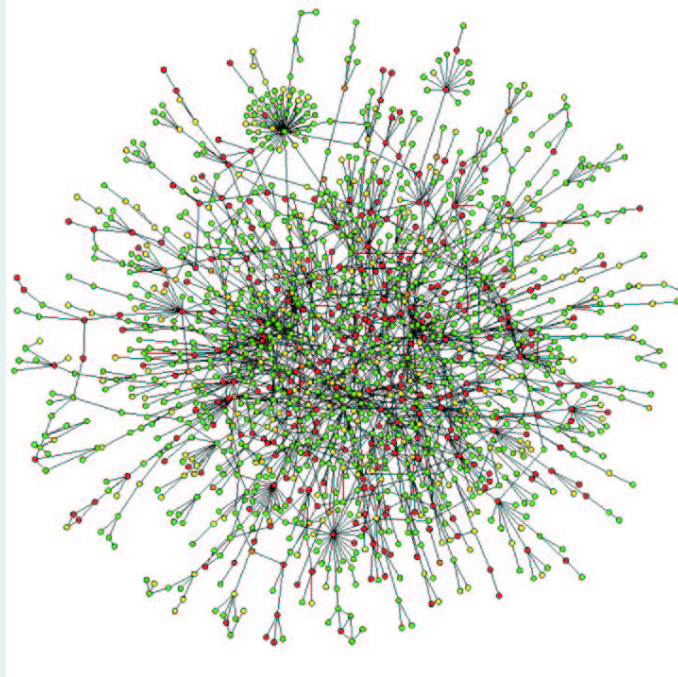


Statistical Mechanics of Signaling Processes on Complex Biological Networks

ACC Coolen – King's College London

with

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I Perez-Castillo, NS Skantzios, B Wemmenhove*



OVERVIEW

Stochastic processes on large networks in biology

<i>interacting cells</i>	<i>(neural & immune networks)</i>
<i>interacting proteins</i>	<i>(proteomic networks)</i>
<i>interacting genes</i>	<i>(gene regulation networks)</i>

Complex networks – definitions, characterization

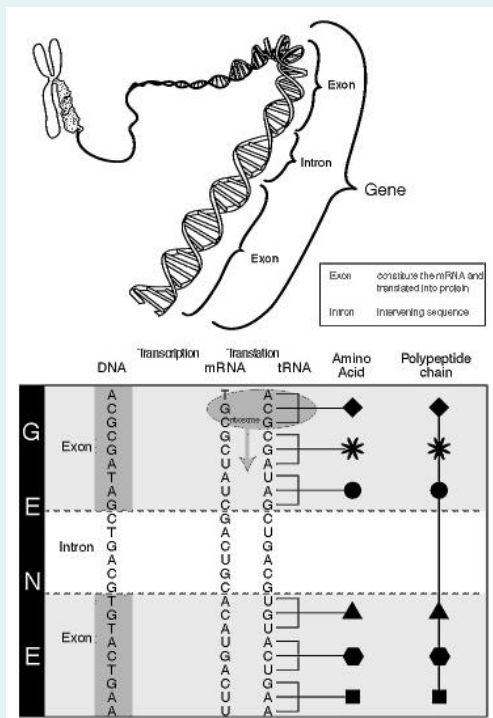
random graphs, degree distribution
small-world networks
scale-free networks

Theory of processes on large complex networks

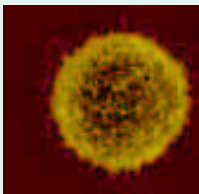
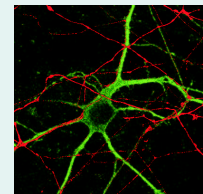
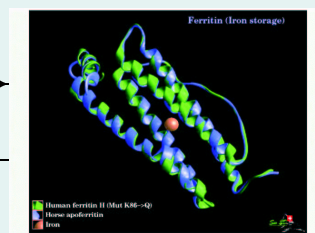
methods and their applicability
statics – finite connectivity replica theory
dynamics – generating functional analysis
dynamics – dynamical replica & cavity techniques

PROCESSES ON LARGE NETWORKS IN BIOLOGY

networks: defined functionally, by interaction partners



- *gene level*
- *protein level*
- *cell level*



NEURAL NETWORKS

Dense networks of $\sim 10^4 - 10^8$ brain cells (neurons)
connected via electro-chemical terminals (synapses)

models

$$J_{ij} = c_{ij} K_{ij} \quad \left\{ \begin{array}{ll} c_{ij} \in \{1, 0\} & \text{bond } j \rightarrow i \text{ present/absent} \\ & \text{(architecture)} \\ K_{ij} \in \mathbb{R} & \text{strength \& type of bond} \end{array} \right.$$

- binary variables $\sigma_i = \pm 1$,
reacting to incoming signals V_i

$$\sigma_i(t+1) = \text{sgn} \left[\sum_j J_{ij} \sigma_j(t) + \theta_i + \eta_i(t) \right]$$

$\eta_i(t)$: noise

- neuron voltages V_i

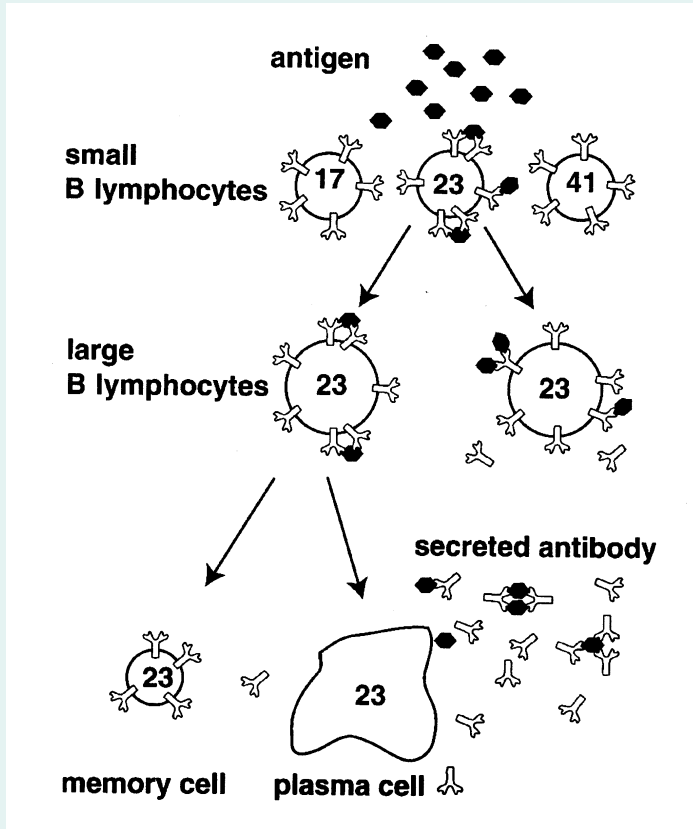
$$\frac{d}{dt} V_i(t) = \sum_j J_{ij} \tanh[\gamma V_j(t)] - V_i(t) + \theta_i + \eta_i(t)$$

- coupled oscillators, phases ϕ_i

$$\frac{d}{dt} \phi_i(t) = \omega_i + \sum_j J_{ij} \sin[\phi_j(t) - \phi_i(t)] + \eta_i(t)$$



IMMUNE NETWORKS



the enemy:

invaders, abnormal cells (antigens)

the defense:

lymphocytes (white blood cells)

B-cells: secrete tags (antibodies)

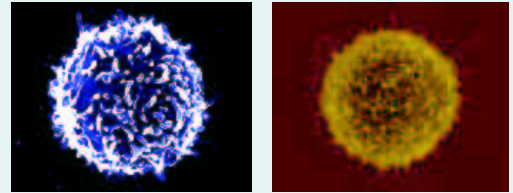
helper T-cells: assist B-cells

cytotoxic T-cells: cell killers

*phagocytic cells: vacuum cleaners
(eat anything tagged ...)*



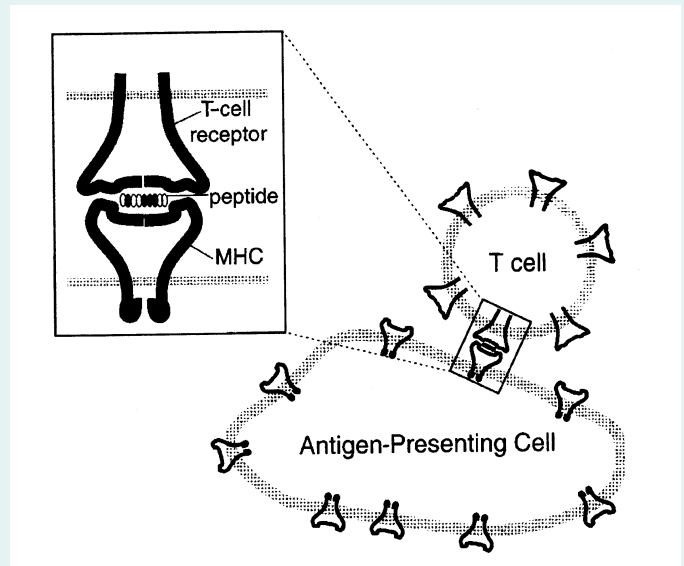
*Lymphocytes recognize
surface shapes of antigens*



- each lymphocyte has surface receptors of a specific type
- antigen binding to receptor triggers the lymphocyte into reproducing
- shapes of encountered antigens are memorized
- recognize as many shapes as possible but **not** healthy self molecules ...

models of the immune system:

dynamics of concentrations of many different competing cell types



How is memory achieved in the immune system?

