Statistical physics for non-physics problems

Application of paradigms of equilibrium statistical physics to social sciences:
from obesity epidemic to diffusion of innovation in society

Collaborators

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Geography

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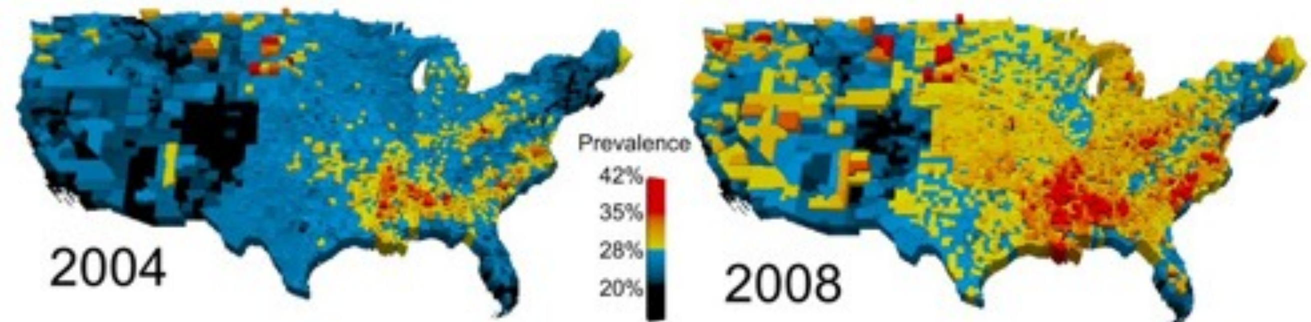
City College of New York
Physics

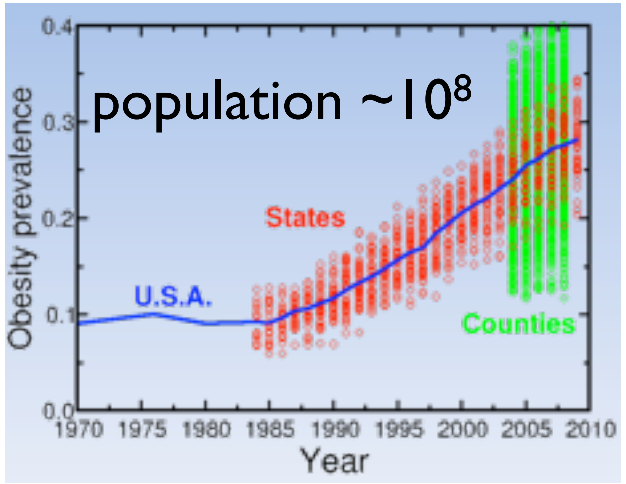
Funding: NSF, ARL, EC

BIG DATA: Statistical physics ~10^{23} molecules in a dm^3 (Avogadro)

1. Obesity epidemic in US: drivers

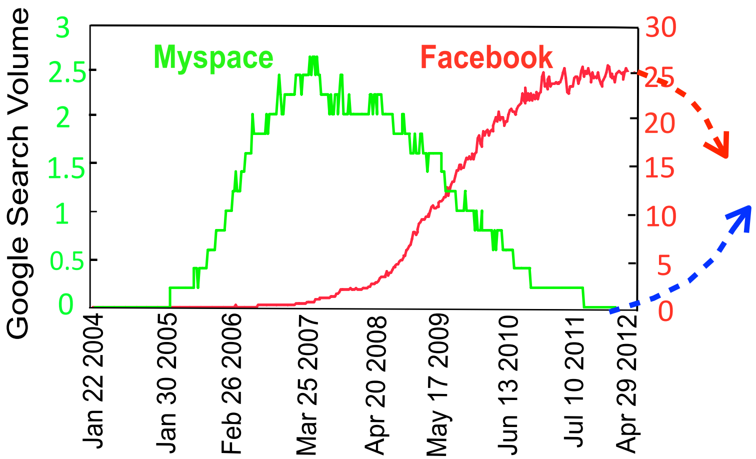


Change in obesity levels from 2004 to 2008 (data from



2. Theory that predicts the tipping point of disintegration

facebook ~ 10^9 users



myspace vs facebook

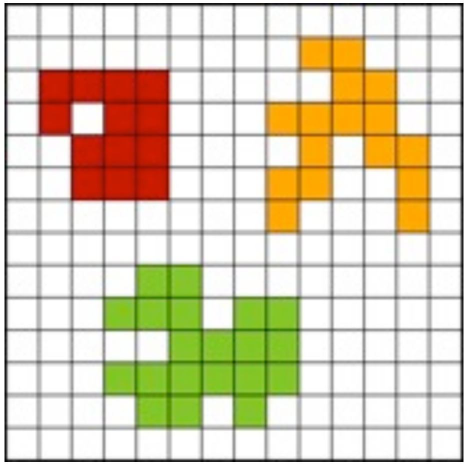
Can we predict the next facebook?

Predict the minimum number of pioneers that, upon leaving, will fragment the network

Tools: Percolation theory and collective behavior in critical phase transitions

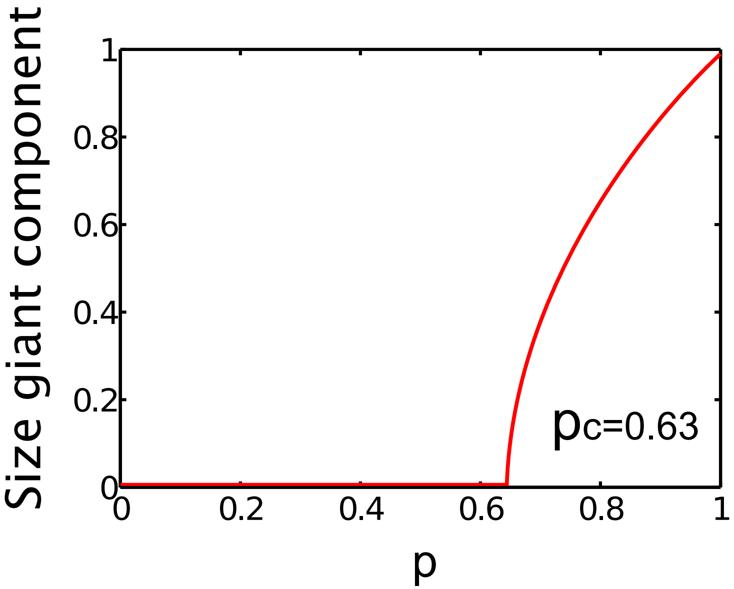
Common physical model: Percolation theory

Low $p<p_c=0.63$

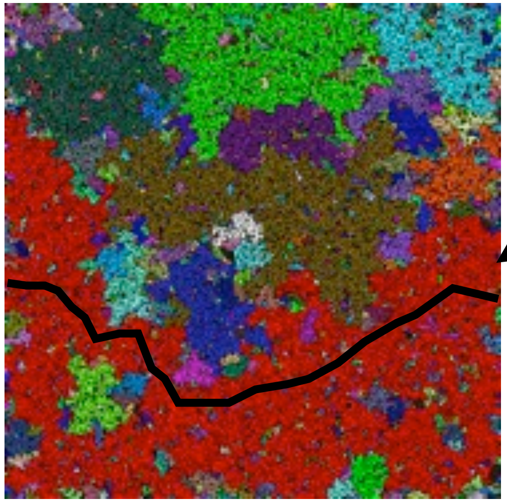


Percolation: simple model of cluster connectivity

Occupy each site with occupancy probability p



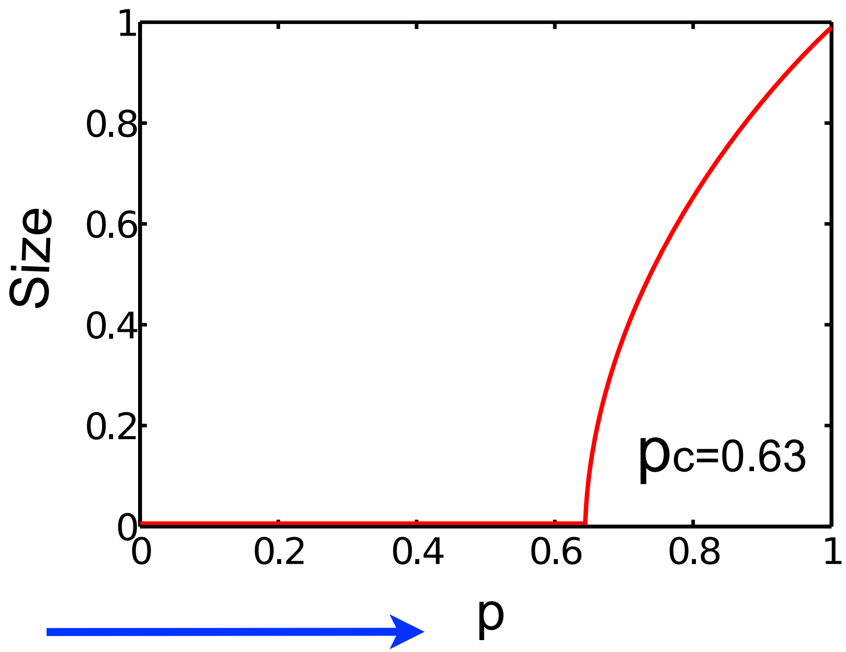
At $p_c=0.63$



spanning cluster

At a certain critical value: $p_c=0.63$ there is a critical spanning cluster with long-range correlations and long-range connectivity

Percolation models two processes: growth and attack



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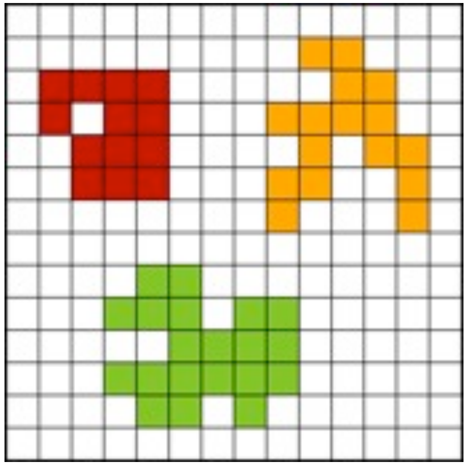

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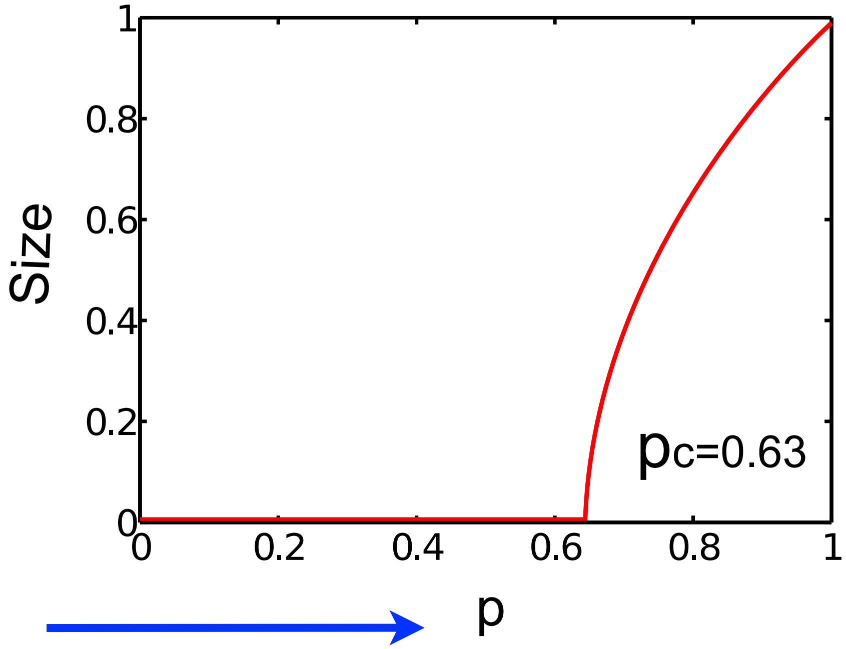

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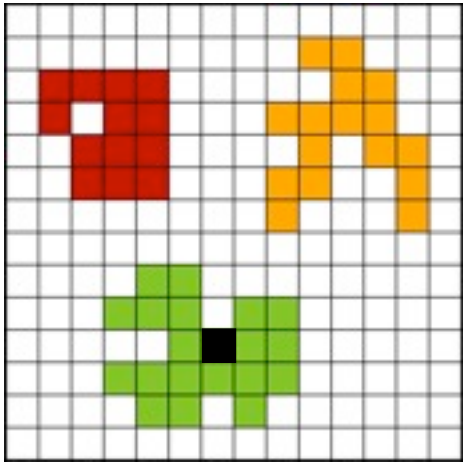

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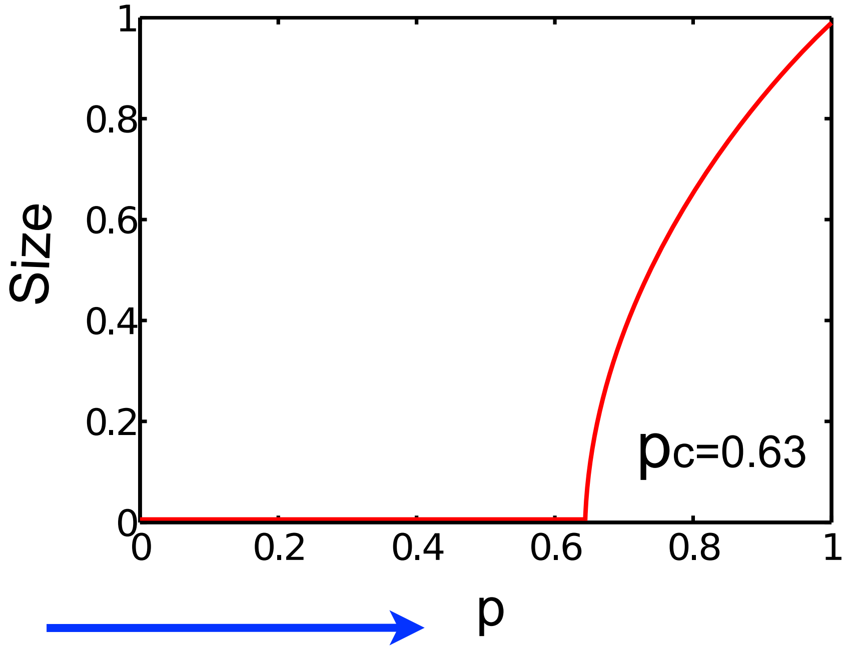

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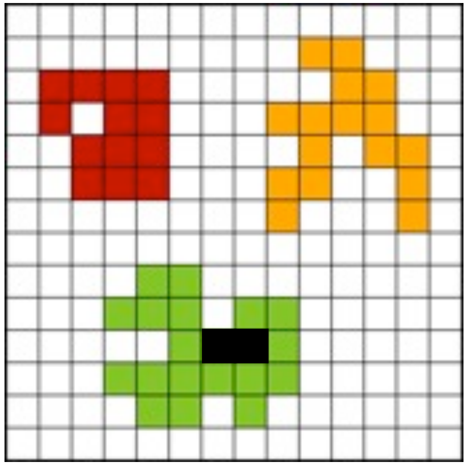

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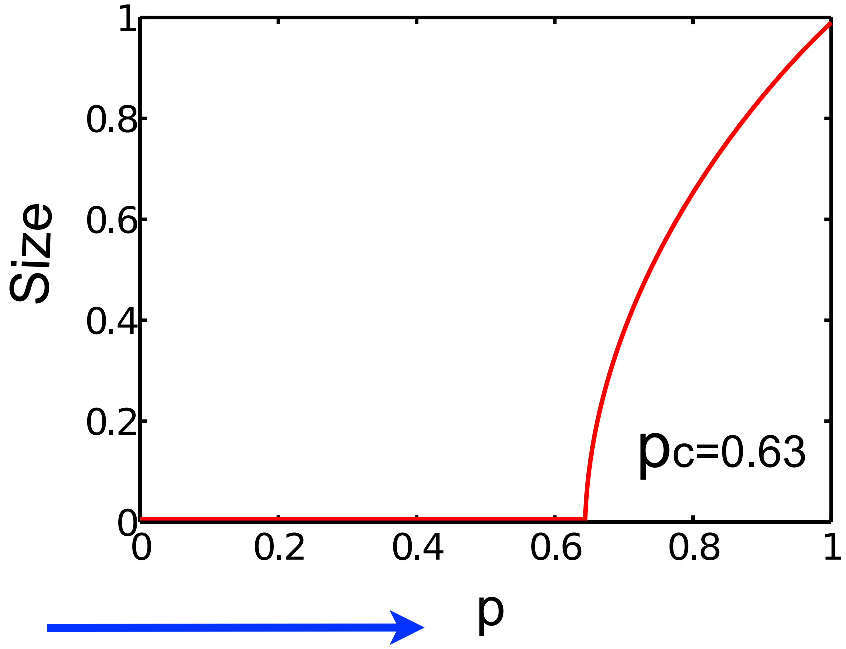

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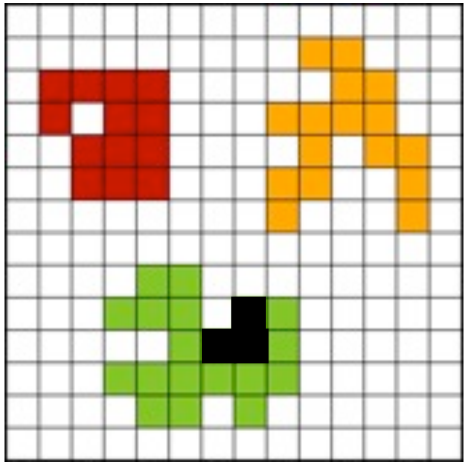

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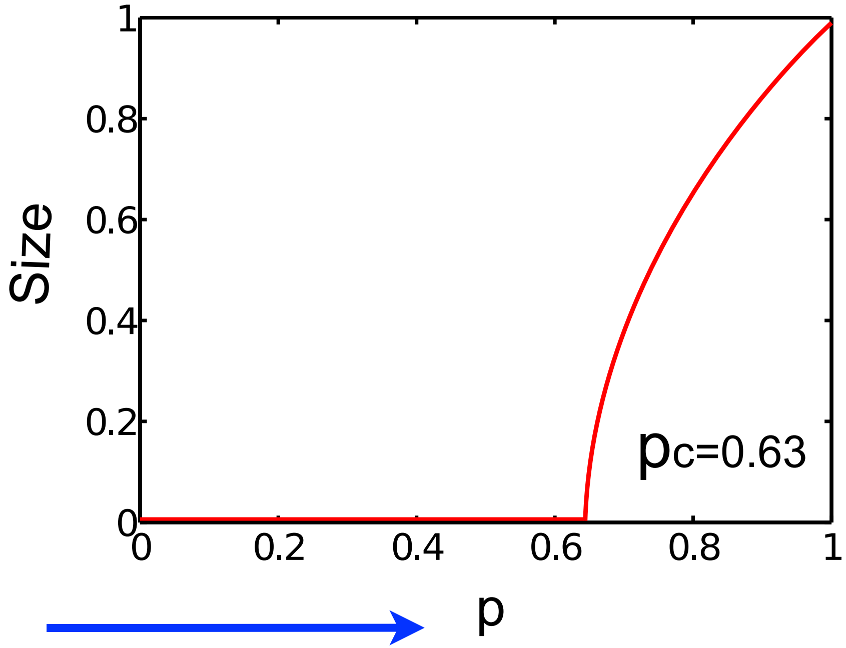

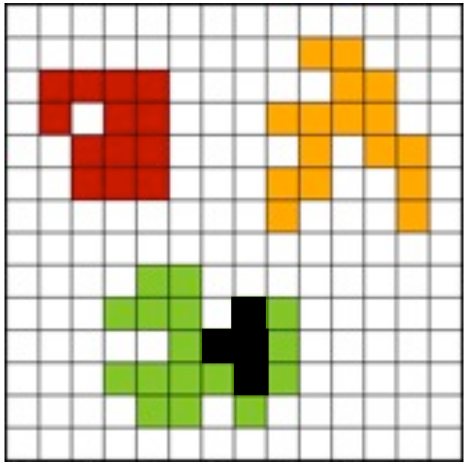

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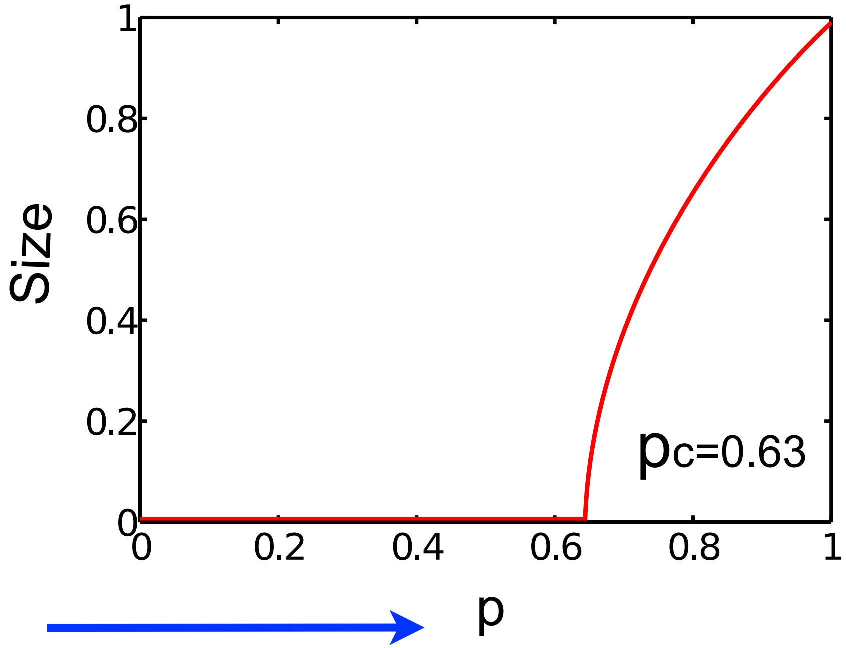

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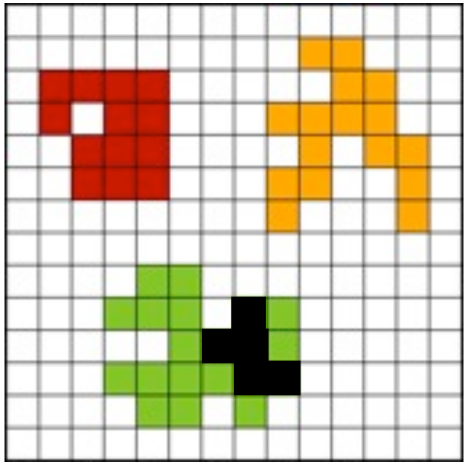

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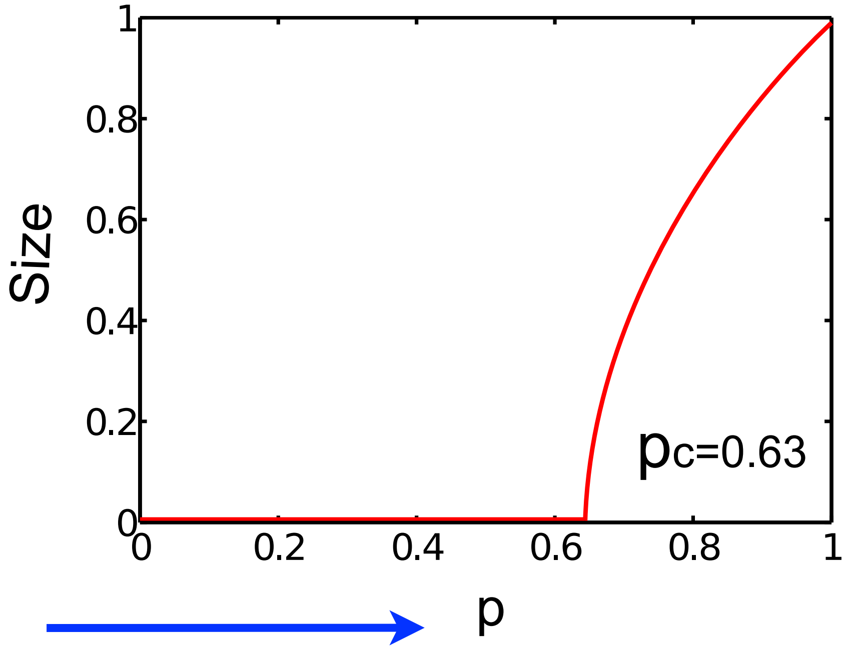

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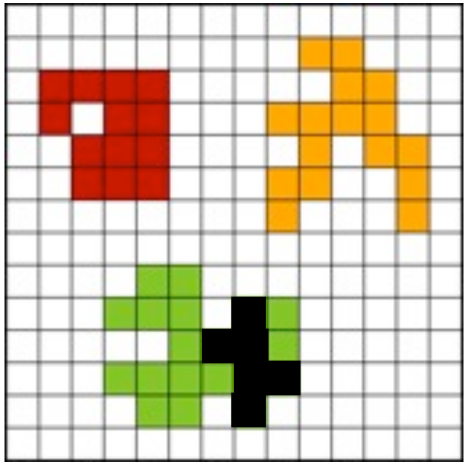

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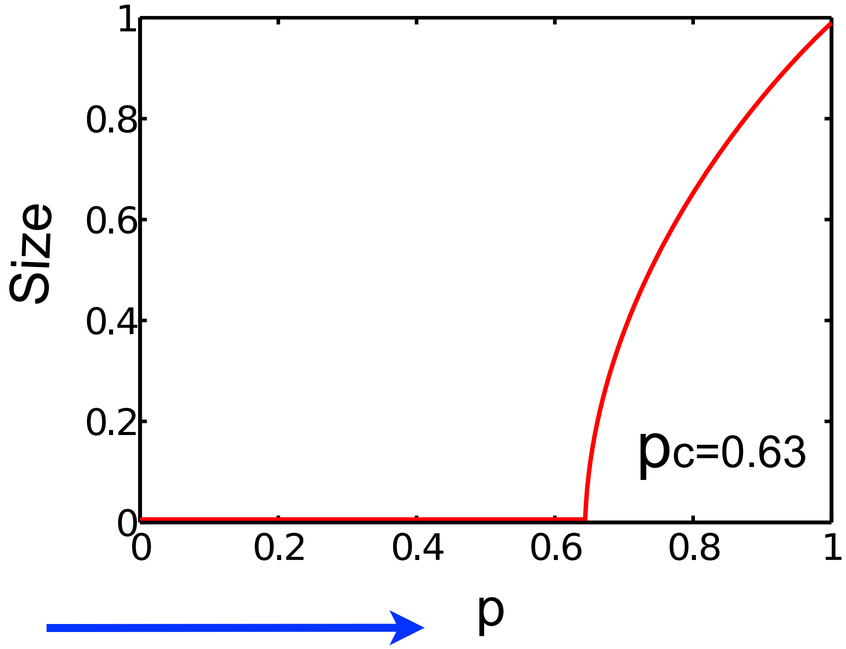

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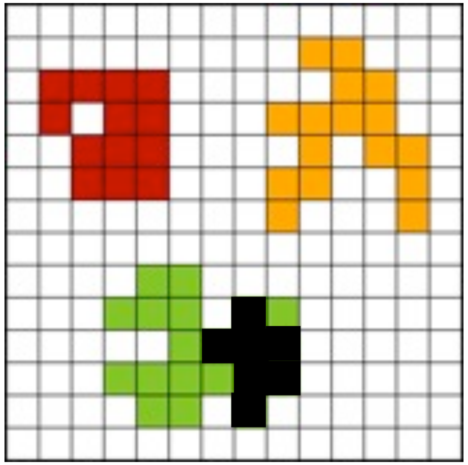

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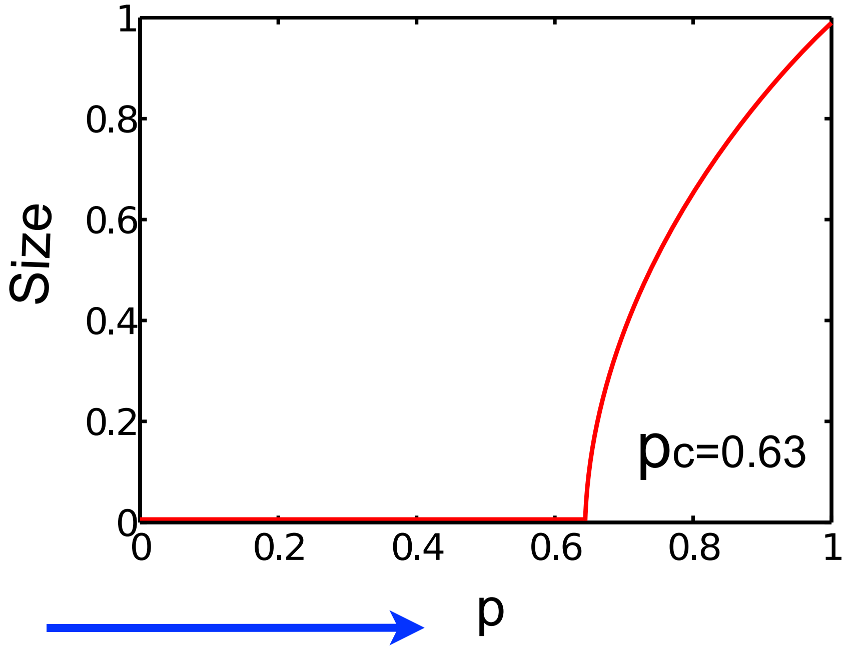

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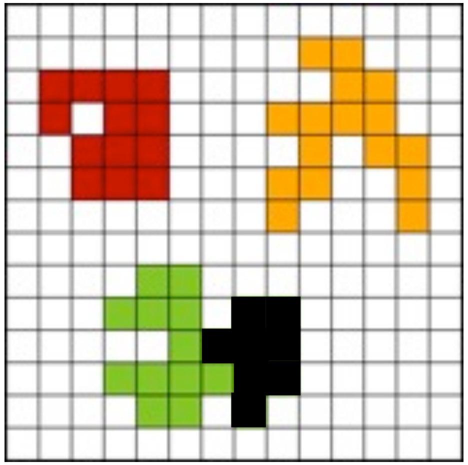

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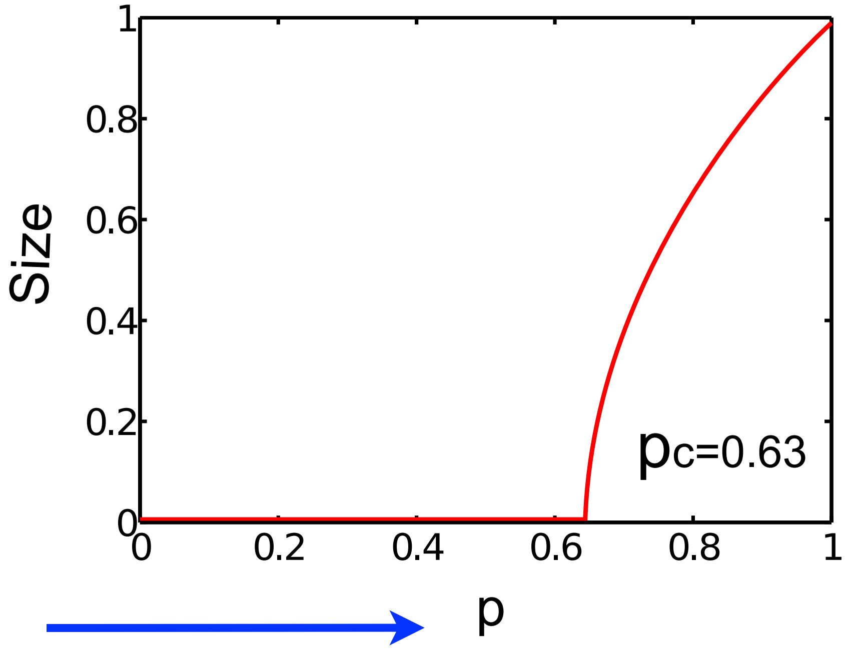

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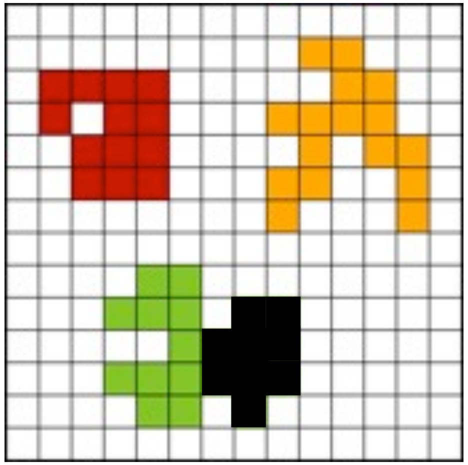

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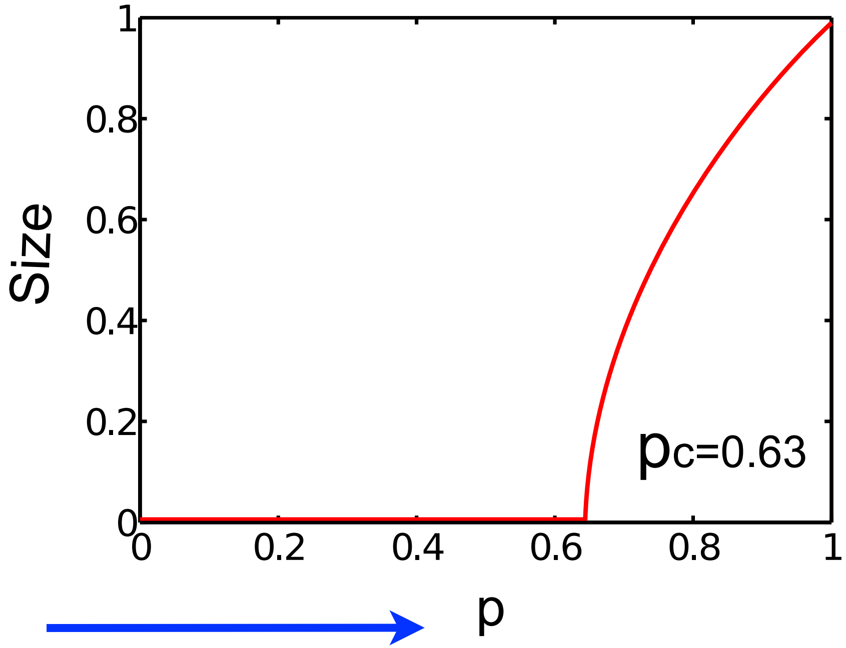

