

New Complex Networks for Social Relations

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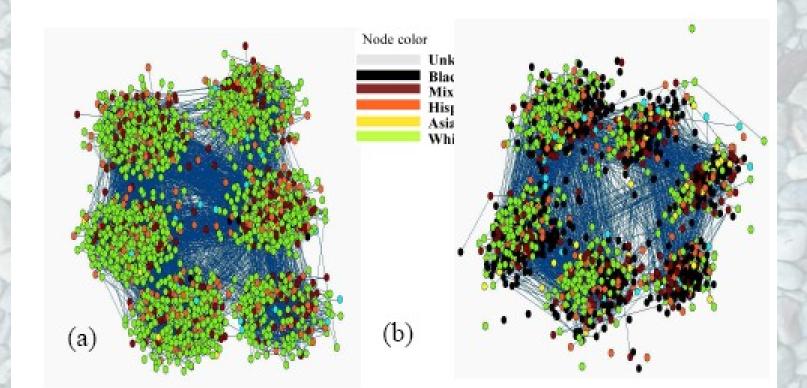


Motivation

- * The statistical spreading of information or contacts in societies has many practical implications. It involves non-equilibrium phenomena where fluctuations and correlations play an important role.
- Usually these processes are studied by sociologists using surveys including many parameters and obtaining qualitative results. Recently techniques from statistical physics and in particular complex networks and nonlinear dynamics have been used to make simplified models and obtain quantitative laws. International Workshop on Challenges and Visions in the Social Sciences, ETH Zürich, Aug. 18-23, 2008

Data from schools

Survey interviewing 90118 student from 84 schools in US (Add Health Program)



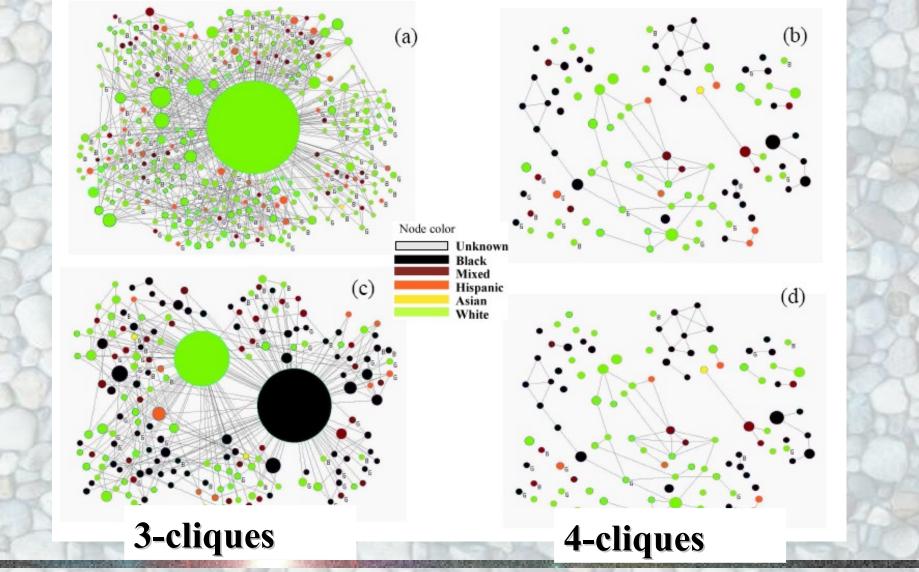
visualization using "pajec"

ETH

with T. Vicsek and J. Kertész

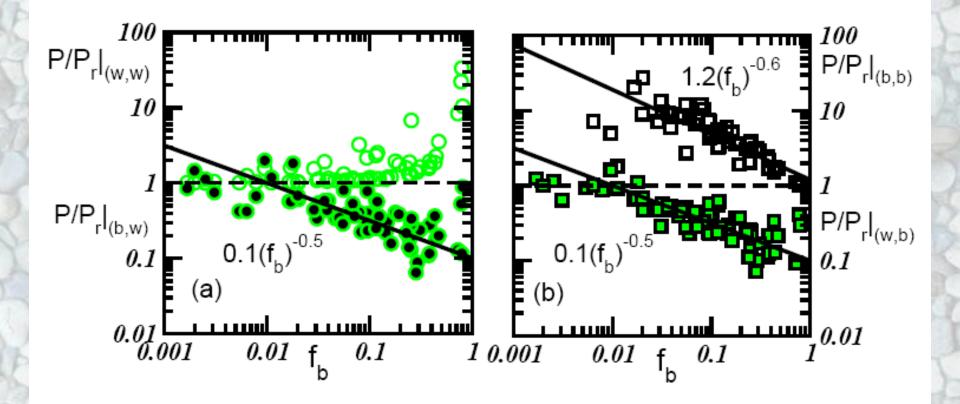


Schools



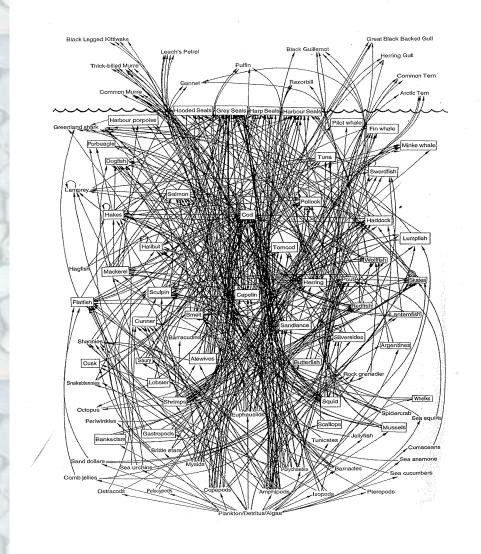
Schools

ETH



affinities between black and white students

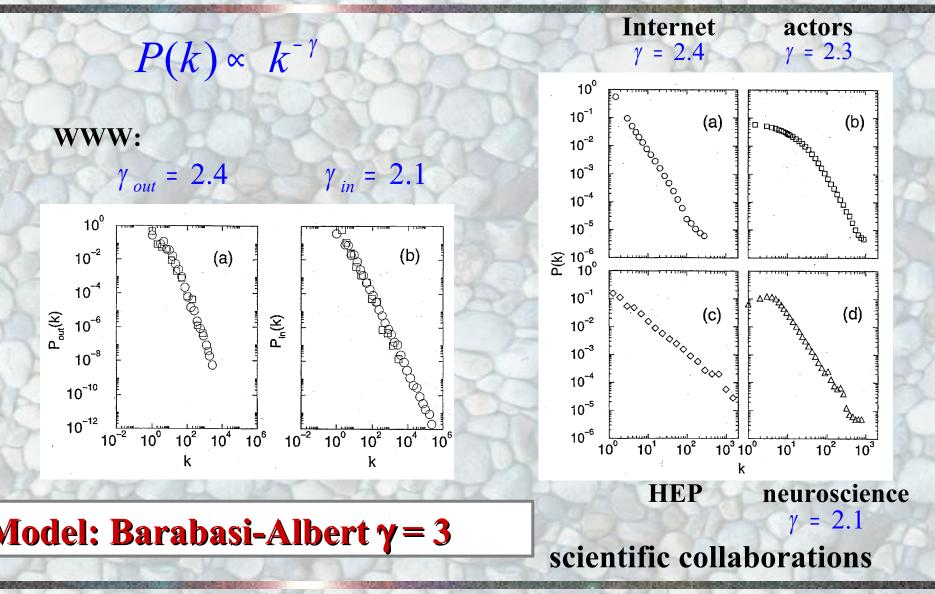
Complex Networks



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Food web of the North Atlantic Ocean

Scale-free networks



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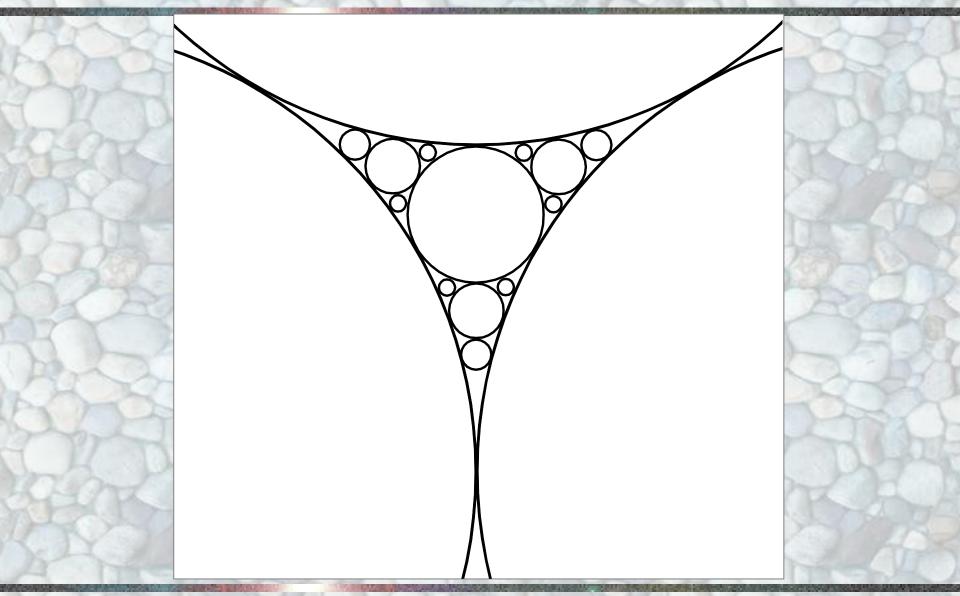


Apollonian network

- scale-free
- (ultra) small world
- Euclidean
- space-filling
- matching



Apollonian packing





Other applications

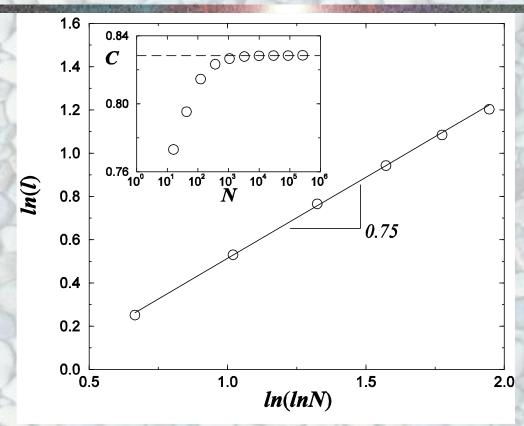
- Force networks in polydisperse packings
- Highly fractured porous media
- Networks of roads
- Systems of electrical supply lines

Degree distribution

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 N_n = number of sites at generation *n* scale-free: $P(k) \propto k^{-\gamma}$ m(k,n) = number of vertices of degree k $W(k) \propto k^{1-\gamma}$ cummulative distribution $W(k) = \frac{m(k, n)}{N_n}$ k > kk m(k,n) 3^n 3 P_2 3ⁿ⁻¹ 3X 2 3ⁿ⁻² 3×2^2 $3 \times 2^{n-1}$ 3^{2} 3×2^n 3 2^{n+1} $\gamma = 1 + \frac{\ln 3}{\ln 2} \approx 2.585$ \mathbf{P}_1 **P**₃