Jerne (1974): network models of the immune system

Varela et al (1991): 2nd generation immune network theory

$$\frac{d}{dt}f_i = -K_1 f_i h_i - K_2 f_i + K_3 b_i M(h_i) + \text{noise}$$

$$\frac{d}{dt}b_i = -K_4 b_i + K_5 b_i P(h_i) + K_6 + \text{noise}$$

$$h_i = \sum_j c_{ij} f_j + \theta_i \quad \text{'activation' of clone } i$$

f_i : concentration of antibody (idio)type i

b_i : concentration of B-cell (idio)type i

θ_i : concentration of antigen type i

$M(\cdot), P(\cdot)$: nonnegative bell-shaped functions

single-clone stationary states:

- *non-suppressed clone:* $h_i \ll 1, f_i \sim 1$
- *suppressed clone:* $h_i \gg 1, f_i \sim 0$

net result:

- *network of antibody clones with negative mutual interactions*
- *clone-anticlone pairs support stable (\uparrow, \downarrow) and (\downarrow, \uparrow) states*

GENE REGULATION & PROTEOMIC NETWORKS

protein interaction networks

(‘yeast two-hybrid method’)

nodes: protein species

links: direct physical pair-interaction

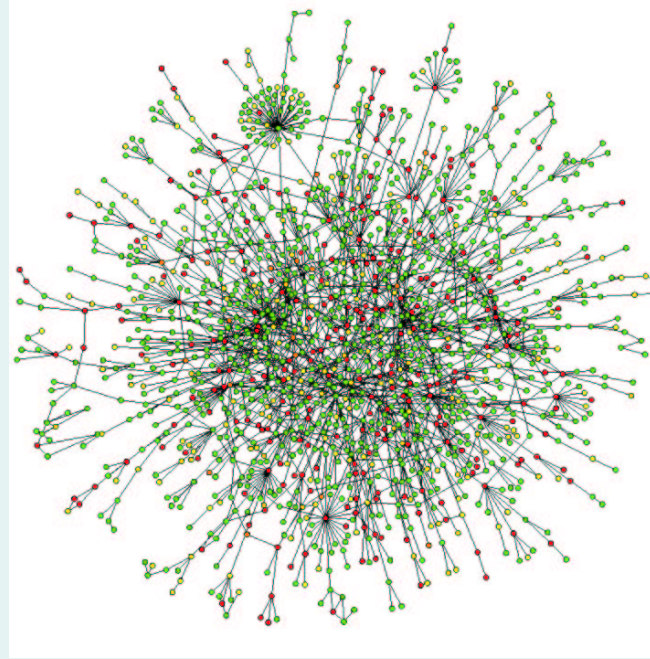
simple models:

f_i : concentration of i -th protein type

$$\frac{d}{dt}f_i = \sum_j J_{ij}f_j + \sum_{jk} J_{ijk}f_jf_k + \sum_{jkl} J_{ijkl}f_jf_kf_l + \dots$$

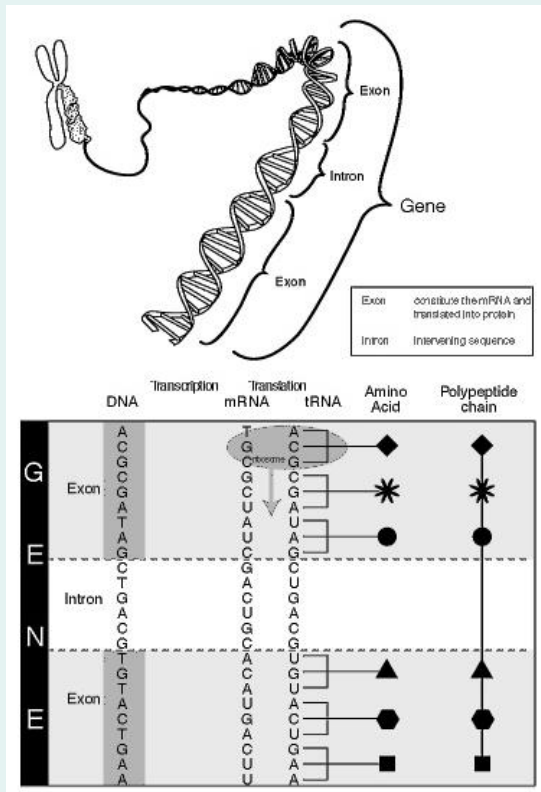
in addition:

- indirect interactions via regulation of gene expression
- conformation changes of proteins
- spatial effects (localized proteins, diffusion, ...)
- conservation laws
- functional versus actual interactions

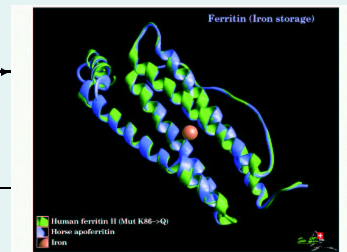


Gene regulation networks

Initial objective: understand and explain cell differentiation



- gene expression: conversion of information into protein production
- expression level of a gene: controlled by specific proteins
- protein concentrations controlled by: other proteins, other expressed genes, external stimuli



Models of Gene Regulation Networks:

- *basic variables are expression levels of genes (e.g. on/off)*
- *replace genes→proteins→genes feedback loop
by effective gene→gene interactions*

The Kauffman model (1969)

$$N \text{ Boolean genes : } \begin{cases} \sigma_i = 0 & \text{gene } i \text{ switched off} \\ \sigma_i = 1 & \text{gene } i \text{ switched on} \end{cases}$$

dynamics:
$$\sigma_i(t+1) = \mathcal{F}_i[\sigma_{j_1(i)}(t), \dots, \sigma_{j_k(i)}(t)]$$

each i :

$$\begin{array}{ll} j_1(i), \dots, j_k(i) & \text{drawn randomly from } \{1, \dots, N\} \\ \mathcal{F}_i : \{0, 1\}^k \rightarrow \{0, 1\} & \text{random function, } \text{Prob}(\mathcal{F} = 0) = p \end{array}$$

- *critical connectivity: $k_c = [2p(1-p)]^{-1}$*
- *$k < k_c$: frozen phase (trajectories end in fixed-points)*
- *$k > k_c$: chaotic phase (limit cycles, diverging trajectories)*
- *number, length of attractors? dependence on N ?*

Networks – definition and characterization

links : $c_{ij} \in \{0, 1\}$ $c_{ij} = 1$: link $j \rightarrow i$ present
 $c_{ij} = 0$: link $j \rightarrow i$ absent

Diagram illustrating the number of lines passing through a point k for $k = 1, 2, 3, 4, 5$.

- $k = 1$: One line passes through the point.
- $k = 2$: Two lines intersect at the point.
- $k = 3$: Three lines intersect at the point.
- $k = 4$: Four lines intersect at the point.
- $k = 5$: Five lines intersect at the point.

average connectivity:

$$c = \frac{1}{N} \sum_{i=1}^N k_i = \sum_{k \geq 0} P(k)k$$

$$C_i = \frac{\text{actual nr of links amongst the } k_i \text{ neighbours of } i}{\text{possible nr of links amongst the } k_i \text{ neighbours of } i}$$

- ★ distance between nodes (i, j) : ℓ_{ij}
length of the shortest path connecting nodes (i, j)
- distance distribution $\Pi(\ell)$: histogram of distances ℓ_{ij}
- mean path-length:

$$\bar{\ell} = \sum_{\ell \geq 0} \Pi(\ell) \ell$$

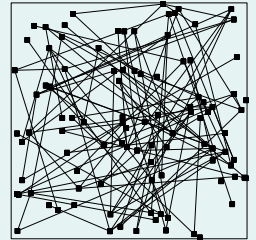
Examples

- Poissonnian (Erdos-Renyi) random networks
for each pair (i, j) : form a link with probability c/N

k_i random for all i

N large : $P(k) = c^k e^{-c}/k!$ $c = \sum_{k \geq 0} P(k)k$

$$\bar{\ell} \sim \log(N)$$



- ‘small-world’ networks’ (epidemics, etc)

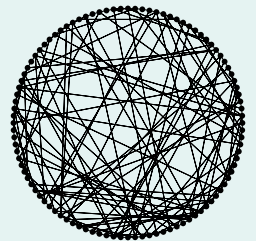
e.g. connect nearest neighbours on a ring

+
Poissonnian random graph

‘small world effect’:

due to even very small number of random links

- reduction of distances: $\bar{\ell} \sim \mathcal{O}(N) \rightarrow \bar{\ell} \sim \mathcal{O}(\log N)$
- greater robustness of processes against noise



complex network (definition in a nutshell)

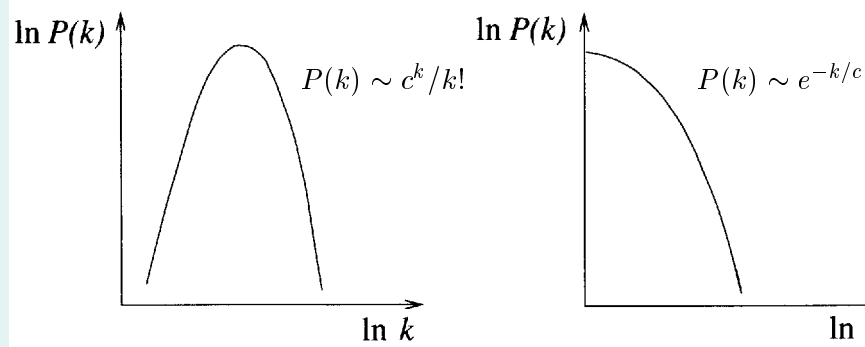
Simple network:

- degree distribution $P(k)$ decays faster than power law
- clustering coeff C_i independent of degrees k_i
- conventional path lengths $\bar{\ell} \sim \log(N)$