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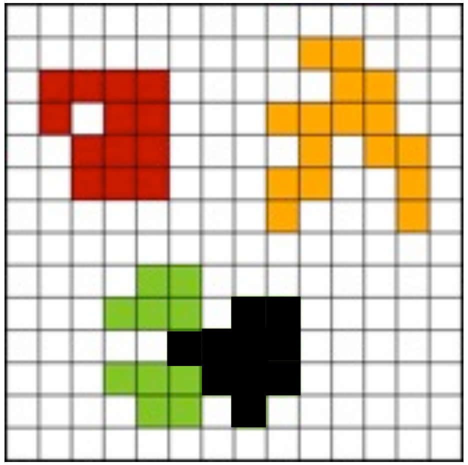

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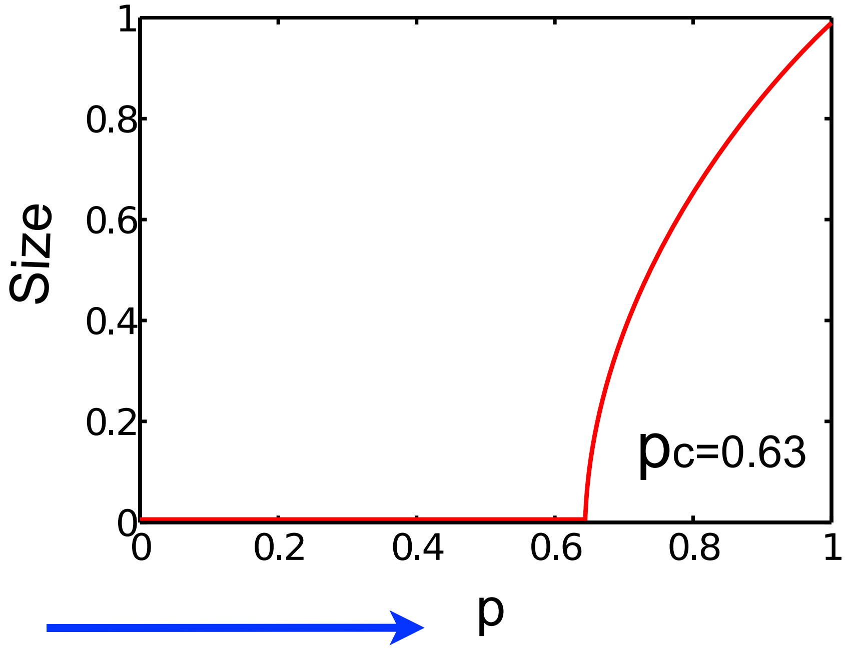

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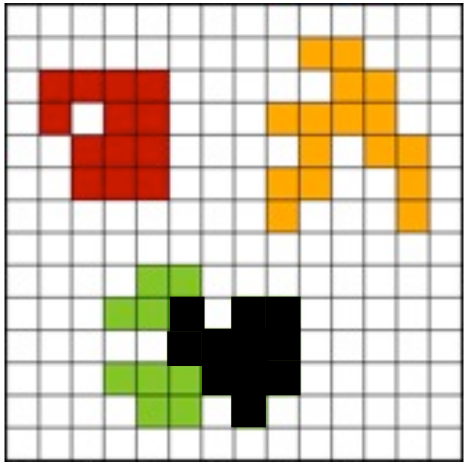

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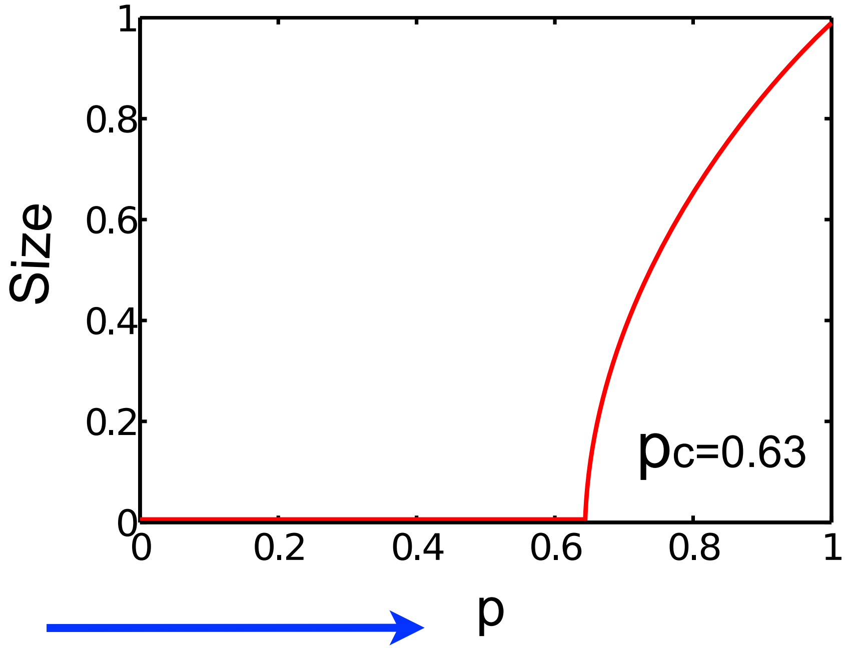

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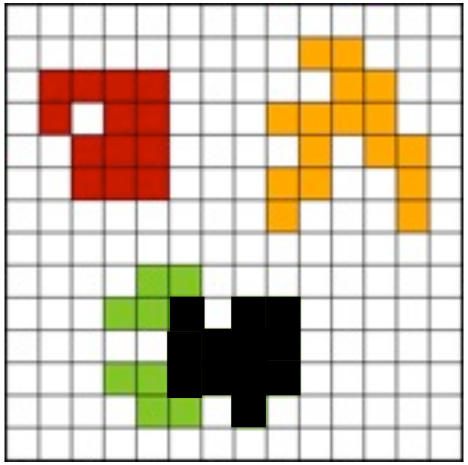

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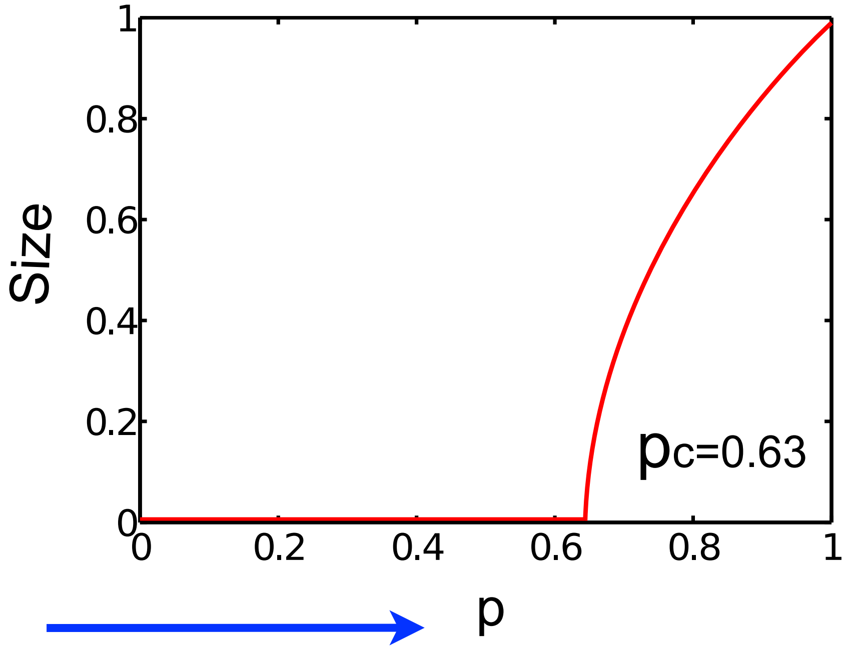

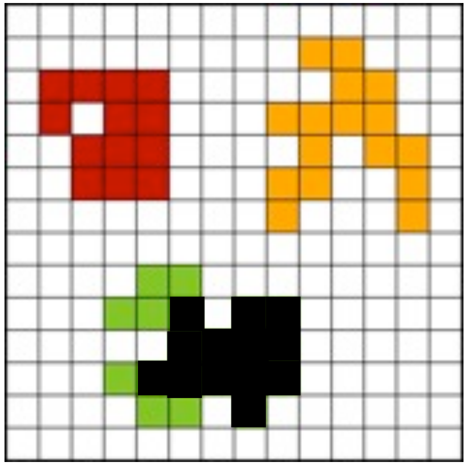

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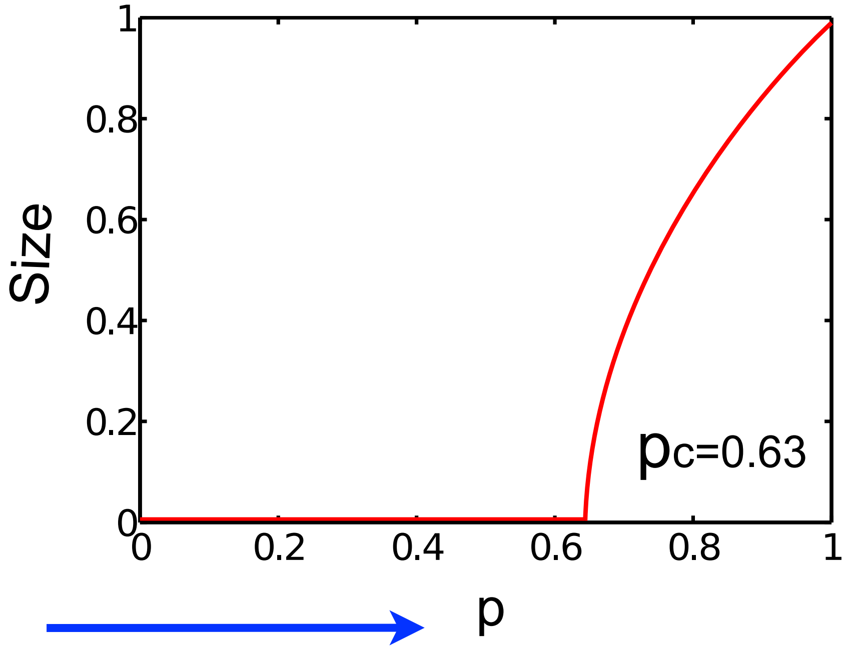

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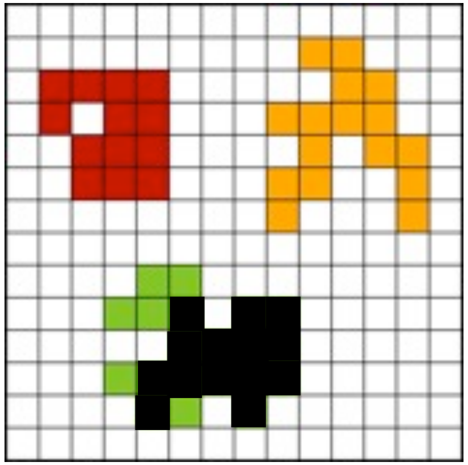

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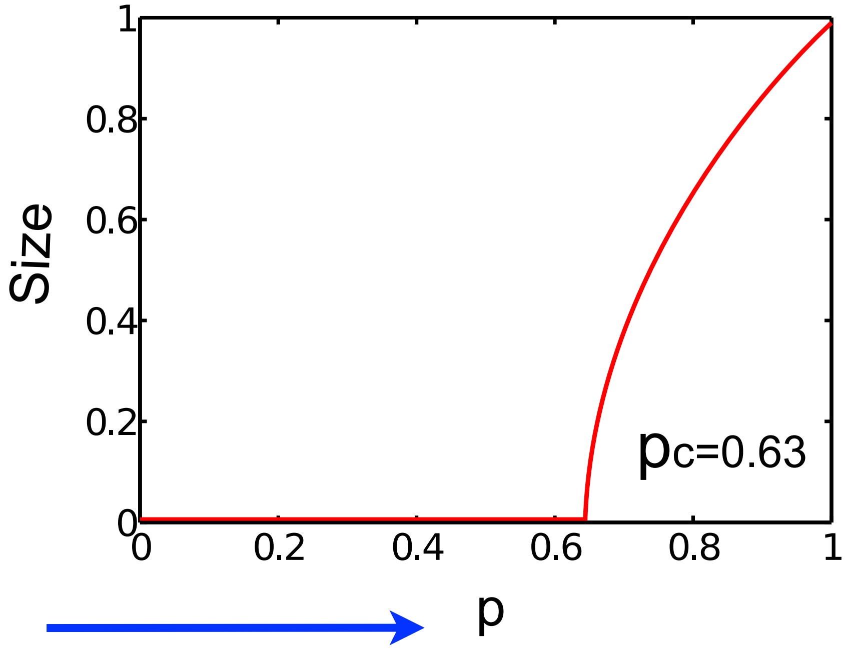

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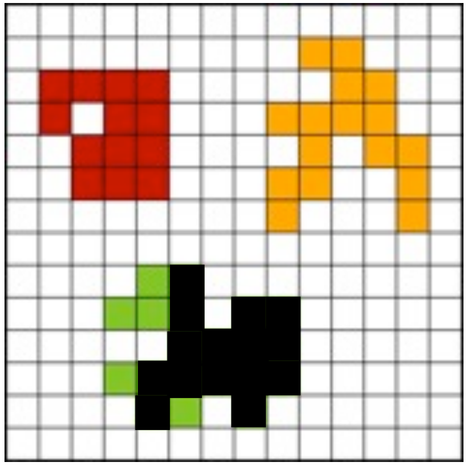

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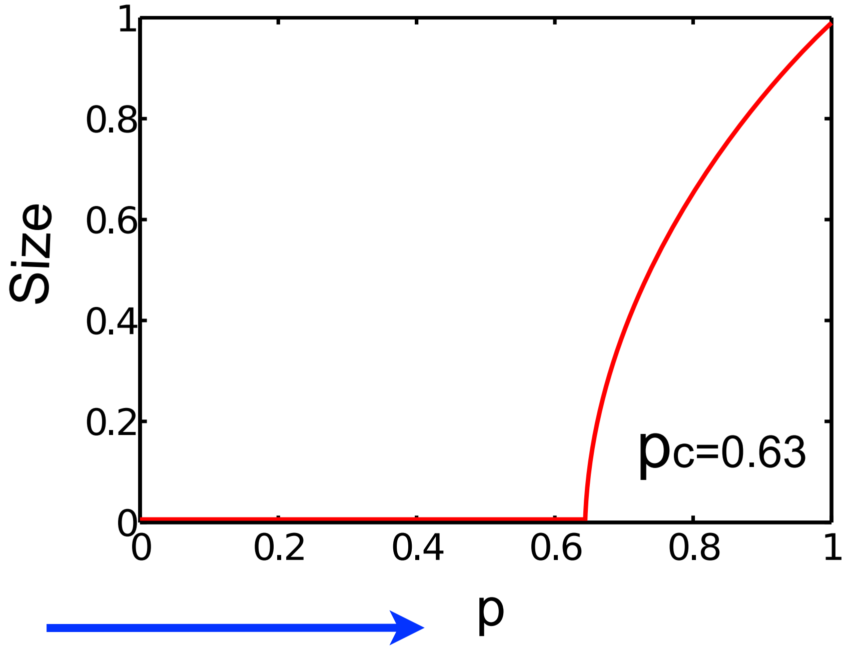

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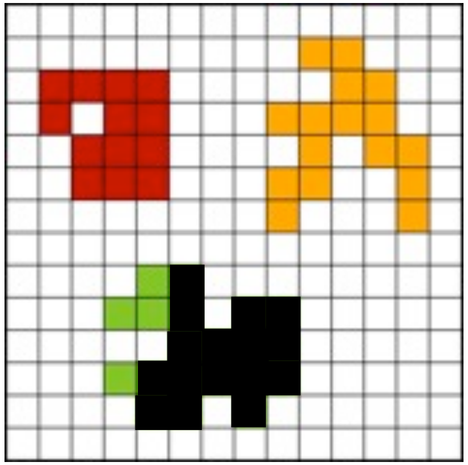

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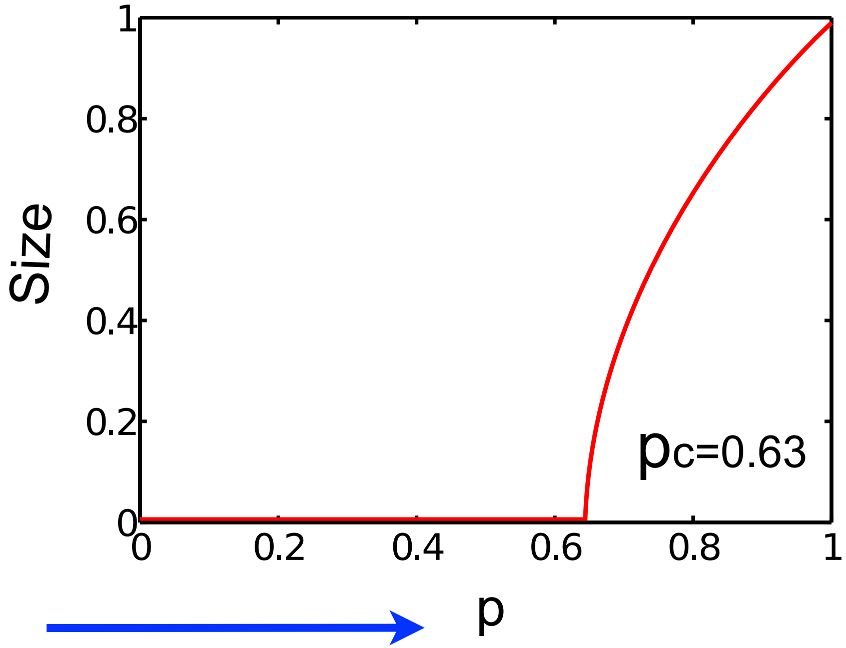

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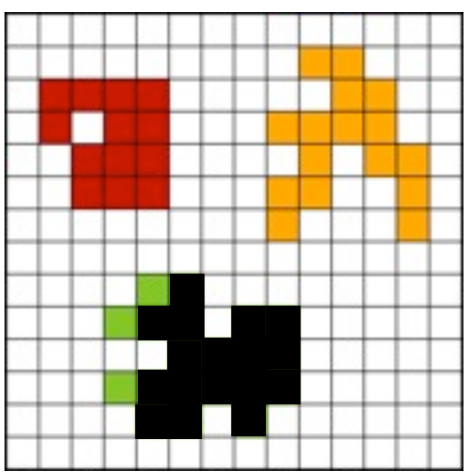

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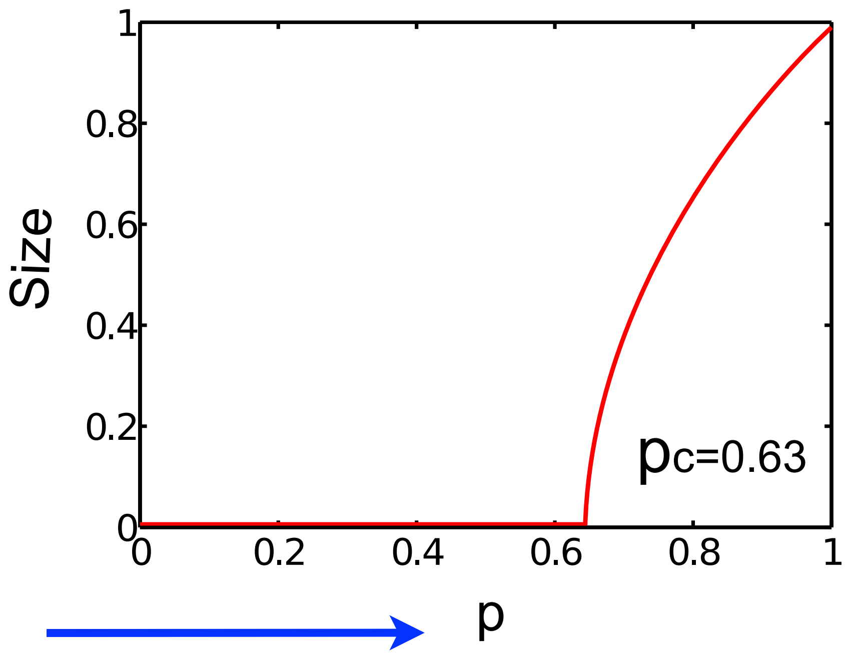

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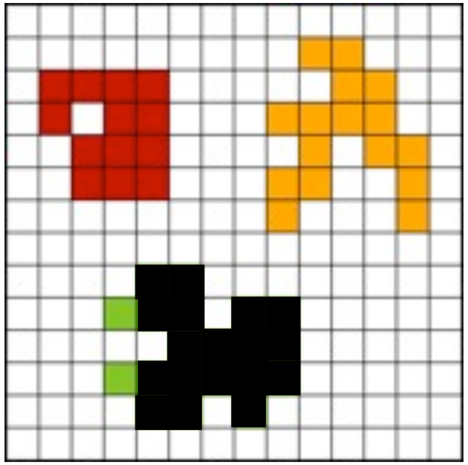

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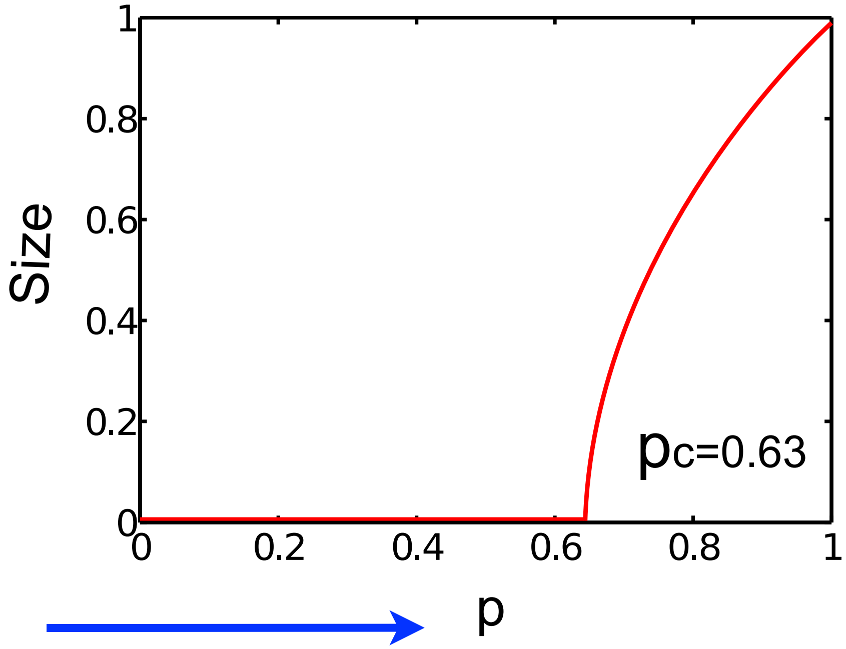

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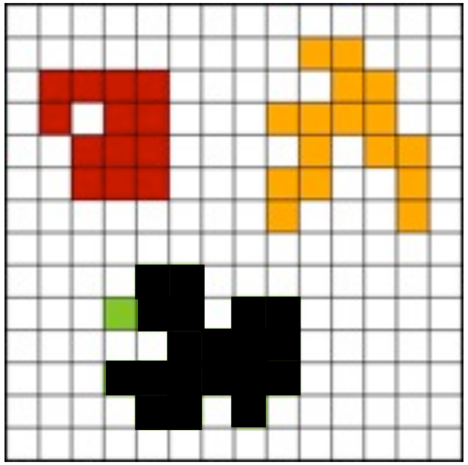

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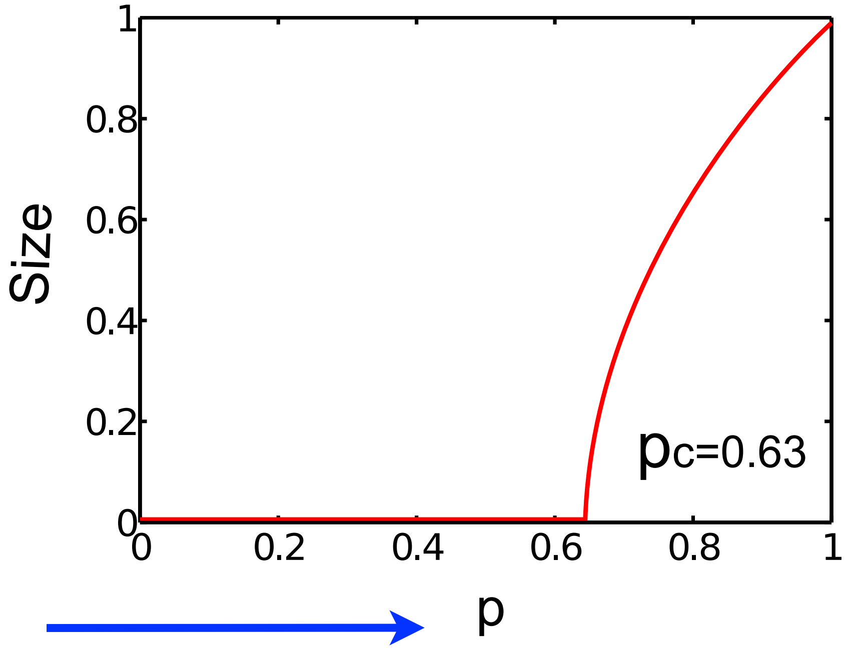

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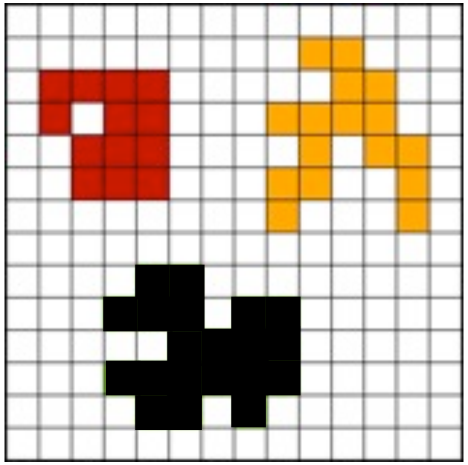

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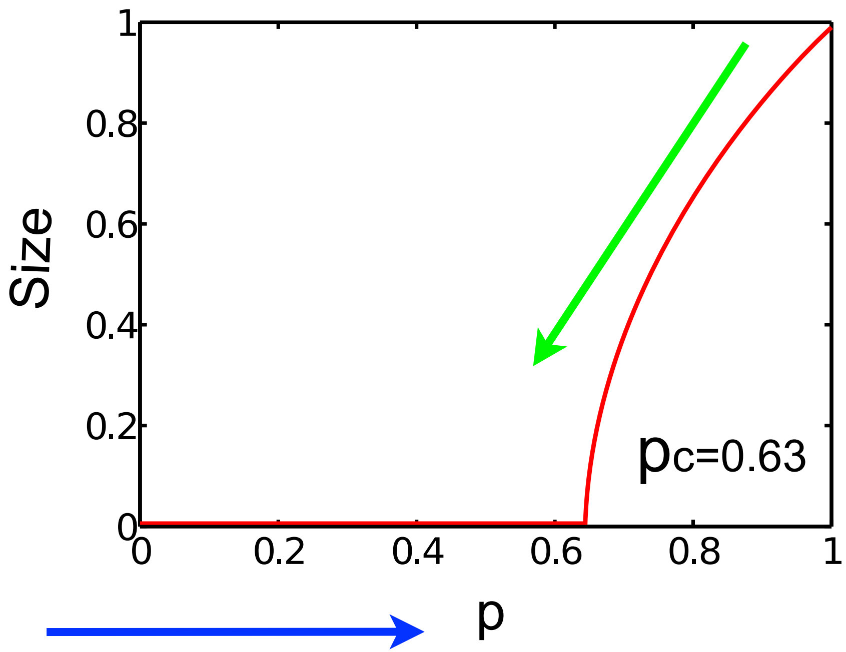
"Attack" a network: Fragmentation of social networks



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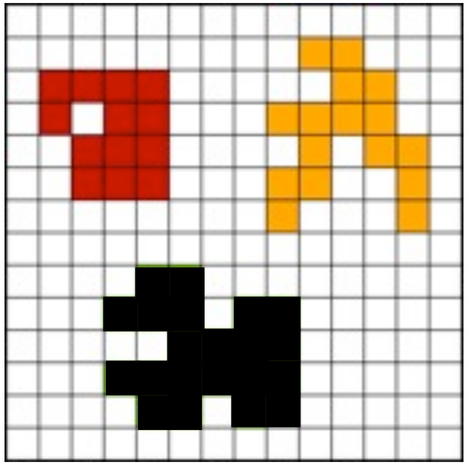

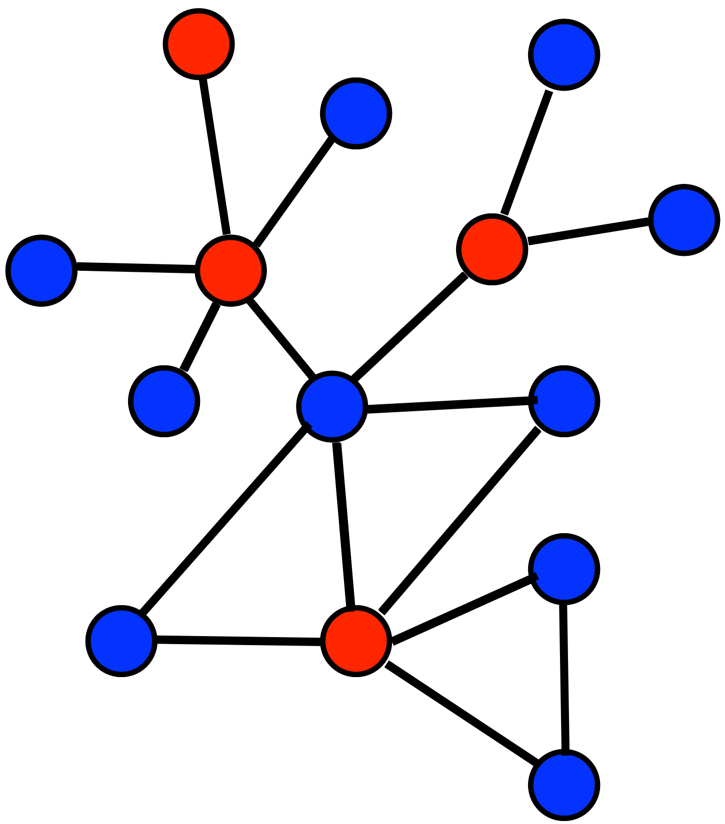

1-p: minimum number of nodes to disrupt the network

Two processes: growth and attack

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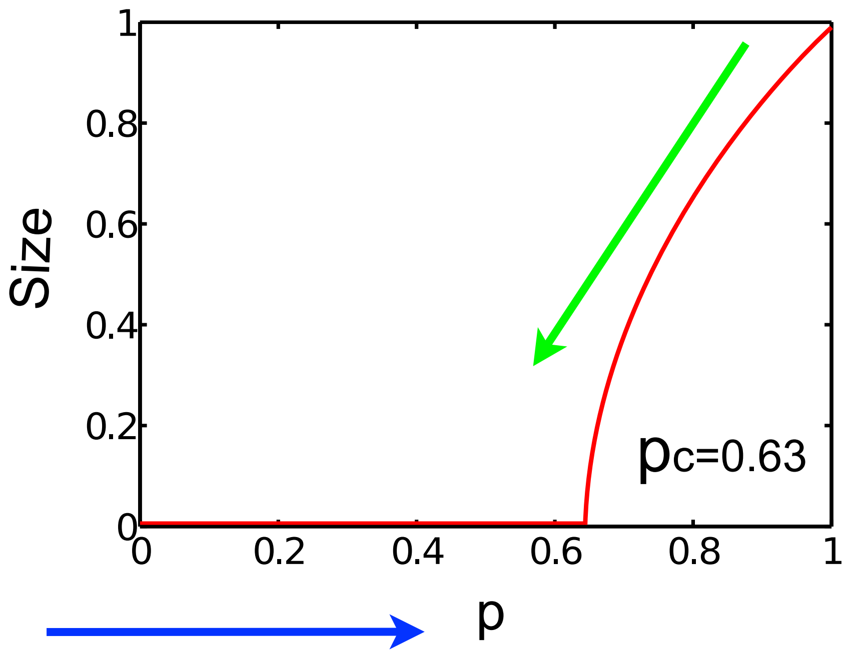

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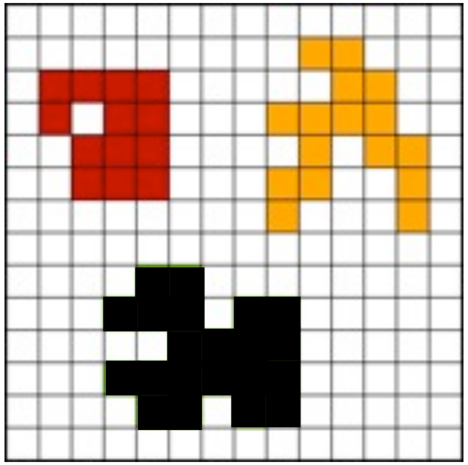