Small-world properties



P₂ P₁ P₃

clustering coefficient

ETH

 $C = \frac{2}{k(k-1)} \times$ number of connections between neighbors

C = 0.828

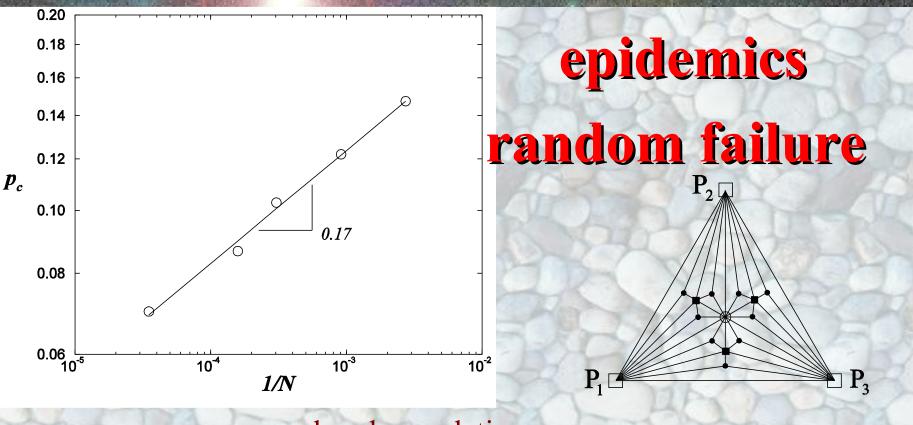
shortest path

 $l = \langle \text{chemical distance between two sites} \rangle$

$$l \propto (\ln N)^{\frac{3}{4}}$$

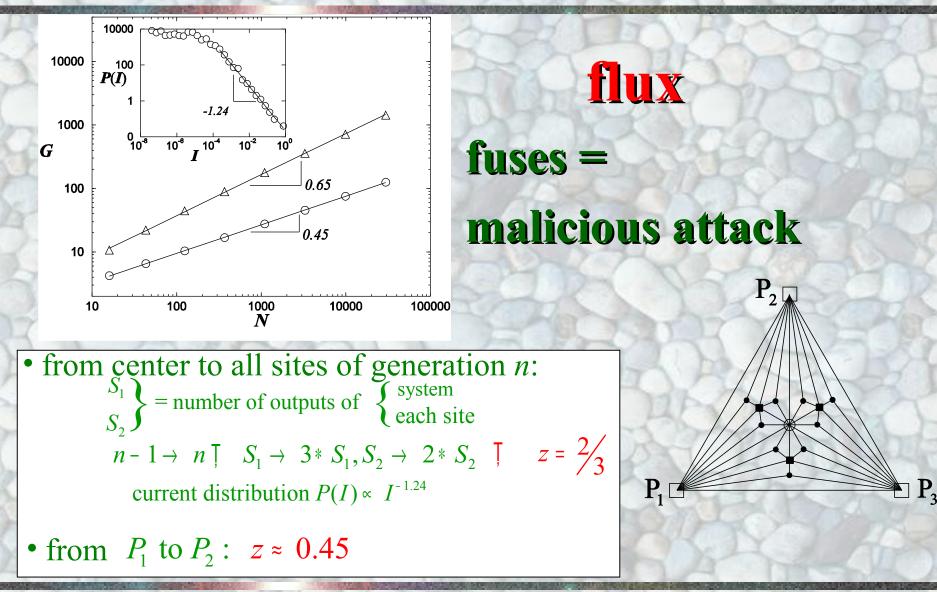
Percolation threshold

ETH

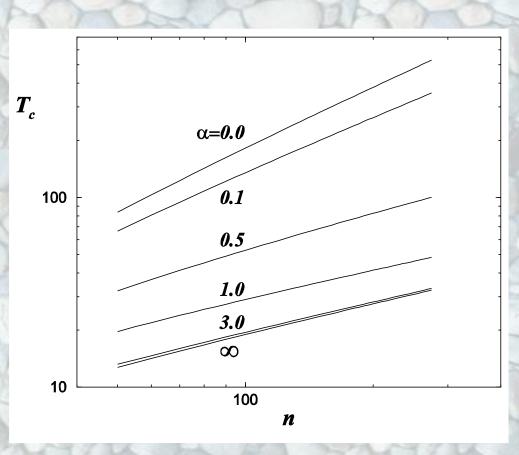


bond percolation at $p_c: P_1, P_2$ and P_3 simultaneously connected $p_c \propto L^{\frac{1}{\nu}}, L = \sqrt{N} \downarrow \nu \approx 3$ porous media \downarrow Archie's law

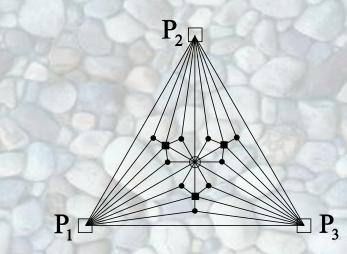
Electrical conductance



Critical temperature of Ising model



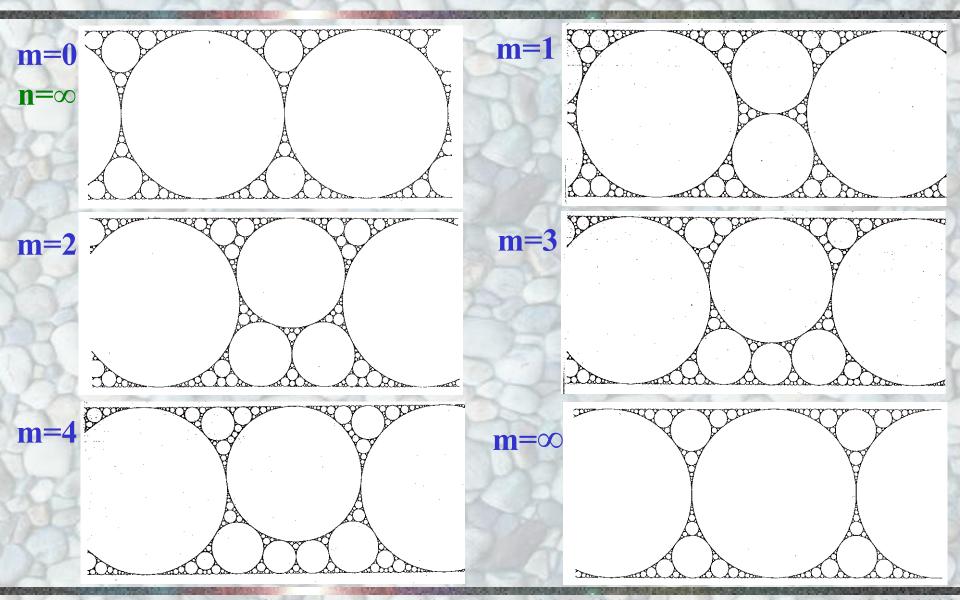
opinion



coupling constant $J_n \propto n^{-\alpha}$ correlation length J_n diverges at T_c free energy, entropy, specific heat are smooth magnetization $m: e^{-T^{\lambda}} \quad T \to A$

Generalized Apollonians

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Osculatory packing

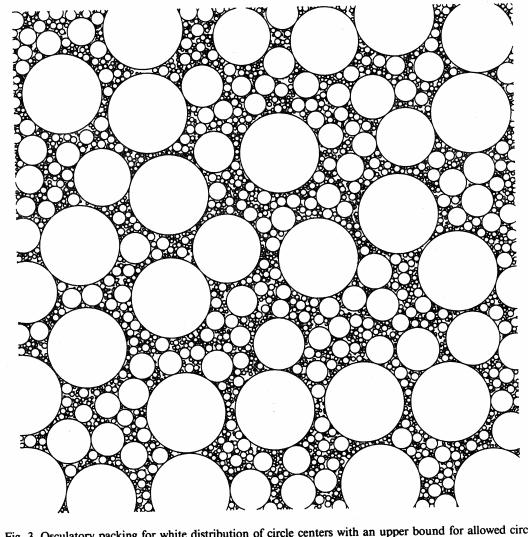
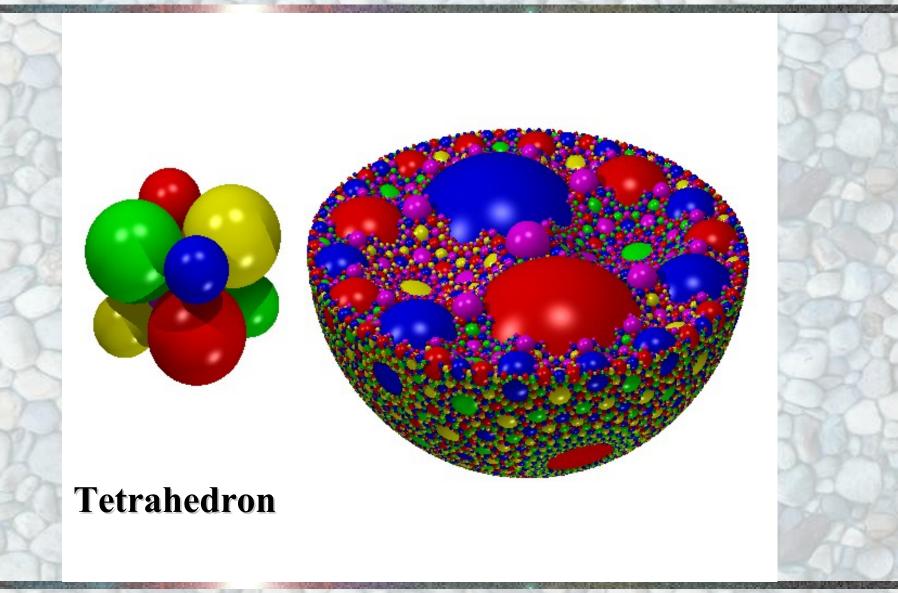


Fig. 3. Osculatory packing for white distribution of circle centers with an upper bound for allowed circle radii.