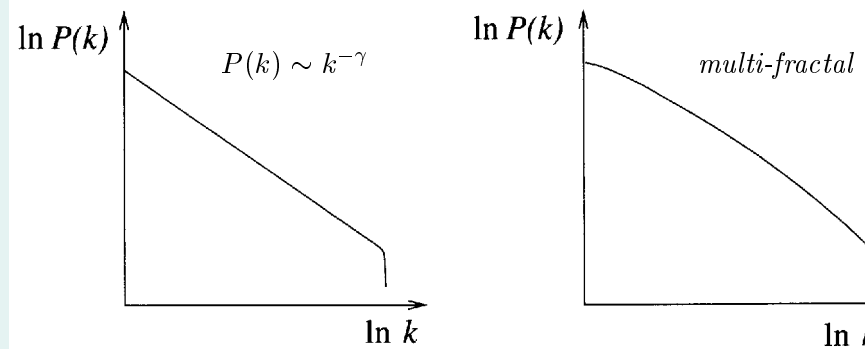
Complex ('scale-free') network:

- degree distribution $P(k)$ decays according to power law
- clustering coeff C_i positively correlated with degrees k_i
- shorter path lengths

simple:



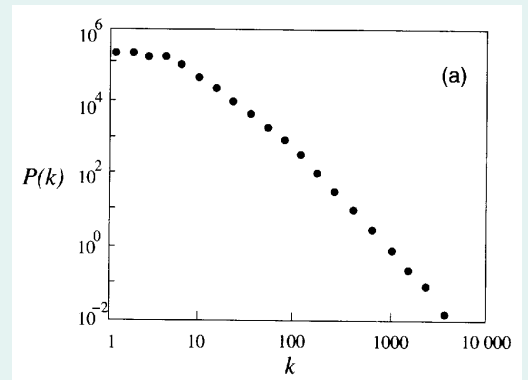
complex:



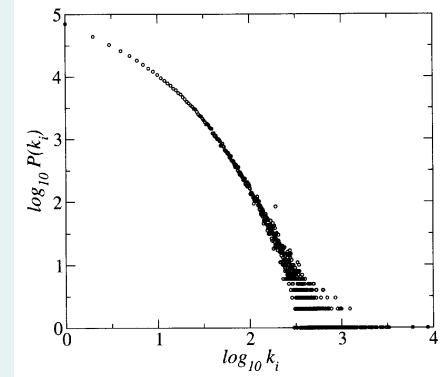
mechanism:
growth with preferential attachment

Social networks

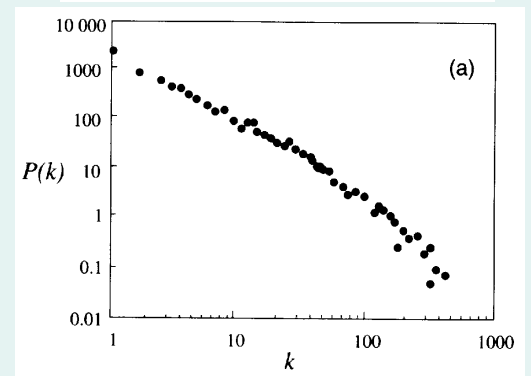
author networks:



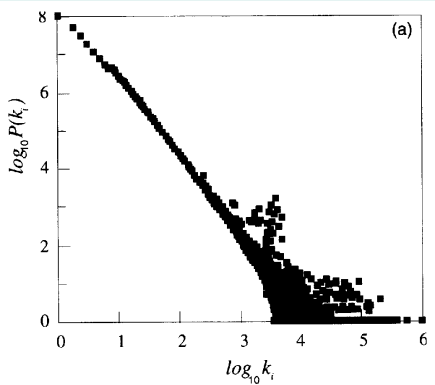
citation networks:



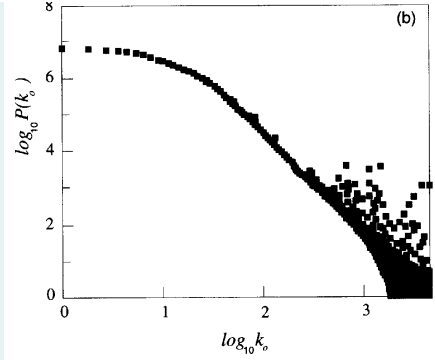
E-mail networks:



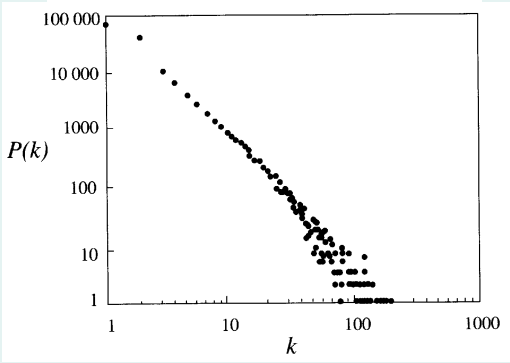
WWW *in-links*:



WWW *out-links*:

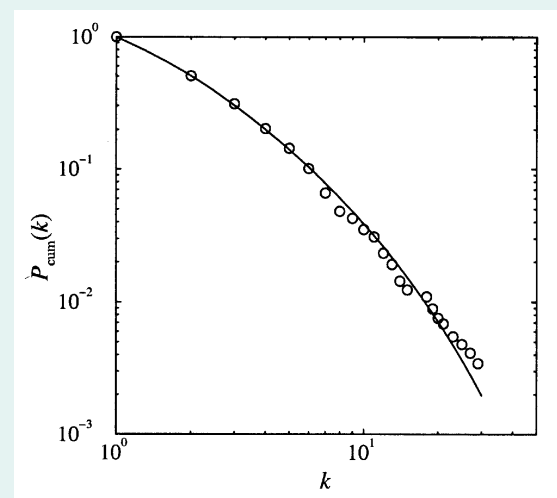
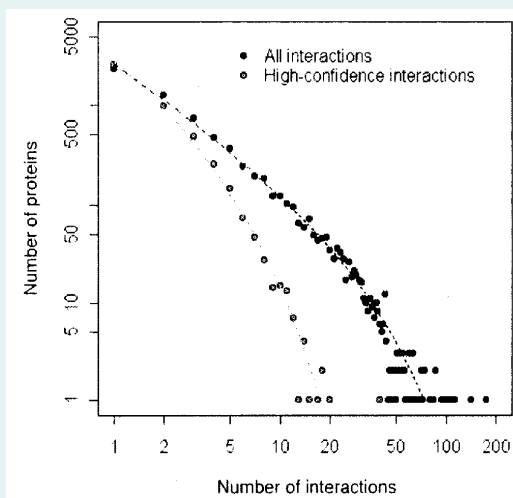
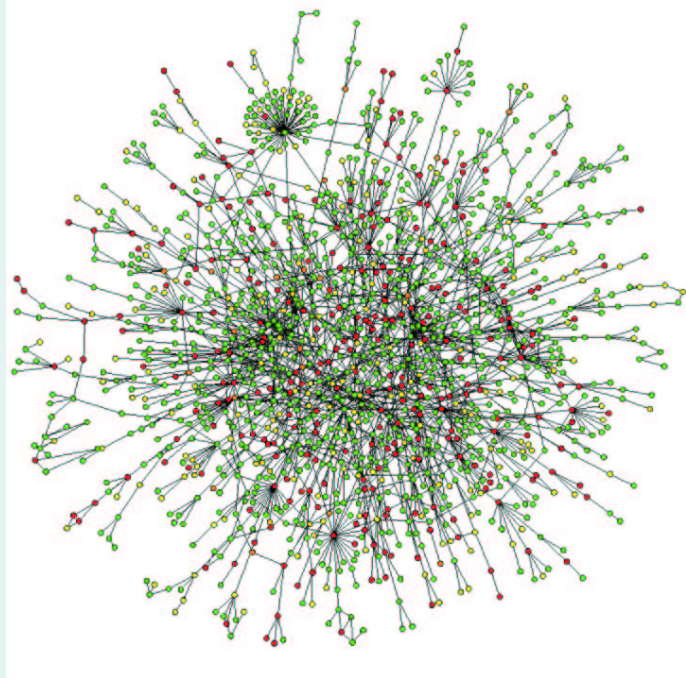


WWW *routers*:



Protein interaction networks

(*yeast two-hybrid method*)



Theory of many-particle systems: 'statistical mechanics'



Objective (Baxter):

'predict the relations between the observable macroscopic properties of the system, given only a knowledge of the microscopic forces between the components'

- equilibrium (± 1870)

$$\text{Prob}[\text{state}] = \frac{e^{-E(\text{state})/kT}}{\sum_{\text{states}} e^{-E/kT}} \quad \begin{array}{ll} E : & \text{energy} \\ T : & \text{temperature} \end{array}$$

e.g.

molecules \longrightarrow pressure/temp/volume phase diagrams, gas-liquid-solid transitions
atomic electrons \longrightarrow magnetism (ferro, anti-ferro, para)
cells in suspensions \longrightarrow blood rheology, visco-elastic properties

- non-equilibrium (± 1905)
- statistical mechanics of disordered (or complex) systems
 - ± 1975 : systems with large connectivity
 - ± 1990 : statics of systems with finite connectivity
 - ± 2002 : dynamics of systems with finite connectivity

Applicability of statistical mechanics – how large is large?

stat mech: finds macroscopic laws for $N \rightarrow \infty$

effects of finite N on macroscopic quantities:

- fluctuations around ‘infinite system’ values: $\Delta x/x \sim 1/\sqrt{N}$
- ‘escape’ time from ‘infinite system’ trajectories: $t_{\text{esc}} \sim e^N \tau$
(τ : typical microscopic time scale)

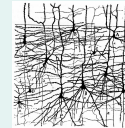
Example: $\tau \sim 10^{-15}$ sec, $N = 1000$

$\Delta x/x \sim 0.03$, $t_{\text{esc}} \sim 10^{400}$ sec

- **neural networks:**

$N \sim 10^4$ - 10^8 , $\langle k \rangle \sim 10^2$ - 10^4

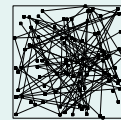
random (hippocampus) to regular (cerebellum)



- **immune networks:**

$N \sim 10^6$ - 10^7 , $\langle k \rangle \sim \text{small ?}$

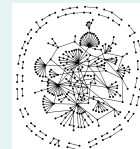
narrow distribution $P(k)$?