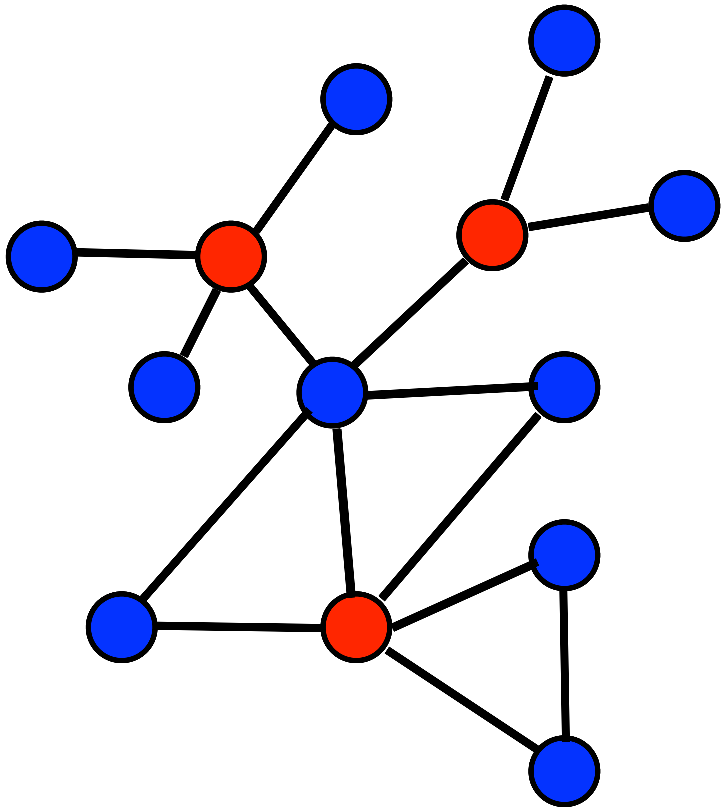

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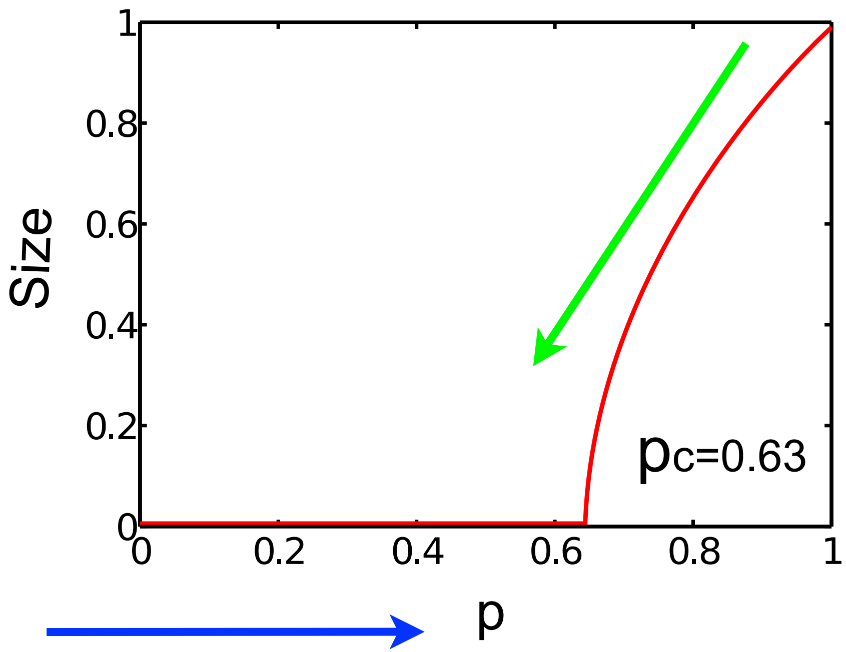

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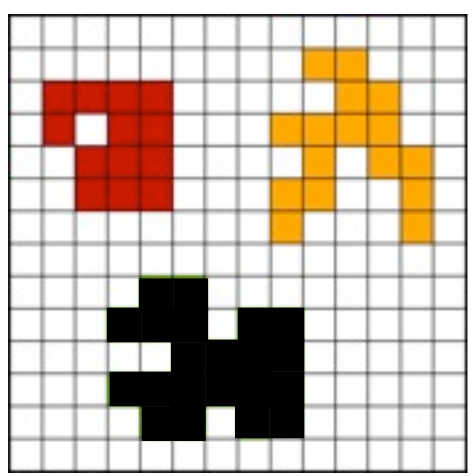

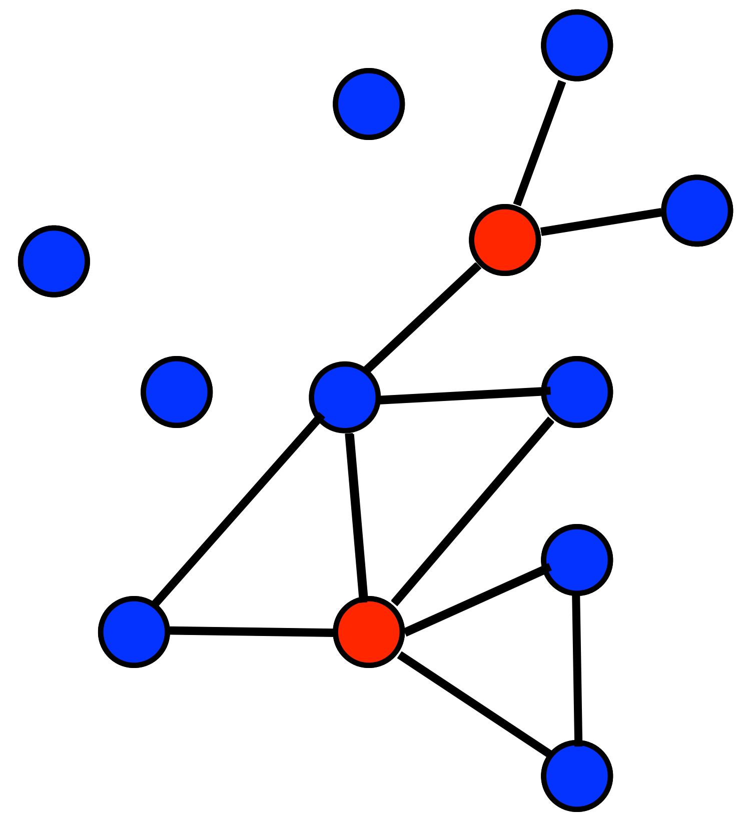

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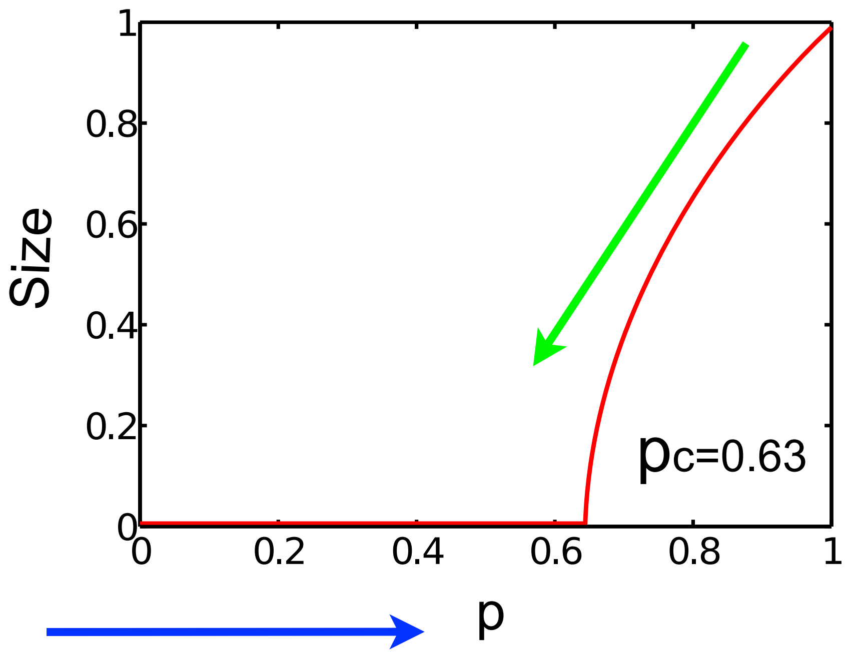

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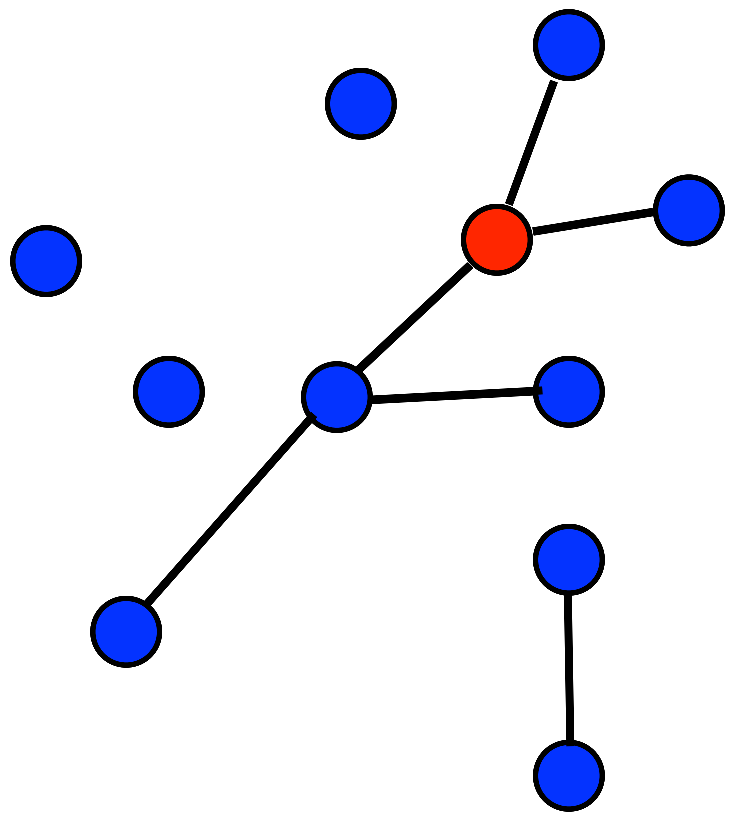

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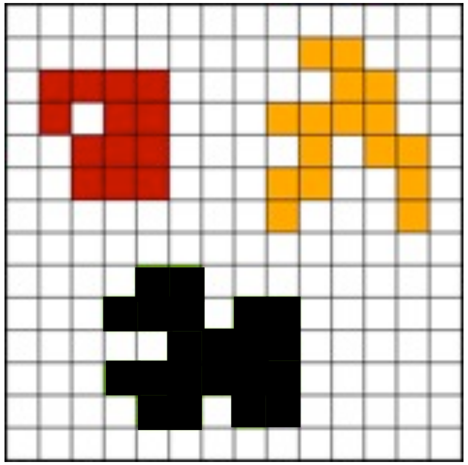

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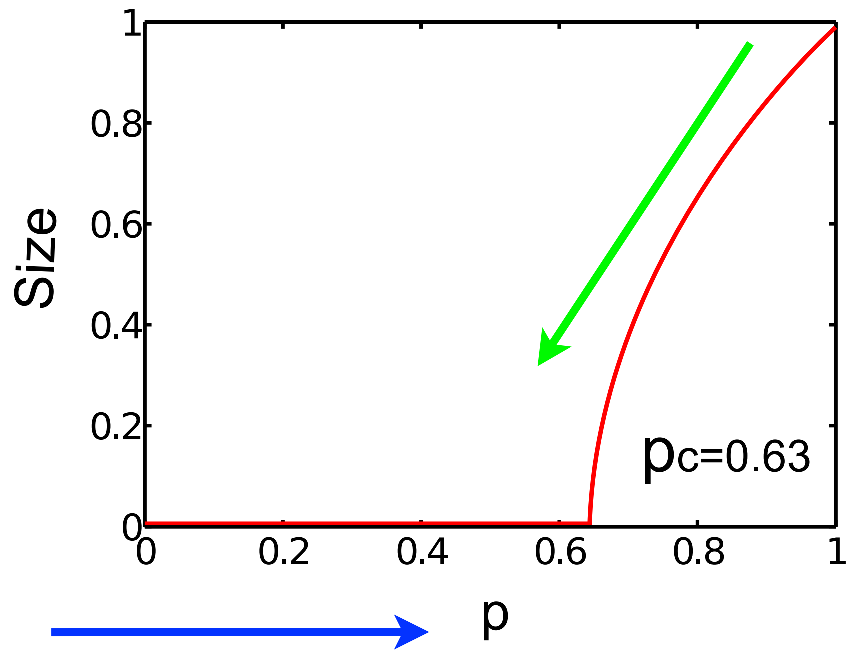

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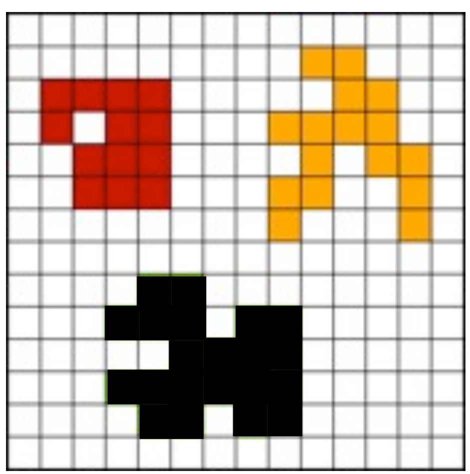

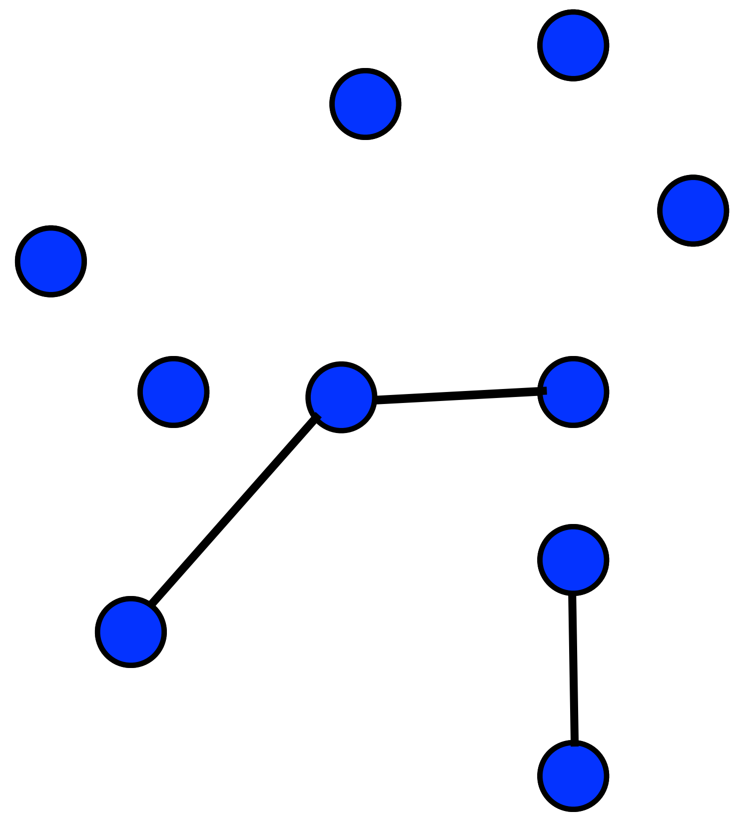

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Obesity percolation: hierarchical clustering

Using CDC data at county level to investigate the spatial spreading of obesity

red bond: Mc Lean, KY

2004

red bond: Rich, UT

Obese: BMI>30

epicenter: Greene county, AL

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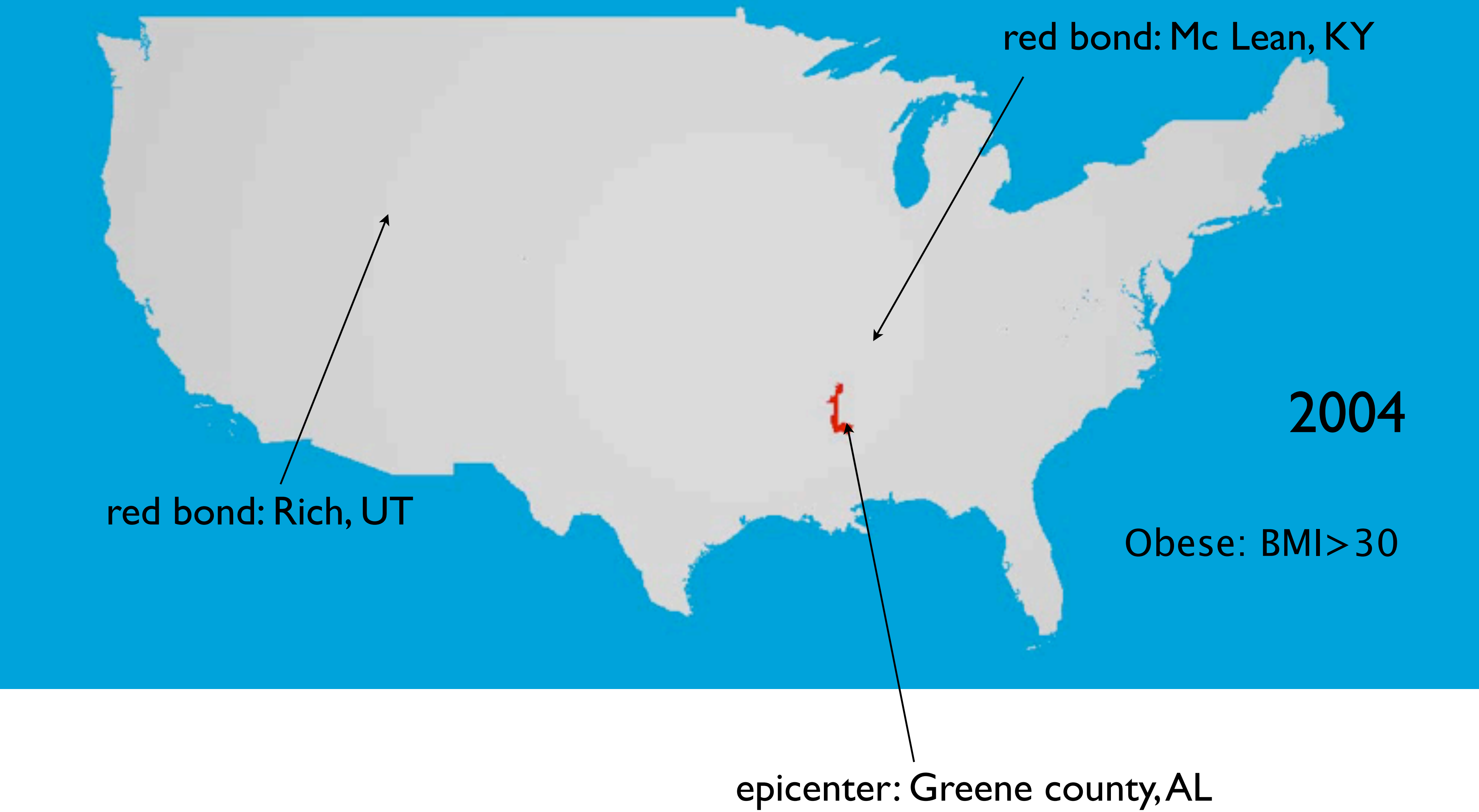

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What is driving the global obesity epidemic?

Hotly debated question: relevant for implementing health policies

Experts say:

A. Individuals responsibility:

Genetic make-up

Individual habits: poor diet

Peer pressure via social network

(Christakis, JAMA, 2007)

B. Environmental global effect

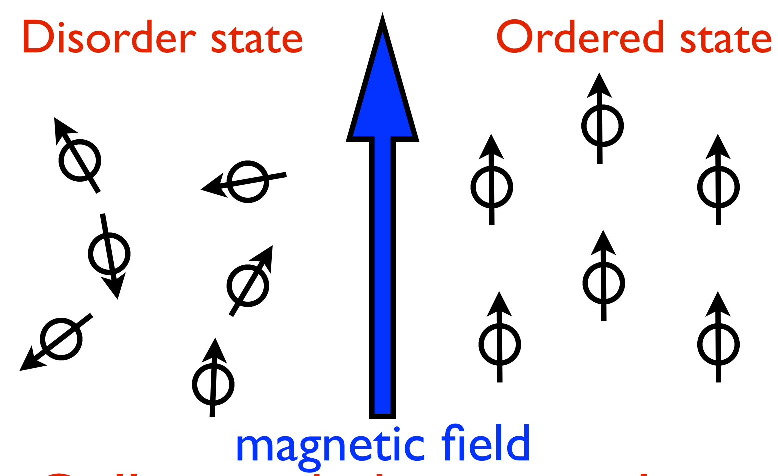
(The Lancet, 2011):

Obesity is driven by global food marketing system: a predictable outcome of market economies predicated on consumption-based growth.

Physics says:

Spin up = obese

Spin down = not obese



Collective behavior analysis:

correlations at a critical point.

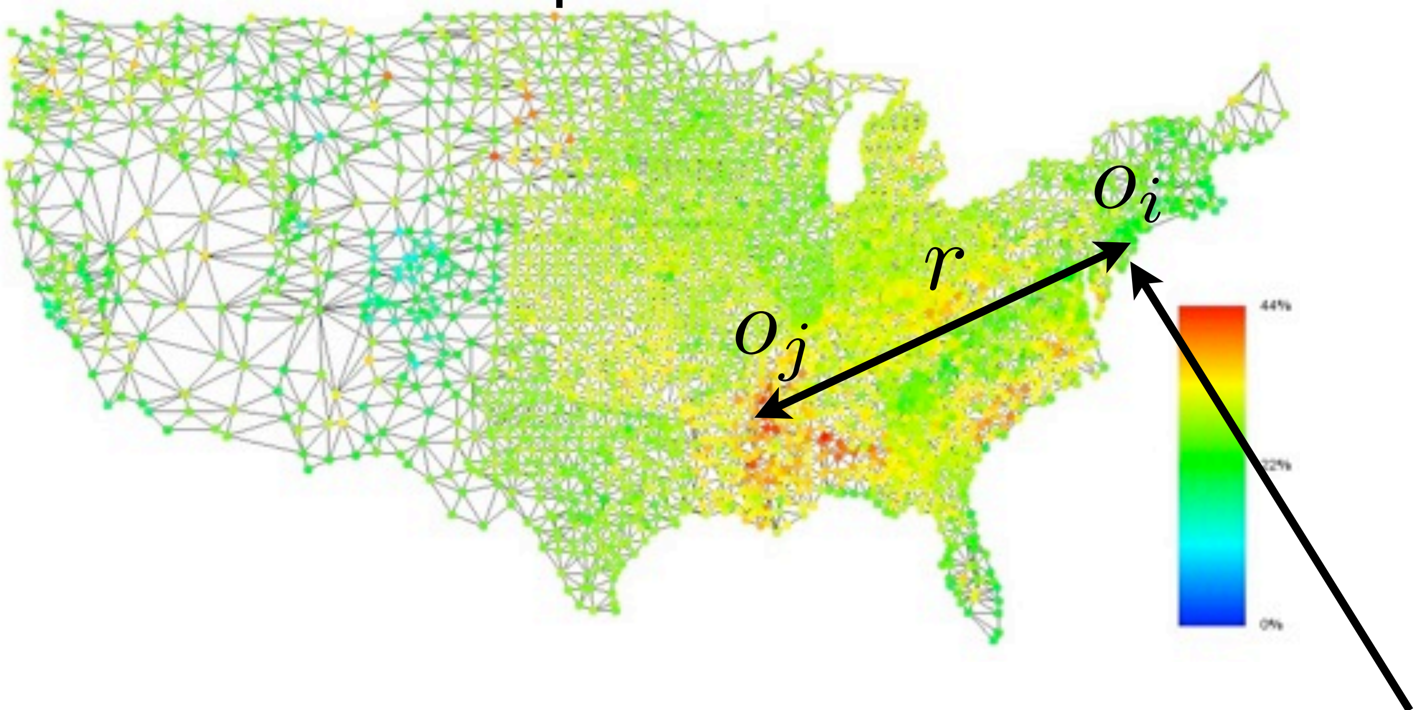
Allows to hint at the driver of the transition

Important issue for policy makers:

Individual vs Industry responsibility

Searching for correlations

Drivers of the epidemic: collective behavior or individual habits



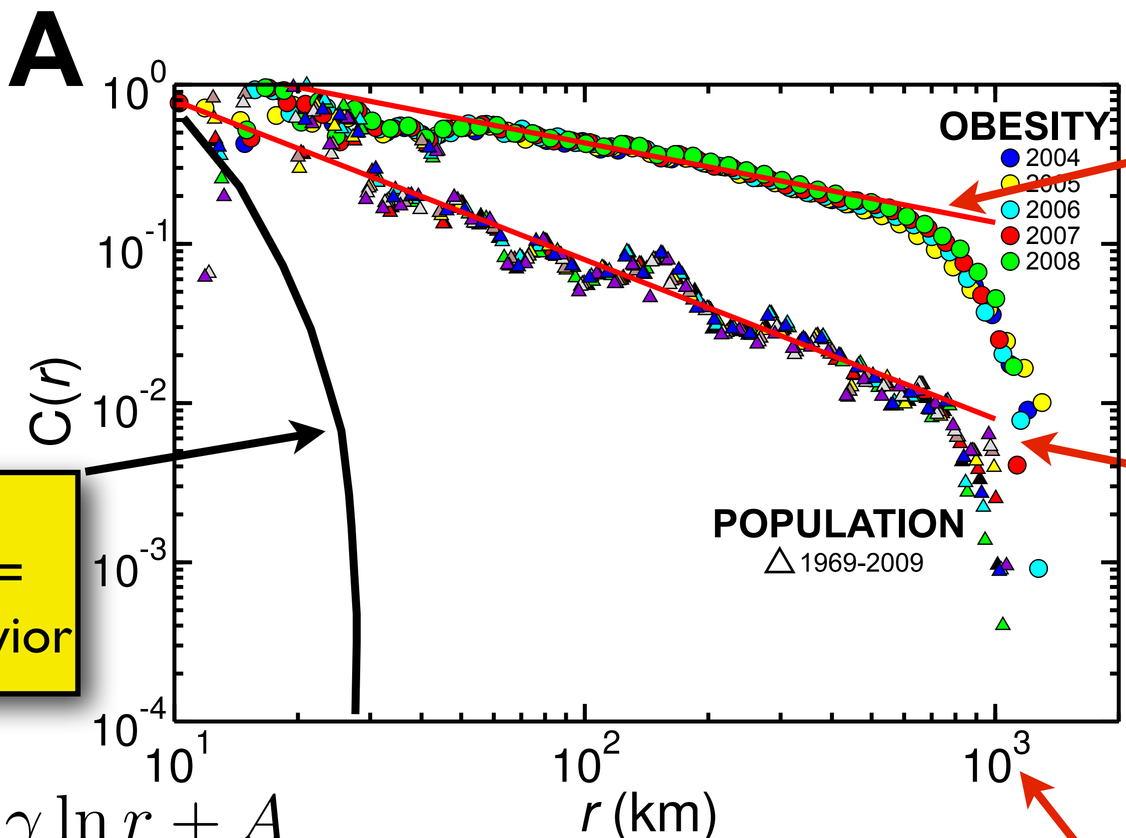
Correlation function of the obesity prevalence, o_i, defined at the county level. Data from CDC

How obesity prevalence at position *i* influences the obesity at a distance *r*

$$C(r) = \frac{1}{\sigma^2} \sum_{ij} \Big(o_i - \bar{o} \Big) \Big(o_j - \bar{o} \Big)$$

Obesity is long-ranged correlated up to 1000km

Obesity and diabetes prevalence in the USA from 2004-2008



$\gamma = 1/2$
Obesity/diabetes

Short-range correlations = individual behavior

$\gamma = 1$
Population

$$\ln C(r) = -\gamma \ln r + A$$

$$C(r) \sim r^{-\gamma}, \qquad r < \xi \qquad\qquad \xi_{\text{pop}} = 1000\text{km}$$

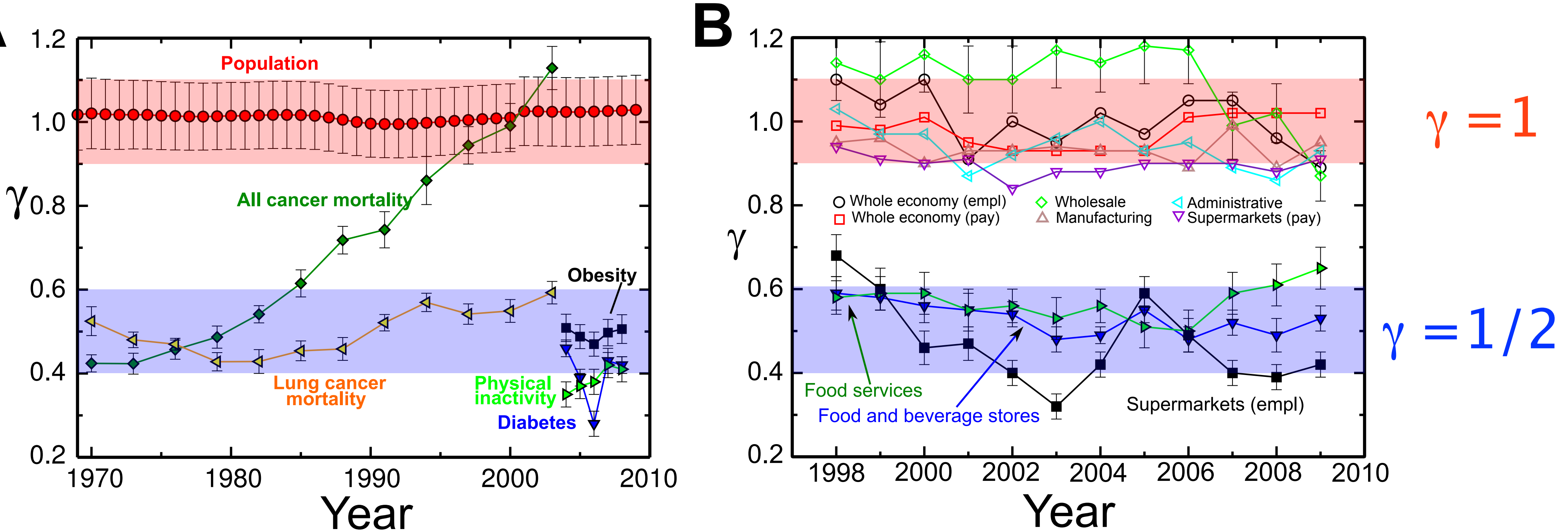
Correlation exponent

$$\gamma_{\text{ob}} = \gamma_{\text{diab}} = 1/2$$

Long-range correlations in obesity = collective behavior

What about the food industry's activity?

Industry: measured by employees and payroll per county, US Census Bureau
Cancer mortality rates per county, National Cancer Institute, SEER



Obesity fluctuations are synchronized with supermarket fluctuations

Conjecture:

Driving force of obesity: economic activity of food industry?

It may not be all about calories

- Obesity spreading is analogous to strongly correlated physical systems
- We live in ‘obesity cities’ which are much larger than real cities (~ 1000 km)
- The obesity problem is the same all across USA, including the lower prevalence areas (NY, West coast)
- Population distribution has much weaker correlations
- Strong correlations in food industry too (driver?)

Should policies target mainly the global food system, rather than individual behaviors?