Apollonian packing in 3D

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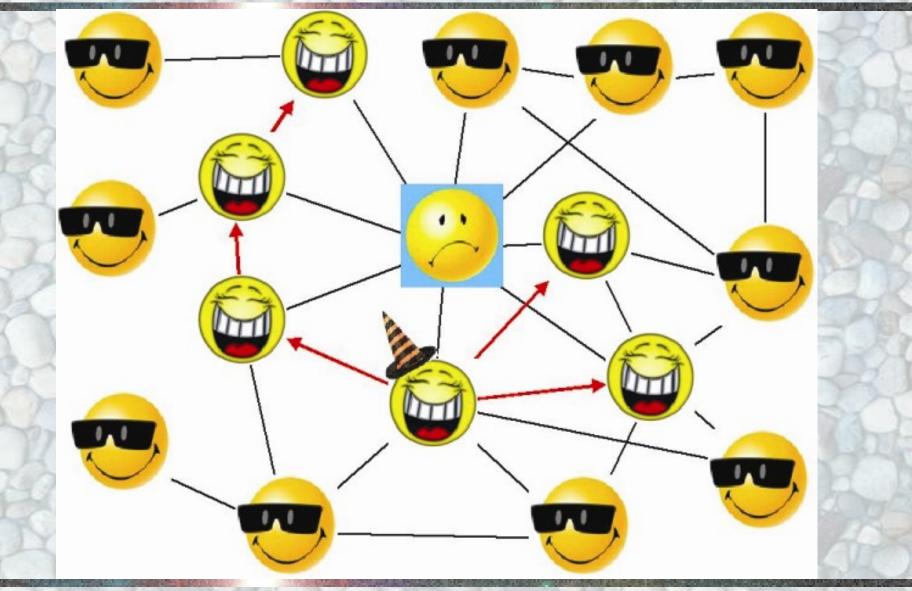


ETH Conclusions on Apollonian networks

- Stable against random failure.
- Opinions stabilize at any interaction strength.
- Supply current distribution follows power-law while point-to-point distribution is log-normal.
- Apollonian networks are between small world (l × ln N) and ultrasmall world ln ln N)
- Force networks of polydisperse packings have few contacts between grains and their rigidity increases with density like a power-law.
- Porous medium follows Archie's law. $\Phi_{\chi} = 0$

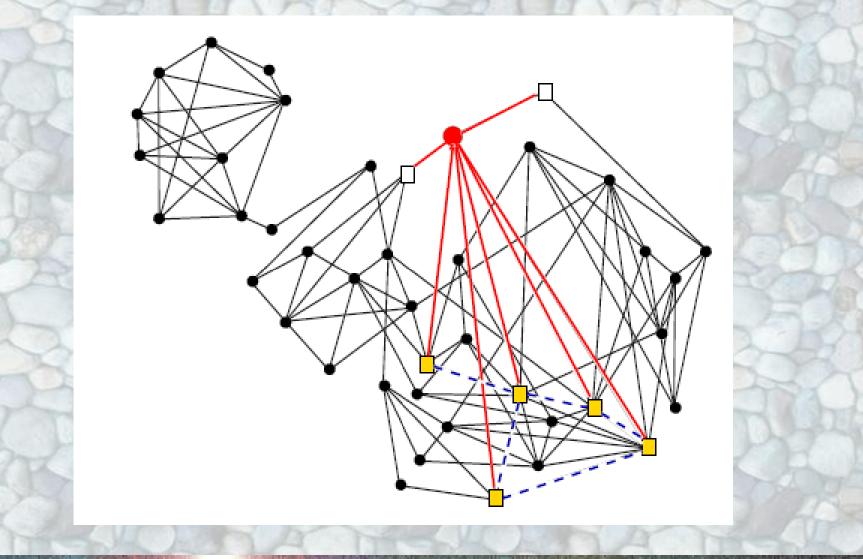
Gossip

ETH



Gossip on network

ETH



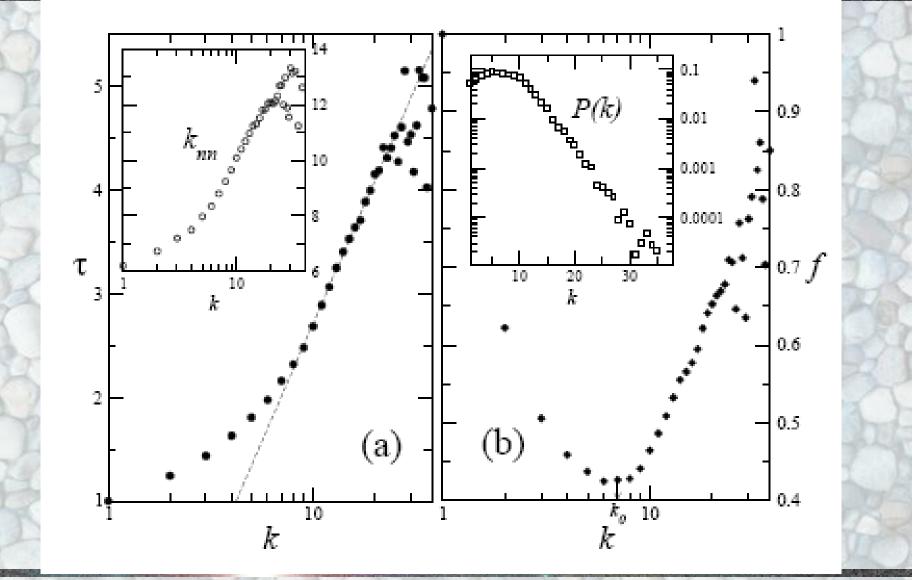
ETH Gossip propagation

Spreading time τ is the minimum time it takes for a gossip to reach all accessible persons.

n is the total number of persons that eventually get the gossip. We also define the "spread factor" *f*: $f = \frac{f}{k}$ where *k* is the degree of the victim.

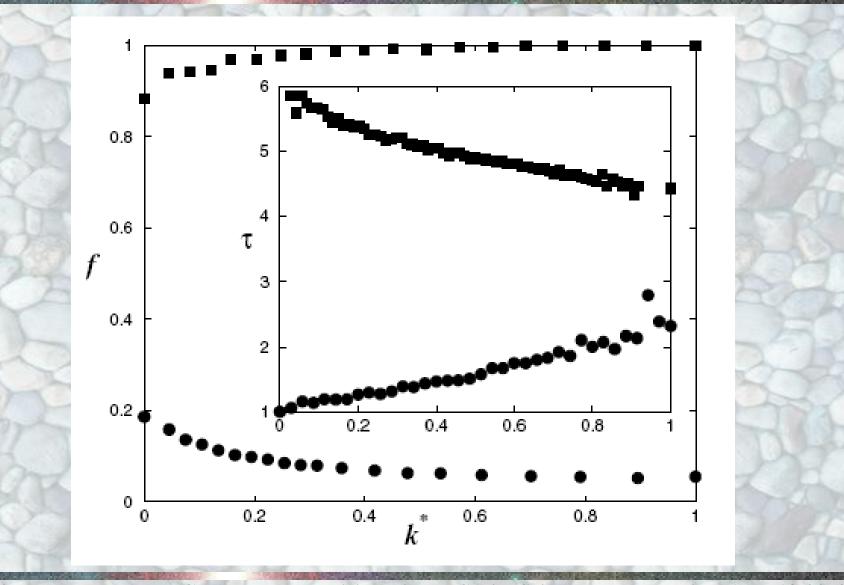
Gossip in schools

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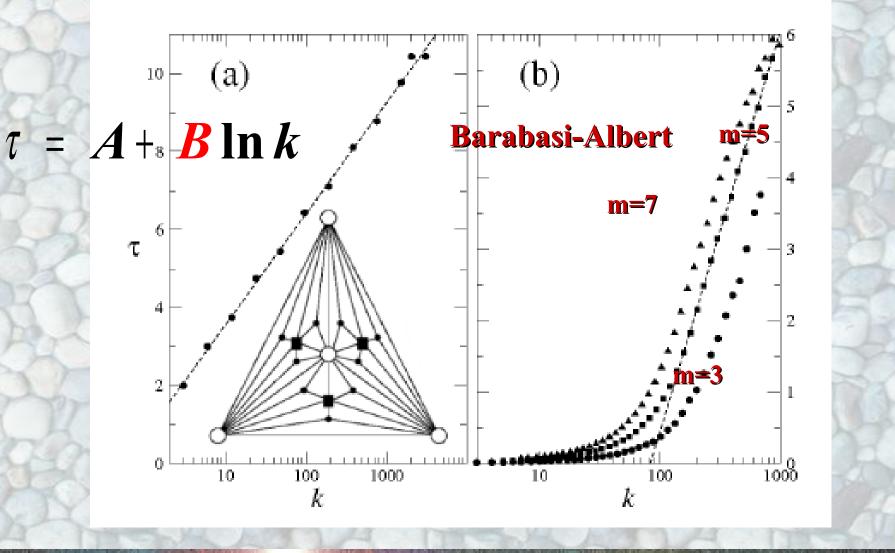