- **protein interaction networks:**

$N \sim 10^4$, $\langle k \rangle \sim 2 - 7$?

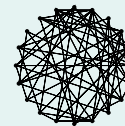
scale-free, complex (‘hub’ proteins, etc)



- **gene regulation networks:**

$N \sim 10^4$, $\langle k \rangle \sim 1$ - 10 ?

structure? complexity?



ANALYSIS OF STOCHASTIC PROCESSES ON LARGE RANDOM NETWORKS

state-of-the-art in statistical mechanics

Equilibrium methods

	<i>asymmetric</i>	<i>partially symm</i>	<i>symmetric</i>
$\langle k \rangle \sim N$	–	–	<i>ok</i>
$1 \ll \langle k \rangle \ll N$	–	–	<i>ok</i>
$\langle k \rangle \sim 1$	–	–	<i>hard</i>

Dynamical methods

	<i>asymmetric</i>	<i>partially symm</i>	<i>symmetric</i>
$\langle k \rangle \sim N$	<i>ok</i>	<i>hard</i>	<i>hard</i>
$1 \ll \langle k \rangle \ll N$	<i>ok</i>	<i>hard</i>	<i>hard</i>
$\langle k \rangle \sim 1$	<i>ok</i>	<i>–/hard</i>	<i>–/hard</i>

*mundane definition of complexity, at the workflow level ...
(for those who study stochastic processes on networks)*

Simple network:

connectivity $\langle k \rangle$ diverges as $N \rightarrow \infty$

Complex network:

connectivity $\langle k \rangle$ does not grow with N

The language of disordered systems theory

core problem: carrying out disorder averages
of macroscopic ensemble averages



replica trick/method (Hardy & Littlewood, 1934)

statics: ± 1975

dynamics: ± 1993

$$\begin{aligned}\left\langle \sum_x f(x, \text{dis}) P(x|y, \text{dis}) \right\rangle_{\text{dis}} &= \left\langle \frac{\sum_x f(x, \text{dis}) P(x, y|\text{dis})}{\sum_x P(x, y|\text{dis})} \right\rangle_{\text{dis}} \\ &= \lim_{n \rightarrow 0} \left\langle \sum_x f(x, \text{dis}) P(x, y|\text{dis}) \left[\sum_{x'} P(x', y|\text{dis}) \right]^{n-1} \right\rangle_{\text{dis}} \\ &= \lim_{n \rightarrow 0} \sum_{x_1, \dots, x_n} \langle f(x_1, \text{dis}) P(x_1, y|\text{dis}) \dots P(x_n, y|\text{dis}) \rangle_{\text{dis}}\end{aligned}$$

result mathematically equivalent to having
 n copies (replicas) of the system

- one disordered system \rightarrow n coupled homogeneous systems
- new forces between pairs and quartets of elements
- however: at the end $n \rightarrow 0$!

Dynamics: generating functional analysis

Interpret dynamics of N -particle system $\{\sigma_1(t), \dots, \sigma_N(t)\}$ as a ‘path’ of a single particle in an N -dimensional ‘world’

target:

generating functional

$$\overline{\mathcal{Z}[\psi]} = \langle \langle e^{i \int_0^t ds \sum_{i=1}^N \psi_i(s) \sigma_i(s)} \rangle_{\text{paths}} \rangle_{\text{disorder}}$$

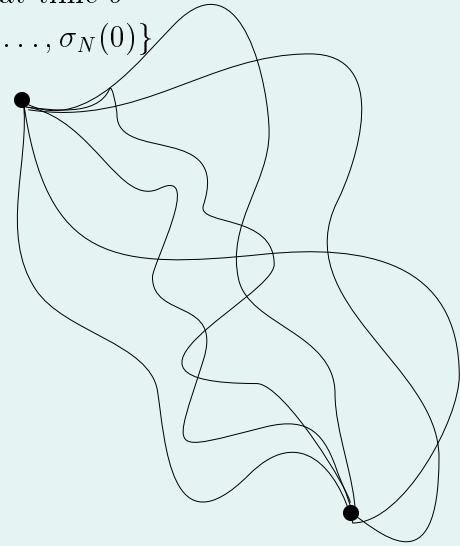
‘generates’ all relevant macroscopic multiple-time observables via (functional) differentiation
e.g.

$$\langle \langle \sigma_i(t) \rangle_{\text{paths}} \rangle_{\text{disorder}} = -i \lim_{\psi \rightarrow 0} \frac{\delta \overline{\mathcal{Z}[\psi]}}{\delta \psi_i(t)}$$

$$\langle \langle \sigma_i(t) \sigma_j(t') \rangle_{\text{paths}} \rangle_{\text{disorder}} = - \lim_{\psi \rightarrow 0} \frac{\delta^2 \overline{\mathcal{Z}[\psi]}}{\delta \psi_i(t) \delta \psi_j(t')}$$

- theory involving ‘path-integrals’
- disordered system \rightarrow non-disordered ‘effective’ particle
- new forces: non-trivial noise, retarded self-interaction

state at time 0
 $\{\sigma_1(0), \dots, \sigma_N(0)\}$



state at time t
 $\{\sigma_1(t), \dots, \sigma_N(t)\}$

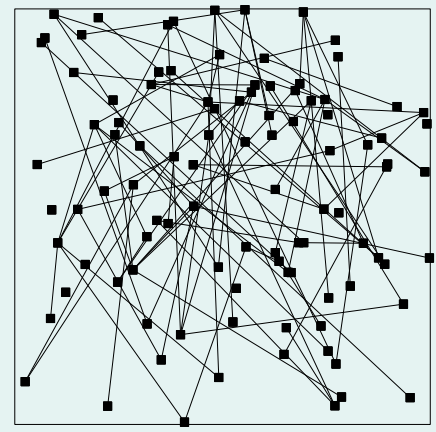
FINITE CONNECTIVITY

STATICS

N spins on random graph, $c_{ij} \in \{0, 1\}$

$$H = - \sum_{i < j} c_{ij} J_{ij} \sigma_i \sigma_j + \sum_i V(\sigma_i)$$

- $P(c_{ij}) = \frac{c}{N} \delta_{c_{ij}, 1} + (1 - \frac{c}{N}) \delta_{c_{ij}, 0}$, $c = \mathcal{O}(N^0)$
- indep random bonds J_{ij}
- disorder: $\{c_{ij}, J_{ij}\}$



$N = 100, c = 2$

Replica theory order parameters

Dependence on connectivity c
(average number of bonds/spin)

connectivity	variables	order param	RS ansatz
$c = N$	discrete	$\{q_{\alpha\beta}\}$	numbers, e.g. q
$c = N$	continuous	$\{q_{\alpha\beta}\}$	numbers, e.g. q
$1 \ll c \ll N$	discrete	$\{q_{\alpha\beta}\}$	numbers, e.g. q
$1 \ll c \ll N$	continuous	$\{q_{\alpha\beta}\}$	numbers, e.g. q
$c = \mathcal{O}(1)$	discrete	$P(\sigma_1, \dots, \sigma_n)$	functions, $P(h)$
$c = \mathcal{O}(1)$	continuous	$P(\sigma_1, \dots, \sigma_n)$	functionals, $W[\{P\}]$

CASE STUDY – STATICS

N Kuramoto-type oscillators,
 $\phi_i \in [0, 2\pi]$, $\boldsymbol{\phi} = (\phi_1, \dots, \phi_N)$

$$H(\boldsymbol{\phi}) = -J \sum_{i < j} c_{ij} \cos(\phi_i - \phi_j - \omega_{ij}), \quad J > 0$$

- *network connectivity: random variables* $c_{ij} \in \{0, 1\}$
finite connectivity regime: $k_i = \sum_j c_{ij} = \mathcal{O}(N^0)$
degree distribution: $p_k = N^{-1} \sum_i \delta_{k, k_i}$

$$P(c_{ij}) = \frac{c}{N} \delta_{c_{ij}, 1} + \left(1 - \frac{c}{N}\right) \delta_{c_{ij}, 0} \quad \text{for all } i < j$$

$$c = \mathcal{O}(N^0)$$

$$p_k = e^{-c} c^k / k! \quad \text{for } N \rightarrow \infty$$

- *random interactions between oscillators:* $\omega_{ij} \in [0, 2\pi]$
independently drawn from $P(\omega)$, *with* $P(-\omega) = P(\omega)$
e.g.

$$\begin{aligned} \omega_{ij} = 0 & \rightarrow \text{synchronization of oscillators } (i, j) \\ \omega_{ij} = \pi & \rightarrow \text{antisynchronization of oscillators } (i, j) \end{aligned}$$

Strategy

- calculate disorder-averaged free energy per oscillator

$$\bar{f} = - \lim_{N \rightarrow \infty} (\beta N)^{-1} \overline{\log Z}, \quad Z = \int d\boldsymbol{\phi} e^{-\beta H(\boldsymbol{\phi})}$$

$\overline{\cdot \cdot \cdot}$: average over $\{c_{ij}, \omega_{ij}\}$

- use replica identity

$$\overline{\log Z} = \lim_{n \rightarrow 0} n^{-1} \log \overline{Z^n}$$

- evaluate $\overline{Z^n}$ for integer n , in terms of n system copies, and evaluate disorder average first:

$$\overline{Z^n} = \int d\boldsymbol{\phi}^1 \dots d\boldsymbol{\phi}^n \overline{e^{-\beta \sum_{\alpha=1}^n H(\boldsymbol{\phi}^\alpha)}}$$