Michelle Obama’s “Let’s move” campaign
vs
NYC Major Bloomberg’s super-sized soda ban

The rise of scientific ideas

Cascades of followers triggered by pioneers

Courtesy of A. Barabasi

Times cited

Years

The rise of scientific ideas

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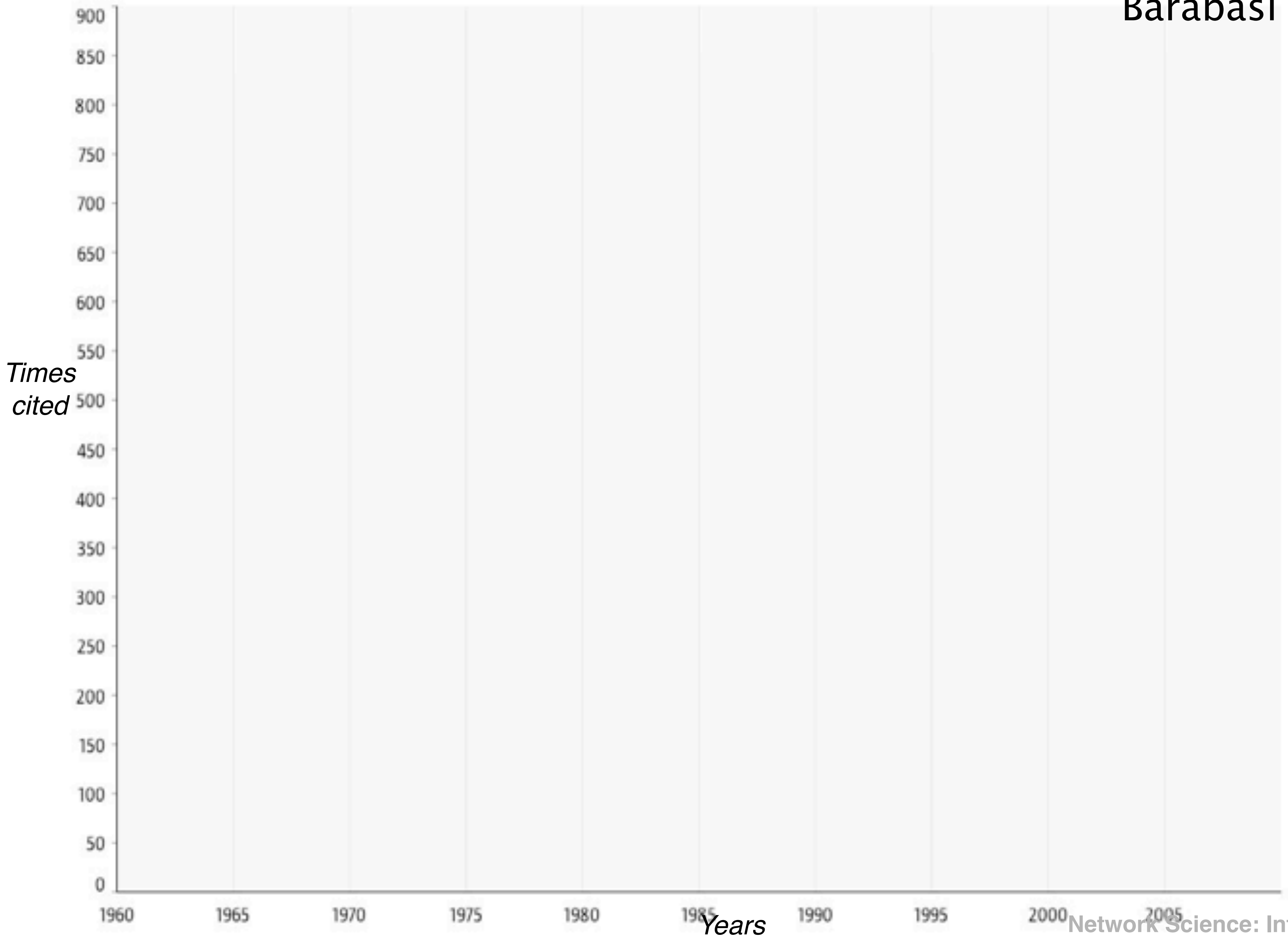


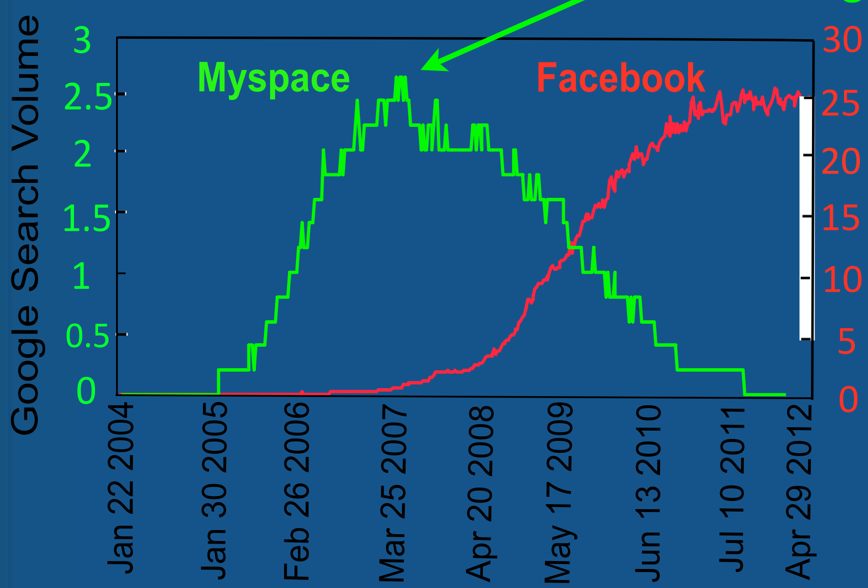
Rise and fall of social networks: how novel ideas are adopted in a social community

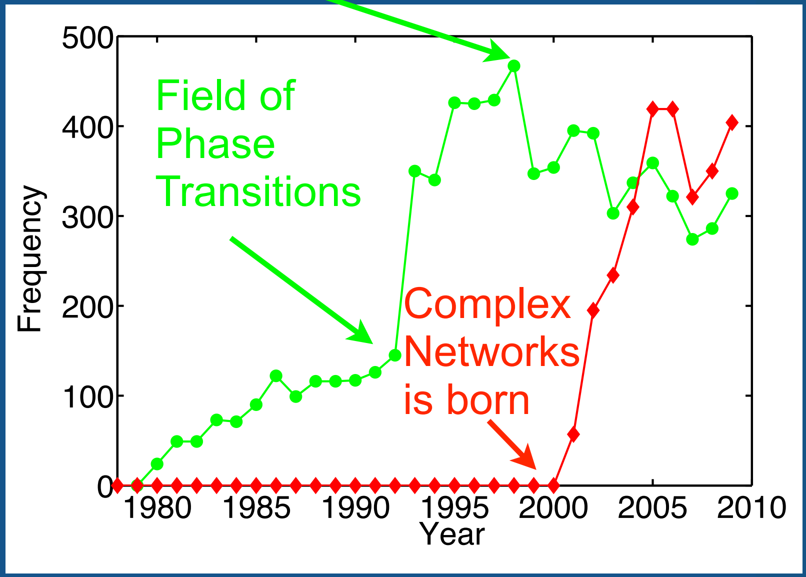
Myspace vs Facebook

Scientific communities:

"Phase Transition" vs "Networks science"

Predicting the tipping point





Collaboration of scientists publishing in the American Physical Society (APS)

Other applications:
Disintegration of political systems: "Arab spring"
Adoption of consumer products, art and scientific trends
Marketing of brand new products
Market crash

How to identify the conditions for fragmentation?

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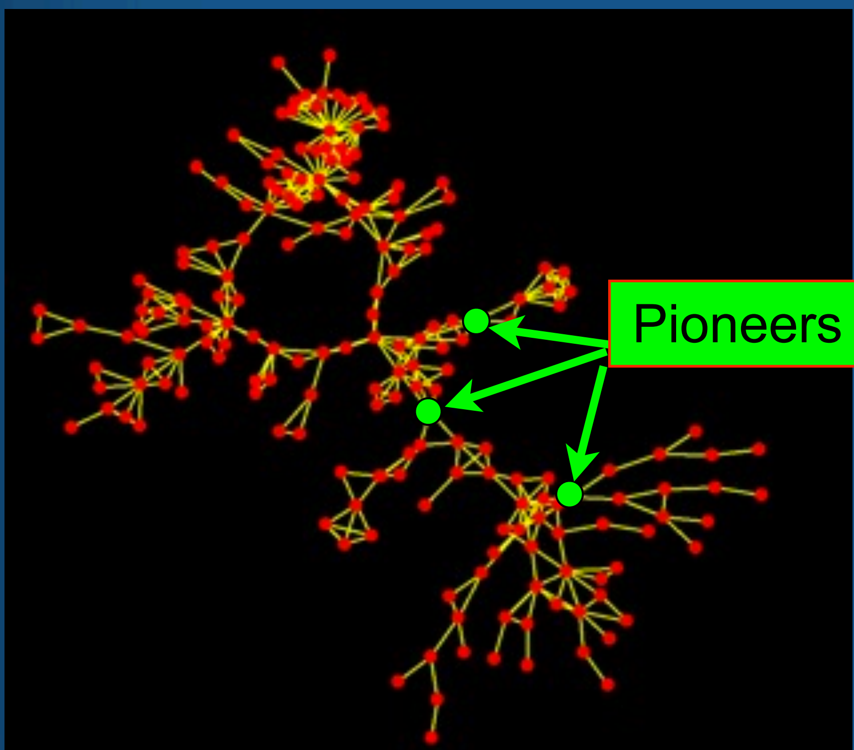
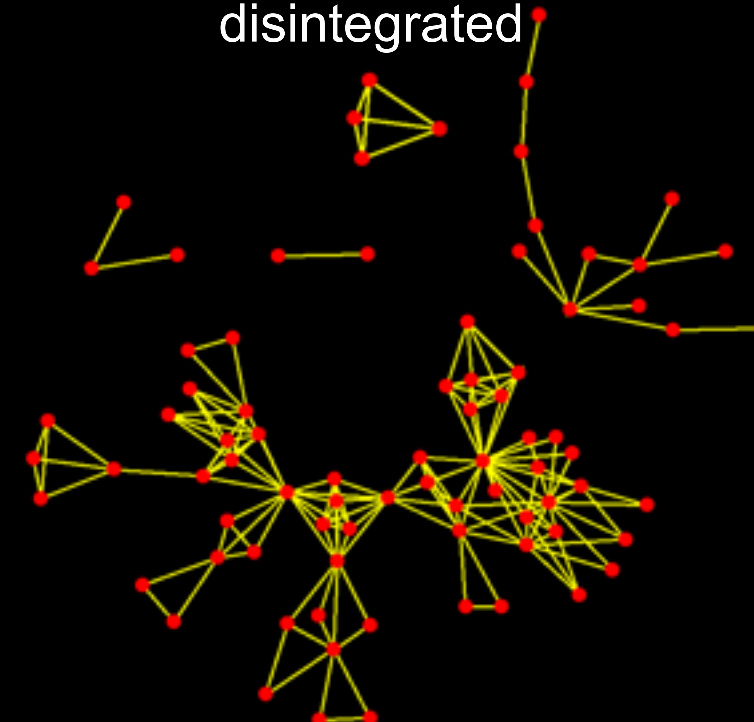
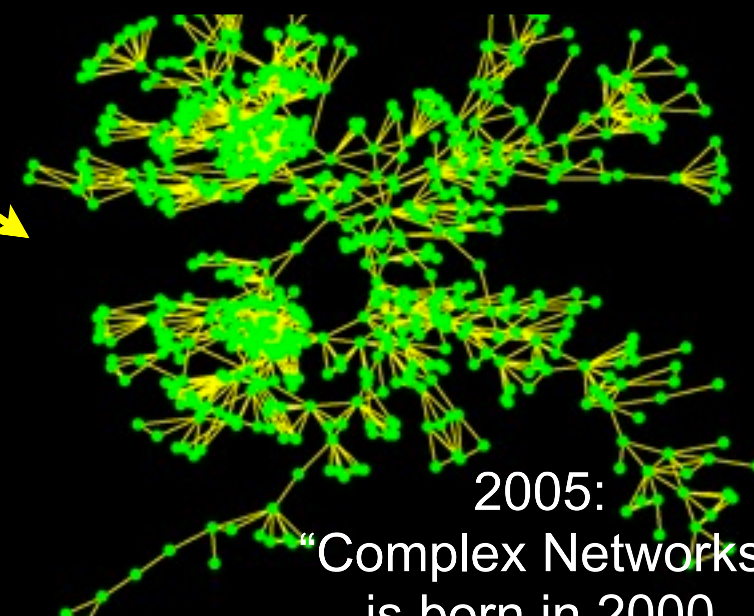
Fragility of scientific communities

Network of scientists in the Field of “Phase Transitions” in 2000



2005:
“Phase Transition” is disintegrated

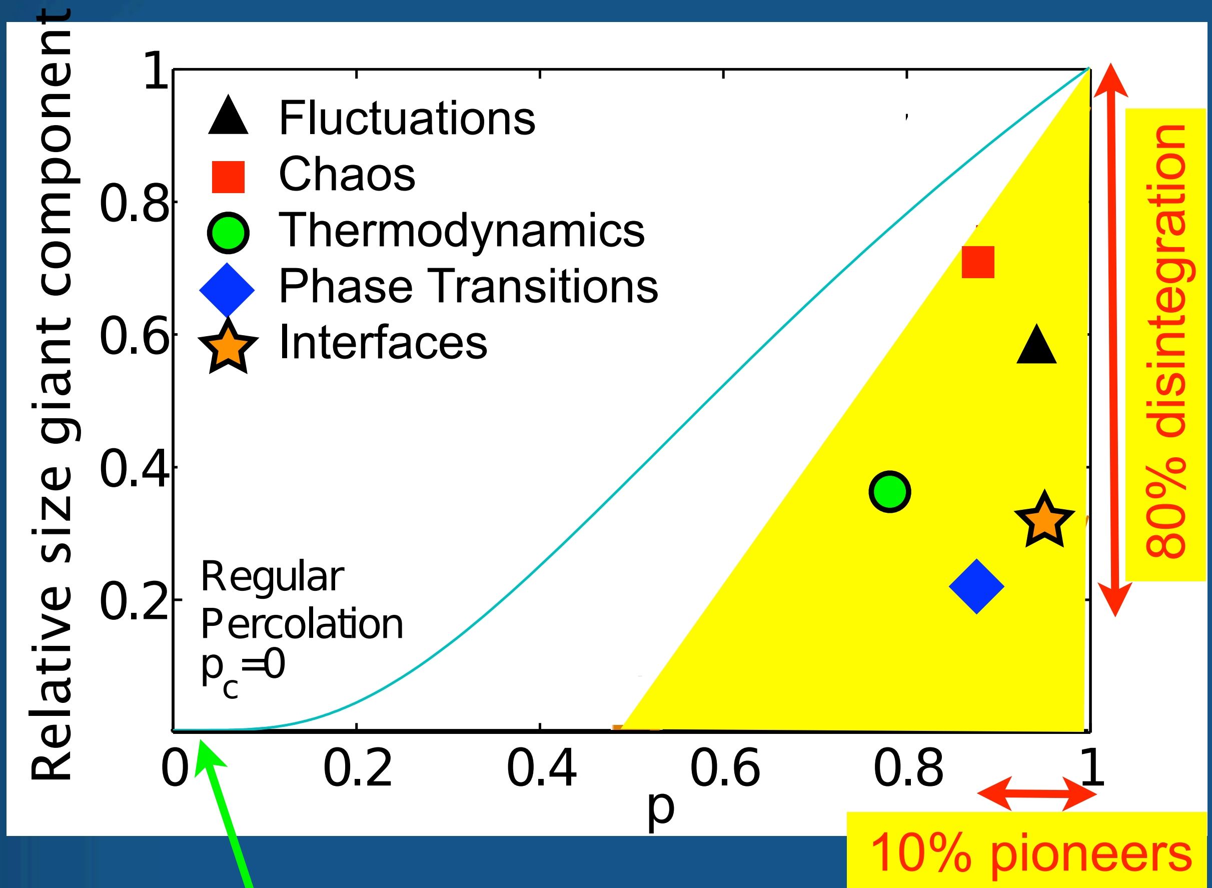




The pioneers are not the hubs!

Einstein, Newton: outsiders

Fragility of scientific communities



Social networks are scale-free, yet they are extremely fragile to the departure of a few pioneers, who are not hubs.

We find:

$$p_c \in [0.5, 0.9]$$

Data contrasts with prediction of percolation theory on scale-free networks:

$$p_c = \frac{\langle k \rangle}{\langle k^2 \rangle}$$

$$P(k) \sim k^{-\gamma}$$
$$p_c = 0$$

Scale-free networks:
Robust to random attack,
yet fragile to hub attack.

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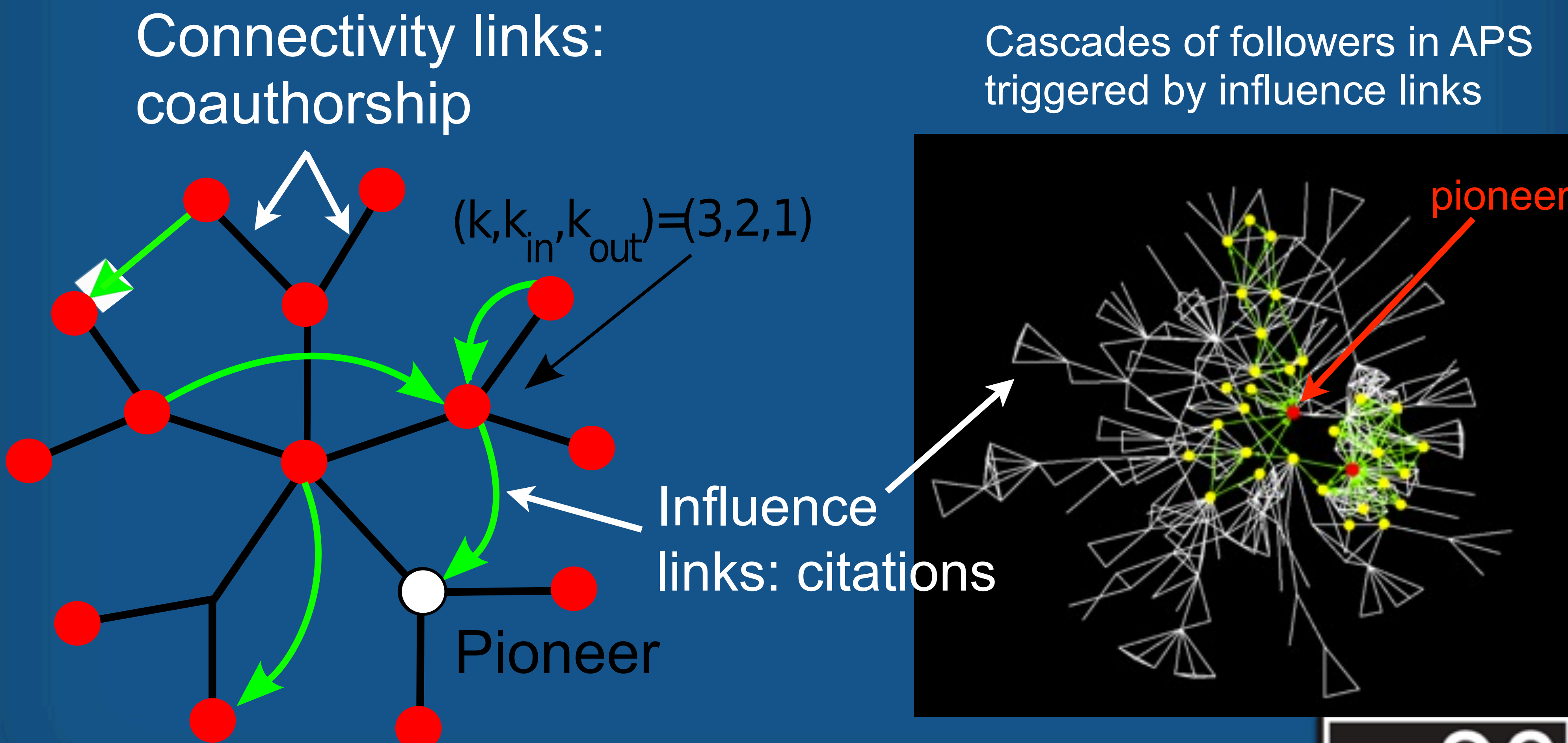
Two networks: connectivity + influence



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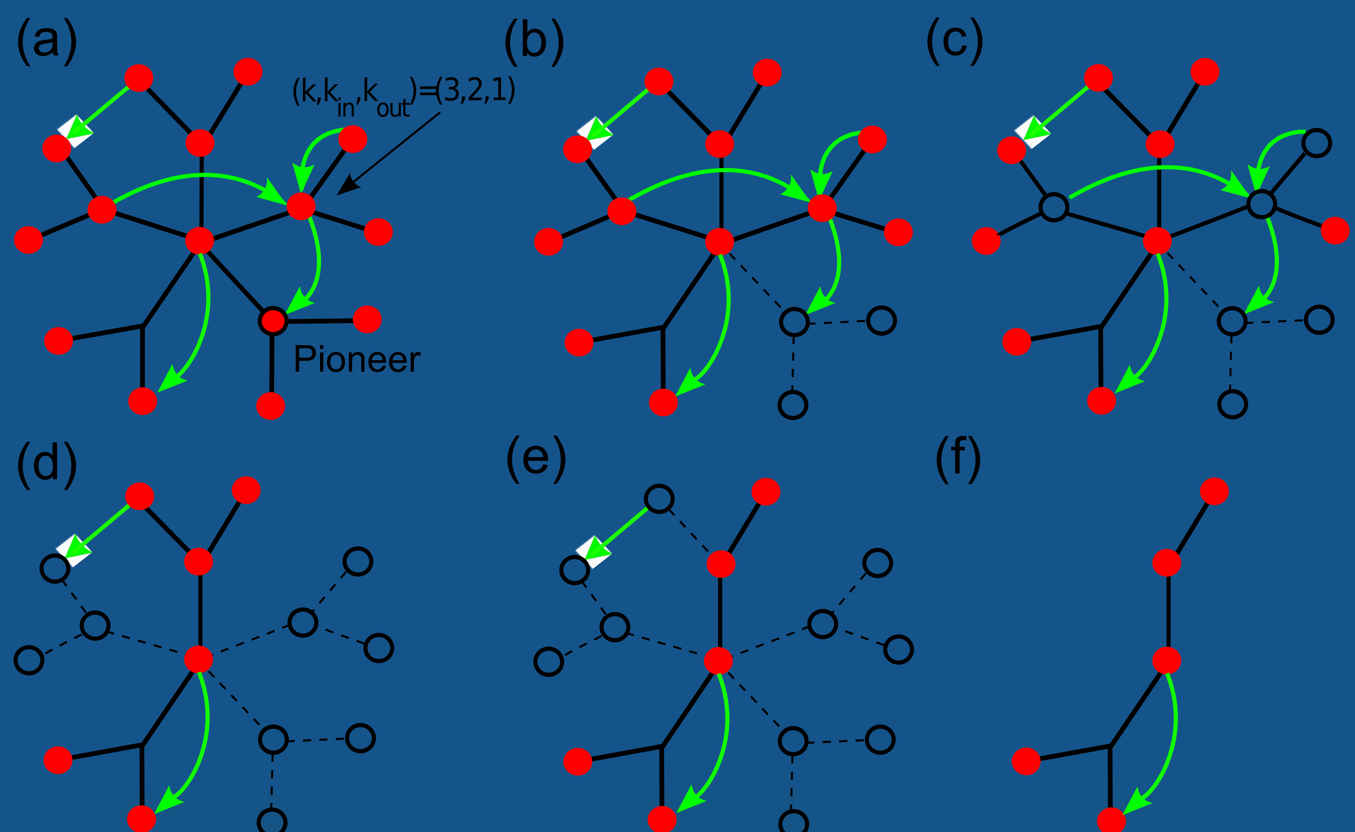
Modeling Cascades of followers triggered by innovators

Model: percolation removal of nodes in a network with influence links and connectivity links



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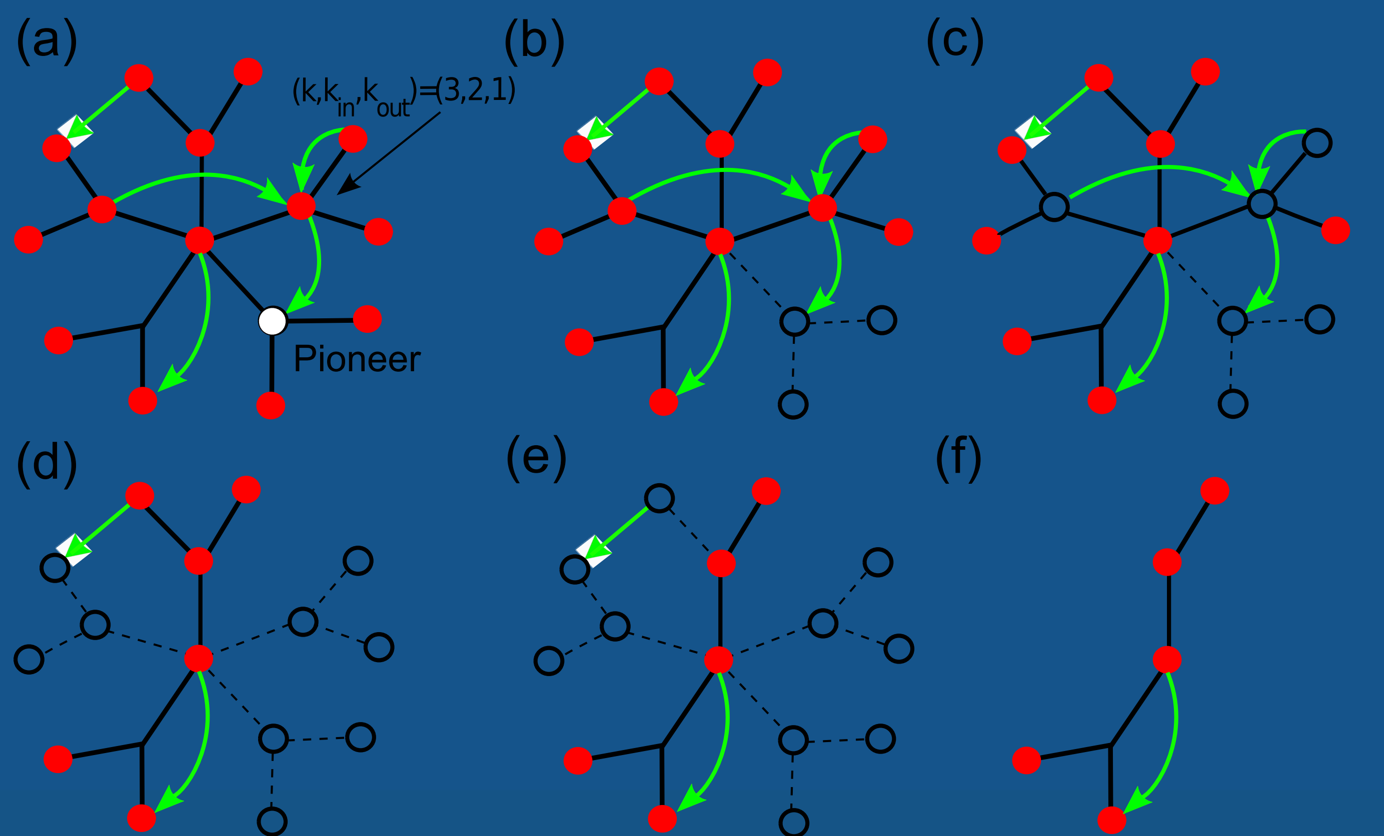

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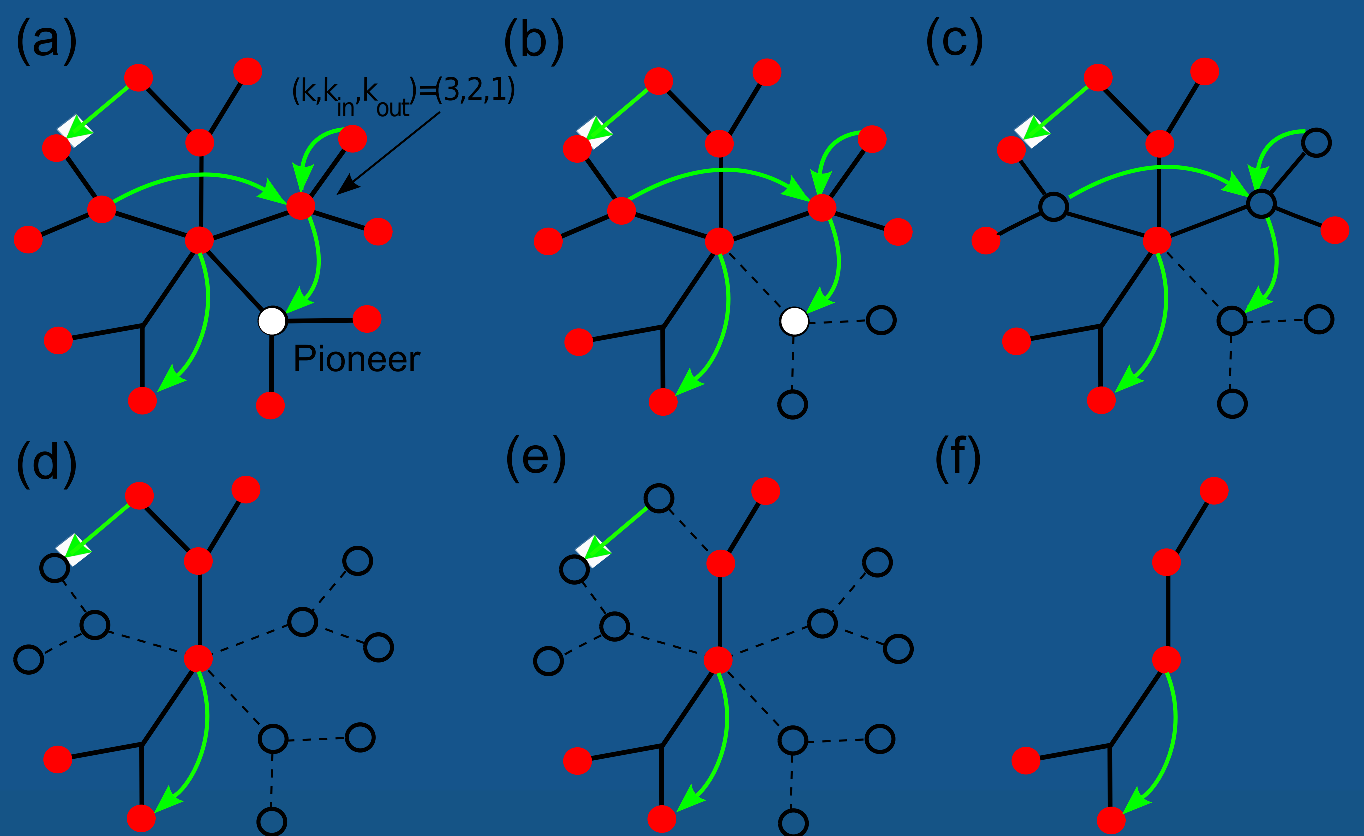

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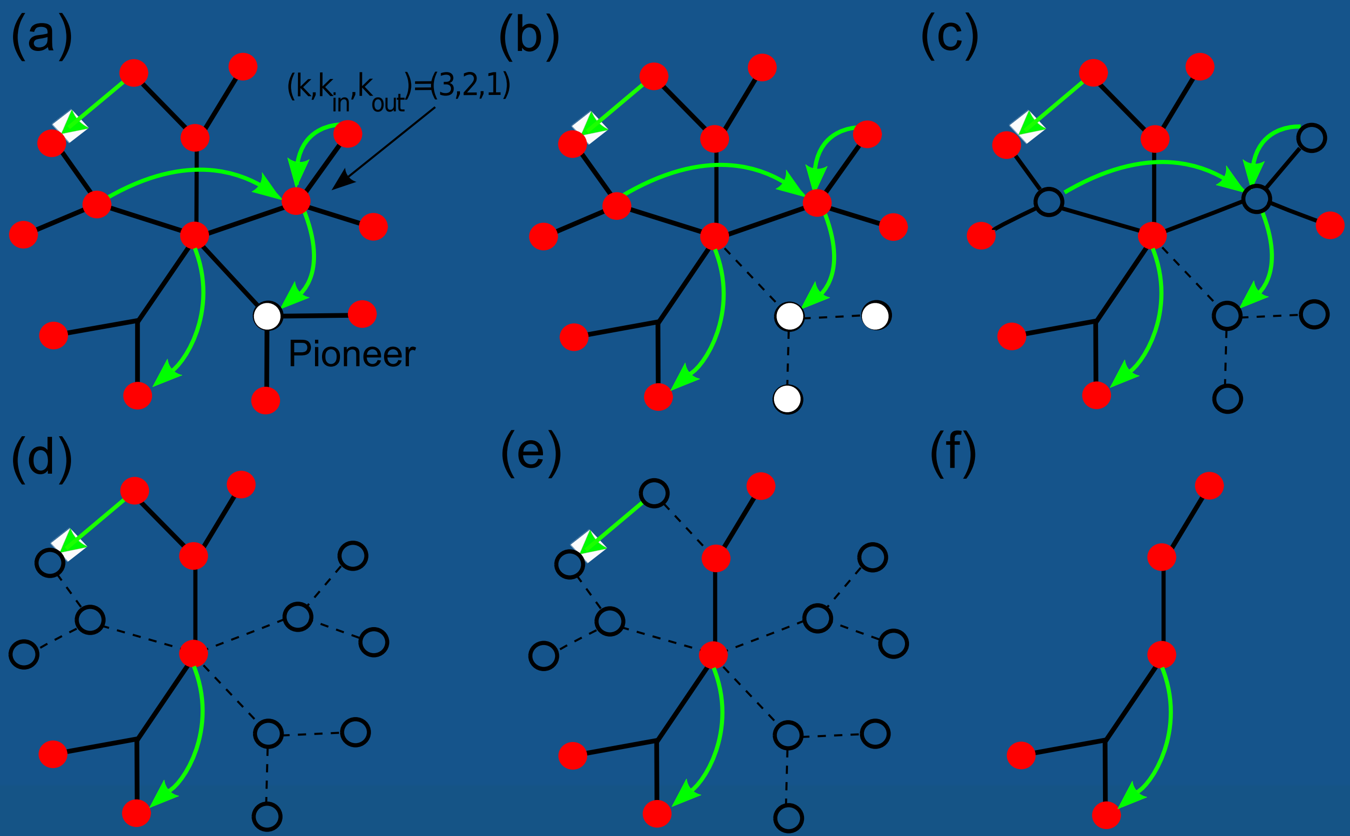