Gossip on random graph

ETH



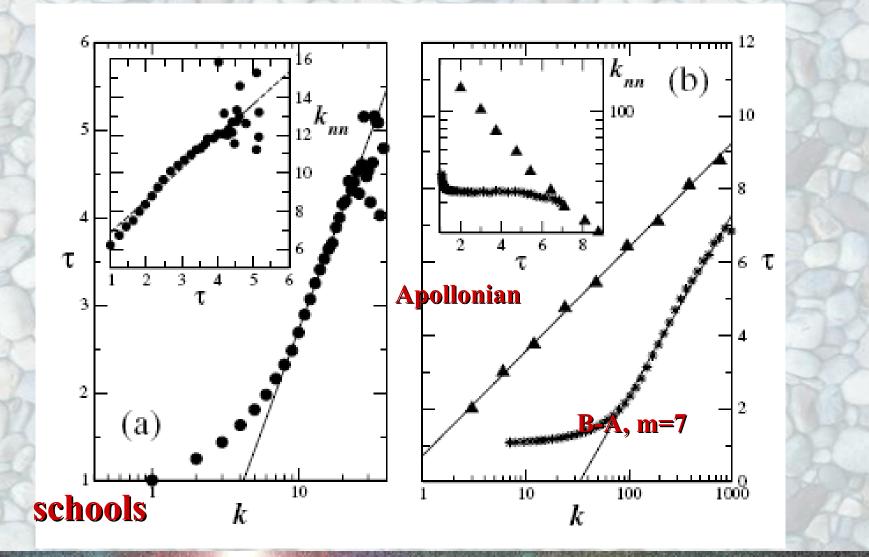
Spreading time



ETH

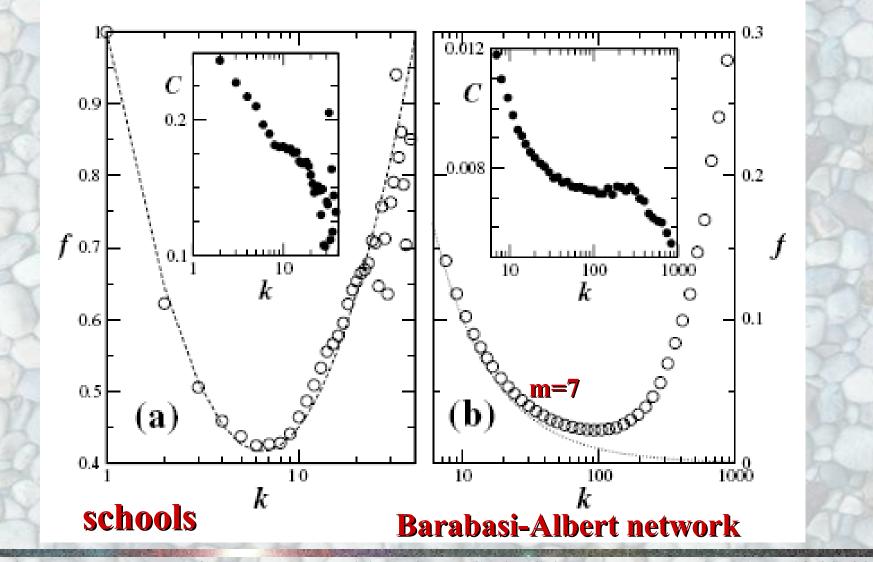
Spreading time

ETH

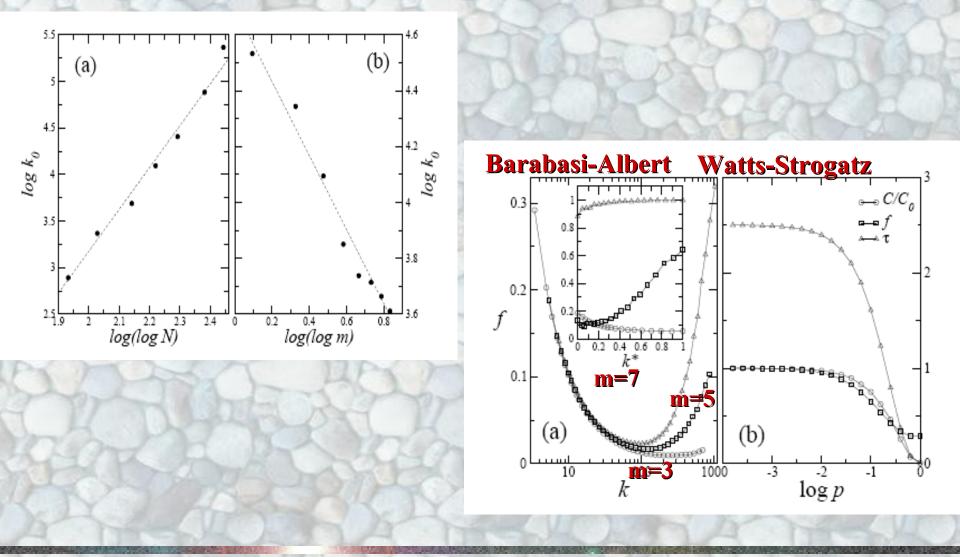


Spreading factor

ETH

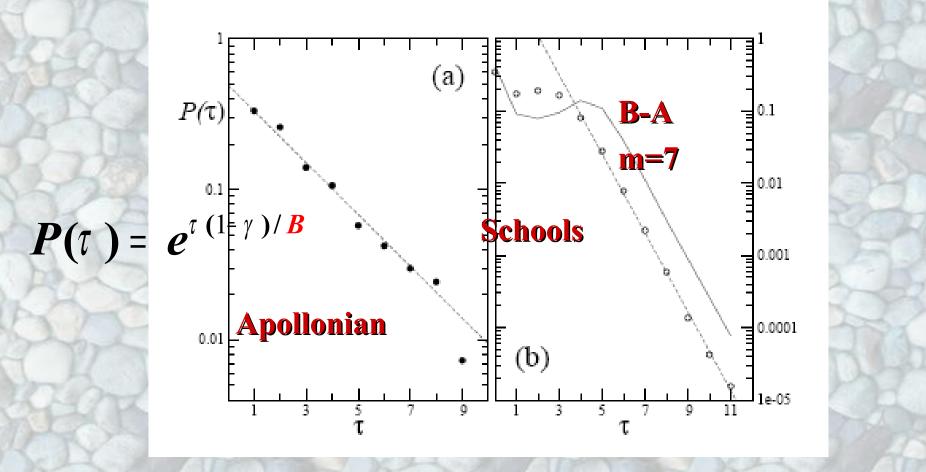


ETH Spreading factor

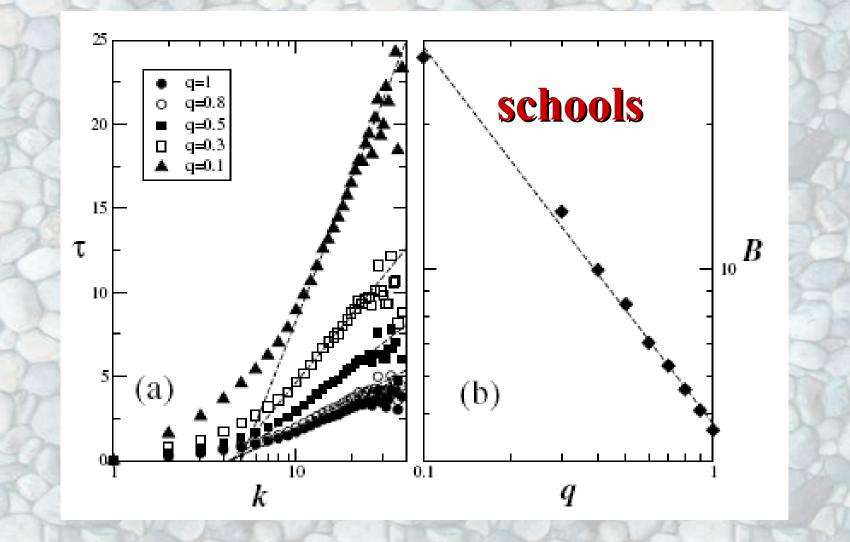


Distribution of t

ETH

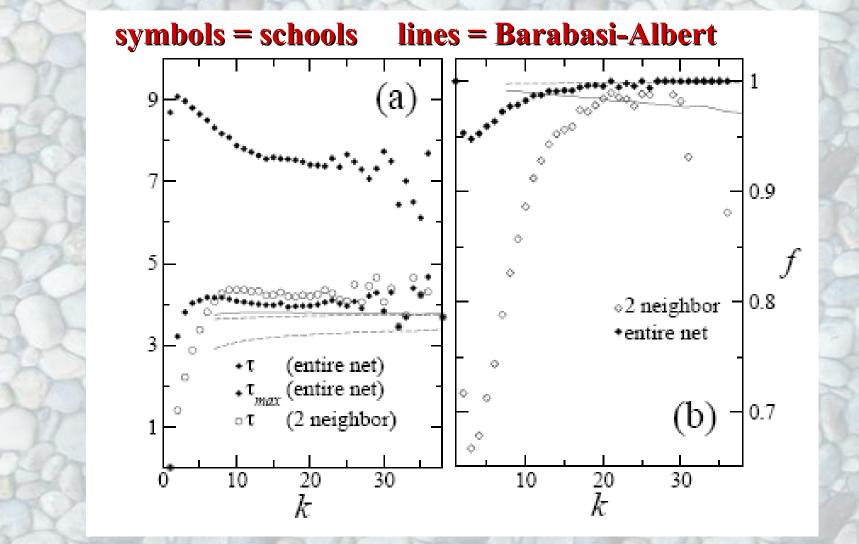


Gossip with probability q

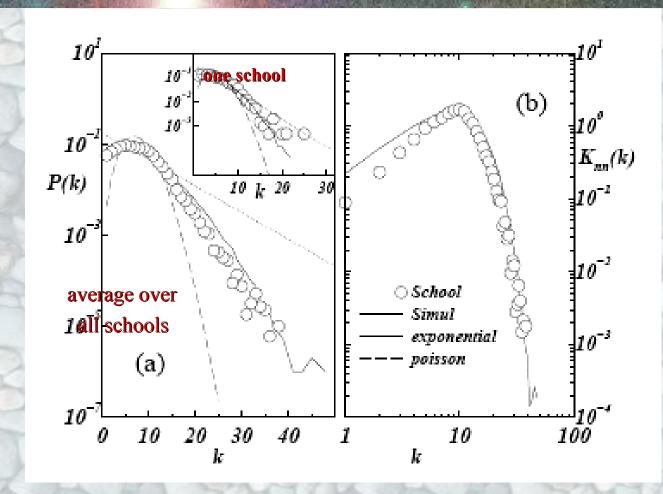


Gossip about famous people

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Degree distribution



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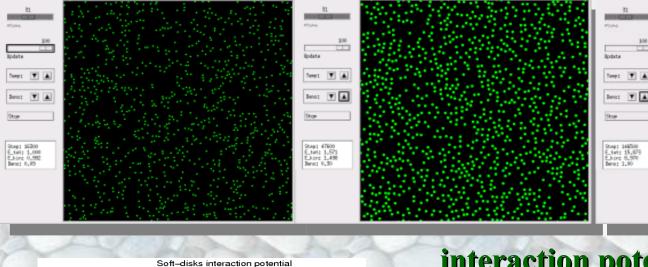
Sexual contact networks

heterosexual (Sweden) homosexual (Colorado Springs) 10⁰ **(b) (a) 10**⁻¹ model ales P_{cum}(K) *10⁻²* agents females **10**⁻¹ 00 **C(K)** *10⁻³ 10⁻²* 10⁻⁴ **10**¹ $\overline{\mathbf{K}}$ 10² 10⁰ **K** 10¹ $\overline{10}^2 \overline{10}^0$ $\boldsymbol{1\boldsymbol{\theta}}^{\boldsymbol{3}}$ F. Liljeros et al, Nature 411, 907 (2001)

ETH



soft-disks in 2d



6

dimensionless MD units, $r = 2^{1/6}$

ETH

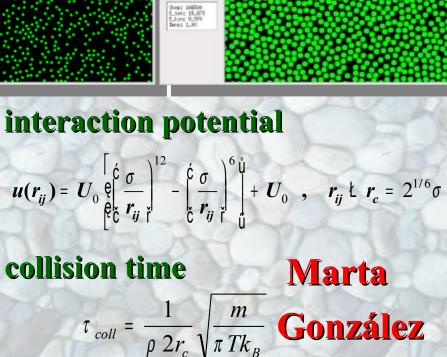
10°

10[°]

10°

0

u(r)





Evolution of network

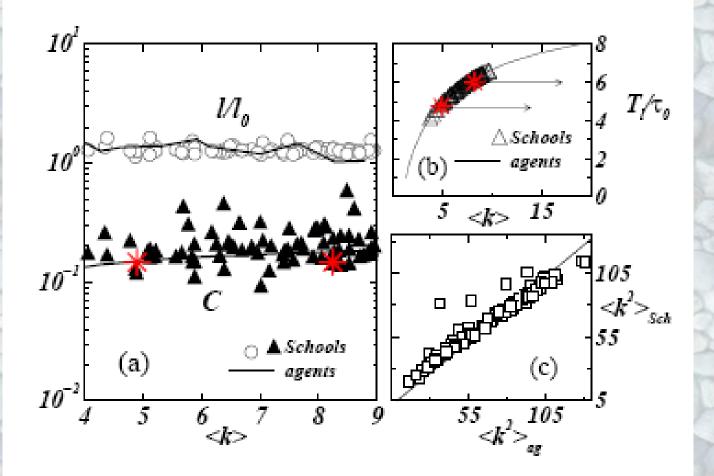


ETH Evolution of network with life-times



ETH Comparison to schools

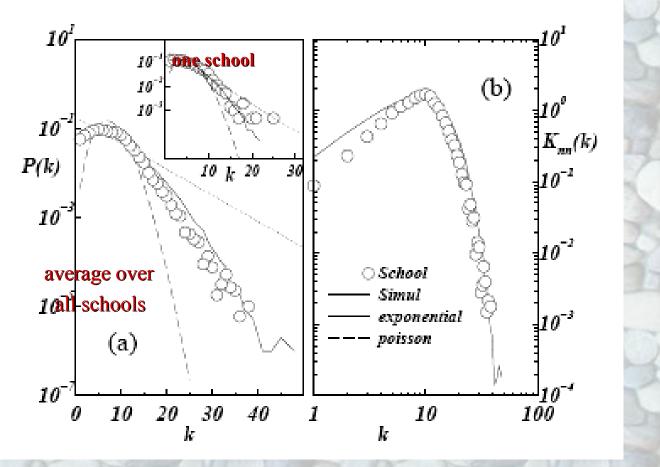
Shortest path and clustering coefficient