- In result:

exchange the limits $N \rightarrow \infty$ and $n \rightarrow 0$

$$\begin{aligned} \bar{f} &= - \lim_{N \rightarrow \infty} (\beta N)^{-1} \overline{\log Z} \\ &= - \lim_{N \rightarrow \infty} (\beta N)^{-1} \lim_{n \rightarrow 0} n^{-1} \log \overline{Z^n} \\ &= - \lim_{N \rightarrow \infty} (\beta N)^{-1} \lim_{n \rightarrow 0} n^{-1} \log \int d\boldsymbol{\phi}^1 \dots d\boldsymbol{\phi}^n \overline{e^{-\beta \sum_{\alpha=1}^n H(\boldsymbol{\phi}^\alpha)}} \\ &= \lim_{n \rightarrow 0} n^{-1} \left\{ - \lim_{N \rightarrow \infty} (\beta N)^{-1} \log \int d\boldsymbol{\phi}^1 \dots d\boldsymbol{\phi}^n \overline{e^{-\beta \sum_{\alpha=1}^n H(\boldsymbol{\phi}^\alpha)}} \right\} \end{aligned}$$

Replica calculation of the disorder-averaged free energy

Disorder-averaged free energy per oscillator:

$$\bar{f} = \lim_{n \rightarrow 0} \frac{1}{n} \left\{ - \lim_{N \rightarrow \infty} \frac{1}{\beta N} \log \int d\phi^1 \dots d\phi^n \overline{e^{-\beta \sum_{\alpha=1}^n H(\phi^\alpha)}} \right\}$$

Disorder average:

$$\begin{aligned} \overline{e^{-\beta \sum_{\alpha=1}^n H(\phi^\alpha)}} &= \prod_{i < j} \overline{e^{\beta J \sum_{\alpha=1}^n c_{ij} \cos(\phi_i^\alpha - \phi_j^\alpha - \omega_{ij})}} \\ &= \exp \left\{ \frac{c}{2N} \sum_{ij} \left[\int d\omega P(\omega) e^{\beta J \sum_{\alpha=1}^n \cos(\phi_i^\alpha - \phi_j^\alpha - \omega)} - 1 \right] + \mathcal{O}(N^0) \right\} \end{aligned}$$

replica-order parameter:

$$\phi = (\phi_1, \dots, \phi_n), \quad \phi_i = (\phi_i^1, \dots, \phi_i^n)$$

$$P(\phi) = \frac{1}{N} \sum_i \delta[\phi - \phi_i]$$

$$\overline{e^{-\beta \sum_{\alpha=1}^n H(\phi^\alpha)}} = \exp \left\{ \frac{cN}{2} \int d\phi d\phi' P(\phi) P(\phi') \left[\int d\omega P(\omega) e^{\beta J \sum_{\alpha} \cos(\phi_{\alpha} - \phi'_{\alpha} - \omega)} - 1 \right] + \mathcal{O}(N^0) \right\}$$

minor technicalities

- discretize domain $[0, 2\pi]^n$ of ϕ
- insert appropriate functional δ -distributions to isolate order parameter function $P(\phi)$
integral representations: conjugate functions $\hat{P}(\phi)$
- take continuum limit for domain $[0, 2\pi]^n$ of ϕ ,
gives path integral measure:

$$\prod_{\phi} [dP(\phi) d\hat{P}(\phi) / 2\pi] = \{dP d\hat{P}\}$$

$$\begin{aligned} \overline{f} = & - \lim_{n \rightarrow 0} \lim_{N \rightarrow \infty} \frac{1}{\beta N n} \log \int \{dP d\hat{P}\} e^{iN \int d\phi P(\phi) \hat{P}(\phi) + N \log \int d\phi e^{-i\hat{P}(\phi)}} \\ & \times \exp \left\{ \frac{cN}{2} \int d\phi d\phi' P(\phi) P(\phi') \left[\int d\omega P(\omega) e^{\beta J \sum_{\alpha} \cos(\phi_{\alpha} - \phi'_{\alpha} - \omega)} - 1 \right] \right\} \end{aligned}$$

$N \rightarrow \infty$:

$$\begin{aligned} \overline{f} = & - \lim_{n \rightarrow 0} \frac{1}{\beta n} \text{extr}_{\{P, \hat{P}\}} \left\{ i \int d\phi P(\phi) \hat{P}(\phi) + \log \int d\phi e^{-i\hat{P}(\phi)} \right. \\ & \left. + \frac{1}{2} c \int d\phi d\phi' P(\phi) P(\phi') \left[\int d\omega P(\omega) e^{\beta J \sum_{\alpha} \cos(\phi_{\alpha} - \phi'_{\alpha} - \omega)} - 1 \right] \right\} \end{aligned}$$

saddle-point eqns:

$$P(\phi) = \frac{e^c \int d\phi' P(\phi') [\int d\omega P(\omega) e^{\beta J \sum_{\alpha} \cos(\phi_{\alpha} - \phi'_{\alpha} - \omega)} - 1]}{\int d\phi' e^c \int d\phi'' P(\phi'') [\int d\omega P(\omega) e^{\beta J \sum_{\alpha} \cos(\phi'_{\alpha} - \phi''_{\alpha} - \omega)} - 1]}$$

Replica symmetric theory

$$P(\phi_1, \dots, \phi_n) = \frac{1}{N} \sum_i \prod_{\alpha=1}^n \delta[\phi_\alpha - \phi_i^\alpha]$$

next:

limit $n \rightarrow 0$ in saddle-point eqns

RS ansatz for continuous variables?

$$P_{\text{RS}}(\phi_1, \dots, \phi_n) = \int \{dP\} W[\{P\}] \prod_{\alpha} P(\phi_{\alpha})$$

RS order parameter:

functional measure $W[\{P\}]$

interpretation:

$$\int \{dP\} W[\{P\}] \prod_{\alpha} \left[\int d\phi P(\phi) f_{\alpha}(\phi) \right] = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_i \overline{\prod_{\alpha} \langle f_{\alpha}(\phi_i) \rangle}$$

RS saddle-point eqns:

$$\begin{aligned} W[\{P\}] &= \sum_{k \geq 0} \frac{e^{-c} c^k}{k!} \int \prod_{\ell \leq k} [\{dP_{\ell}\} W[\{P_{\ell}\}] d\omega_{\ell} P(\omega_{\ell})] \\ &\times \prod_{\phi \in [0, 2\pi]} \delta \left[P(\phi) - \frac{\prod_{\ell=1}^k \int d\phi' P_{\ell}(\phi') e^{\beta J \cos(\phi - \phi' - \omega_{\ell})}}{\int d\phi'' \prod_{\ell=1}^k \int d\phi' P_{\ell}(\phi') e^{\beta J \cos(\phi'' - \phi' - \omega_{\ell})}} \right] \end{aligned}$$

PHASE DIAGRAMS

bifurcation analysis
of order parameter eqn:

$$W[\{P\}] = \sum_{k \geq 0} p_k \int \prod_{\ell \leq k} [\{dP_\ell\} W[\{P_\ell\}] d\omega_\ell P(\omega_\ell)] \\ \times \prod_{\phi \in [0, 2\pi]} \delta \left[P(\phi) - \frac{\prod_{\ell=1}^k \int d\phi' P_\ell(\phi') e^{\beta J \cos(\phi - \phi' - \omega_\ell)}}{\int d\phi'' \prod_{\ell=1}^k \int d\phi' P_\ell(\phi') e^{\beta J \cos(\phi'' - \phi' - \omega_\ell)}} \right]$$

$\beta = 0$:

$$\text{paramagnetic state : } W[\{P\}] = \prod_{\phi \in [0, 2\pi]} \delta \left[P(\phi) - \frac{1}{2\pi} \right]$$

phase transitions

Continuous bifurcations away from paramagnetic state
located by Guzai (i.e. functional moment) expansion

- transform:

$$P(\phi) \rightarrow \frac{1}{2\pi} + \Delta(\phi), \quad \int_0^{2\pi} d\phi \Delta(\phi) = 0, \quad W[\{P\}] \rightarrow \tilde{W}[\{\Delta\}]$$

- expand saddle-point eqns
in functional moments

$$\int \{d\Delta\} \tilde{W}[\{\Delta\}] \Delta(\phi_1) \dots \Delta(\phi_r)$$

- assume: close to continuous bifurcation
 $\exists \epsilon \ll 1$ such that

$$\int \{d\Delta\} \tilde{W}[\{\Delta\}] \Delta(\phi_1) \dots \Delta(\phi_r) = \mathcal{O}(\epsilon^r)$$

Lowest order bifurcation ϵ^1

$$\Psi(\phi) = \frac{c}{2\pi I_0(\beta J)} \int_0^{2\pi} d\phi' \int d\omega P(\omega) e^{\beta J \cos(\phi - \phi' - \omega)} \Psi(\phi') \quad \int_0^{2\pi} d\phi \Psi(\phi) = 0$$

$$c = \sum_k p_k k$$

$I_k(z)$: modified Bessel functions

- solution: Fourier modes $\Psi(\phi) = e^{ik\phi}$
transition:

$$c = \min_{k>0} \left\{ \frac{I_k(\beta J)}{I_0(\beta J)} \int_{-\pi}^{\pi} d\omega P(\omega) \cos(k\omega) \right\}^{-1}$$

- bifurcating state:

$$\lim_{N \rightarrow \infty} \frac{1}{N} \sum_i \overline{\left\langle \begin{pmatrix} \cos(\phi_i) \\ \sin(\phi_i) \end{pmatrix} \right\rangle} = \frac{1}{2} \epsilon \delta_{k1} \begin{pmatrix} \cos(\lambda) \\ \sin(\lambda) \end{pmatrix} + \dots$$