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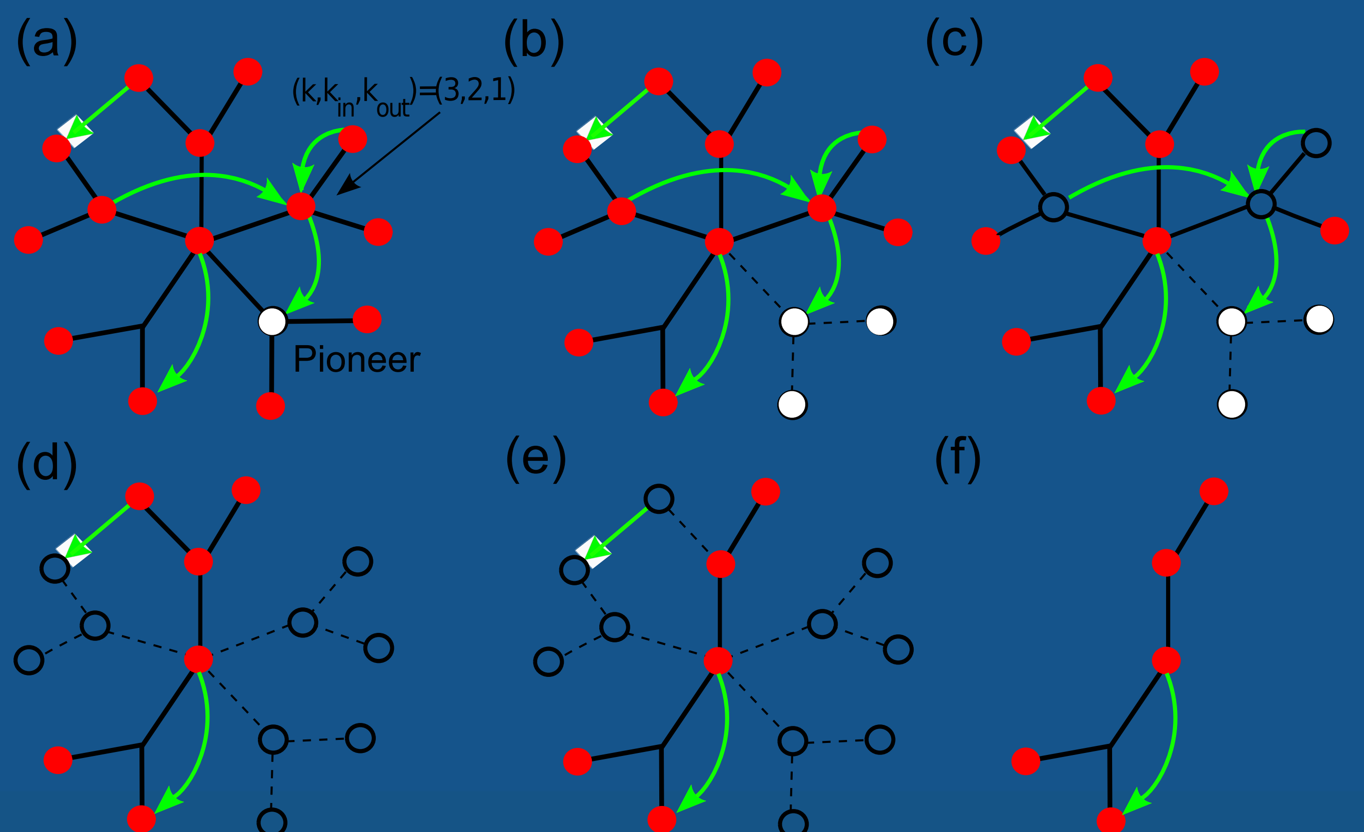

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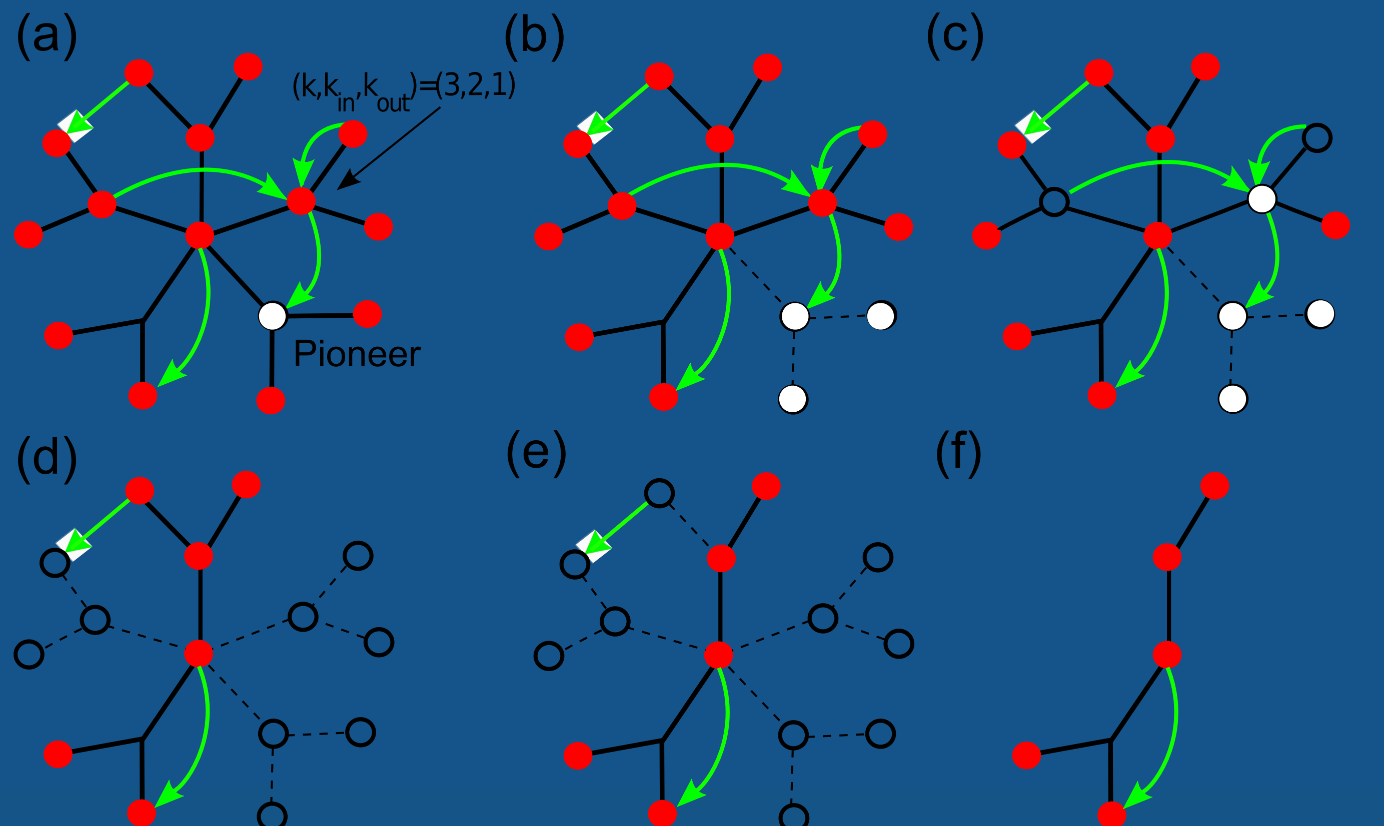

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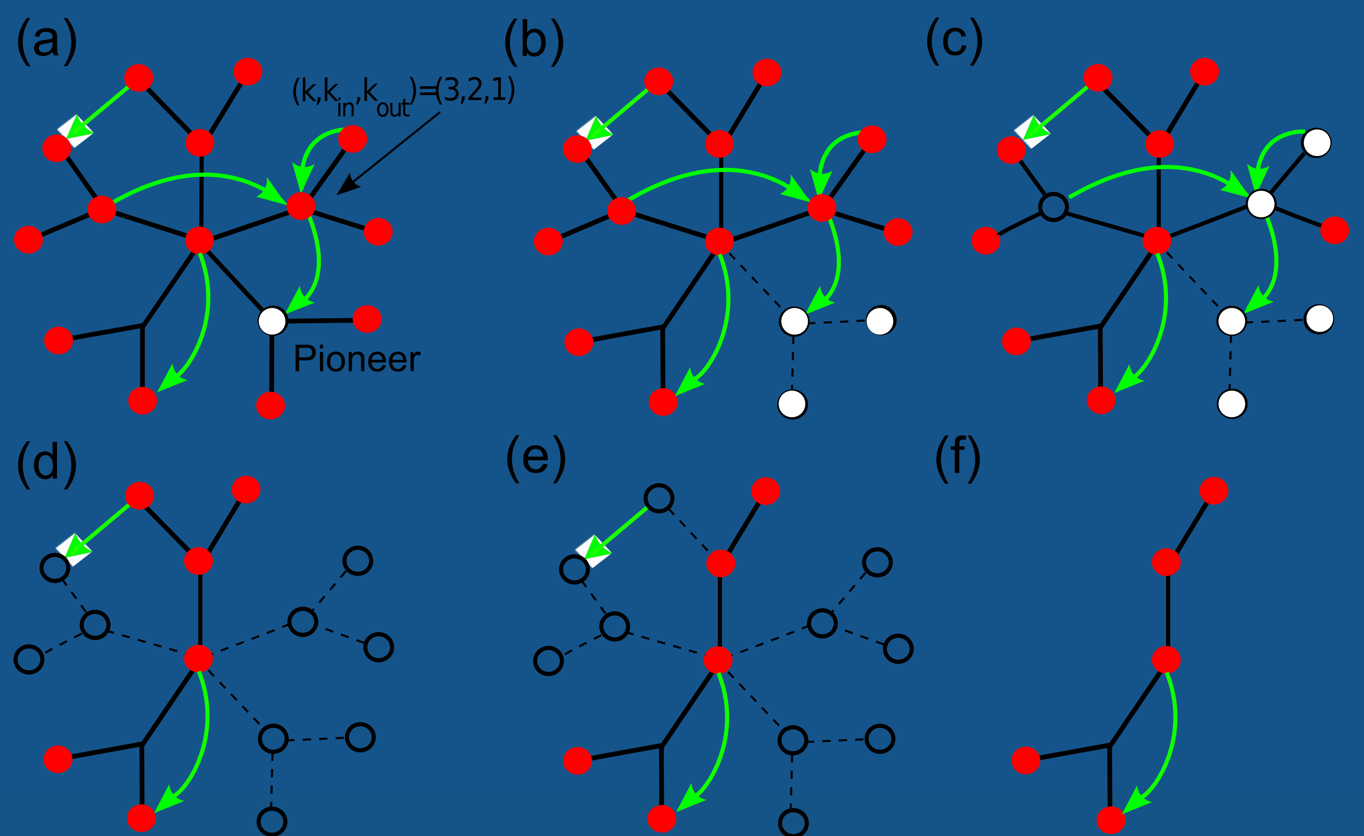

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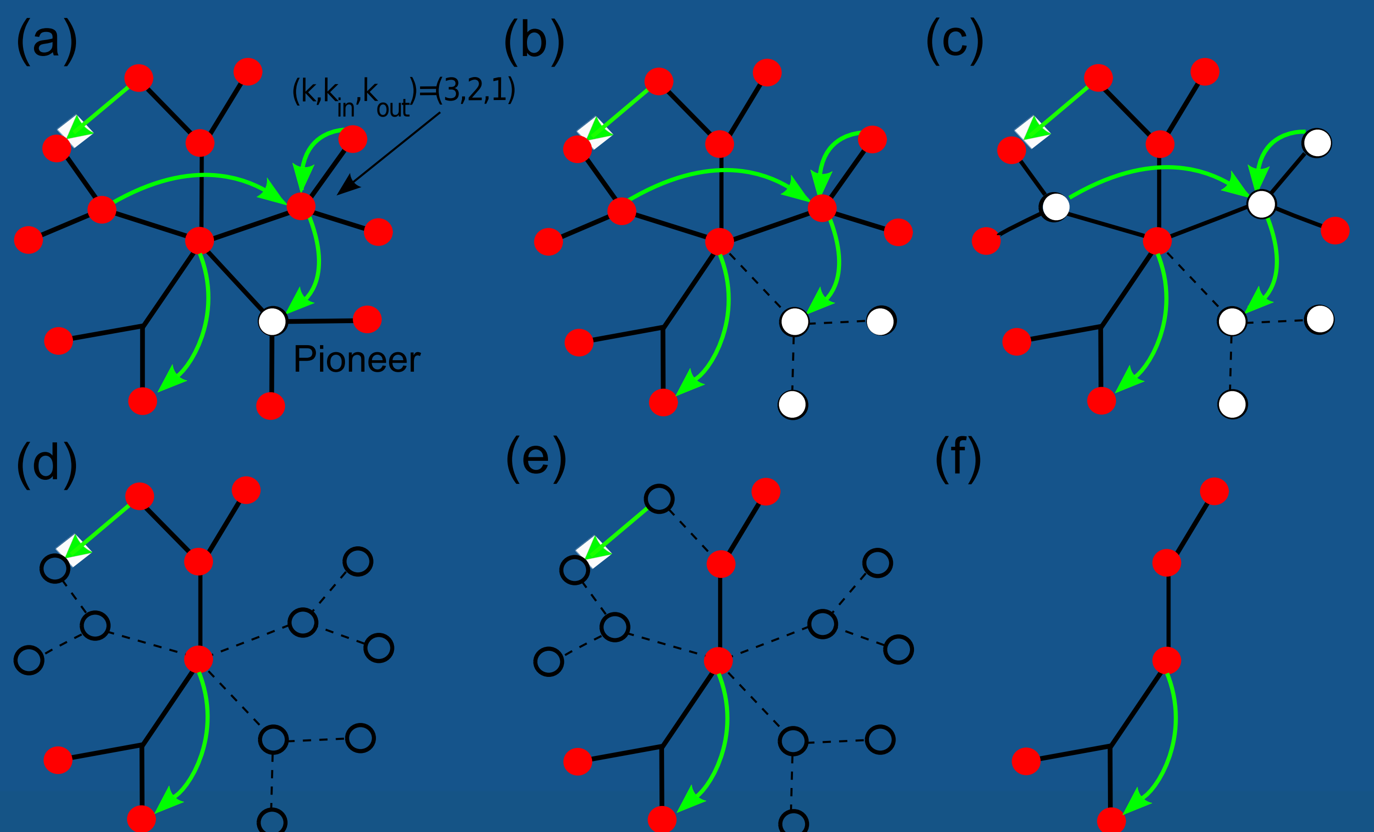

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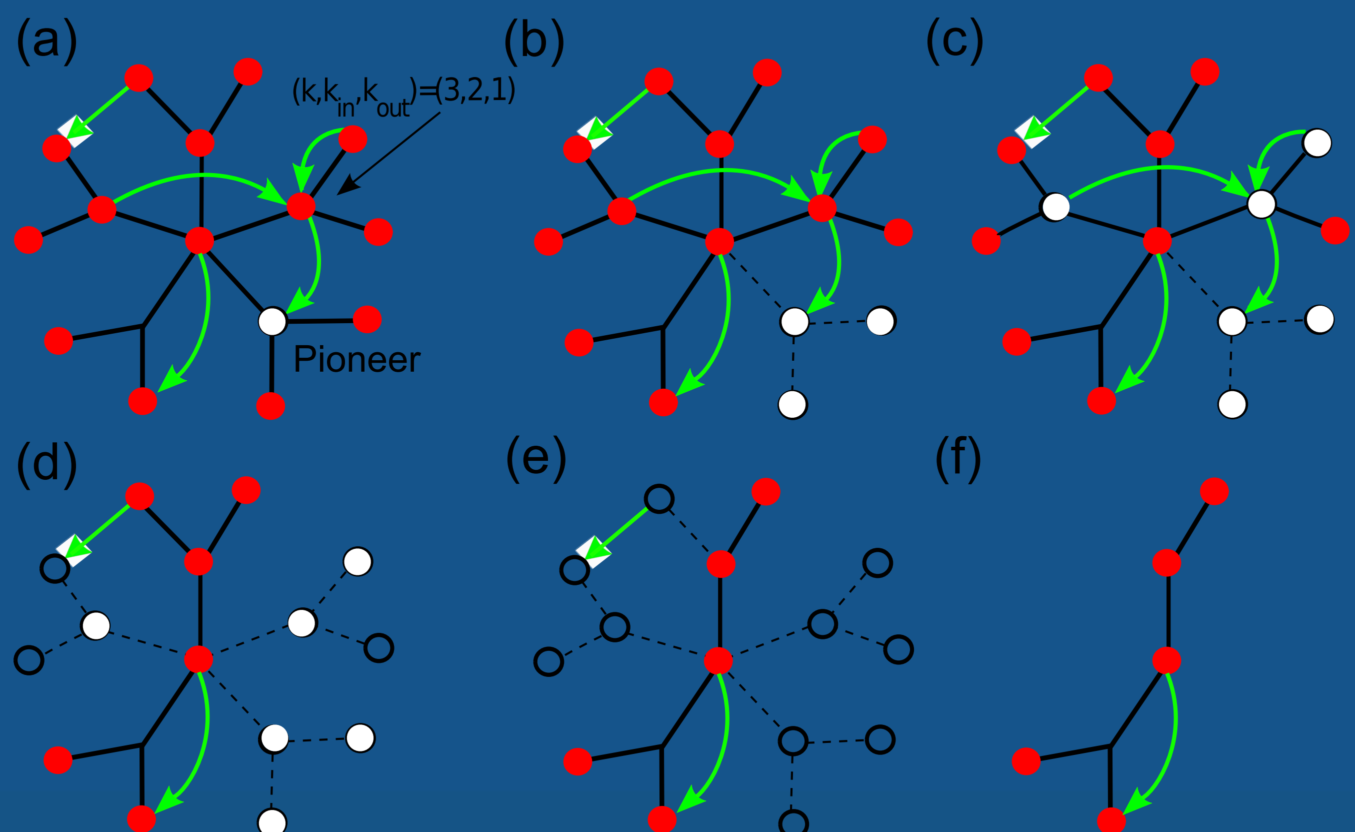

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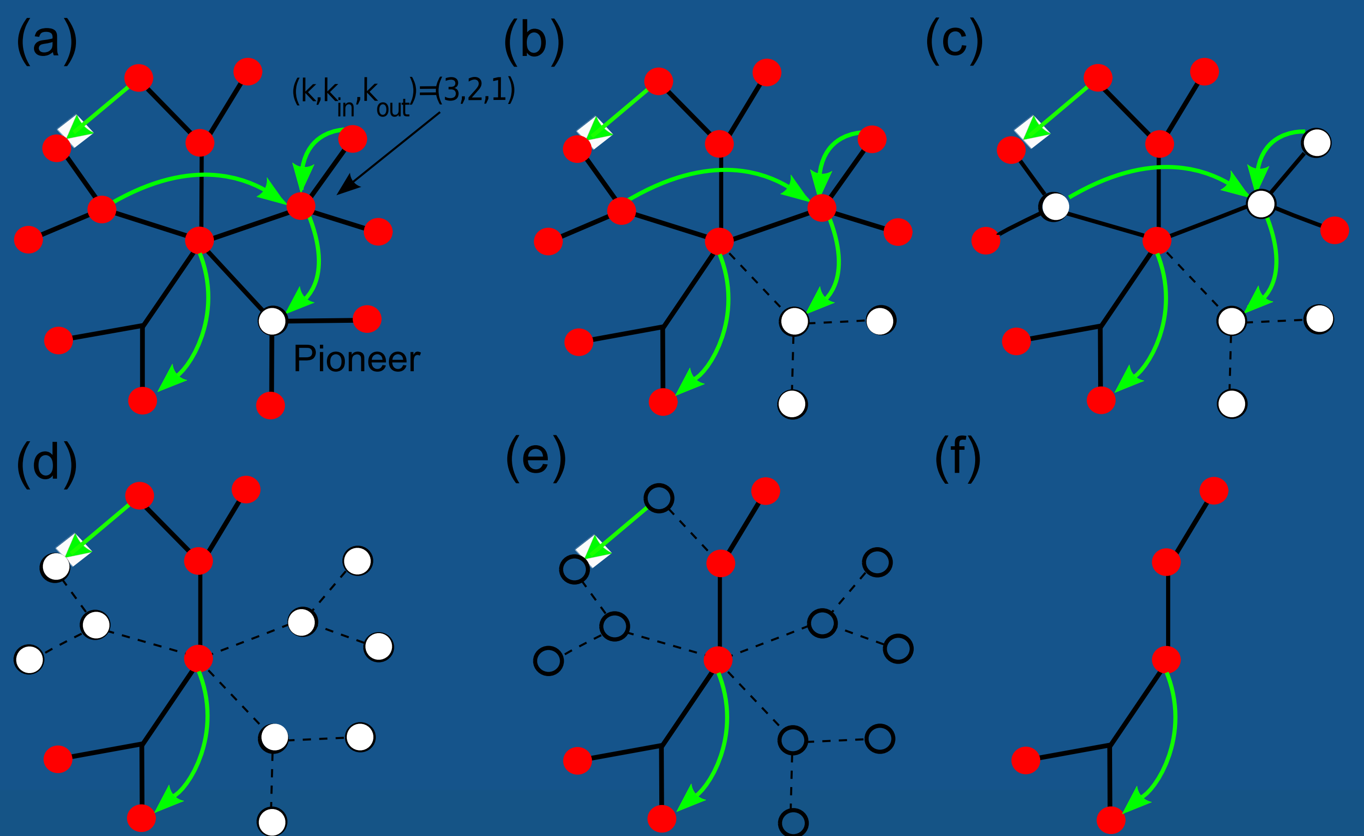

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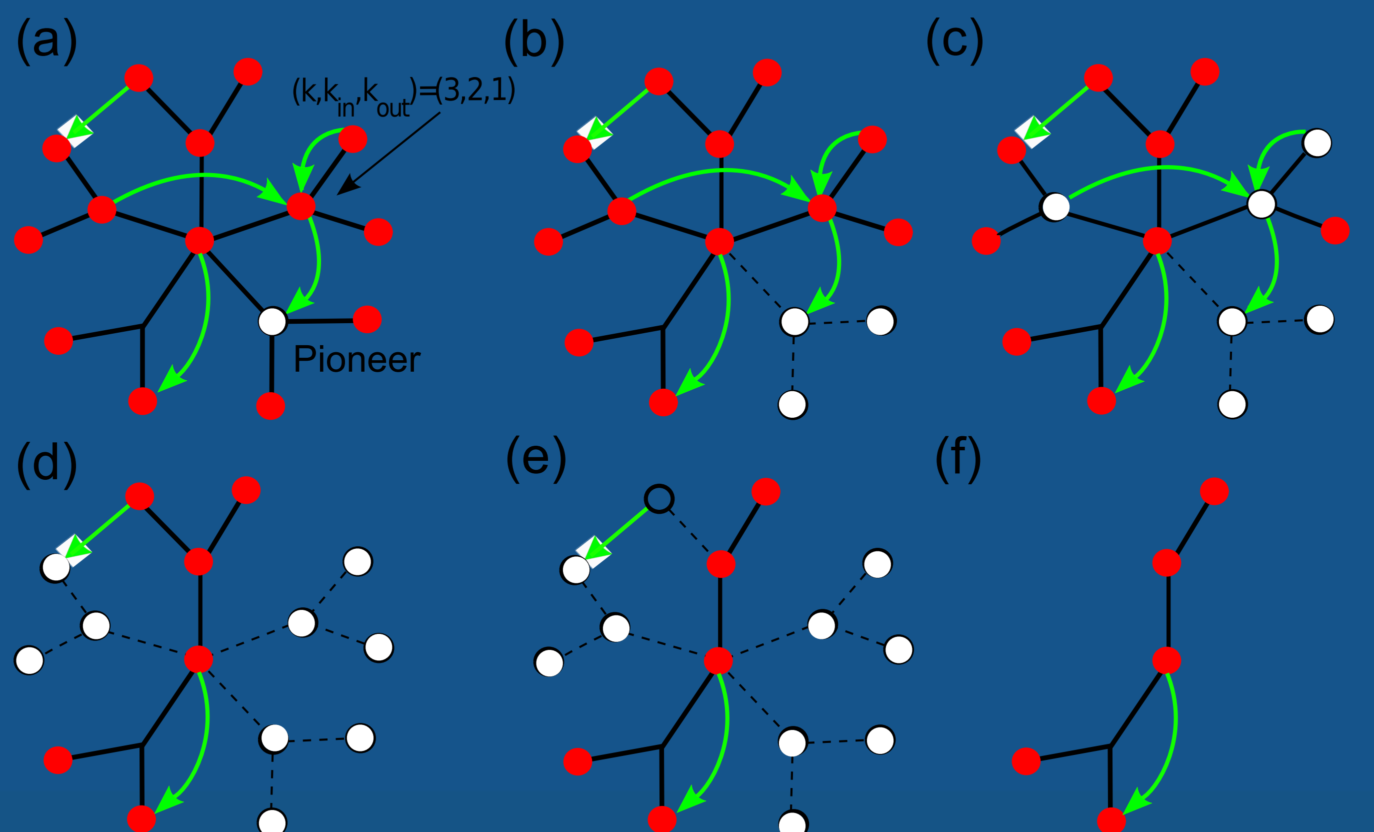

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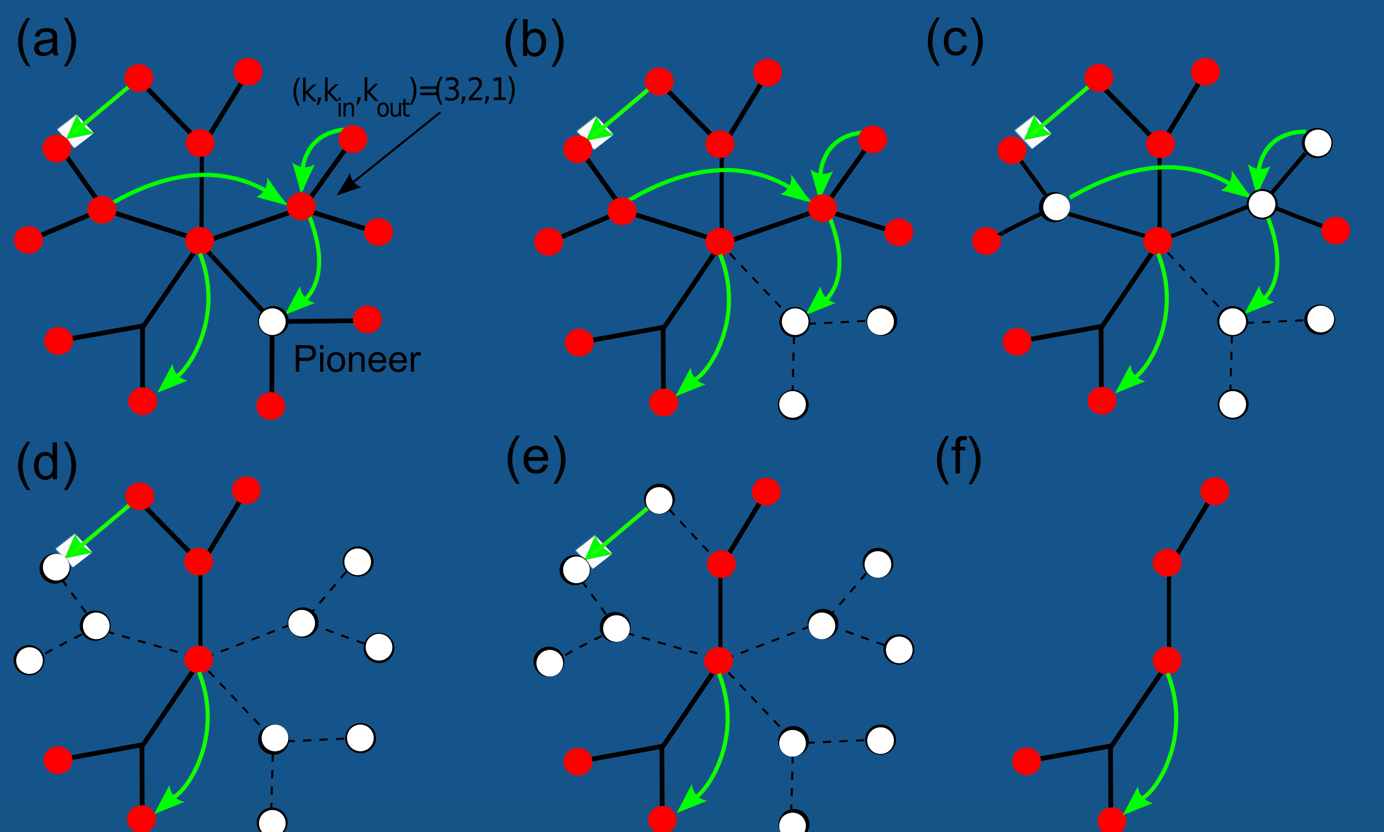

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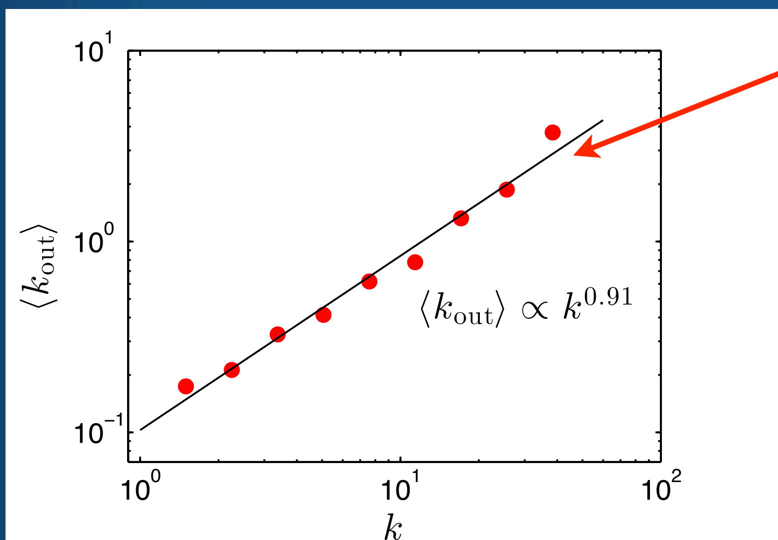
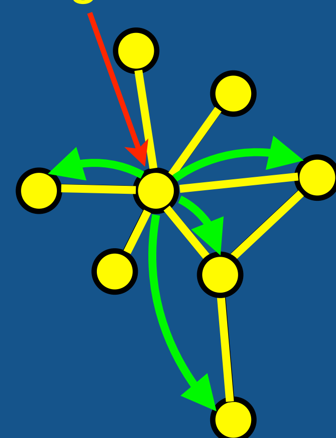
Theoretical prediction of the tipping point

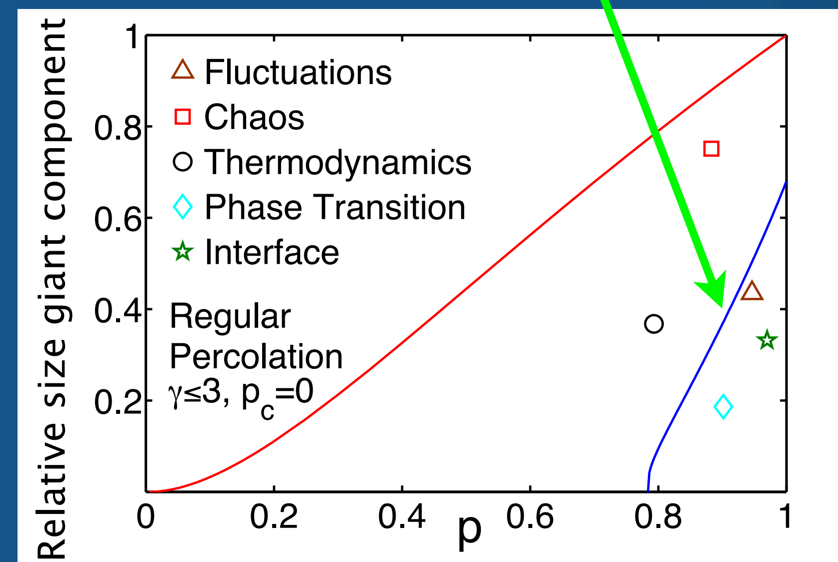
Why networks are so fragile?

Percolation theory with correlated influence links

hubs receive large influence







We predict the conditions at the tipping point:

1. Hubs are not pioneers
2. Pioneers are small players who initiate cascade of followers
3. Hubs jump into the “new idea” and sustain the cascade
4. Fragmentation: strong correlation between hubs connectivity and out-degree of influence

Conclusion: two conditions for fragmentation:

(1) Existence of hubs. (2) Hubs are aware of latest trends

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Conclusions

- Statistical physics applies to dissimilar problems involving big data: obesity epidemics and spreading of innovation.
- The percolation fragility model predicts the conditions for network fragmentation upon the departure of a few innovators.
- Tipping point happens when a network develops strong correlations between the hubs and the degree of influence.
- Results apply to any interconnected system with influence or dependency links, such as political networks, financial markets, infrastructure networks, power grids, etc.