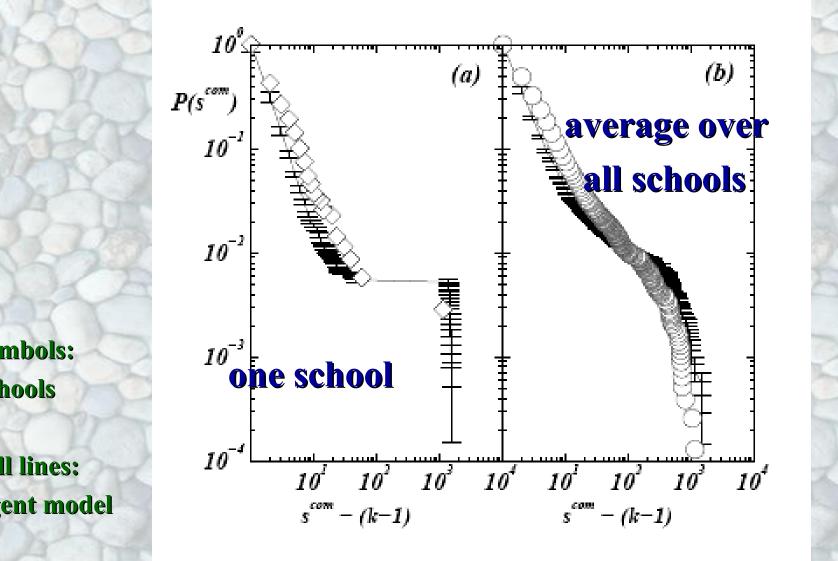
González, Lind and Herrmann, Physical Review Letters 96, 088702 (2006)

ETH Comparison to schools

Degree distribution



3-clique communities

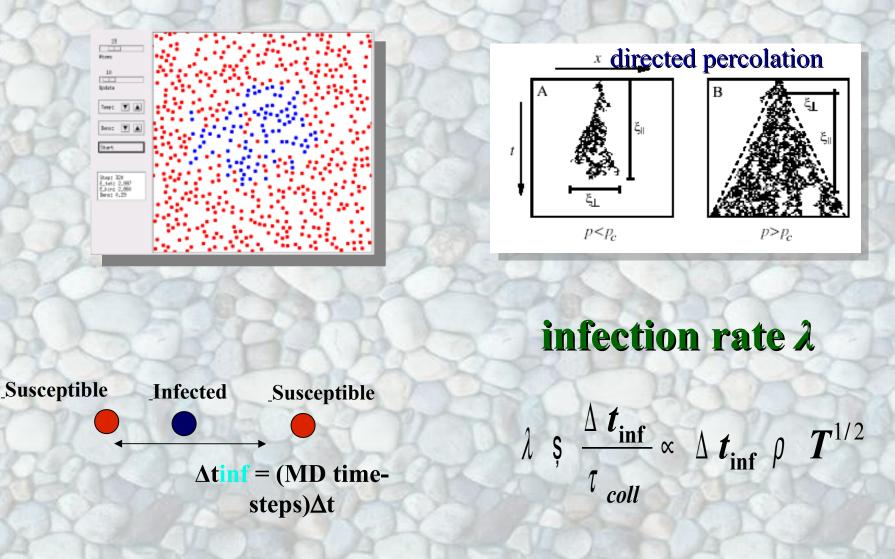


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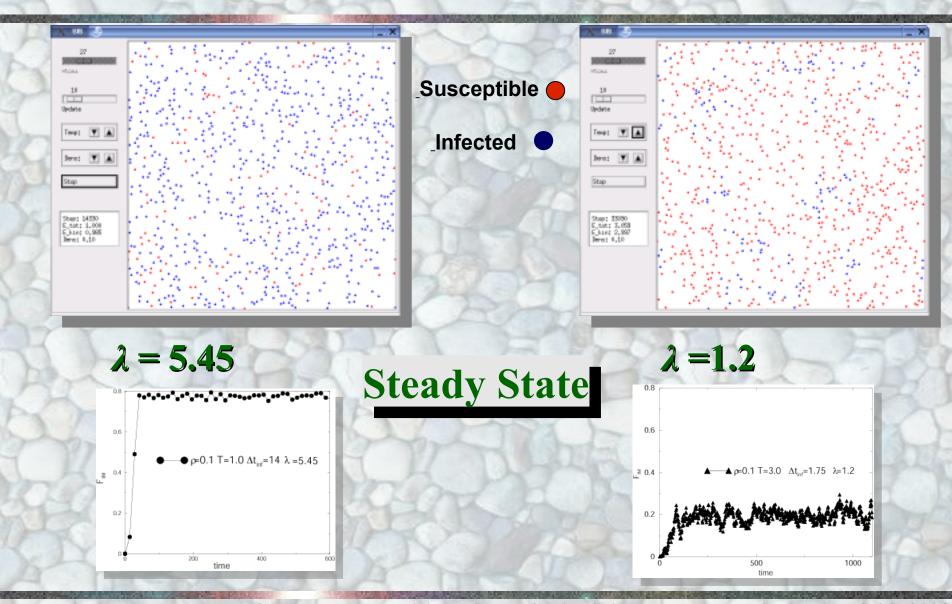
SIS model of epidemic

