{2r(1-r)}$$

FIG. 1: Phase diagram for the standard N-K model. The solid curve is the critical connectivity K_c as a function of p. The shaded area represents the ordered phase ($K < K_c$) whereas the white area represents the chaotic phase ($K > K_c$).

Phase diagram – via Fisher information



$$K_c = \frac{1}{2r(1-r)}$$

r_{max}

Fisher information: summary

- Fisher information about the control parameter has maxima at the critical (K, r) points

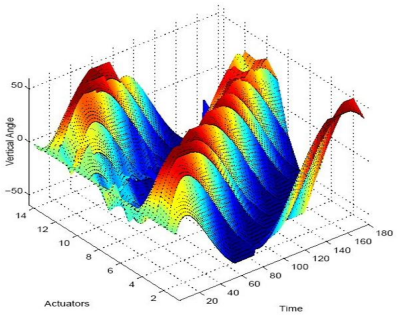
- Phase diagram plotted using r_{max}, where the maximum Fisher information occurs w.r.t. r for fixed K, reveals expected phases

- Fisher information is proportional to the rate of change of the order paramete

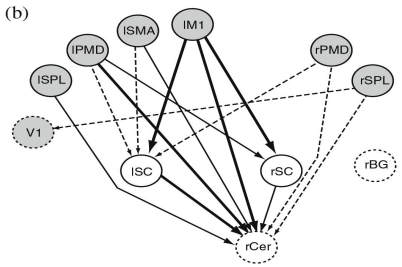
$$F_{ij}(\theta) = \beta \frac{\partial \phi^i}{\partial \theta^j}$$

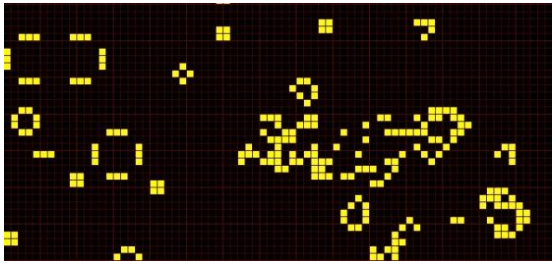
Conclusions

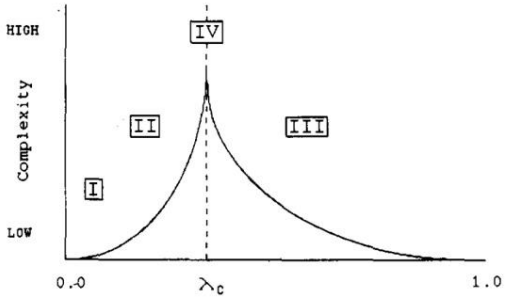
› Information structure = diversity – mismatch



› Information dynamics

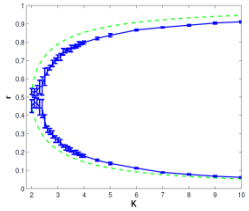






› Information thermodynamics

$$F_{ij}(\theta) = \beta \frac{\partial \phi^i}{\partial \theta^j}$$



References

C. Adami, What is complexity? *Bioessays*, 24, 1085–1094, 2002

K. Binder, Theory of first-order phase transitions, *Reports on Progress in Physics*, 50, 783+, 1987.

E. Bonabeau, G. Theraulaz, J.-L. Deneubourg, S. Camazine. Self-organisation in social insects, *Trends in Ecology and Evolution*, 12(5): 188 193, 1997.

C. G. Langton, Computation at the edge of chaos: Phase transitions and emergent computation, *Physica D*, 42, 12-37, 1990.

J. T. Lizier, J. Heinzle, A. Horstmann, J.-D. Haynes, M. Prokopenko, Multivariate information-theoretic measures reveal directed information structure and task relevant changes in fMRI connectivity, *Journal of Computational Neuroscience*, 30:85–107, 2011.

J. T. Lizier, M. Prokopenko, A. Y. Zomaya. The Information Dynamics of Phase Transitions in Random Boolean Networks, in S. Bullock, J. Noble, R. Watson, and M. A. Bedau (eds) *Artificial Life XI - Proceedings of the Eleventh International Conference on the Simulation and Synthesis of Living Systems*, 374-381, MIT Press, 2008.

J. T. Lizier, M. Prokopenko, A. Y. Zomaya. Local information transfer as a spatiotemporal filter for complex systems, *Physical Review E*, 77, 026110, 2008.

J. T. Lizier, M. Prokopenko, A. Y. Zomaya, Coherent information structure in complex computation, *Theory in Biosciences*, special issue on Guided Self-Organisation (GSO-2010), 131: 193–203, 2012.

M. Piraveenan, M. Prokopenko, A. Y. Zomaya. Assortative mixing in directed biological networks, *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, 9(1): 66–78, 2012.

M. Prokopenko, F. Boschetti, A. Ryan. An information-theoretic primer on complexity, self-organisation and emergence, *Complexity*, 15(1), 11-28, 2009.