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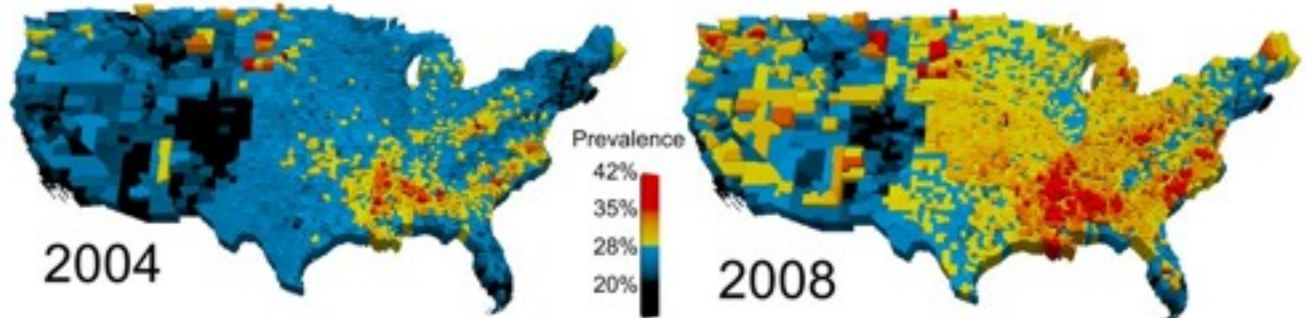
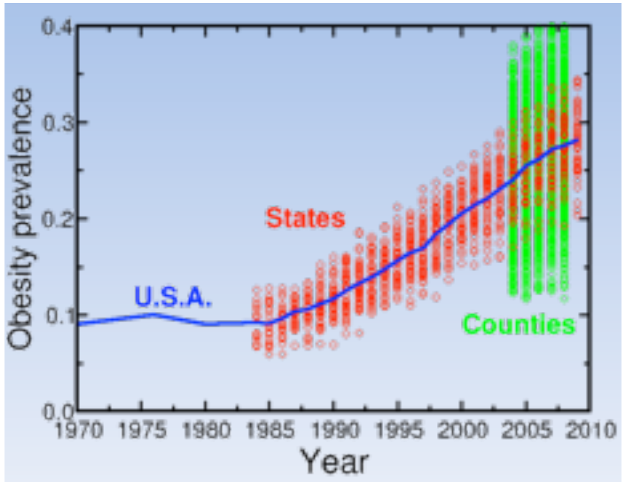
BIG DATA: Statistical physics: 10^{23} molecules in a dm^3 (Avogadro)

1. Obesity epidemic in US population ~10^8



Change in obesity levels from 2004 to 2008 (data from

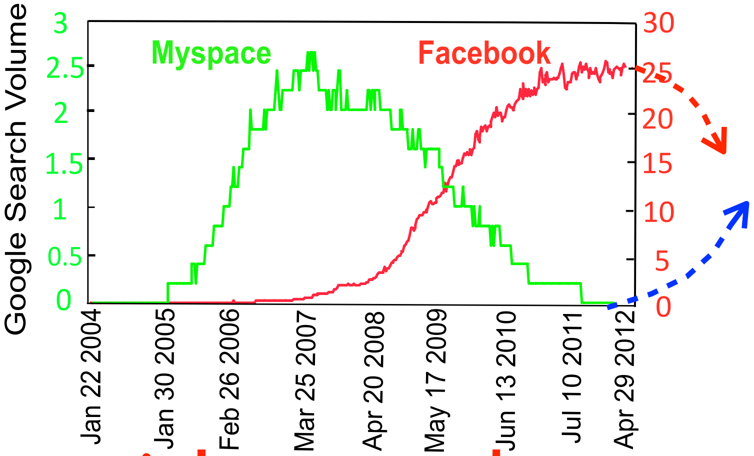


2. Predicting the tipping point

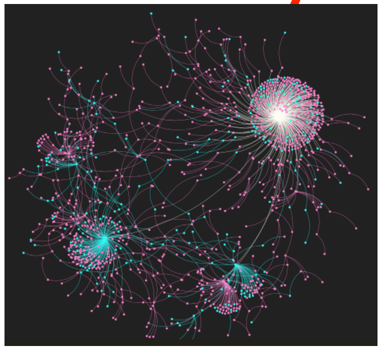
myspace vs facebook

Can we predict the next facebook?

facebook ~ 10^9 users



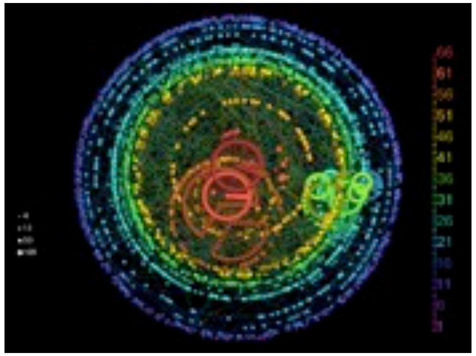
3. Identifying the best spreaders in social networks



weibo.com ~ 0.3×10^9 users

twitter.com ~ 0.3×10^9 users

(not feasible)



livejournal.com:

10^6 users

10^7 links

(feasible)

WHO ARE THE MOST INFLUENTIAL SPREADERS?

Who infects/influences the largest fraction of population?

Modeling disease spreading and spreading of information, rumors, etc

Applications:
1. Marketers: spreading of consumer products.
2. Vaccination strategies.
3. Break-up of a social network.

Location is more important:
Who is at the center of the Web?
Who is the central node in a social network?

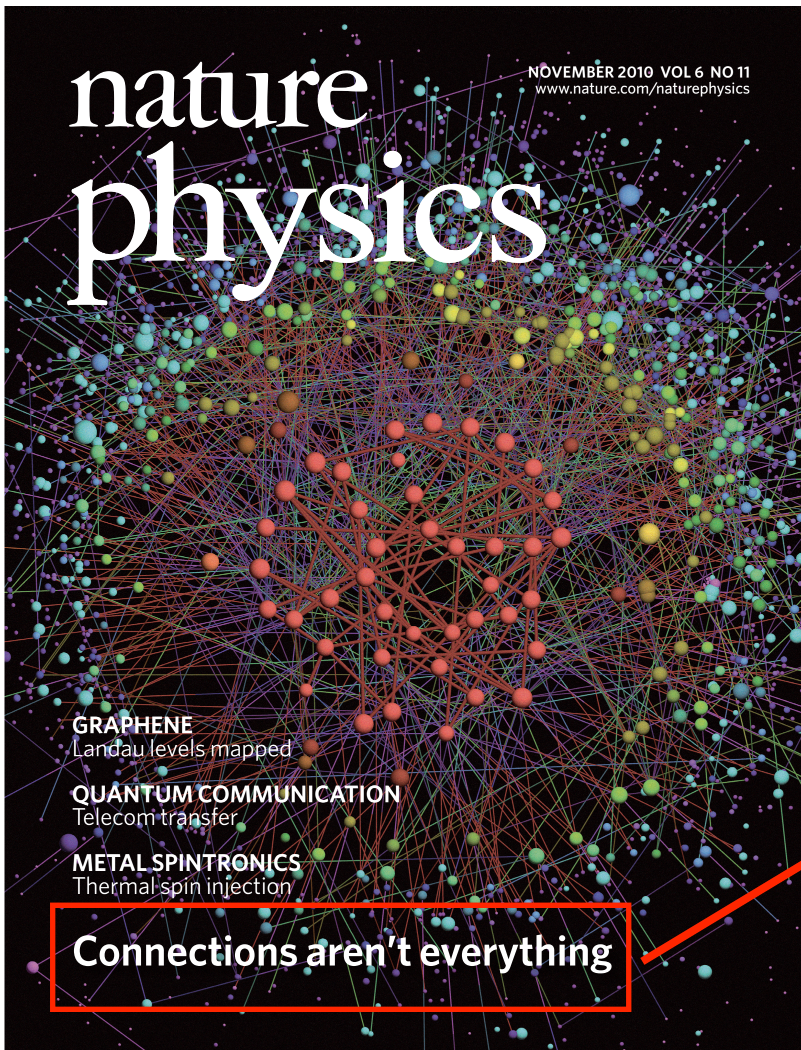
RDECOM

WHO ARE THE MOST INFLUENTIAL SPREADERS?

ARL

Who infects/influences the largest fraction of population?

Not necessarily the most connected people!



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NETWORK SCIENCE CTA

SCNARC
SOCIAL COGNITIVE NETWORKS ACADEMIC RESEARCH CENTER

Spreading process: models

Examples:
Infectious diseases (smallpox, influenza, etc)
Rumor, ideas
Email, bluetooth viruses

Transmission rate $\beta = 0.5$
Recovery rate $\mu = 0.5$

The SIR Model

"**S**usceptible" (unaffected) individual.

"**I**nfected" (affected) individual.

"**R**ecovered" individual.

Time to "recover"

Transmission probability

Recovered individuals can not be infected!!!

Spreading efficiency: $<M_i>$
The average number of infected nodes
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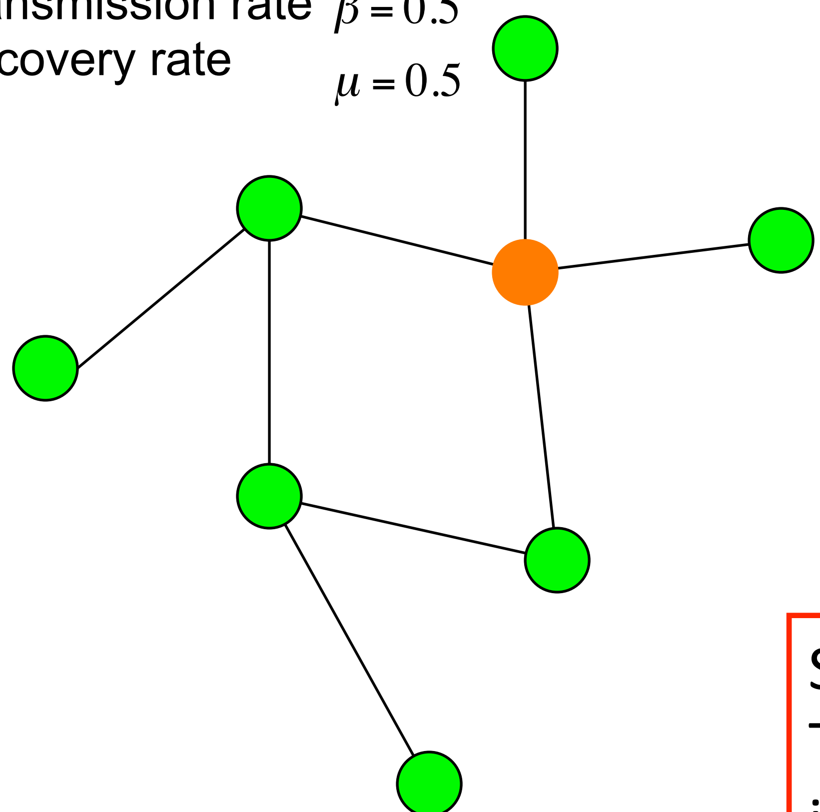

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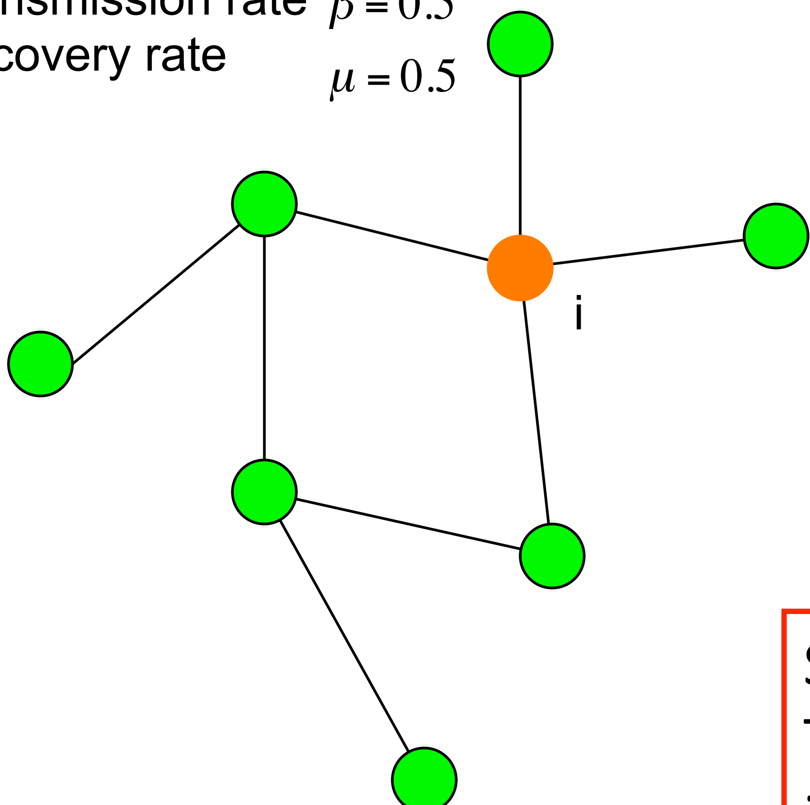

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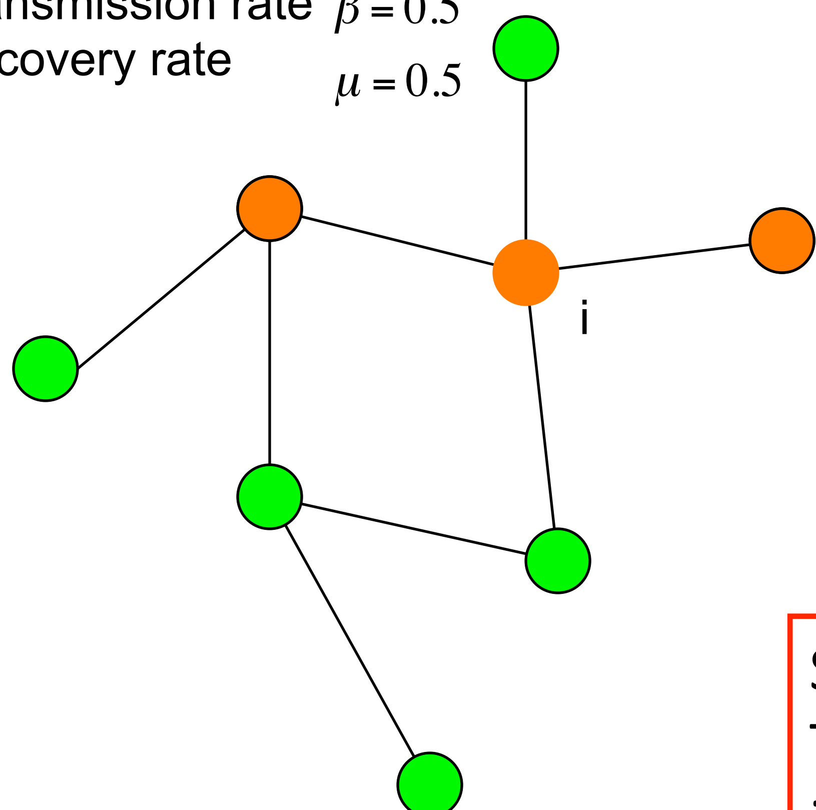

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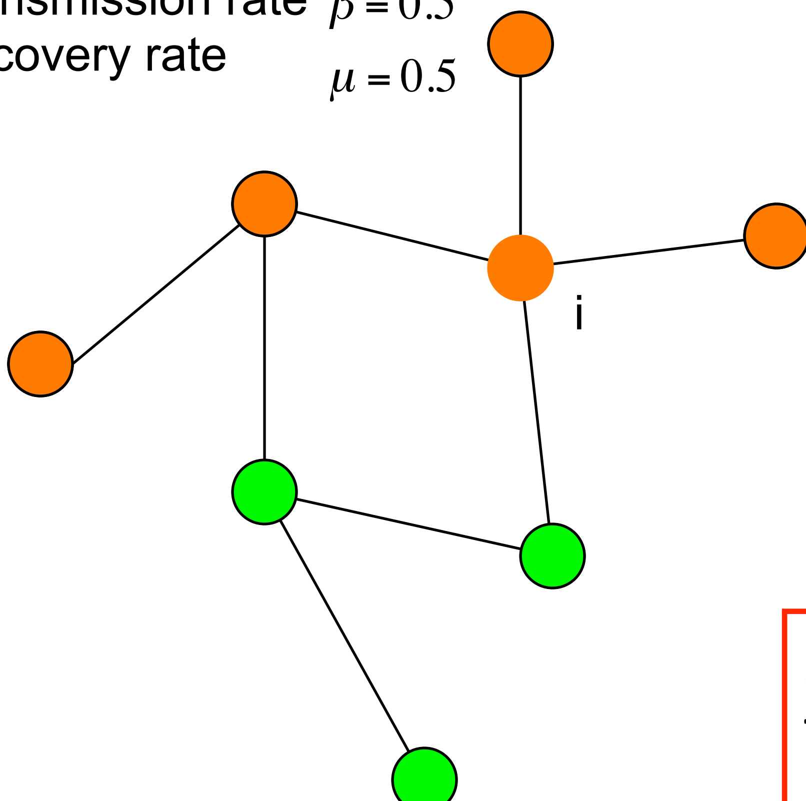

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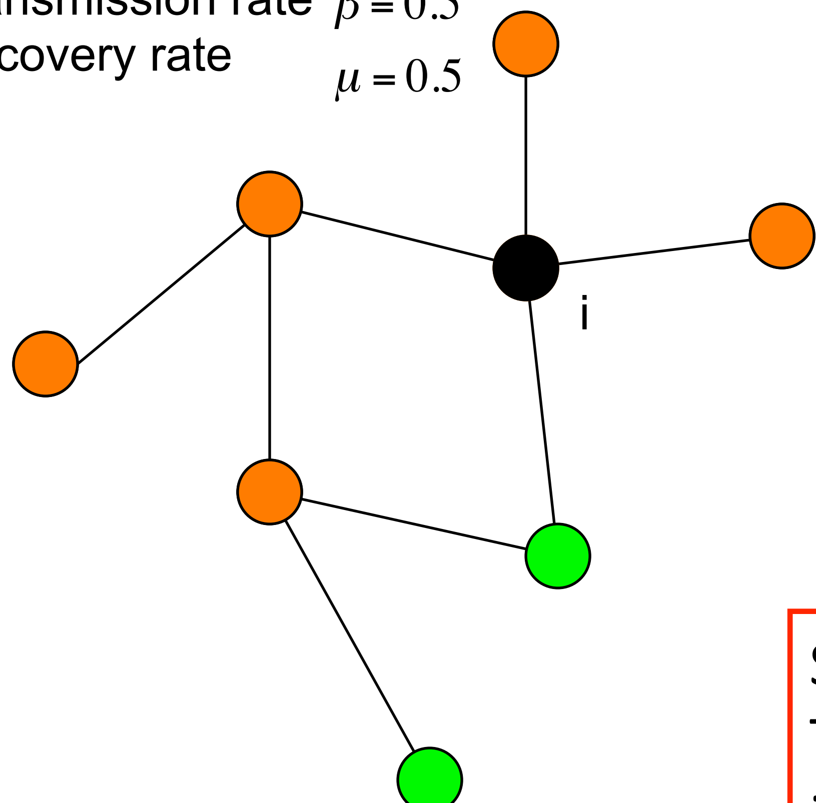

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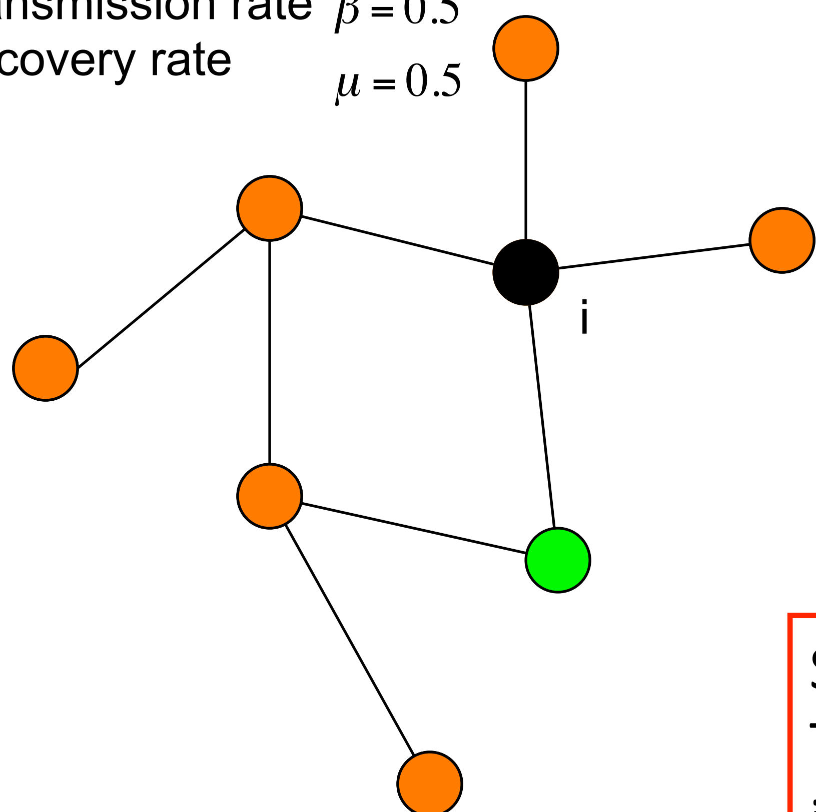

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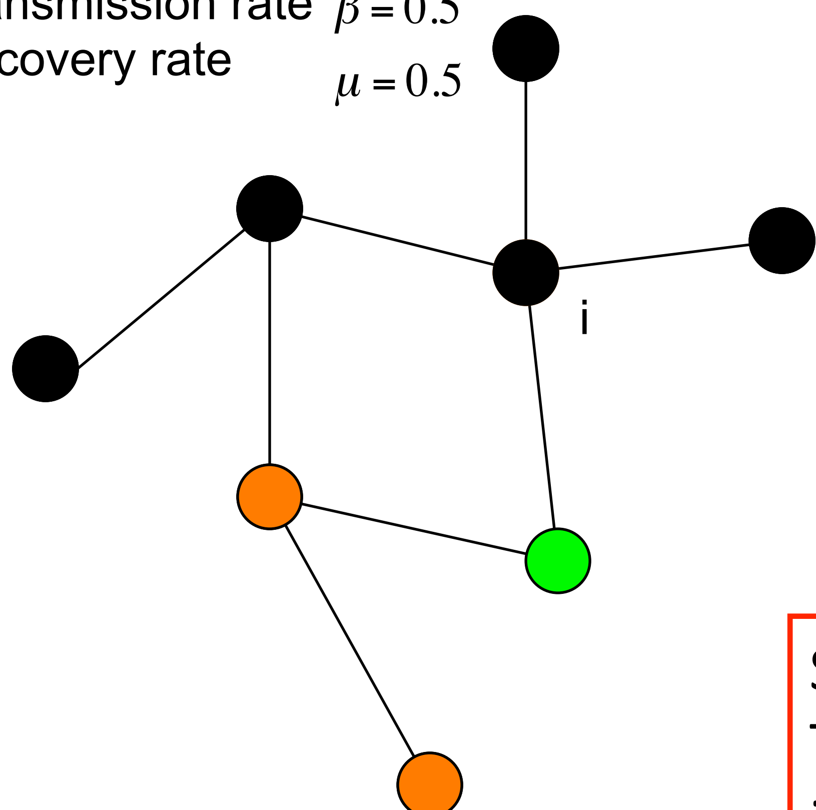

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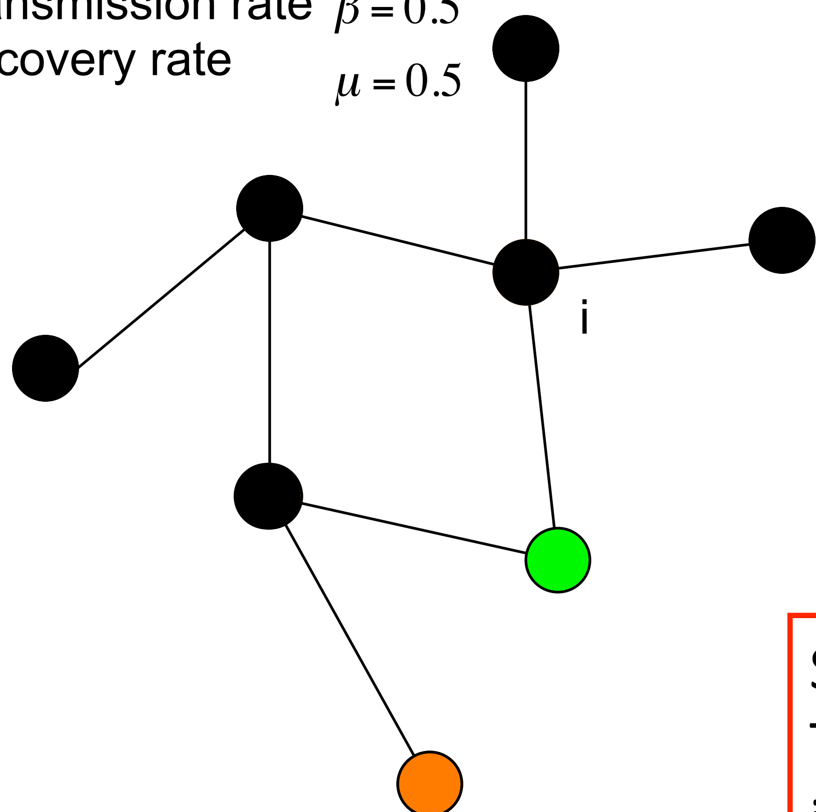

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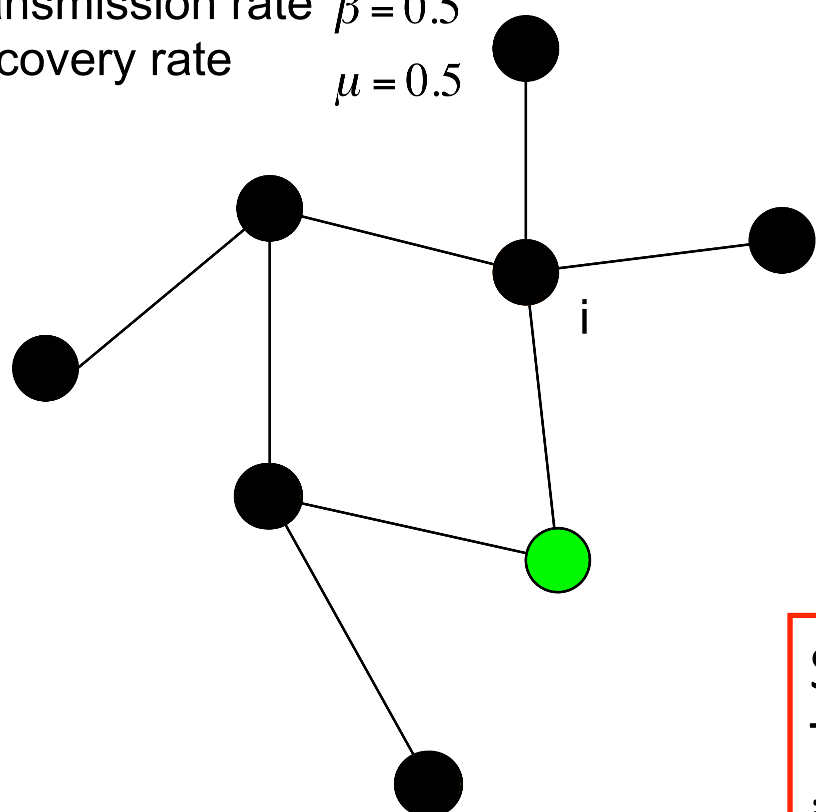

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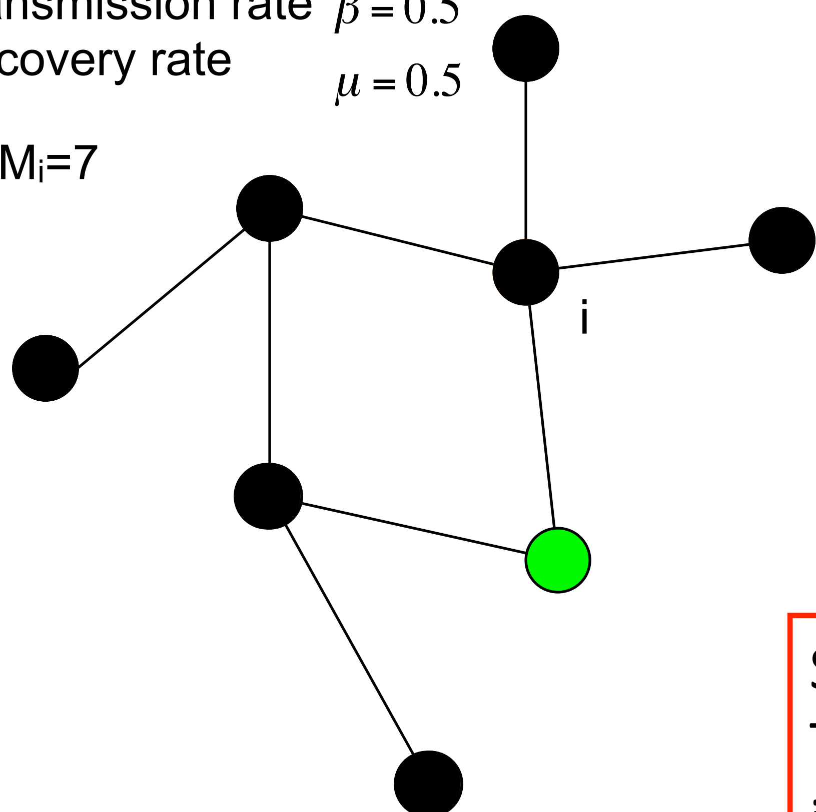
Recovery rate $\mu = 0.5$

M_i=7



The SIR Model

"Susceptible" (unaffected) individual.

"Infected" (affected) individual.

"Recovered" individual.

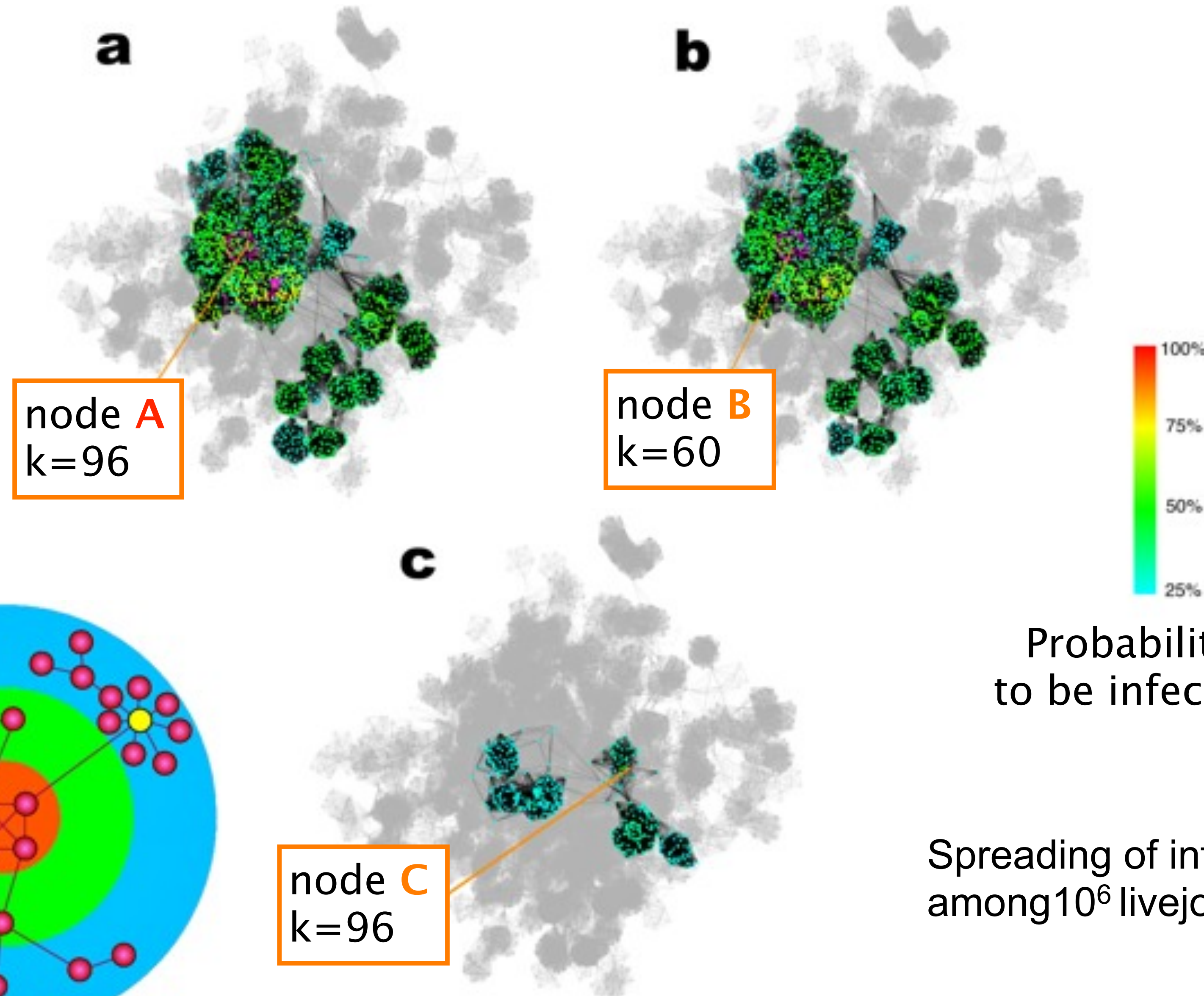
Time to "recover"

Transmission probability

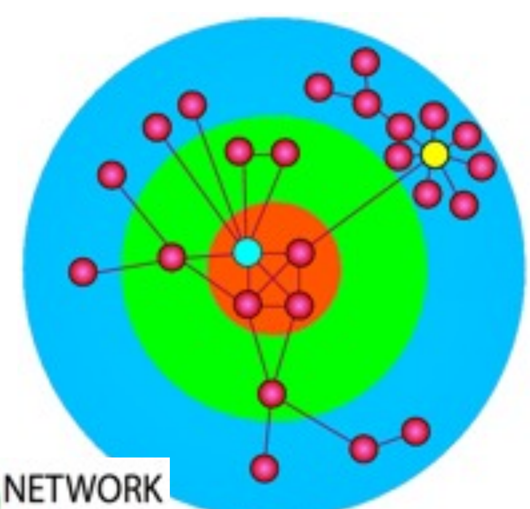
<u>Recovered individuals can not be infected!!!</u>

Spreading efficiency: ***<M_i>***
The average number of infected nodes if spreading starts at node ***i***

SPREADING EFFICIENCY IS DETERMINED BY LOCATION

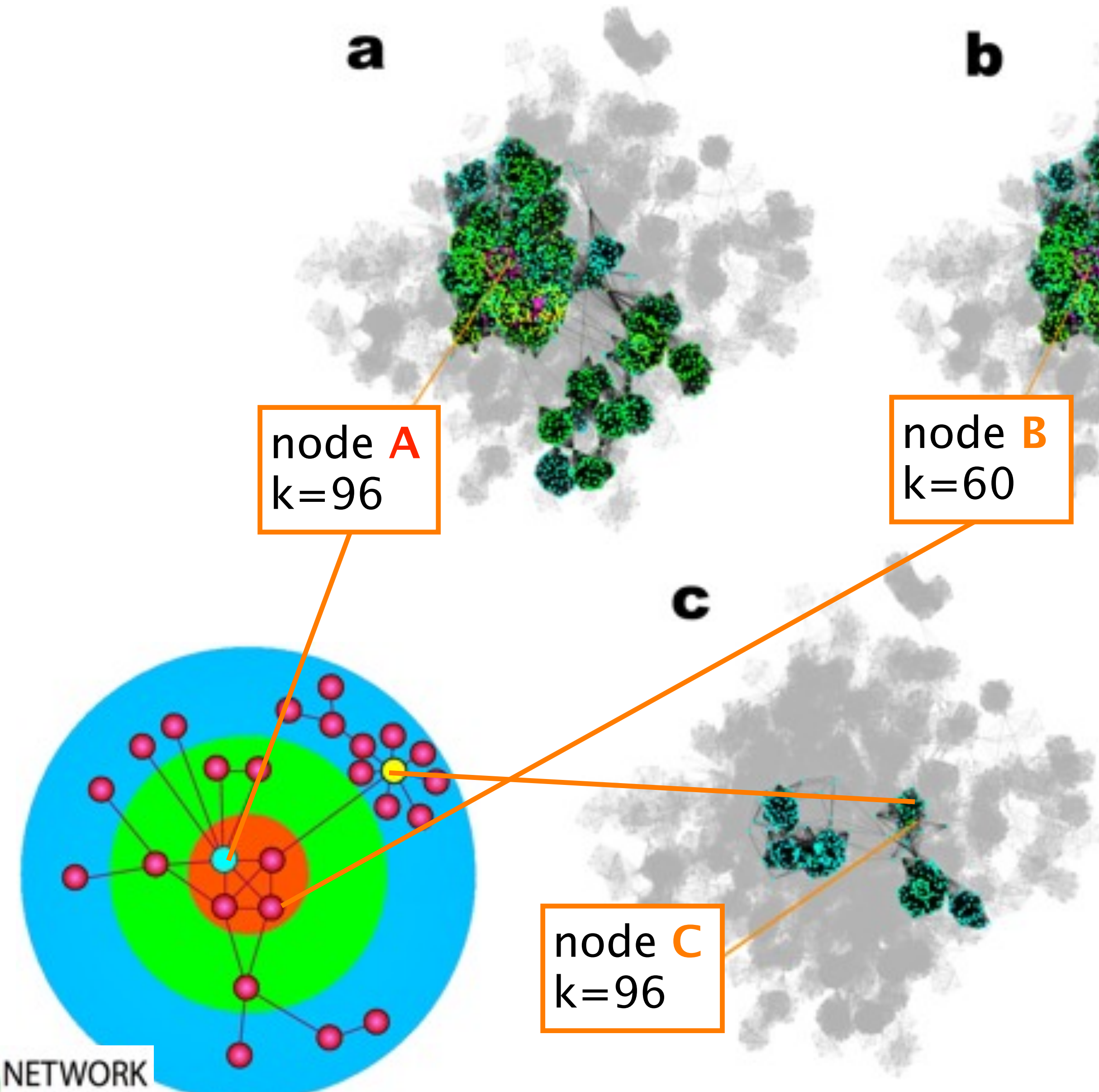


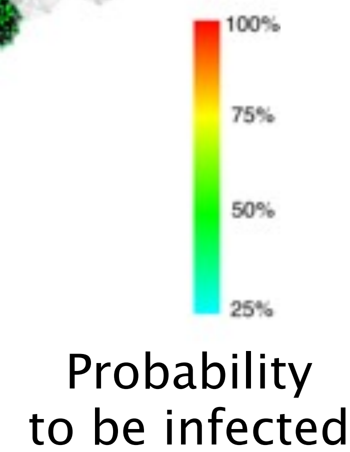
Probability
to be infected



Spreading of information among10^6 livejournal users

SPREADING EFFICIENCY IS DETERMINED BY LOCATION





Spreading of information among 10^6 livejournal users

K-CORE DETERMINES NODE LOCATION (NODE VS PERIPHERY)

***K*-core: sub-graph with nodes of degree at least k inside the sub-graph.**

Pruning Rule:

1)Remove all nodes with k=1.