- $k = 1$: global synchronization
 $k > 1$: no global synchronization

$$\begin{aligned} \text{P} \rightarrow \text{F} : \quad c &= \left\{ \frac{I_1(\beta J)}{I_0(\beta J)} \int_{-\pi}^{\pi} d\omega P(\omega) \cos(\omega) \right\}^{-1} \\ \text{KT} : \quad c &= \min_{k>1} \left\{ \frac{I_k(\beta J)}{I_0(\beta J)} \int_{-\pi}^{\pi} d\omega P(\omega) \cos(k\omega) \right\}^{-1} \end{aligned}$$

Lowest order bifurcation ϵ^2

$$\Psi(\phi_1, \phi_2) = c \int \frac{d\phi'_1 d\phi'_2}{[2\pi I_0(\beta J)]^2} \left[\int d\omega P(\omega) e^{\beta J \cos(\phi_1 - \phi'_1 - \omega) + \beta J \cos(\phi_2 - \phi'_2 - \omega)} \right] \Psi(\phi'_1, \phi'_2)$$

$$\int d\phi_1 \Psi(\phi_1, \phi_2) = \int d\phi_2 \Psi(\phi_1, \phi_2) = 0$$

- *solution: Fourier modes* $\Psi(\phi_1, \phi_2) = e^{i(k_1 \phi_1 + k_2 \phi_2)}$
transition:

$$c = \min_{k_1 \neq 0, k_2 \neq 0} \left\{ \frac{I_{k_1}(\beta J) I_{k_2}(\beta J)}{I_0^2(\beta J)} \int d\omega P(\omega) \cos[(k_1 + k_2)\omega] \right\}^{-1}$$

min: $k_1 = -k_2 = 1$

$$P \rightarrow SG : \quad c = I_0^2(\beta J) / I_1^2(\beta J)$$

- *bifurcating state: no global synchronization, yet*

$$\lim_{N \rightarrow \infty} \frac{1}{N} \sum_i \left[\overline{\langle \cos(\phi_i) \rangle^2} + \overline{\langle \sin(\phi_i) \rangle^2} \right] > 0$$

- *$P \rightarrow SG$ bifurcation precedes $P \rightarrow KT$*
physical transitions away from P : $P \rightarrow F, \quad P \rightarrow SG$

Phase diagrams

phases:

P: paramagnetic state, no freezing of oscillator phases

F: synchronized state, coherent oscillations

SG: spin-glass state, frozen relative phases but incoherent

transitions:

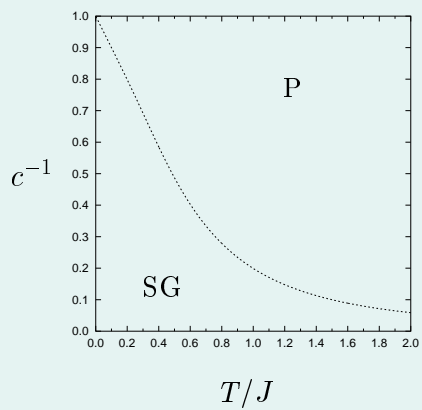
$$P \rightarrow F : \quad c^{-1} = [I_1(\beta J)/I_0(\beta J)] \int_{-\pi}^{\pi} d\omega \, P(\omega) \cos(\omega)$$

$$P \rightarrow SG : \quad c^{-1} = [I_1(\beta J)/I_0(\beta J)]^2$$

$$F \rightarrow SG : \quad \text{cannot yet calculate, Parisi–Toulouse hypothesis ?}$$

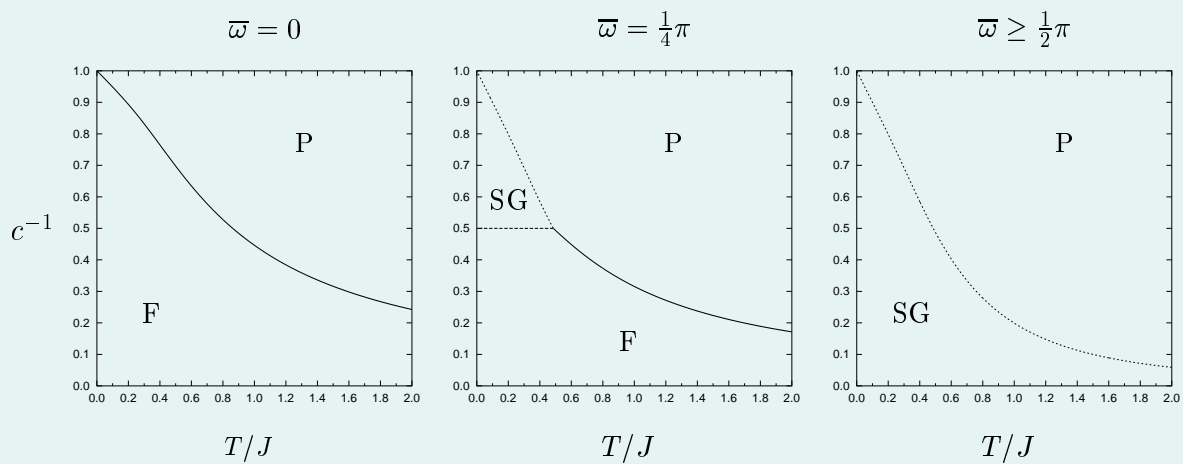
Example:

$$P(\omega) = 1/2\pi$$



Example:

$$P(\omega) = \frac{1}{2}\delta(\omega - \bar{\omega}) + \frac{1}{2}\delta(\omega + \bar{\omega})$$



THEORY VERSUS SIMULATIONS

*Numerical solution of order parameter equations
(via truncated parametrizations) versus simulations*

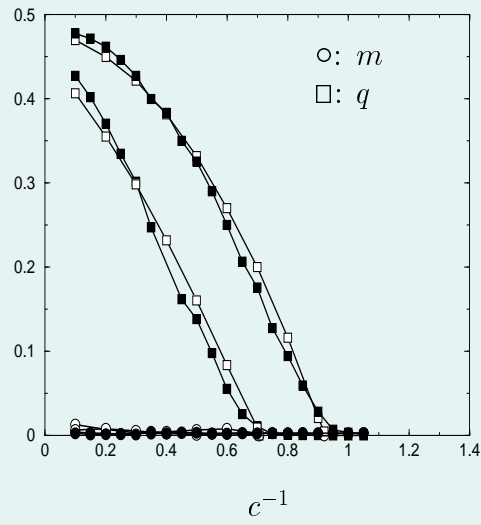
$$m^2 = \left[\frac{1}{N} \sum_i \overline{\langle \cos(\phi_i) \rangle} \right]^2 + \left[\frac{1}{N} \sum_i \overline{\langle \sin(\phi_i) \rangle} \right]^2$$

$$q = \frac{1}{2N} \sum_i \left[\overline{\langle \cos(\phi_i) \rangle^2} + \overline{\langle \sin(\phi_i) \rangle^2} \right]$$

P	:	$q = m = 0$
F	:	$q > 0, m > 0$
SG	:	$q > 0, m = 0$

Example:

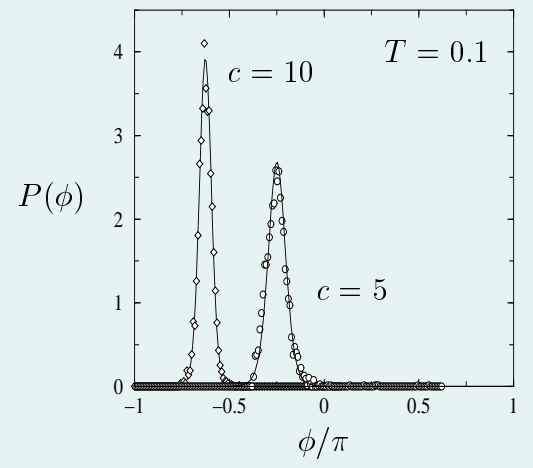
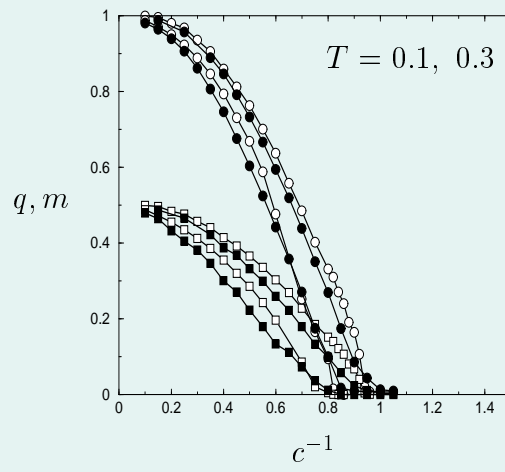
$$P(\omega) = 1/2\pi$$



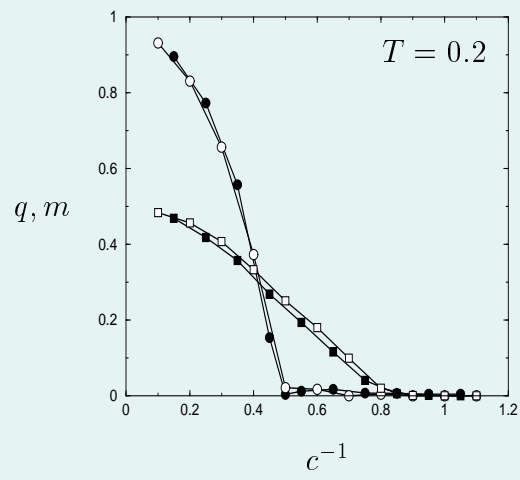
upper: $T = 0.1$

lower: $T = 0.3$

Example:
 $P(\omega) = \delta(\omega)$



Example:
 $P(\omega) = \frac{1}{2}\delta(\omega - \frac{\pi}{4}) + \frac{1}{2}\delta(\omega + \frac{\pi}{4})$