ETH



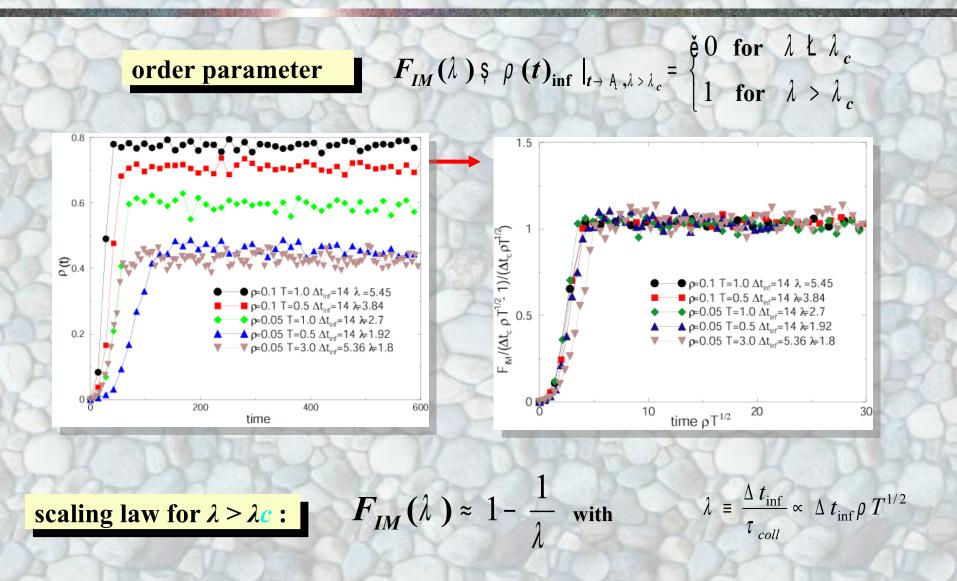
SIS model for epidemics

ETH

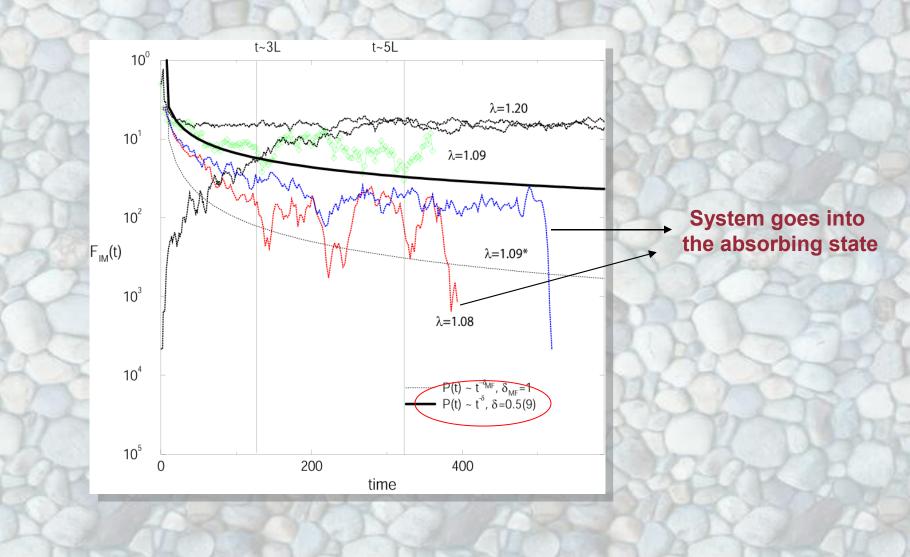


Data collapse

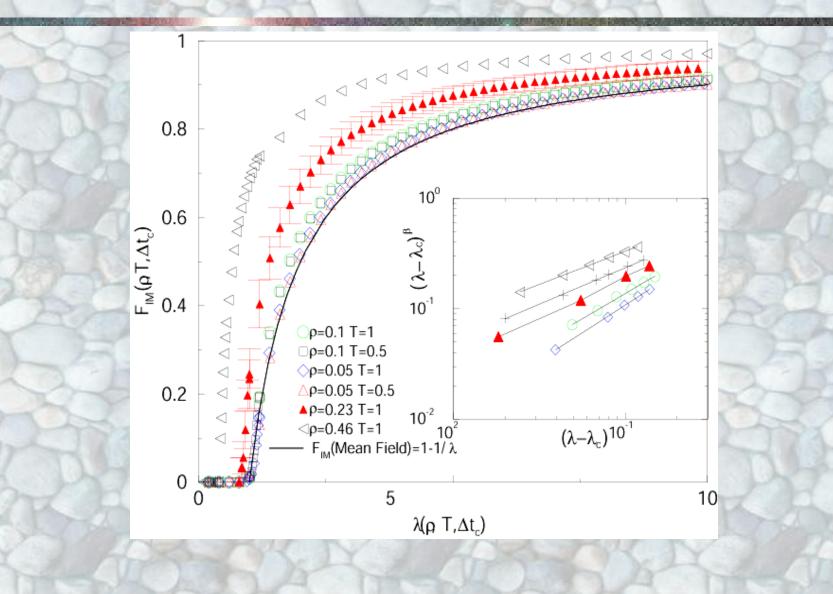
ETH



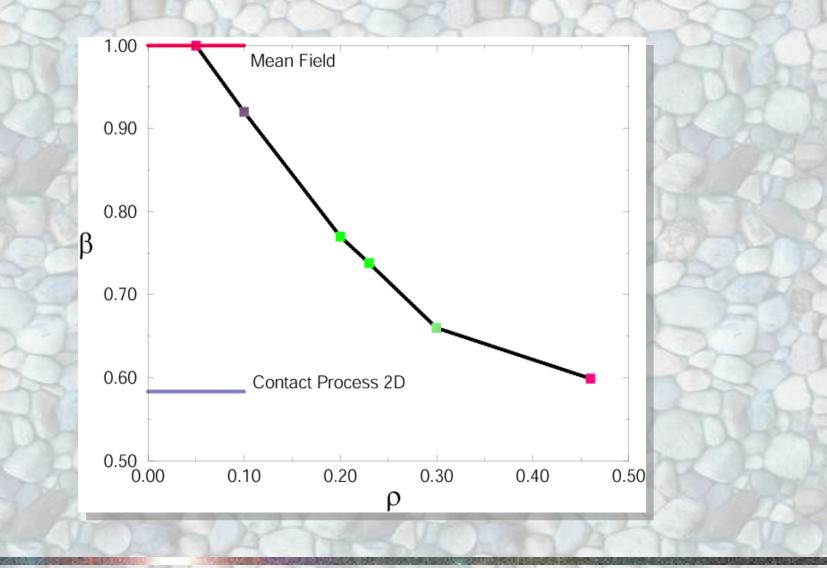
Non-equilibrium phase transitions



Influence of the density



ETH Critical exponent β

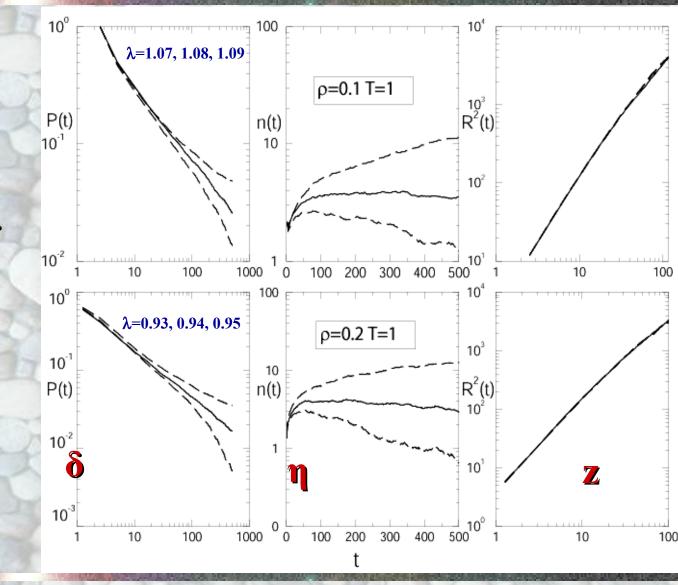


Other critical properties

(t) = probability at infection stays

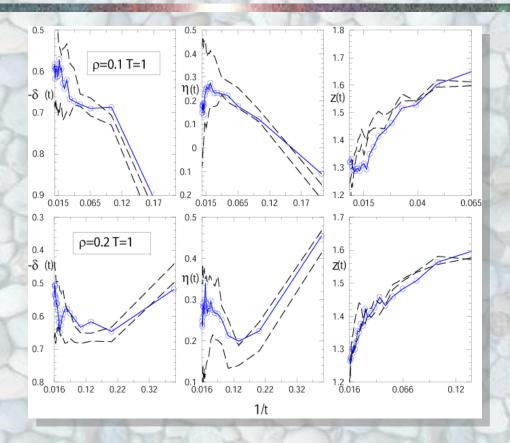
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(t) = average number f infected agents



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Critical exponents



 $\delta_{t} = \frac{\log[P(t)/P(t/\Delta)]}{\log \Delta}$ $P(t) \propto t^{-\delta} \left(1 + \frac{a}{t} + \frac{b}{t^{\delta'}} + \dots\right)$ $\delta_{t} \propto \delta + \frac{a}{t} + \frac{\delta'b}{t^{\delta'}} + \dots$

* P. Grassberger, J. Phys. A., (1989) 3673-3679

J. Marro and R. Dickman, "Non-equilibrium Phase Transitions...", (1999) Cambridge University Press.

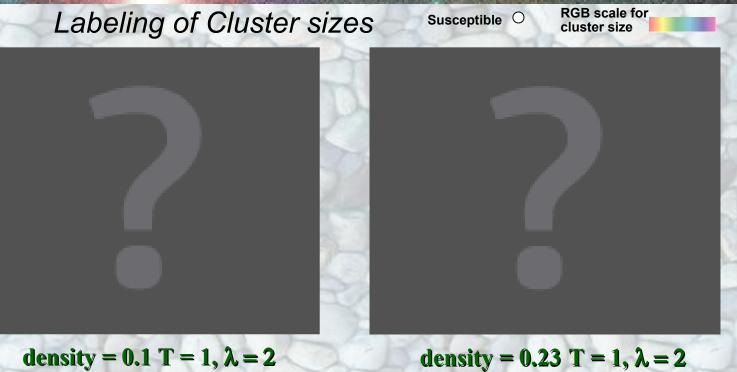


Critical exponents

	Mean Field	Moving Agents ρ=0.1	Moving Agents ρ=0.2	Contact Process 2D
λ_{c}	1	1.0(8)	0.9(4)	1.6488(1)
β	1	0.9(2)	0.7(7)	0.583(4)
δ	1	0.5(9)	0.5(3)	0.4505(10)
η	0	0.1(5)	0.2(5)	0.2295(10)
Z	1	1.3(0)	1.2(7)	1.1325(10)

$4\delta + 2\eta = dz$ holds.

Networks properties



Rules for generating the network

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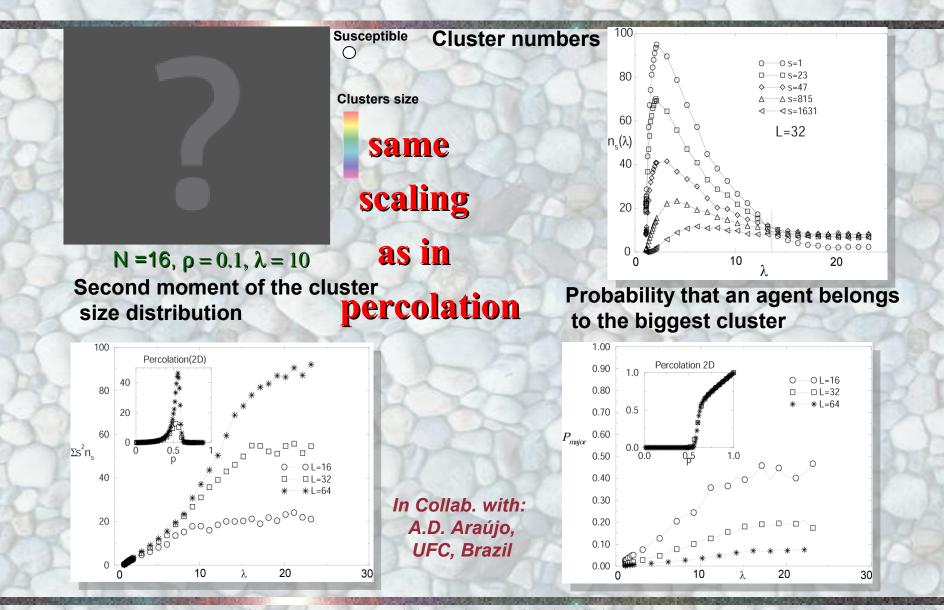
*

Each time one agent infects other a bond between the two is created.

The infection lasts (Atinf time steps), when one of the agents is recovered the bond disappears and the agent becomes susceptible to infection again.

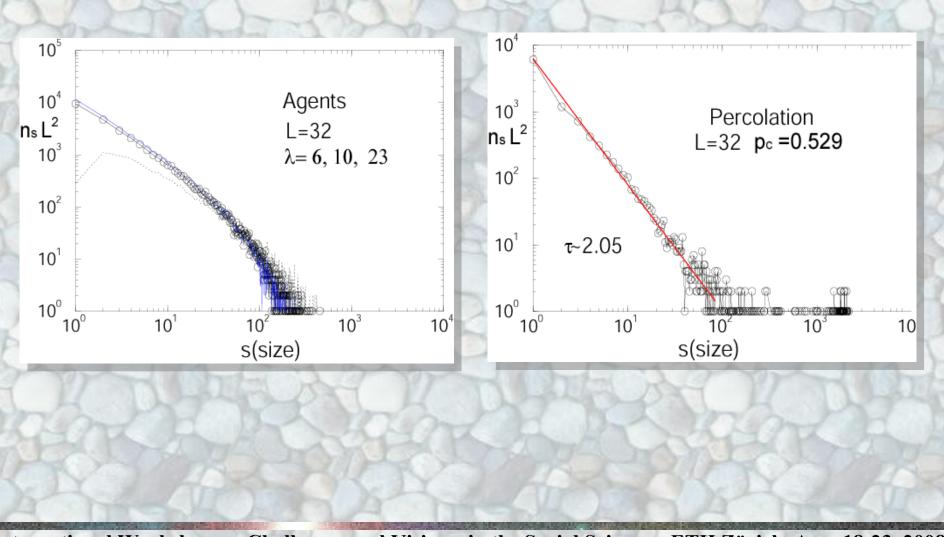
Cluster size distribution

ETH

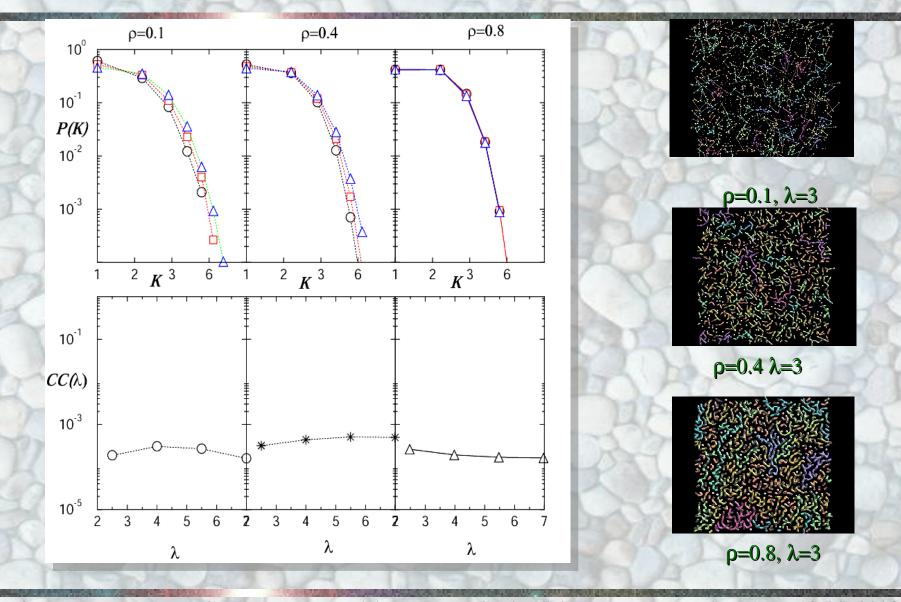


Cluster numbers

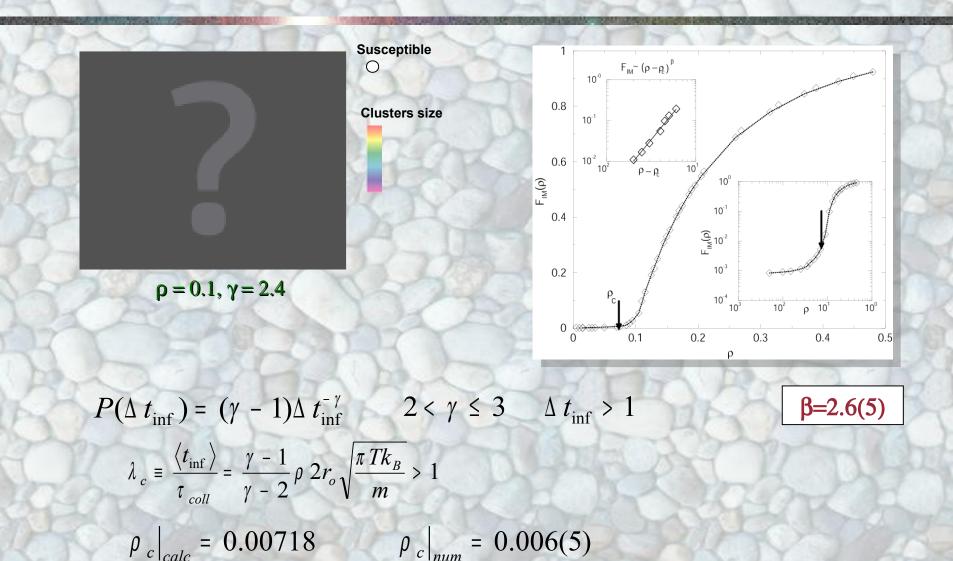
ETH



Clustering coefficient and degree distribution



Power-law distribution of infection time



Conclusions on epidemics

 Novel effects are observed studying the SIS model of infection on a system of moving agents. A continuous range of critical exponents is found as a function of the density number of agents.