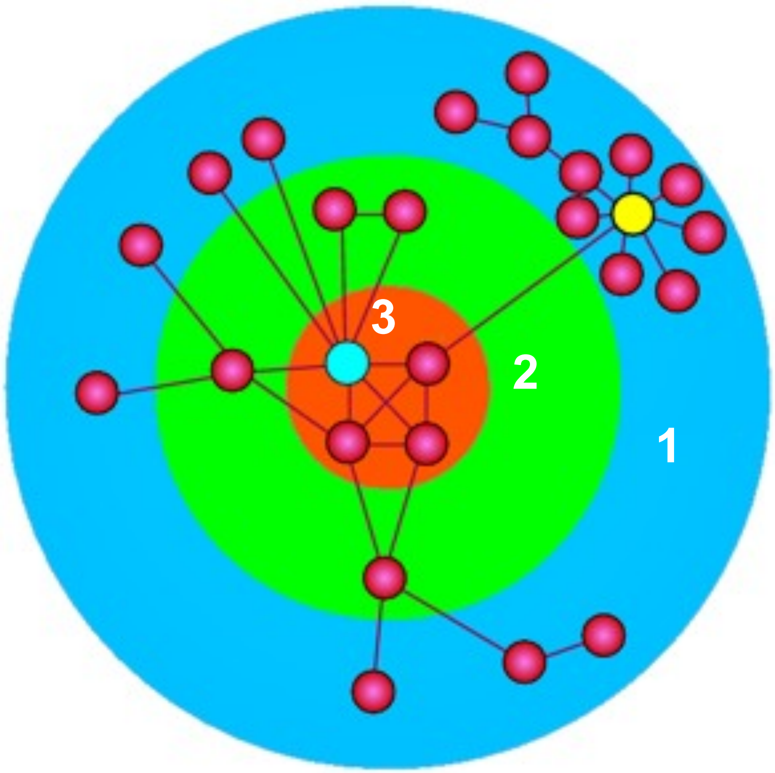
Some remaining nodes may now have k = 1.

2) Repeat until there is no nodes with k = 1.

3) The remaining network forms the 2-core.

4) Repeat the process for higher k to extract

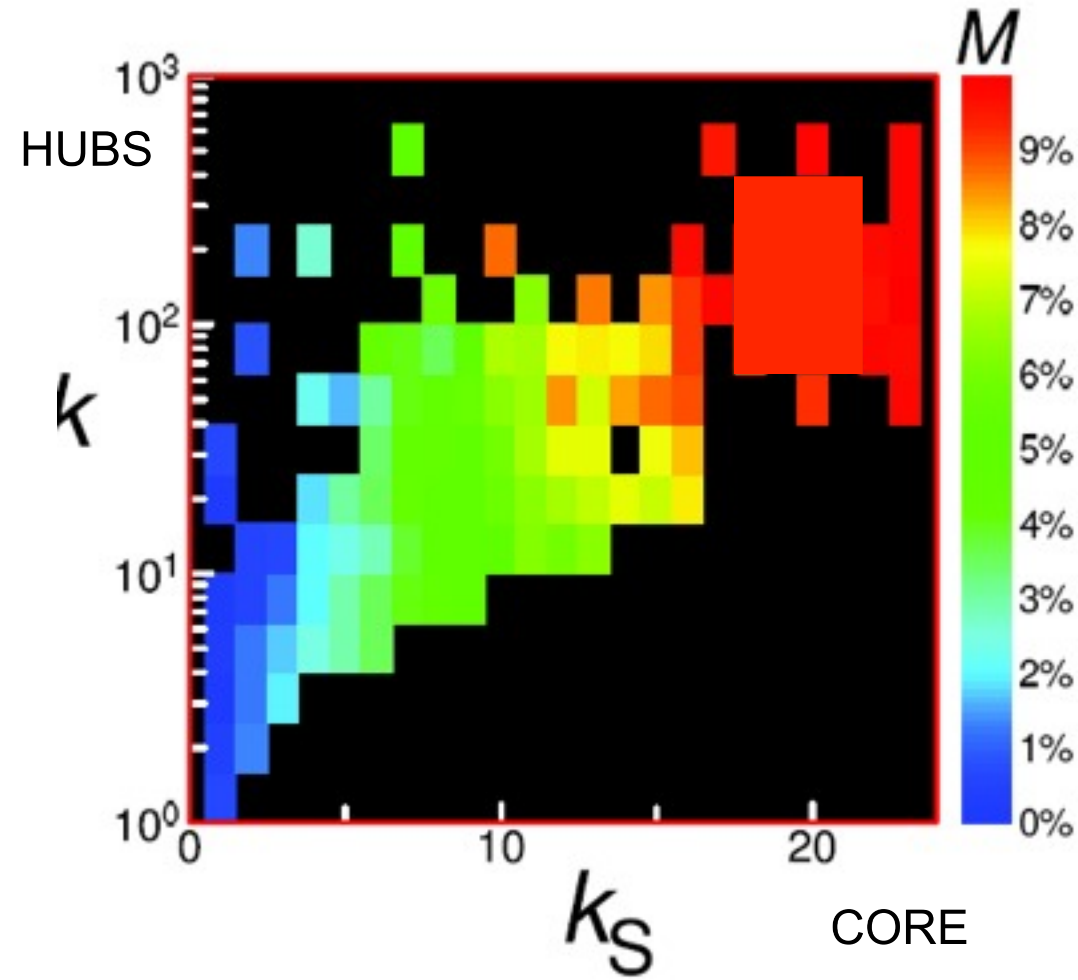
other cores



K-shell is a set of nodes that belongs to the *K*-core but NOT to the *K+1*-core

IDENTIFYING EFFICIENT SPREADERS

(1) For every individual ***i*** measure the average fraction of individuals M_i he or she would infect (spreading efficiency).
(2) Group individuals based on the number of connections and the k-shell value.



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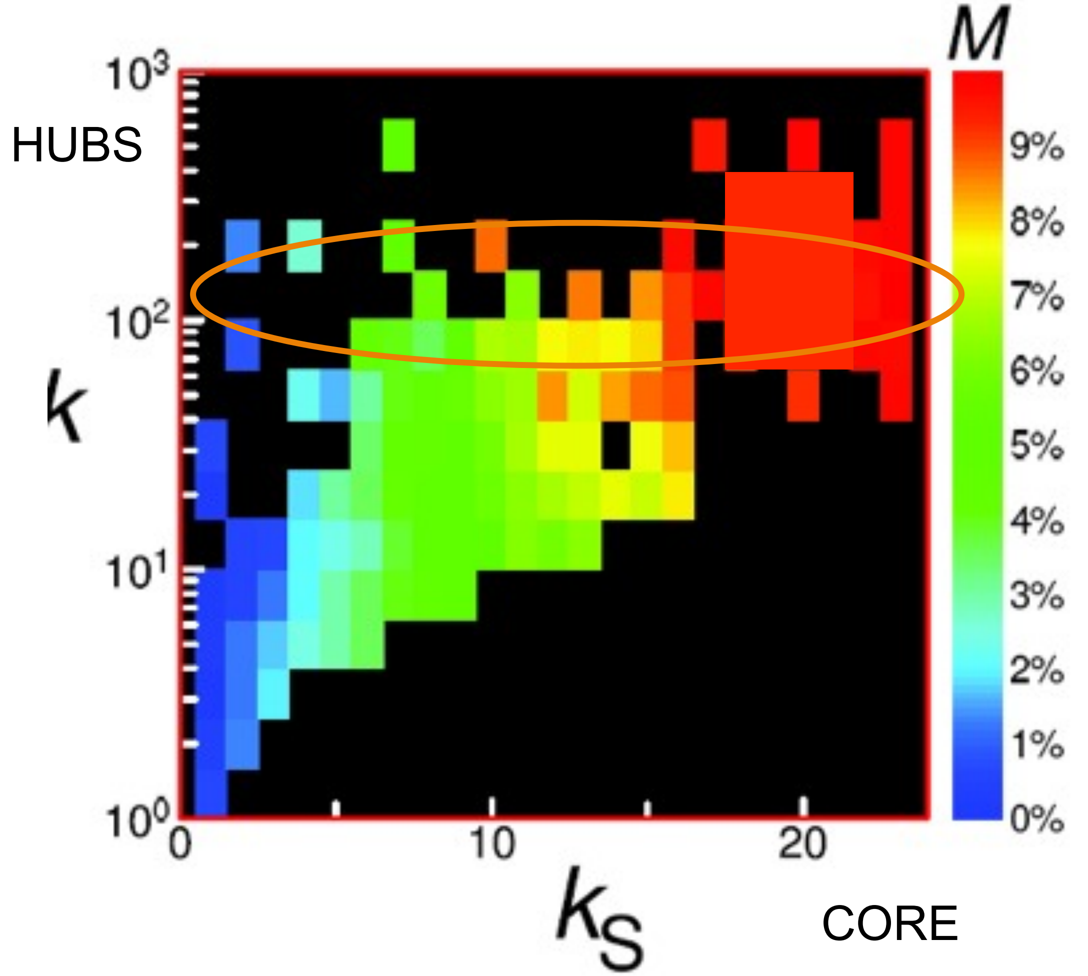
A. Most efficient spreaders occupy high *k*-shells.



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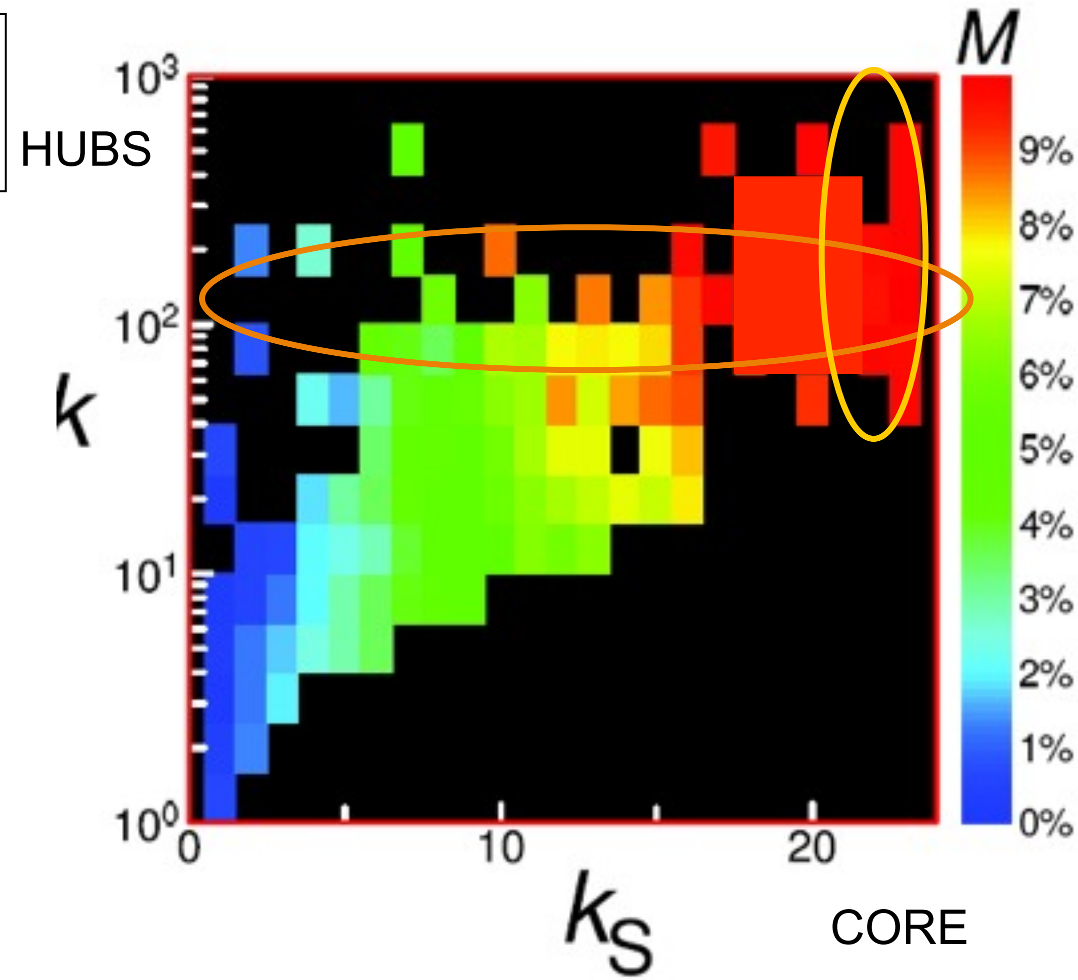
B. For fixed *k*-shell **<*M*>** is independent of ***k*.**



IDENTIFYING EFFICIENT SPREADERS

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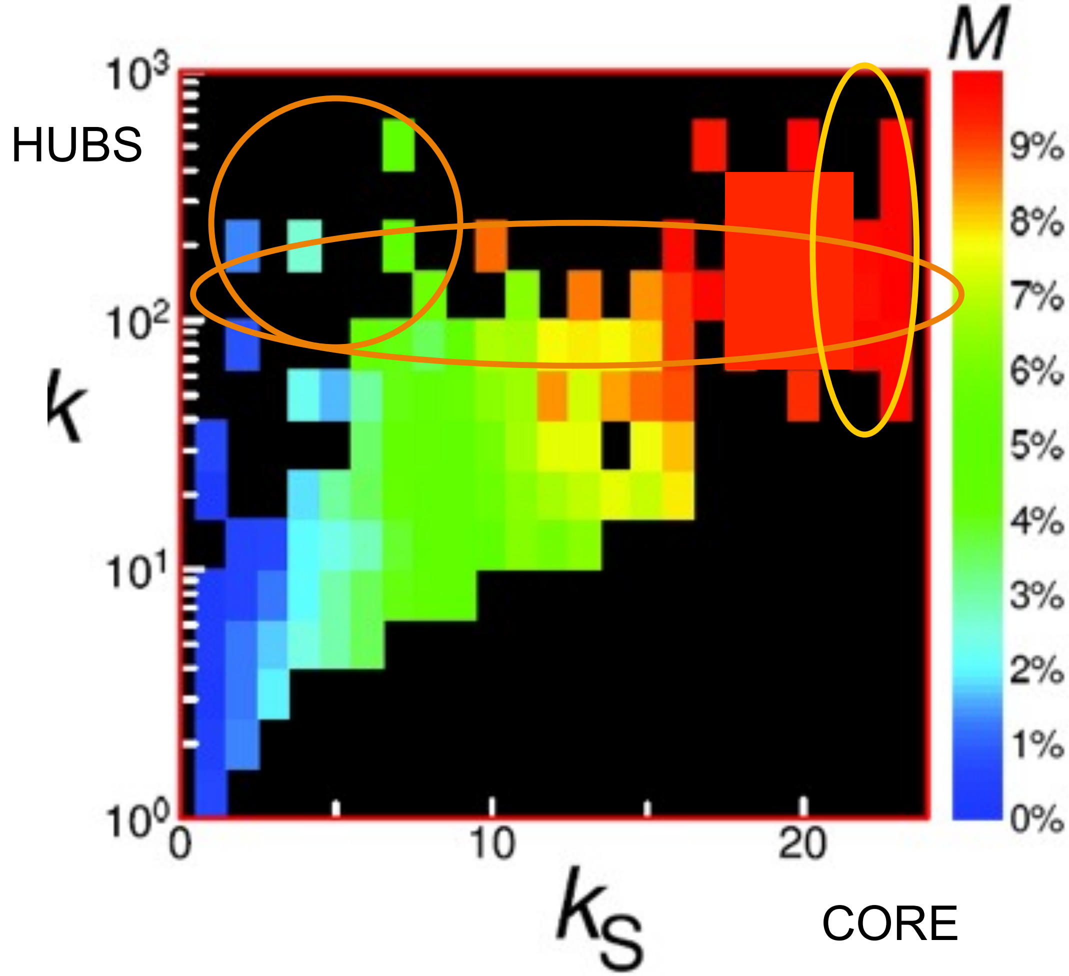
A. Most efficient spreaders occupy high *k*-shells.

B. For fixed *k*-shell **<*M*>** is independent of ***k*.**

C. A lot of hubs are inefficient spreaders.



Take home message

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A. The most influential spreaders are not the hubs

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B. Most influential spreaders occupy the core of the networks as given by large k-shell

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DRIVERS OF SOCIAL NETWORK FORMATION
AND
THE SPREADING OF IDEAS

Lazaros Gallos, Hernan A. Makse (PI)

Levich Institute and Physics Department
City College of New York, CUNY

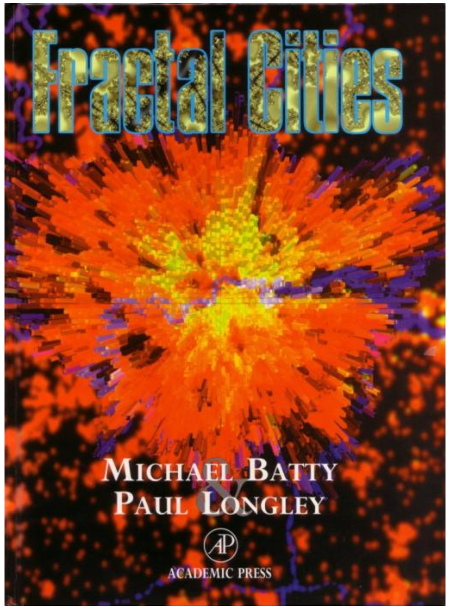
(Collaboration with RPI, NEU)

Summary of obesity percolation

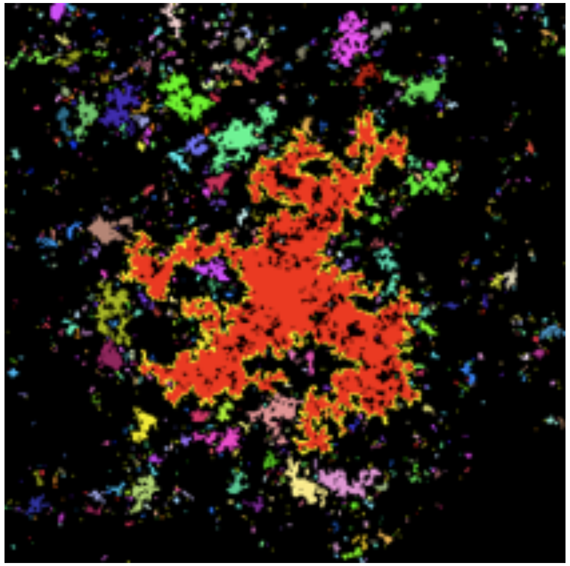
1. Our analysis suggest that obesity spreading is similar to a critical point.
2. Long-range correlations are observed in many other indicators.
3. We classify the indicators in universality classes.
4. The results suggest that a main driver for the obesity epidemic is the food marketing forces in detriment of individual habits.
5. This result might help in designing efficient health policies.

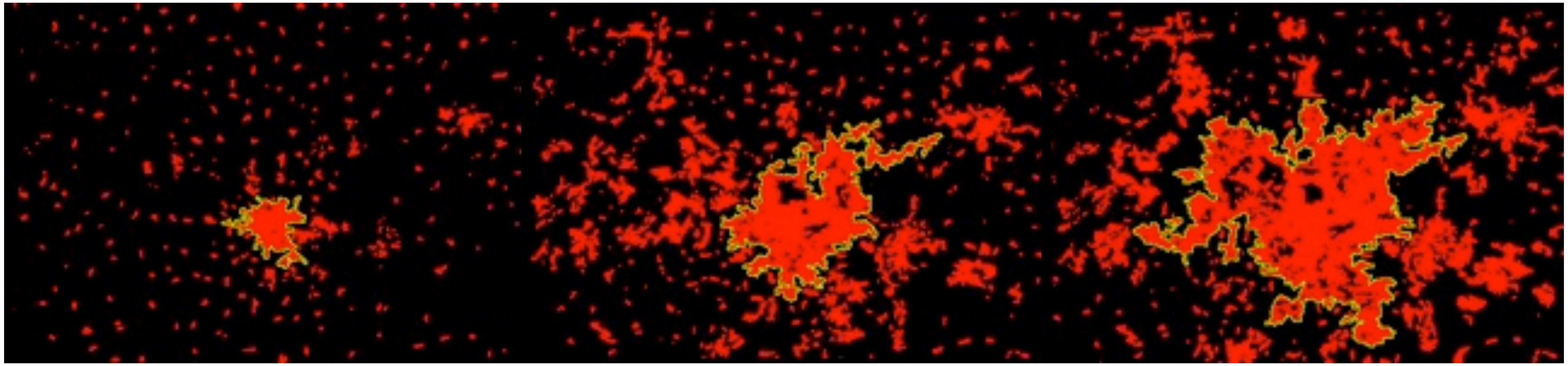
BIG DATA

DLA model:
for
Fractal
Cities



Long-range percolation model of London





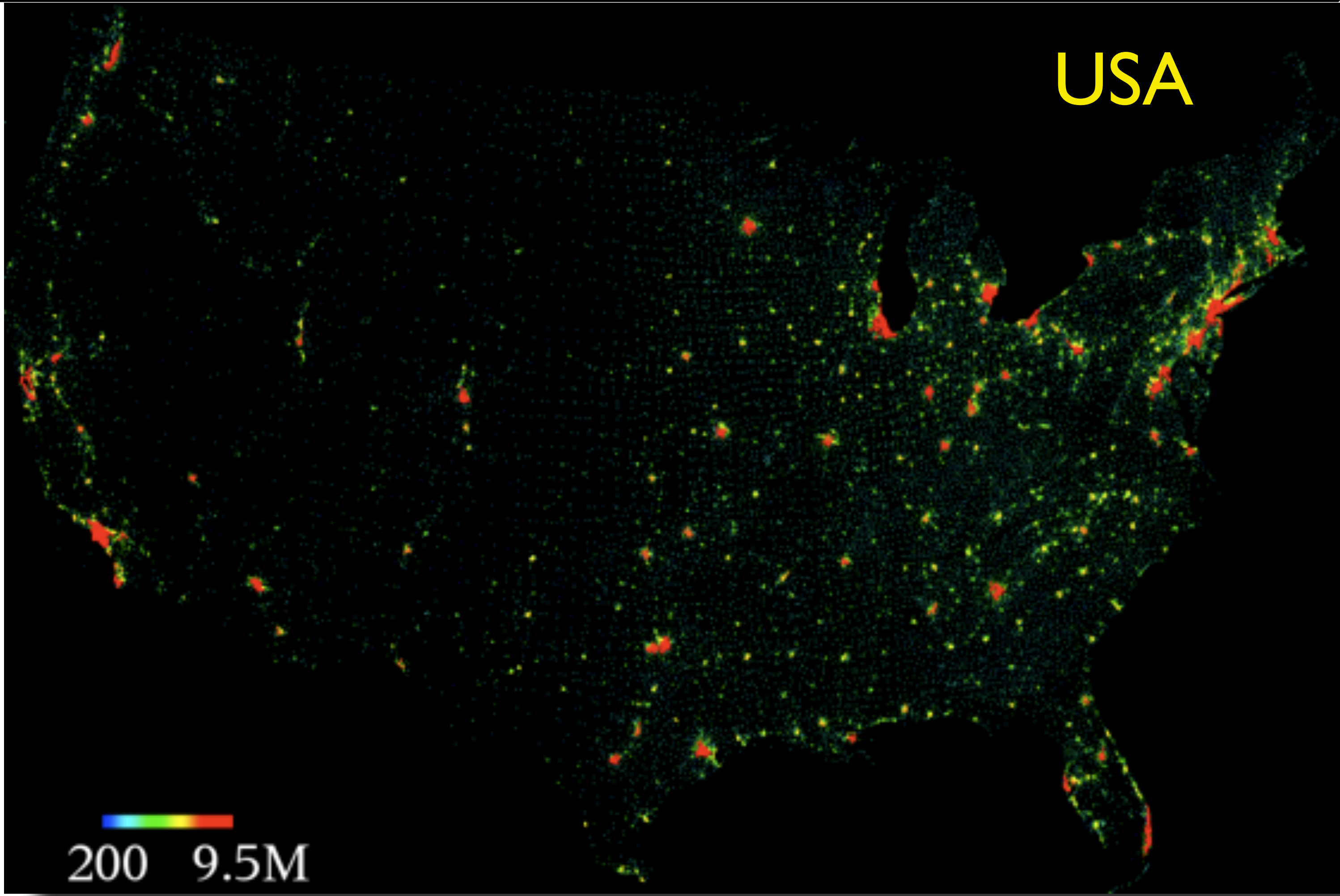
1875 1920 1945

Growth of Berlin

Next: City Clustering Algorithm (CCA)

How to define a city beyond admin boundaries.

London

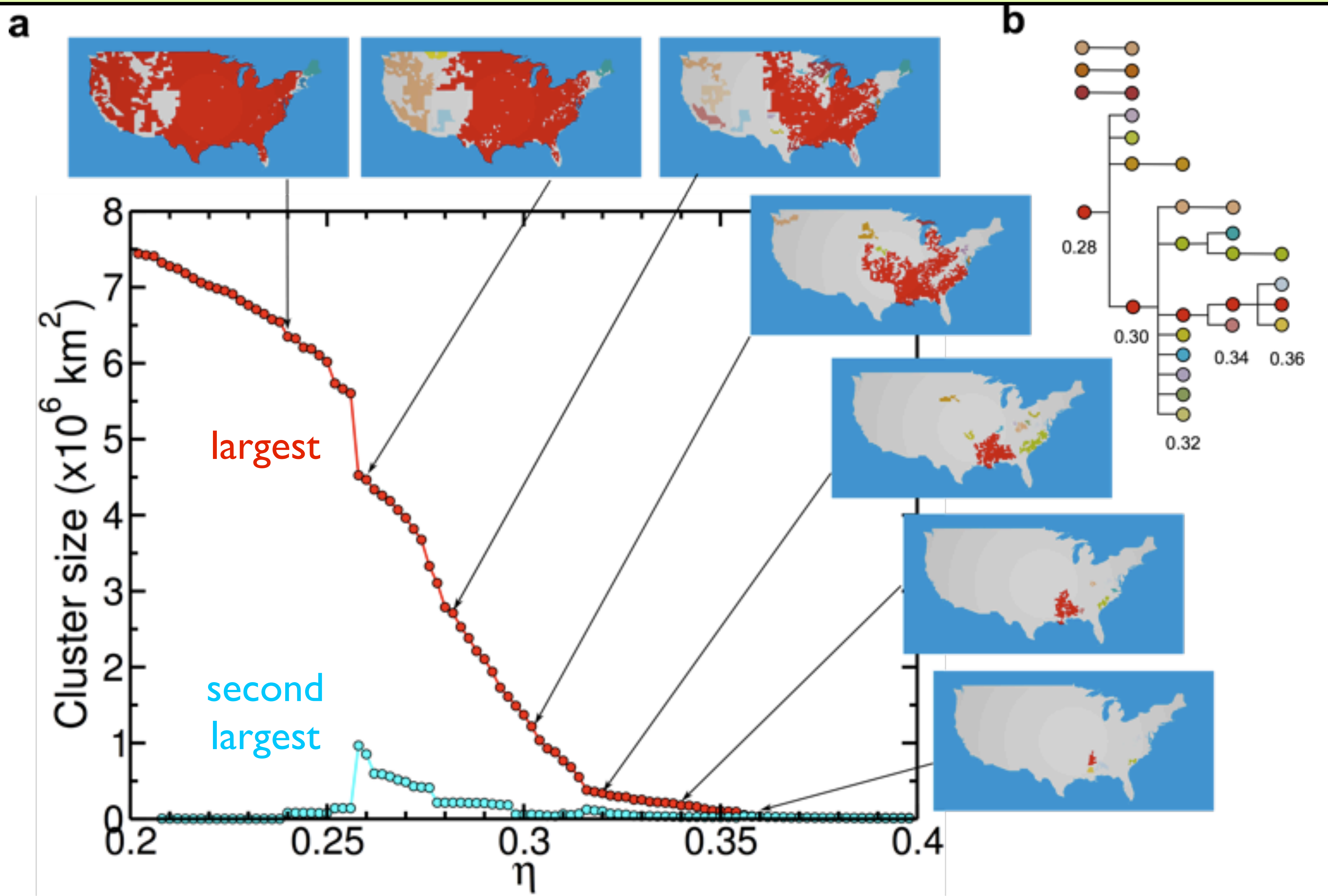


Gibrat Law fails: Rozenfeld, Andrade, Batty, Stanley, Makse. PNAS (2009)
Zipf Law works: Rozenfeld, Gabaix, Makse. American Economic Review (2011)

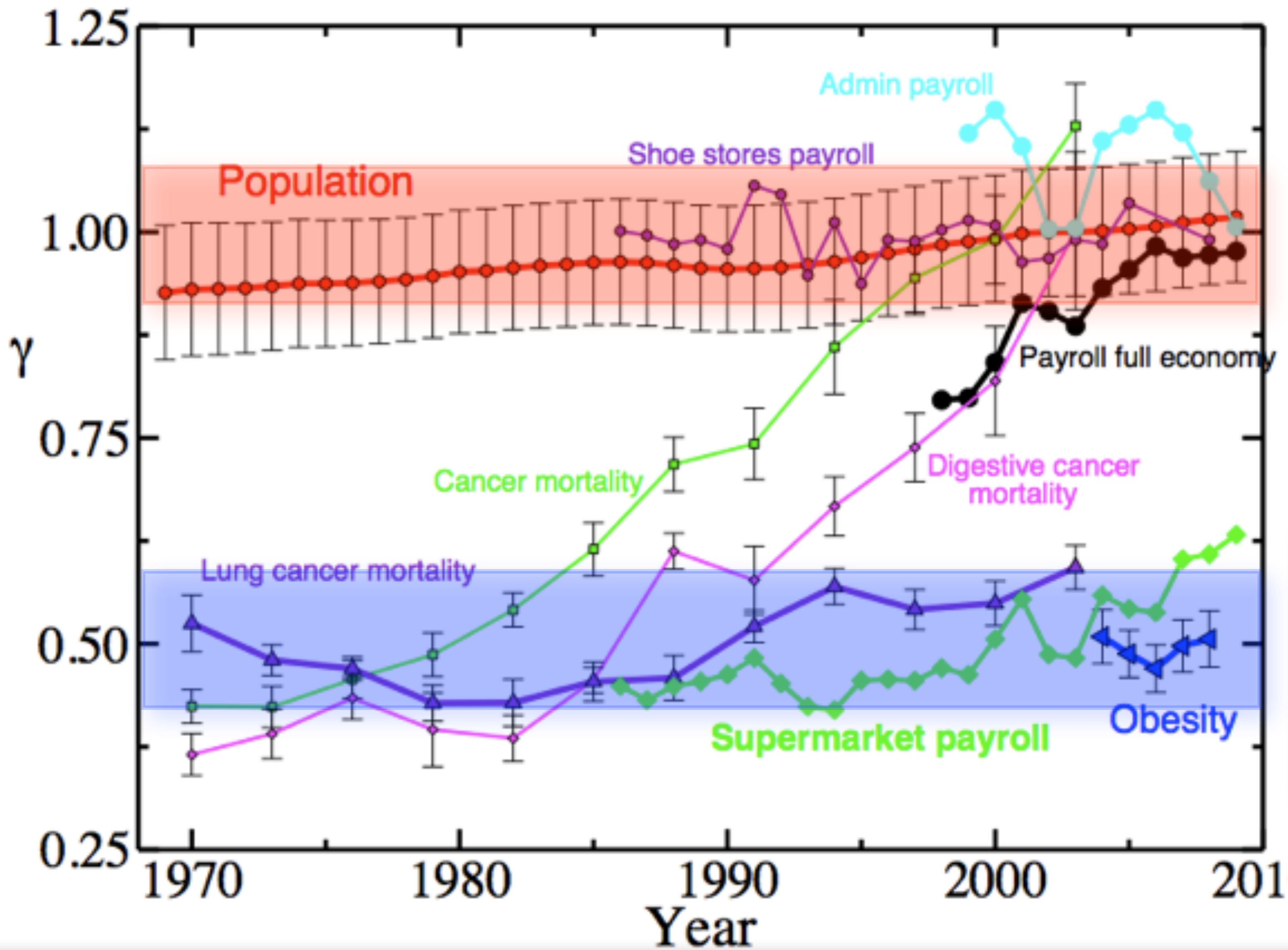
Work in progress: how to reconcile Zipf law without Gibrat

Hierarchical obesity percolation

neither second order
nor first order
(Achlioptas)



Conclusion II: supermarket = obesity



$\gamma_{\text{pop}} = 1$

Weakly correlated

$\gamma_{\text{ob}} = 1/2$

Strongly correlated

Supermarket activity has same fluctuations as obesity.