*confirms Parisi-Toulouse
for $F \rightarrow SG$ transition*

Example: attractor neural networks on scale-free graphs

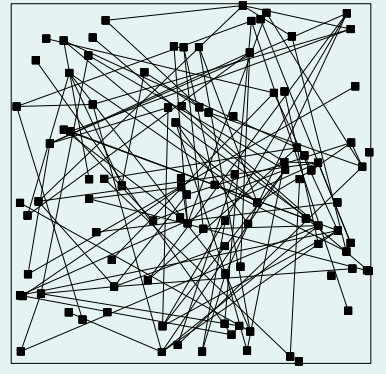
neurons: $\sigma_i \in \{-1, 1\}$

$$H = - \sum_{i < j} \sigma_i c_{ij} J_{ij} \sigma_j, \quad J_{ij} = \frac{1}{\langle k \rangle} \phi \left(\sum_{\mu=1}^p \xi_i^\mu \xi_j^\mu \right)$$

p stored patterns: $(\xi_1^\mu, \dots, \xi_N^\mu)$

$$\phi(-x) = -\phi(x), \quad \phi(1) = 1$$

e.g. Hopfield model on graph: $\phi(x) = x$



random graph:

$$\mathcal{P}(\mathbf{c}) = \frac{\left[\prod_{i < j} \mathcal{P}(c_{ij}) \delta_{c_{ij}, c_{ji}} \right] \left[\prod_i \delta_{k_i, \sum_{j \neq i} c_{ij}} \right]}{\sum_{\mathbf{c}'} \left[\prod_{i < j} \mathcal{P}(c'_{ij}) \delta_{c'_{ij}, c'_{ji}} \right] \left[\prod_i \delta_{k_i, \sum_{j \neq i} c'_{ij}} \right]}$$

$$\mathcal{P}(c_{ij}) = \frac{\langle k \rangle}{N} \delta_{c_{ij}, 1} + \left(1 - \frac{\langle k \rangle}{N} \right) \delta_{c_{ij}, 0}$$

degree distribution:

$$\lim_{N \rightarrow \infty} \frac{1}{N} \sum_i \delta_{k, k_i} = P(k)$$

Phase diagram

based on *finite connectivity RS replica theory*
& *sublattice partitioning (for random patterns)*

$$P \rightarrow R : \quad \frac{\langle k^2 \rangle - \langle k \rangle}{\langle k \rangle} 2^{-p} \sum_{n=0}^p \binom{p}{n} \left(1 - \frac{2n}{p}\right) \tanh \left[\frac{\beta \phi(p-2n)}{\langle k \rangle} \right] = 1$$

$$P \rightarrow SG : \quad \frac{\langle k^2 \rangle - \langle k \rangle}{\langle k \rangle} 2^{-p} \sum_{n=0}^p \binom{p}{n} \tanh^2 \left[\frac{\beta \phi(p-2n)}{\langle k \rangle} \right] = 1$$

Noise resilience of scale-free networks

Single pattern retrieval phase boundary:

$$\beta_{\text{crit}} = -\frac{\langle k \rangle}{2} \log \left(1 - \frac{2\langle k \rangle}{\langle k^2 \rangle} \right)$$

- *simple Poissonnian network* $P(k) = e^{-c} c^k / k!$:
 $\langle k \rangle = c, \quad \langle k^2 \rangle = c^2 + c$

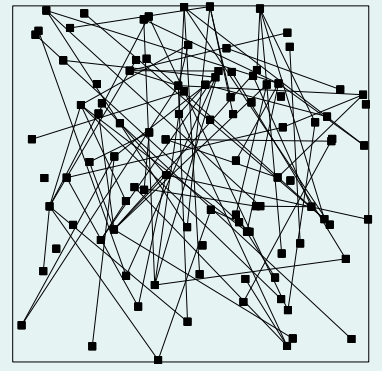
$$T_{\text{crit}} = \frac{1}{2} c \log \left(\frac{c+1}{c-1} \right) \quad \begin{array}{ll} c = 1 : & T_{\text{crit}} = 0 \\ c = 2 : & T_{\text{crit}} = 1/\log 3 \\ c \rightarrow \infty : & T_{\text{crit}} = 1 \end{array}$$

- *scale-free network* $P(k) \sim k^{-\gamma}, \quad \gamma > 2$:
if $\gamma \leq 3$: $\langle k^2 \rangle = \infty$

$$T_{\text{crit}} = \infty, \quad \text{order at any noise level, for any } c > 0 !$$

Example: parallel dynamics on finitely connected random graphs

*finitely connected Ising model with
parallel stochastic dynamics:*



$$p_{t+1}(\boldsymbol{\sigma}) = \sum_{\boldsymbol{\sigma}'} W_t[\boldsymbol{\sigma}; \boldsymbol{\sigma}'] p_t(\boldsymbol{\sigma}')$$

$$W_t[\boldsymbol{\sigma}; \boldsymbol{\sigma}'] = \prod_i \frac{e^{\beta \sigma_i h_i(\boldsymbol{\sigma}'; t)}}{2 \cosh[\beta h_i(\boldsymbol{\sigma}'; t)]}$$

local fields:

$$h_i(\boldsymbol{\sigma}; t) = \sum_{j \neq i} c_{ij} J_{ij} \sigma_j + \theta(t)$$

controlled symmetry:

$$\begin{aligned} i < j : \quad & \text{Prob}(c_{ij}) = W(c_{ij}) \\ i > j : \quad & \text{Prob}(c_{ij}) = \epsilon_1 \delta_{c_{ij}, c_{ji}} + (1 - \epsilon_1) W(c_{ij}) \\ i < j : \quad & \text{Prob}(J_{ij}) = P(J_{ij}) \\ i > j : \quad & \text{Prob}(J_{ij}) = \epsilon_2 \delta[J_{ij} - J_{ji}] + (1 - \epsilon_2) P(J_{ij}) \end{aligned}$$

$$W(x) = \frac{c}{N} \delta_{x,1} + (1 - \frac{c}{N}) \delta_{x,0} \quad c = \mathcal{O}(N^0)$$

*detailed balance &
equil stat mech:*

$$\epsilon_1 = \epsilon_2 = 1$$

effective single spin problem

$P(\boldsymbol{\sigma}|\boldsymbol{\theta})$: *fraction of sites i which exhibit*
 a single spin path $\boldsymbol{\sigma} = (\sigma(0), \sigma(1), \sigma(2), \dots)$
 given a field path $\boldsymbol{\theta} = (\theta(0), \theta(1), \theta(2), \dots)$

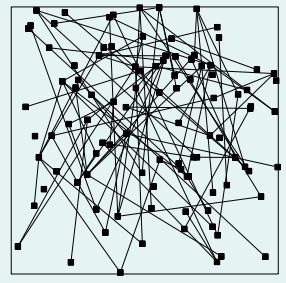
$$\begin{aligned}
 P(\boldsymbol{\sigma}|\boldsymbol{\theta}) = & p_0(\sigma(0))e^{-c} \left\{ \prod_t \left[\frac{e^{\beta\sigma(t+1)\theta(t)}}{2 \cosh[\beta\theta(t)]} \right] + \sum_{k>0} \frac{c^k}{k!} \int dJ_1 P(J_1) \dots dJ_k P(J_k) \sum_{\boldsymbol{\sigma}'_1 \dots \boldsymbol{\sigma}'_k} \right. \\
 & \times \prod_{\ell=1}^k \left[(1-\epsilon_1) P(\boldsymbol{\sigma}'_\ell | \mathbf{0}) + \epsilon_1 [\epsilon_2 P(\boldsymbol{\sigma}'_\ell | J_\ell \boldsymbol{\sigma}) + (1-\epsilon_2) \langle P(\boldsymbol{\sigma}'_\ell | J' \boldsymbol{\sigma}) \rangle_{J'}] \right] \\
 & \left. \times \prod_t \frac{e^{\beta\sigma(t+1)[\theta(t) + \sum_{\ell \leq k} J_\ell \sigma'_\ell(t)]}}{2 \cosh[\beta[\theta(t) + \sum_{\ell \leq k} J_\ell \sigma'_\ell(t)]]} \right\}
 \end{aligned}$$

$\epsilon_1 \in [0, 1]$: *graph symmetry*

$\epsilon_2 \in [0, 1]$: *bond value symmetry*

DYNAMICS

DYNAMICAL REPLICA METHOD



$$\begin{aligned}\frac{d}{dt}p_t(\boldsymbol{\sigma}) &= \sum_{k=1}^N [p_t(F_k \boldsymbol{\sigma}) w_k(F_k \boldsymbol{\sigma}) - p_t(\boldsymbol{\sigma}) w_k(\boldsymbol{\sigma})] \\ F_k \boldsymbol{\sigma} &= (\sigma_1, \dots, -\sigma_k, \dots, \sigma_N) \\ w_k(\boldsymbol{\sigma}) &= \frac{1}{2} \{1 - \sigma_k \tanh[\beta h_k(\boldsymbol{\sigma})]\} \quad h_i(\boldsymbol{\sigma}) = \sum_{j \neq i} c_{ij} J_{ij} s_j + \theta\end{aligned}$$

macroscopic variables:

$$\begin{aligned}\text{average activity} & \quad m(\boldsymbol{\sigma}) = N^{-1} \sum_i s_i \\ \text{and internal energy} & \quad e(\boldsymbol{\sigma}) = N^{-1} \sum_{i < j} c_{ij} J_{ij} s_i s_j\end{aligned}$$

exact macroscopic laws:

$$\begin{aligned}\frac{d}{dt}m &= -m + \int dh \, D_t(h|m, e) \tanh(\beta h) \\ \frac{d}{dt}e &= -2e - \int dh \, D_t(h|m, e) h \tanh(\beta h)\end{aligned}$$

$$D_t(h|m, e) = \lim_{N \rightarrow \infty} \left\langle \sum_{\boldsymbol{\sigma}} p_t(\boldsymbol{\sigma}|m, e) \frac{1}{N} \sum_{i=1}^N \delta[h - h_i(\boldsymbol{\sigma})] \right\rangle_{\text{disorder}}$$

dynamical replica method:

- assume macroscopic laws are self-averaging
- approximate in macroscopic laws: $p_t(\boldsymbol{\sigma}|m, e) \rightarrow p(\boldsymbol{\sigma}|m, e)$
(maximum entropy)

$$p(\boldsymbol{\sigma}|m, e) = \frac{\delta[m - m(\boldsymbol{\sigma})]\delta[e - e(\boldsymbol{\sigma})]}{\sum_{\boldsymbol{\sigma}'} \delta[m - m(\boldsymbol{\sigma}')] \delta[e - e(\boldsymbol{\sigma}')]}$$

- use replica identity for graph & bond disorder averages

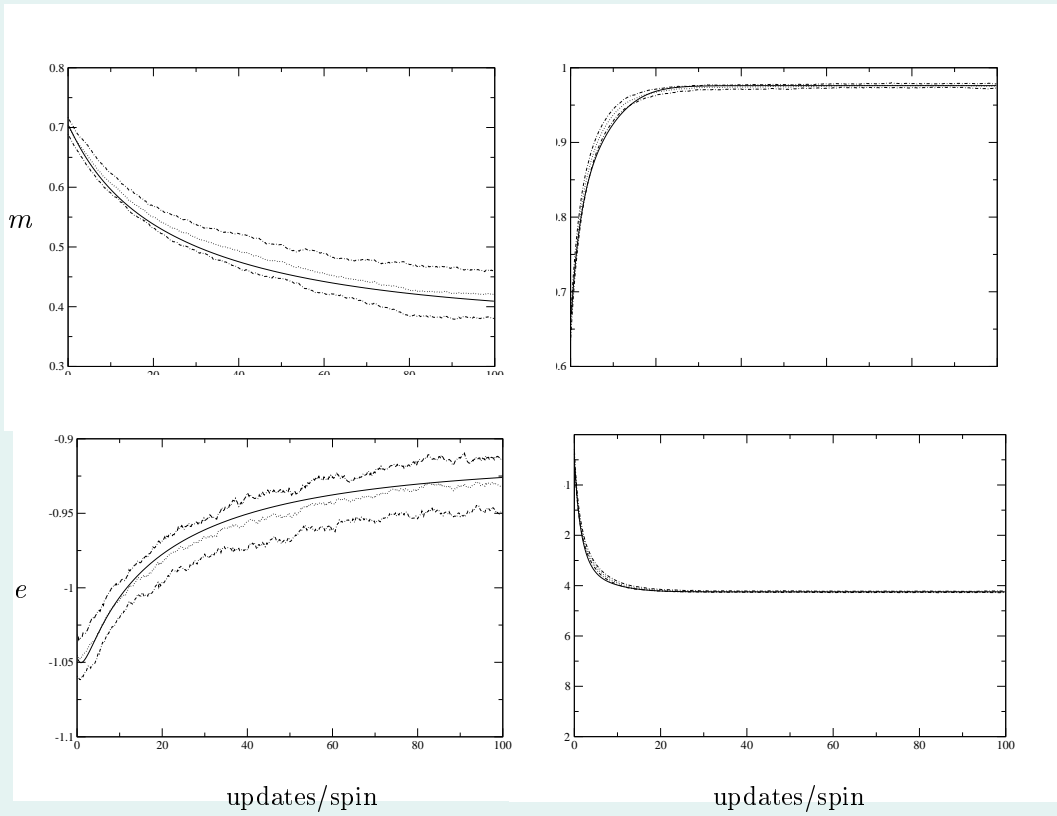
resulting closed laws:

$$\begin{aligned} \frac{d}{dt}m &= -m + \int dh \, D(h|m, e) \tanh(\beta h) \\ \frac{d}{dt}e &= -2e - \int dh \, D(h|m, e) h \tanh(\beta h) \end{aligned}$$

$$\begin{aligned} D(h|m, e) &= \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{i=1}^N \left\langle \sum_{\boldsymbol{\sigma}} p(\boldsymbol{\sigma}|m, e) \delta[h - h_i(\boldsymbol{\sigma})] \right\rangle_{\text{disorder}} \\ &= \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{i=1}^N \left\langle \frac{\sum_{\boldsymbol{\sigma}} \delta[m - m(\boldsymbol{\sigma})] \delta[e - e(\boldsymbol{\sigma})] \delta[h - h_i(\boldsymbol{\sigma})]}{\sum_{\boldsymbol{\sigma}} \delta[m - m(\boldsymbol{\sigma})] \delta[e - e(\boldsymbol{\sigma})]} \right\rangle_{\text{disorder}} \end{aligned}$$

random bonds, uniform degrees

$$P(k) = \delta_{k,3} \quad Q(J) = \eta\delta(J-1) + (1-\eta)\delta(J+1)$$

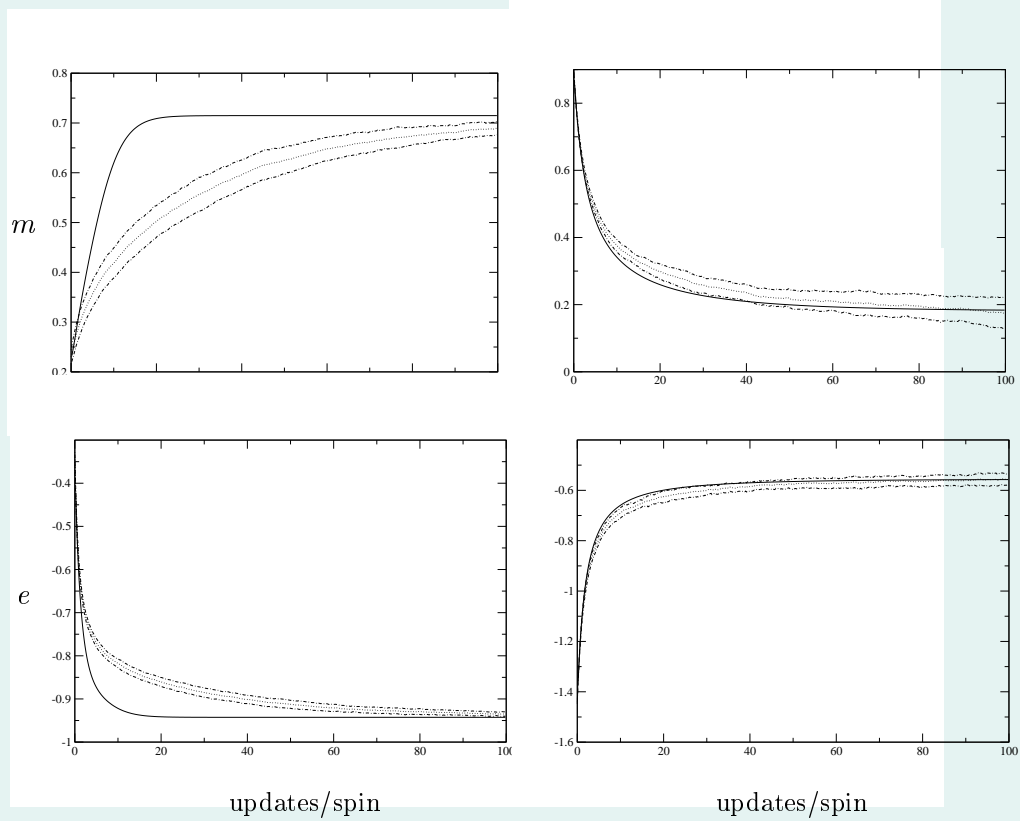


$$\eta = 0.95, \beta = 0.65$$

$$\eta = 0.97, \beta = 1.2$$

Poissonian random degrees, uniform bonds

$$P(k) = e^{-c} c^k / k!$$



$c = 2$

$c = 3$

SUMMARY

- *In biology one finds many instances of process control by large random and/or complex interaction networks*
(e.g. neural networks, immune networks, protein networks, gene regulation networks, ...)
- *Except perhaps for neural networks, most such networks are of the finite connectivity type.*
(large number N of nodes, finite number of links k_i per node)
- *In the mathematical analysis of stochastic processes on random and/or complex networks the regime of finite connectivity is the most demanding*
- *The latter regime is one of increased research activity in disordered systems theory. We are now beginning to acquire the necessary mathematical tools to solve both statics and dynamics.*
 - equilibrium replica theory
 - cavity techniques
 - diagonalization of replicated transfer matrices
 - generating functional analysis
 - dynamical replica theory

The GUZAI Initiative (2003–present)



ACC Coolen, JPL Hatchett, T Nikolettopoulos, I Perez-Castillo,
CJ Perez-Vicente, NS Skantzos, B Wemmenhove

statics

- *Finite connectivity attractor neural networks.* *J. Phys. A* 36 (2003) 9617
- *The Little-Hopfield model on a sparse random graph.* *J. Phys. A* 37 (2004) 9087
- *Analytic solution of attractor neural networks on scale-free graphs.* *J. Phys. A* 37 (2004) 8789
- *Replicated transfer matrix analysis of Ising spin models on ‘small world’ lattices.* *J. Phys. A* 37 (2004) 6455
- *Finitely connected vector spin systems with random matrix interactions.* preprint cond-mat/0504690

dynamics

- *Parallel dynamics of disordered Ising spin systems on finitely connected random graphs.* *J. Phys. A* 37 (2004) 6201
- *Dynamical replica analysis of disordered Ising spin systems on finitely connected random graphs.* preprint cond-mat/0504313

systems with evolving bonds

- *Slowly evolving connectivity in recurrent neural networks I: the extreme dilution regime.* *J. Phys. A* 37 (2004) 7653
- *Slowly evolving random graphs II: adaptive geometry in finite connectivity Hopfield models.* *J. Phys. A* 37 (2004) 7843