References

M. Prokopenko, V. Gerasimov, I. Tanev. Measuring Spatiotemporal Coordination in a Modular Robotic System, in Rocha, L.M., Yaeger, L.S., Bedau, M.A., Floreano, D., Goldstone, R.L., Vespignani, A. (eds.), *Artificial Life X: Proceedings of The 10th International Conference on the Simulation and Synthesis of Living Systems*, 185-191, MIT Press, 2006.

M. Prokopenko, V. Gerasimov, I. Tanev. Evolving Spatiotemporal Coordination in a Modular Robotic System, in Nolfi, S., Baldassarre, G., Calabretta R., Hallam, J. C. T., Marocco, D., Meyer J.-A., Miglino, O., and Parisi, D., eds. *From Animals to Animats 9: 9th International Conference on the Simulation of Adaptive Behavior (SAB 2006)*, Rome, Italy, Springer, Lecture notes in computer science, vol. 4095, 558-569, 2006.

M. Prokopenko, J. T. Lizier, O. Obst, X. R. Wang, Relating Fisher information to order parameters, *Physical Review E*, 84, 041116, 2011.

A. S. Ribeiro, S. A. Kauffman, J. Lloyd-Price, B. Samuelsson, J. E. S. Socolar, Mutual information in random Boolean models of regulatory networks, *Physical Review E*, 77, 011901–10, 2008.

C. E. Shannon, A mathematical theory of communication, *The Bell Systems Technical Journal*, 27, 379–423, 623–656, 1948.

T. Schreiber, Measuring information transfer, *Physical Review Letters*, 85, 461, 2000.

R. V. Sole, S. Valverde, Information theory of complex networks: on evolution and architectural constraints, in *Complex Networks*, Vol. 650: Lecture Notes in Physics; Ben-Naim, E.; Frauenfelder, H.; Toroczkai, Z., Eds.; Springer: Berlin, 2004.

X. R. Wang, J. T. Lizier, M. Prokopenko, Fisher Information at the Edge of Chaos in Random Boolean Networks, *Artificial Life*, special issue on Complex Networks, 17(4), 315-329, 2011.

X. R. Wang, J. M. Miller, J. T. Lizier, M. Prokopenko, L. F. Rossi, Quantifying and Tracing Information Cascades in Swarms, *PLoS ONE*, 7(7): e40084, 2012.

S. Wolfram, Universality and complexity in cellular automata. *Physica D*, 10, 1–35, 1984.

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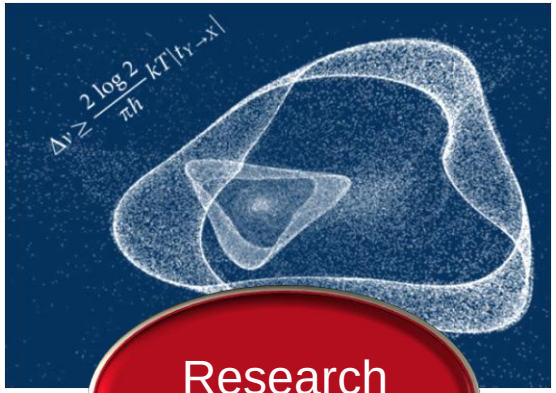
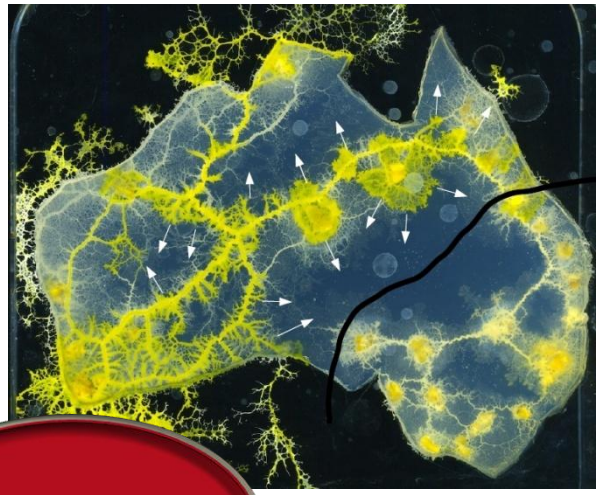
Master of Complex Systems (MCXS): starting in 2017

Anticipate, Control and Manage Complexity of the Unexpected





Research methods

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Biosecurity

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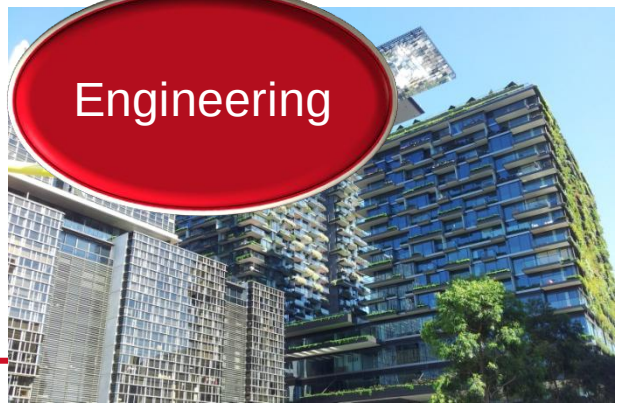

Engineering