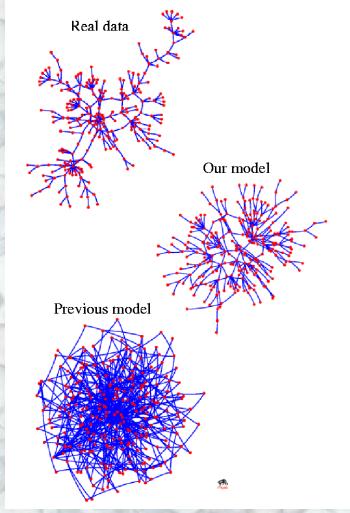
ETH

- Geometrical properties like the degree distribution and the clustering coefficient of the network of infected agents depend on the rate of infection and not on the density of agents. The distribution of cluster sizes is not a power law at the transition to spreading.
 - Introducing a power law distribution of infection times the epidemic threshold becomes zero, but there is still a critical rate of infection that depends on the exponents of the distribution and the mean interaction time among the agents .

heterosexual (Sweden) homosexual (Colorado Springs) 10⁰ **(b) (a) 10**⁻¹ model ales P_{cum}(K) *10⁻²* agents females **10**⁻¹ 00 **C(K)** *10⁻³ 10⁻² 10⁻⁴* **10**¹ $\overline{\mathbf{K}}$ 10² 10⁰ **K** 10¹ $\overline{10}^2 \overline{10}^0$ $\boldsymbol{1\boldsymbol{\theta}}^{\boldsymbol{3}}$ F. Liljeros et al, Nature 411, 907 (2001)

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Comparison with real data



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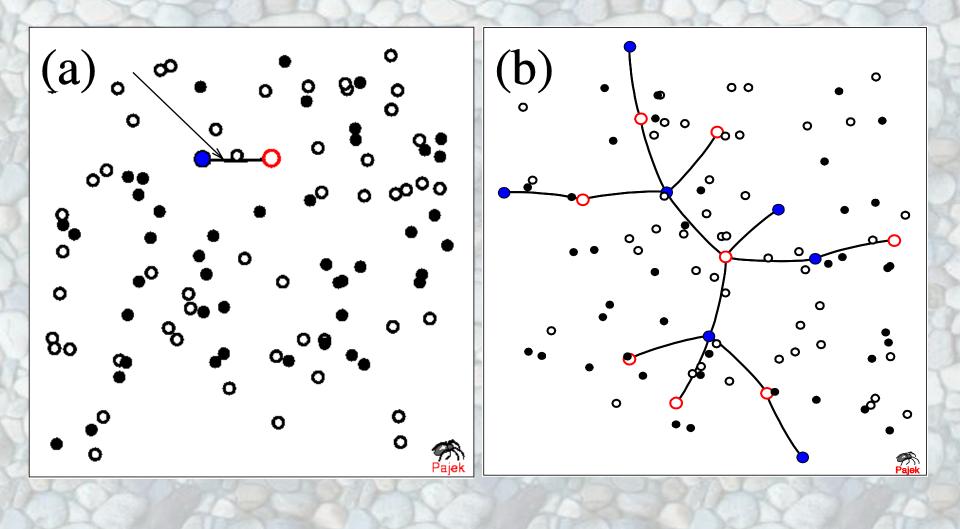
J.J. Potterat et al, Sex.Transm.Infect. 78, 59 (2002)

Velocity of agent proportional

Barabasi-Albert scale-free network

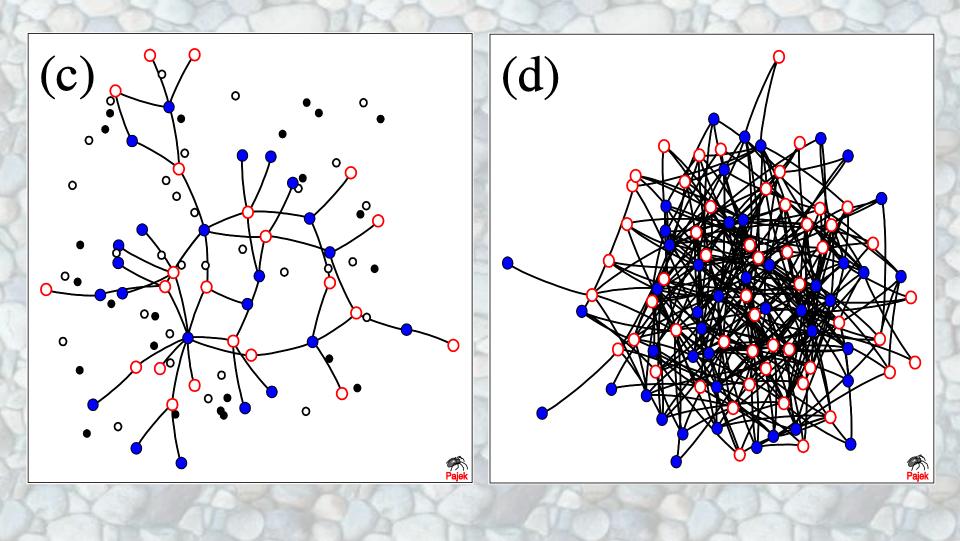
Bipartite growing network

ETH

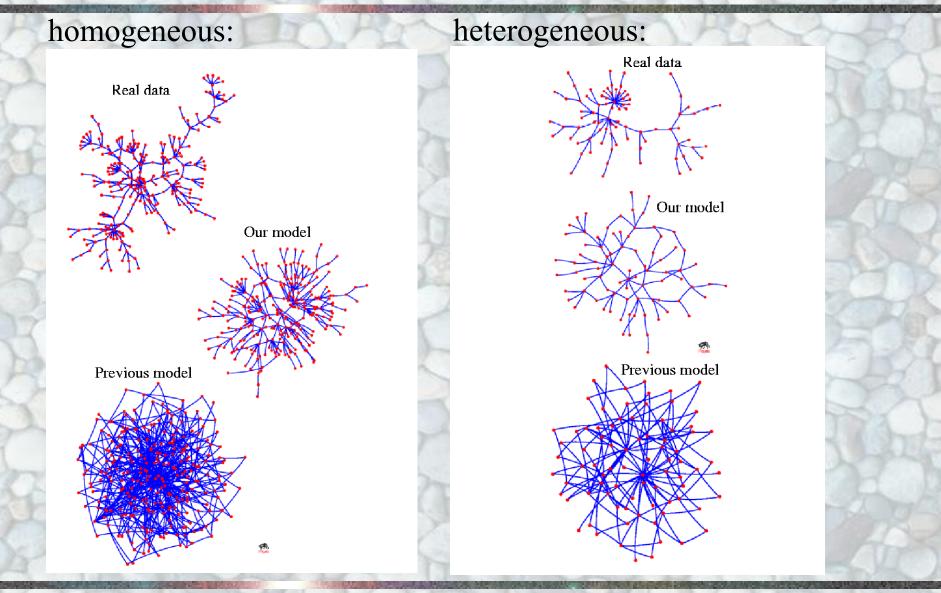


Bipartite growing network

ETH



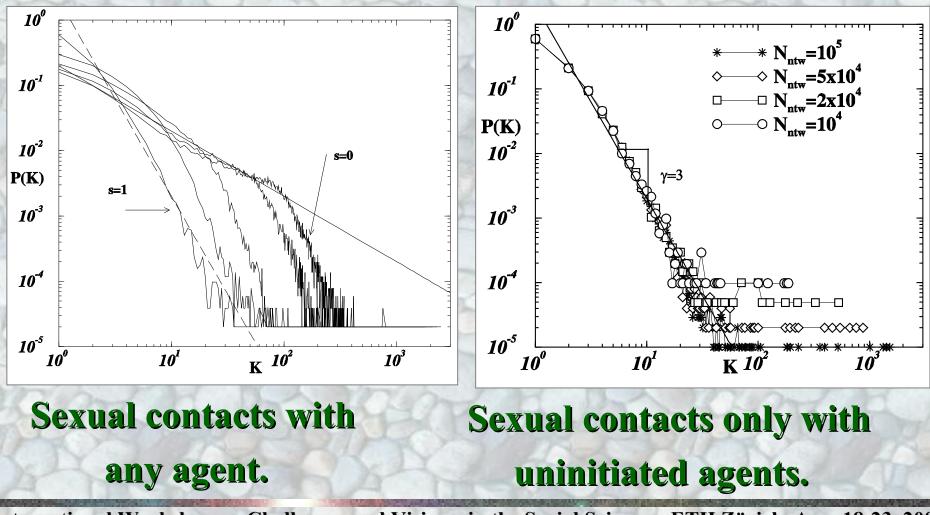
Comparison with real data



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Degree distribution

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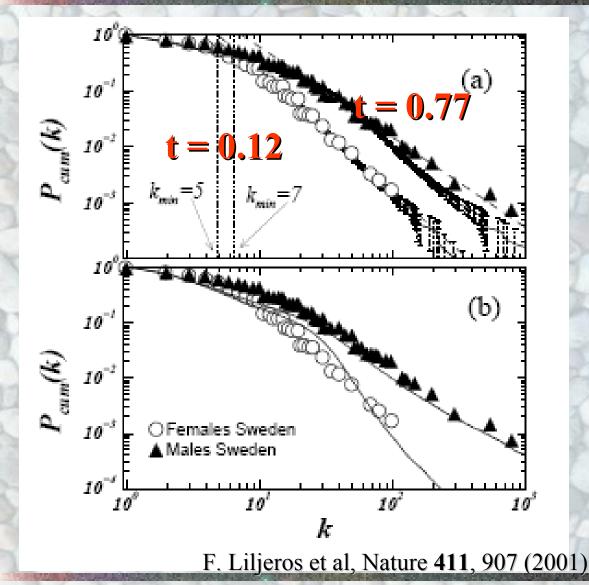


heterosexual (Sweden) homosexual (Colorado Springs) 10⁰ **(b) (a) 10**⁻¹ model ales P_{cum}(K) *10⁻²* agents females **10**⁻¹ 00 **C(K)** *10⁻³ 10⁻² 10⁻⁴* **10**¹ $\overline{\mathbf{K}}$ 10² 10⁰ **K** 10¹ $\overline{10}^2 \overline{10}^0$ $\boldsymbol{1\boldsymbol{\theta}}^{\boldsymbol{3}}$ F. Liljeros et al, Nature 411, 907 (2001)