Alarming numbers! (not so..)

Some relevant numbers:

Body mass index (BMI)

$$\mathrm{BMI} = \frac{\mathrm{mass\ (kg)}}{[\mathrm{height\ (m)}]^2}$$

underweight 18.5 healthy 25 overweight 30 obese

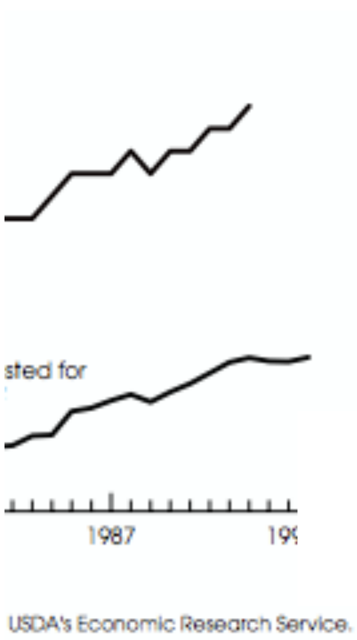
1.79m → 59kg 80kg 96kg

1 billion worldwide undernutrition

5 billion 32% US

1 billion worldwide: 14% 68% in USA

Global paradox of obesity and malnutrition



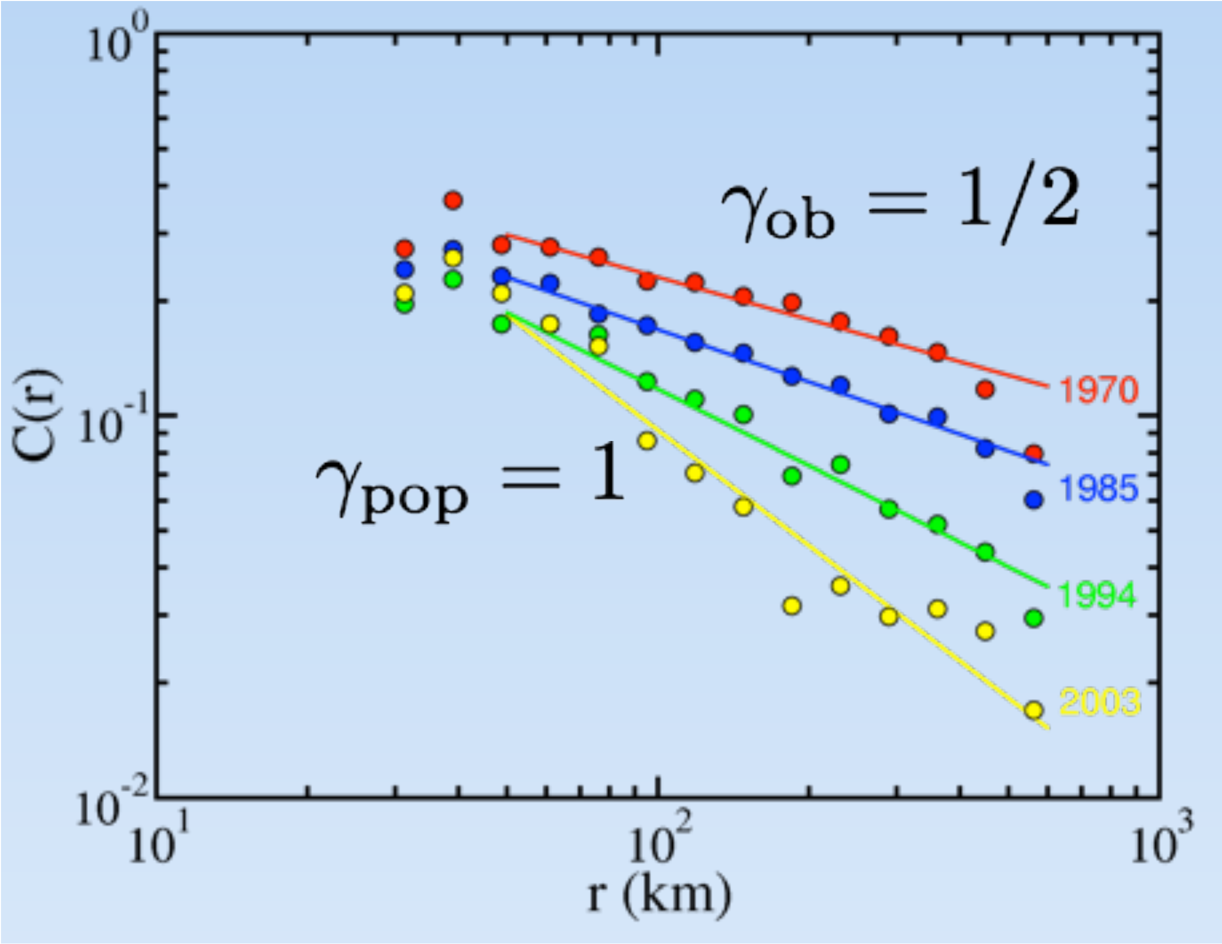
FOOD FACTOIDS
To reduce your weight by a pound of fat a week, eat 500 fewer calories each day.

Only ~500 calories excess = 1 liter Coke

MAIN QUESTION: why did the entire US did it at the same time!!
COLLECTIVE BEHAVIOR

Test universality with other indicators

Test universality: Economic indicators, mortality rates, etc



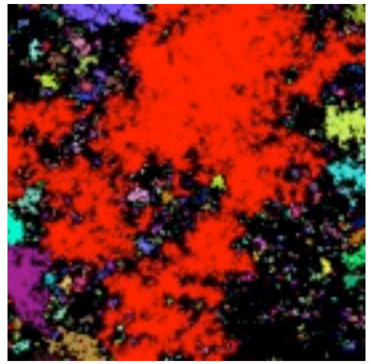
Digestive cancer mortality rates per county in US

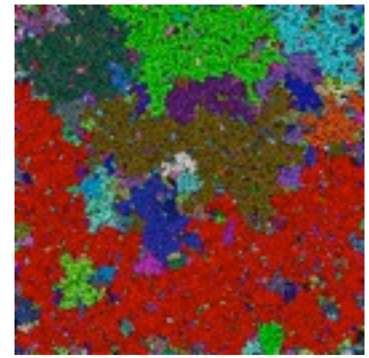
Dramatic change from strong correlations to weak correlations

Morphology of cities: a variation of percolation

Correlated gradient percolation model

Correlated clusters: development attracts more development. Preferential attachment Simon 1955 "rich gets richer"



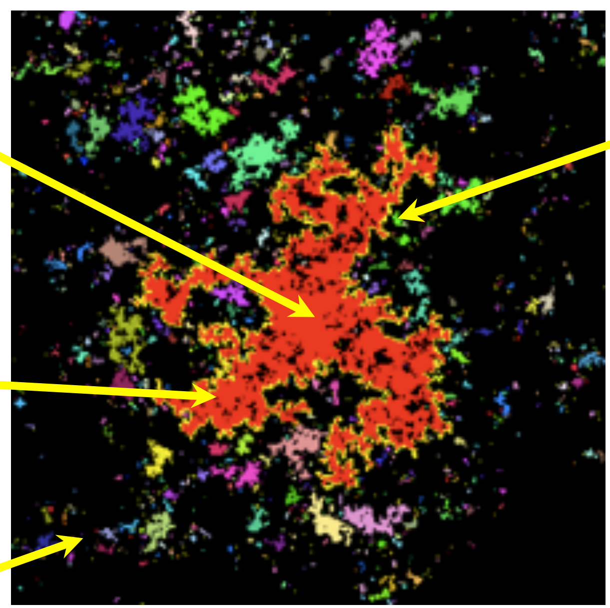


Uncorrelated percolation

Fractal model of London

Center above percolation

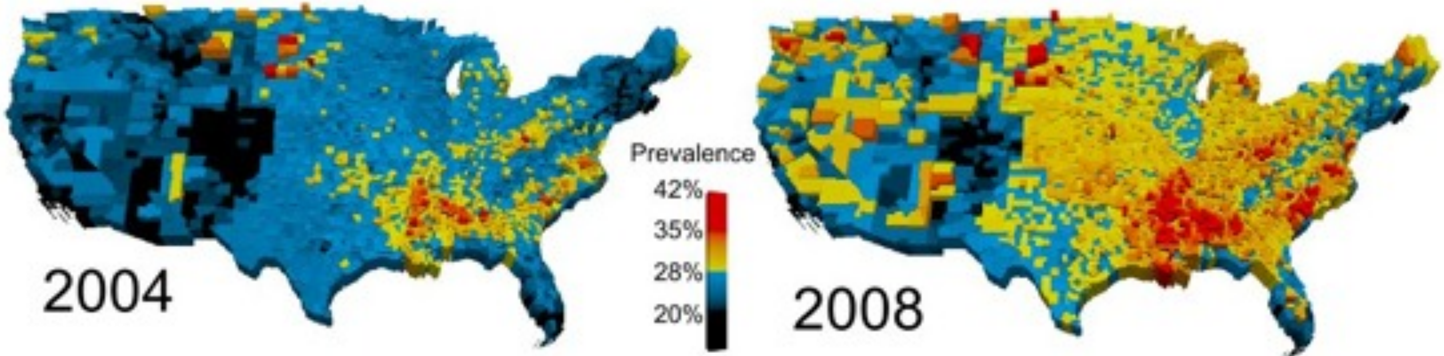
Gradient: Density of occupied sites decreases with distance

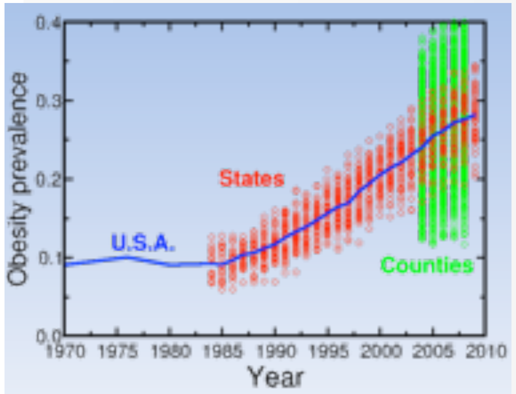


Urban Boundary is at critical percolation with fractal dimension

$$d_e \approx 1.3$$

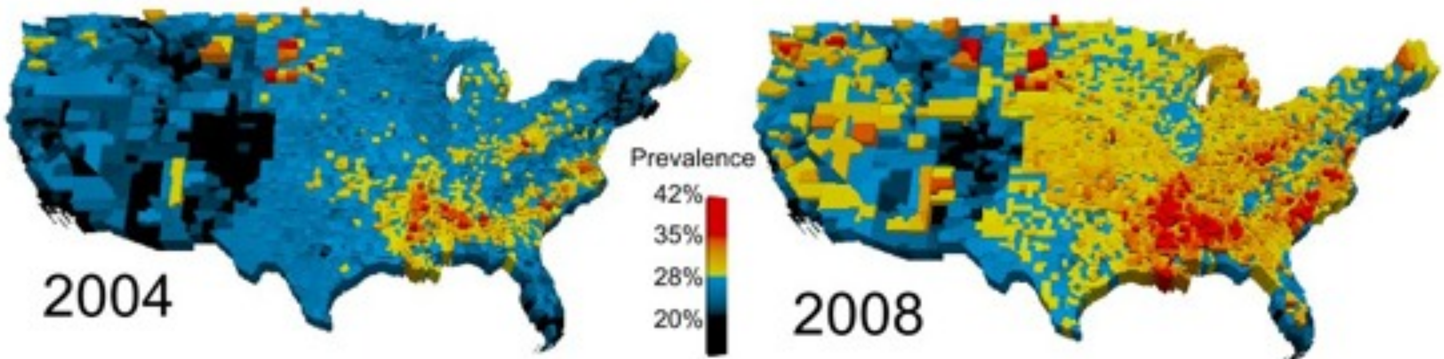
Satellite cities are below critical percolation





Change in obesity levels from 2004 to 2008 (data from

Problem: Obesity rising



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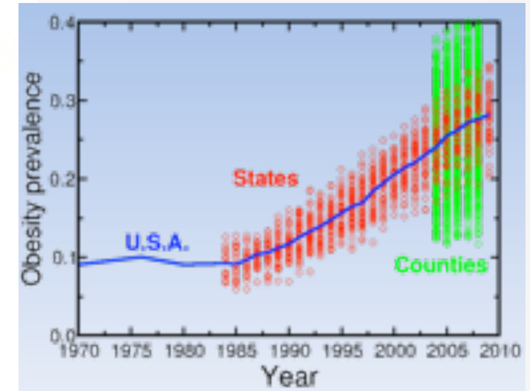
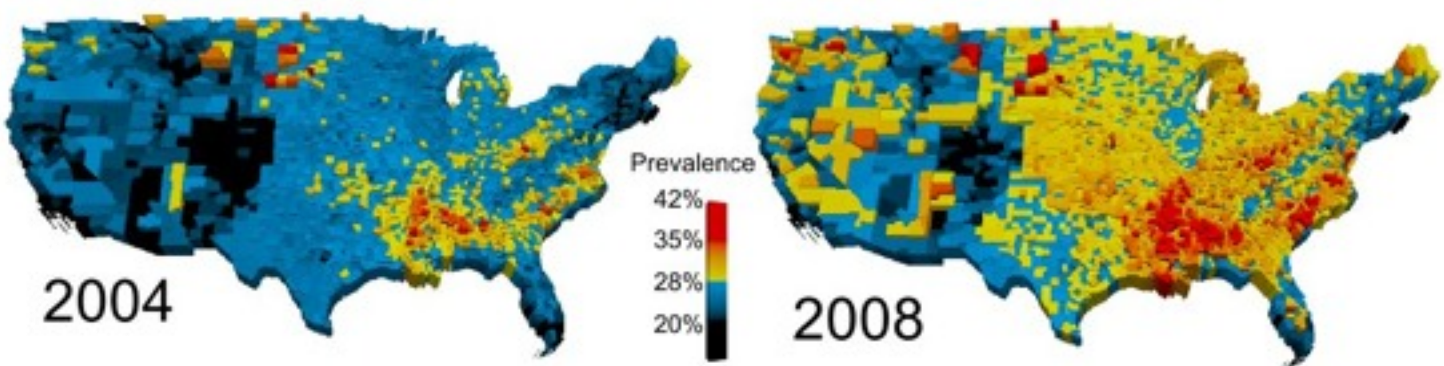


Problem: Obesity rising

How to fight back: Recognize the drivers: Individual vs government/industry responsibility (hot debate!)



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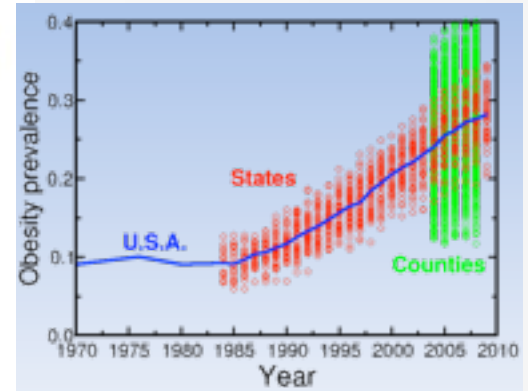

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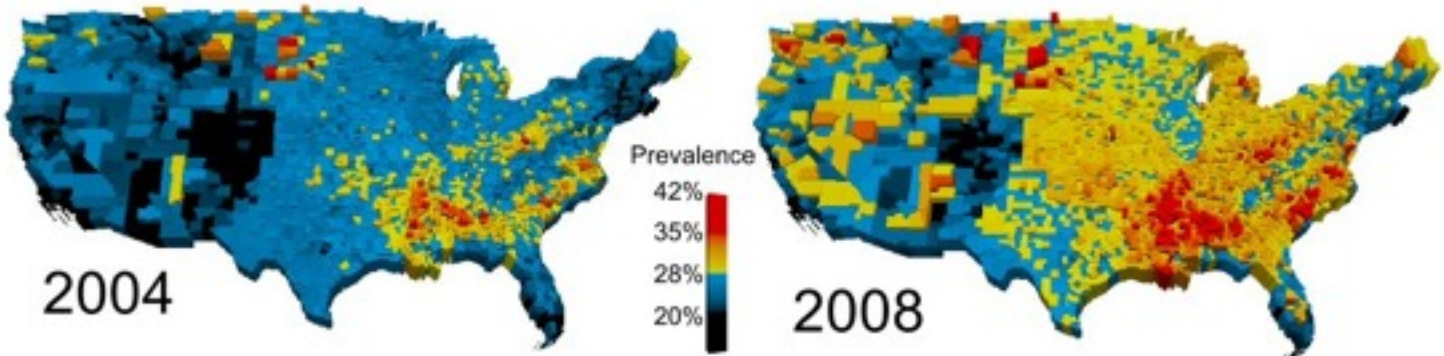
Our approach: Consider obesity rates in each county as the 'particles' of a physical system



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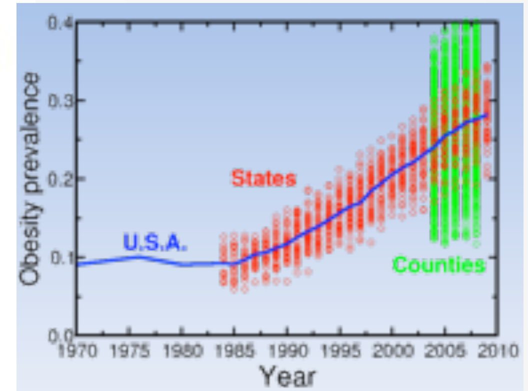

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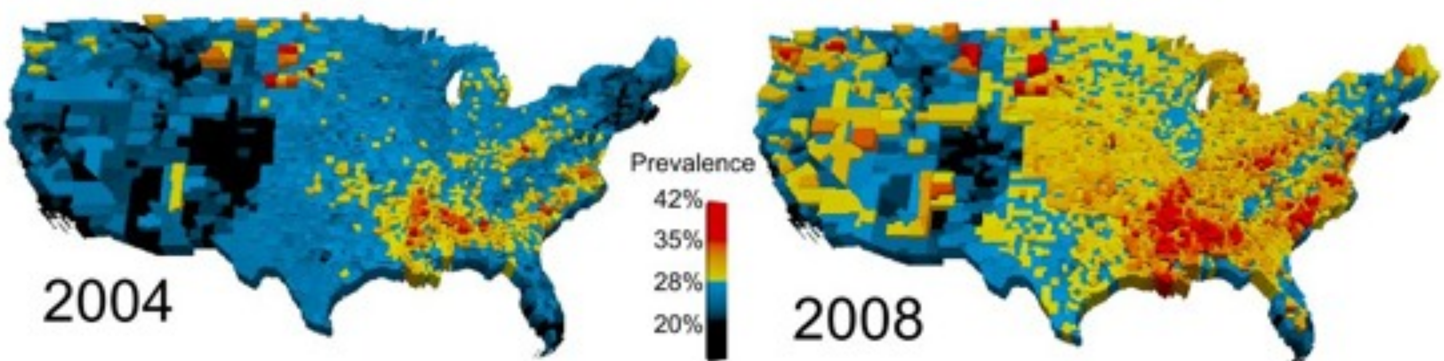

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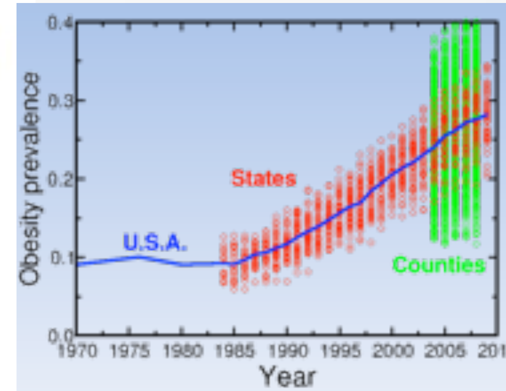

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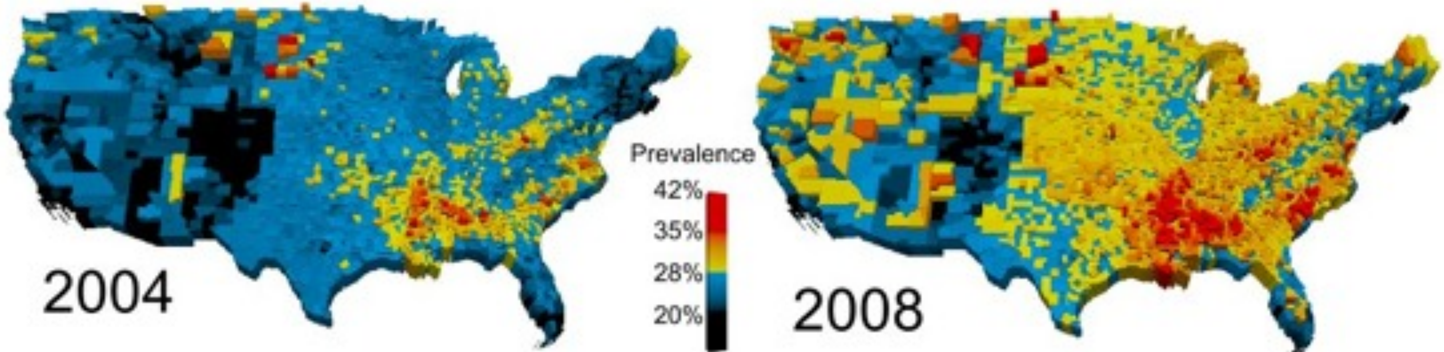

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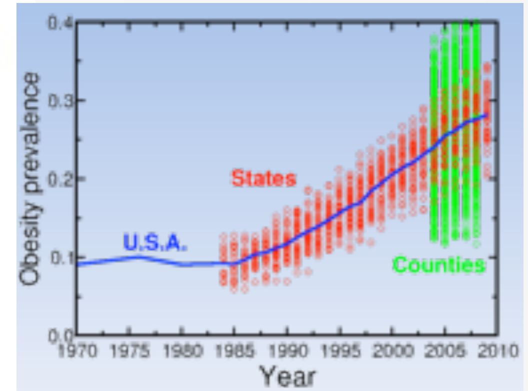

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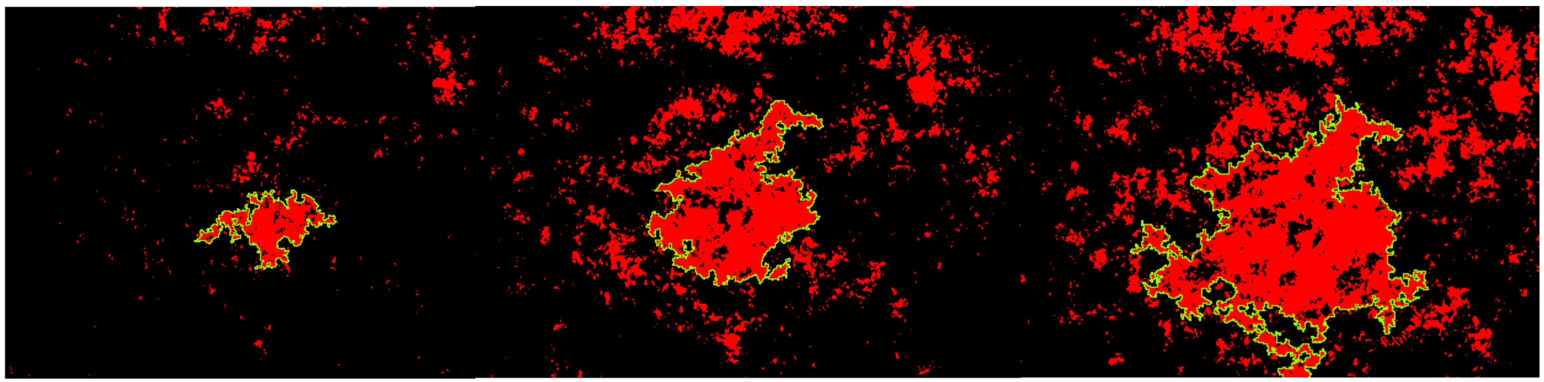
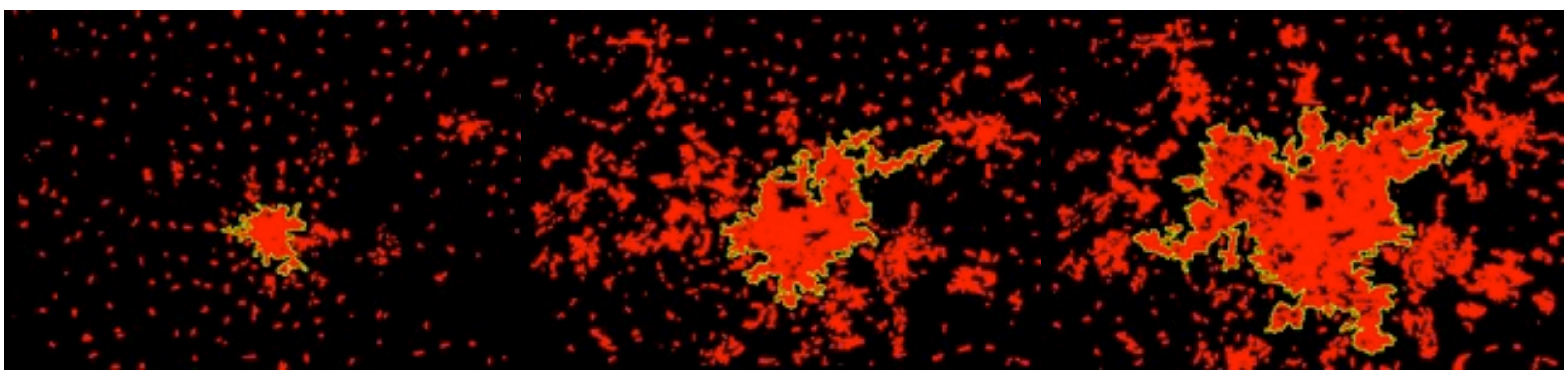
What this means: Individual behaviors are not important

Morphology of cities

Makse, Havlin, Stanley Nature (1995)

Growth of Correlated Percolation Model





1875 1920 1945

Growth of Berlin

What are the drivers of the epidemic?

Marion Nestle, NYU

MAIN ISSUE: Individual responsability vs Industry/Goverment responsibility

Social economic forces promoting calorie imbalance:

1. Overabundance of food: Role of supermarkets and marketing forces.
2. Exacerbated by deregulation of food industry in '80 (Reagan administration).
3. Blame Wall Street! Advent of the "shareholder value movement" in '80. Demand for higher profit by food industry.
4. Obesity as a normal outcome of market economies.
5. Obesity as an "economic bubble".

See the movie: Foods Inc. www.foodincmovie.com

OUTLINE

Application of paradigms of equilibrium statistical physics to help explain a different set of natural phenomena.

Systems:

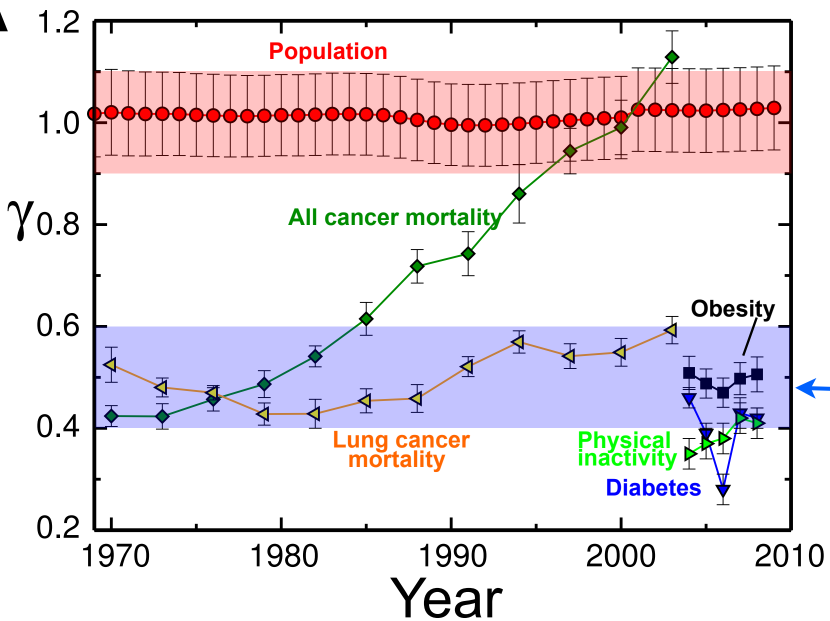
1. Obesity epidemic: geographical clustering and drivers
2. Rise and fall of social communities: cascades of followers triggered by pioneers

Commonality: Clustering and correlations in human activity.

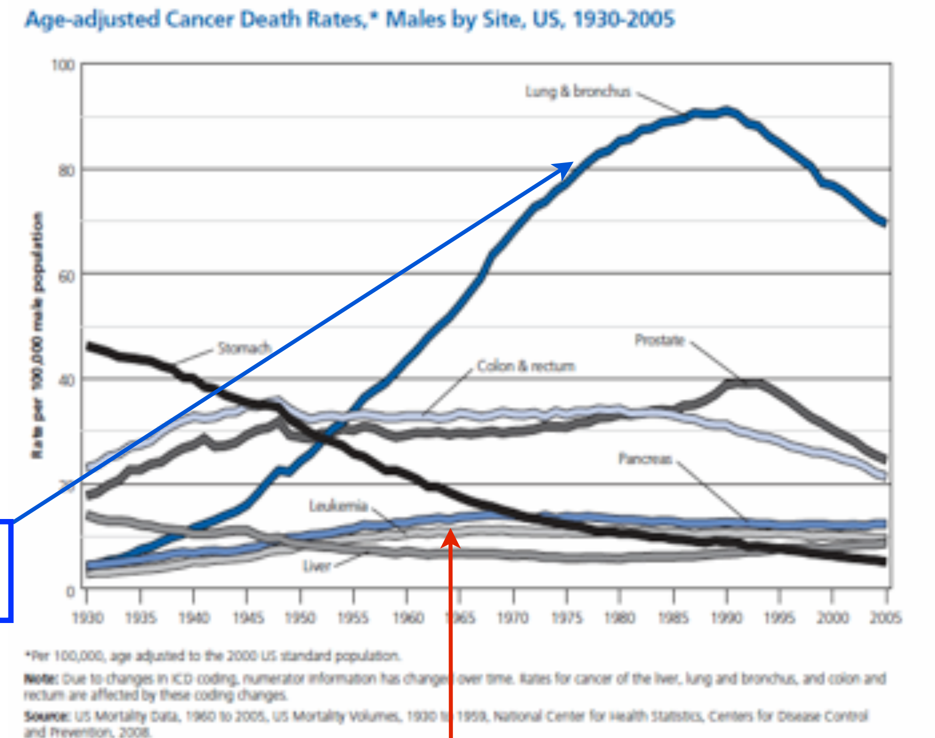
Tools: Percolation theory and collective behavior in complex systems.

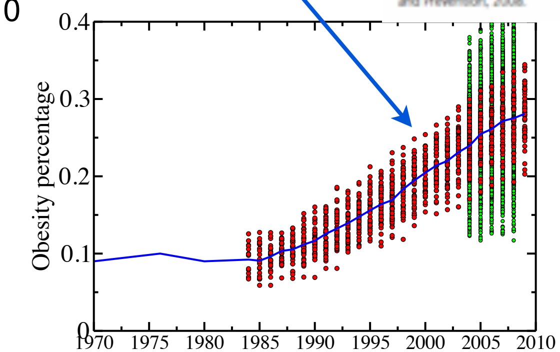
Conjecture 2

A close relation between rapid growth and strong correlations



$\gamma_{\rm ob} = 1/2$





$\gamma_{\rm pop} = 1$

Are all exponentially growing activities in $\gamma_{\rm ob} = 1/2$?