ETH

heterosexual

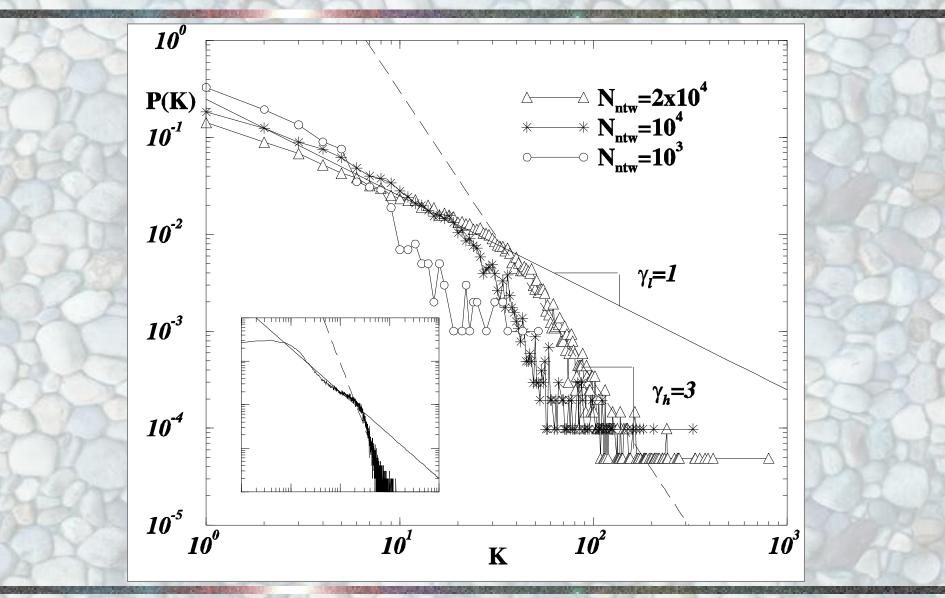
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58% females42% males

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Another friendship model

• Goal

- friendship network model (spatially independent) for a fixed setting (e.g. enrolling at a university)
- reproduce experimentally measurable quantities
- natural emergence of community structures

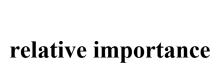
Herman Singer, ETH

Properties of the agent

agent properties

ETH

- **affinity** $a_i \in [0,1]$
- list of past contacts, length n_i
- maximal acquaintance parameter λ_i
- absolute importance



 $\Pi_{i} = \frac{k_{i}}{\sum_{i}^{N} k_{j}}$

$$p_{ij} = \frac{f_{ij}}{\sum_{k=1}^{n_i} f_{ik}}$$

• behavior

- agent can choose between meeting new contacts and meeting again already established contacts
- similar to aging but important difference:
 - agent can accept new contacts throughout the simulations
 - at the expense of dropping old ones
- \rightarrow every agent optimizes its interest
- → local, self organized community structure emerges

Friendship in formulas

- friendship is written as the weighted sum of the contributions
 - number of times n_{ij}
 - interest/affinity a_i, a_j

$$f_{ij} = \gamma f_1(|a_j - a_i|) + (1 - \gamma) f_2(n_{ij})$$

- with $\gamma > 0.8$

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friendship functions:

• affinity f_1

$$f_1(|a_j - a_i|) = (1 - |a_j - a_i|)^{\kappa}$$

- with
$$\kappa \ge 2$$
, here 2,3,5,10

frequency f₂ – exponential

$$f_2(n_{ij}) = 1 - e^{-\lambda_f n_{ij}}$$

- with
$$λ_f$$
=0.2 ↔ saturation on ~25 contacts

Algorithm

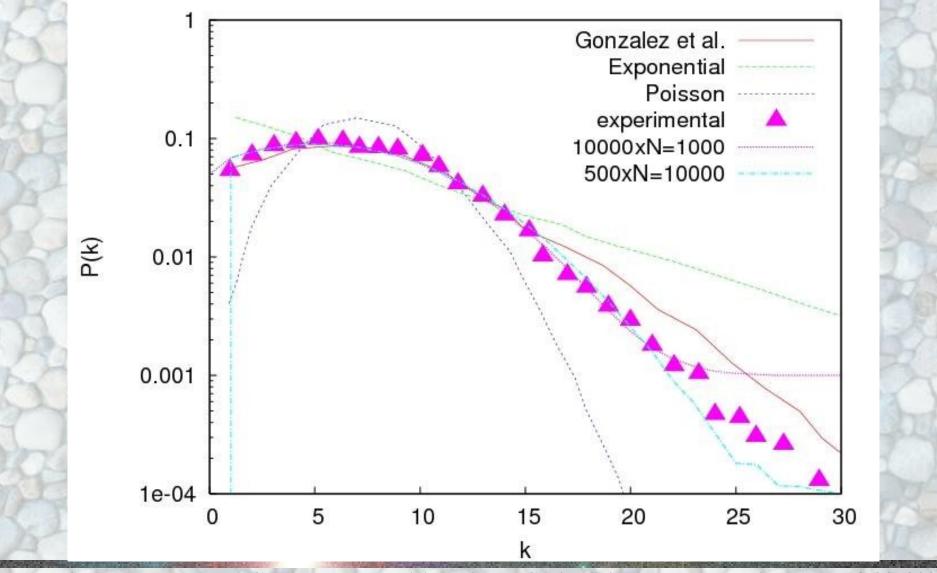
- t=0: initialize N agents, no connections with parameters a_i, n_i=0, λ_i
- $t \rightarrow t+1$:

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- choose an agent randomly: i
- decide on contact mode with probability $p = 1 e^{-\lambda_i n_i}$
 - select an agent from pool with probability Π_{i}
 - add to contact list
 - otherwise select an agent in contact list with propability p_{ii}
- prevent social isolation and take into account random encounters:
 introduce threshold p≥θ_p

Degree distribution

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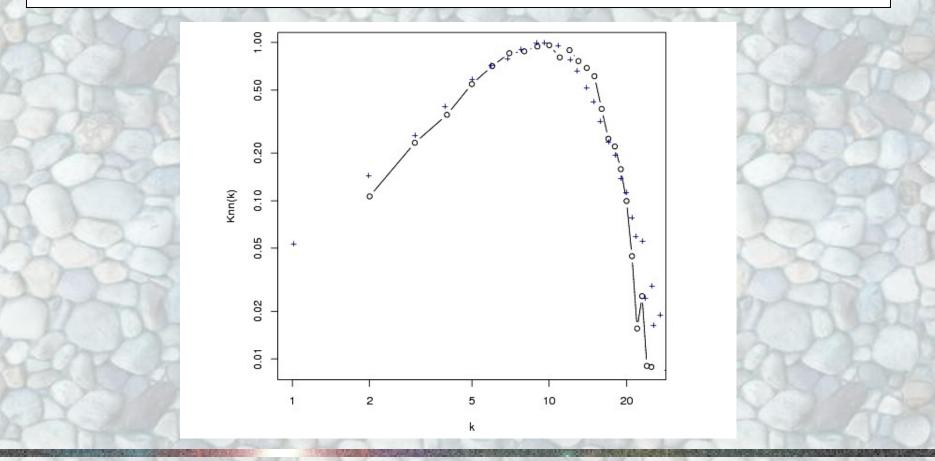


Degree correlation

• P(k|k'): probability at a node with k to find a neighbor with k'

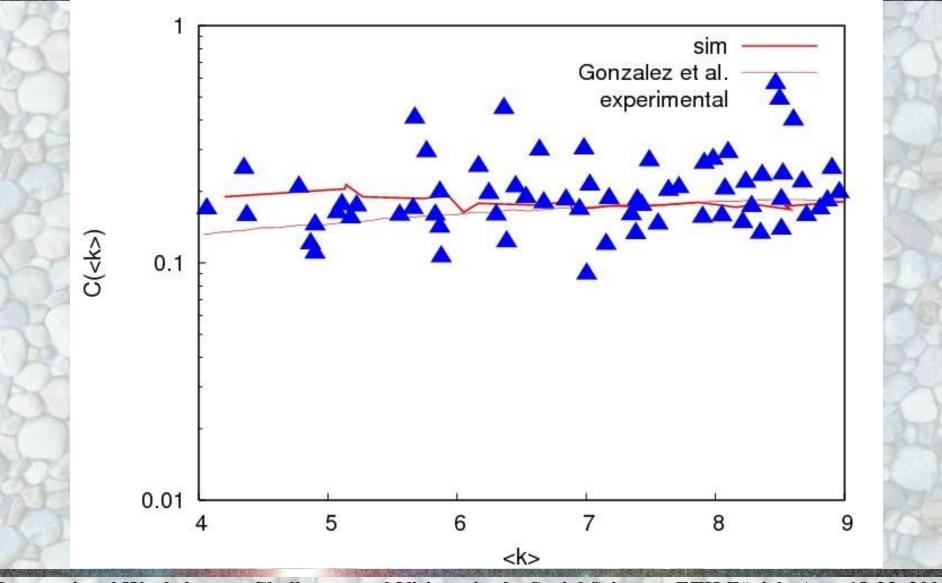
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$$K_{nn}(k) = \sum_{k'=1}^{N} P(k \mid k')k'$$



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Clustering coefficient



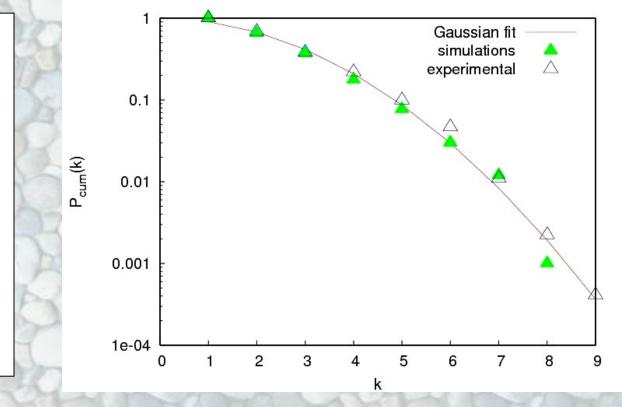
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Friendship distribution

• Experimental results

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- 417 high school students
- "who are your best friends?"
- probability that a person is mentioned n times



Conclusion

- Social relation is difficult to quantify.
- Many simplified models are possible.
- Parameters can be tuned to agree with some data.
 - One can find general conclusions.
- But does anybody believe these generalities?
- Does anybody care about this research?
- Do we need socio-physics?

ETH

• What does one learn from modeling?