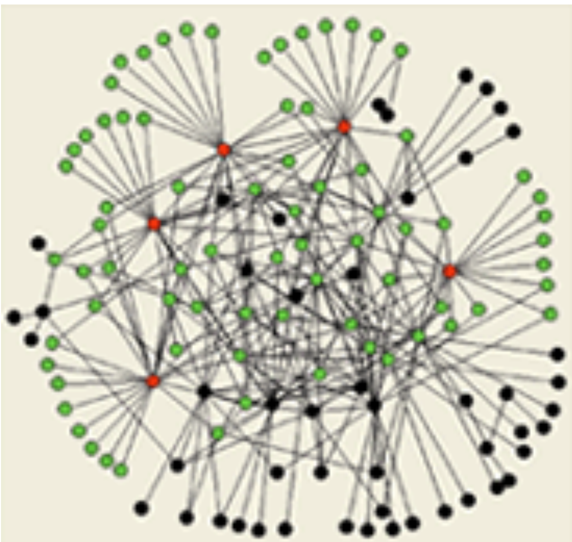
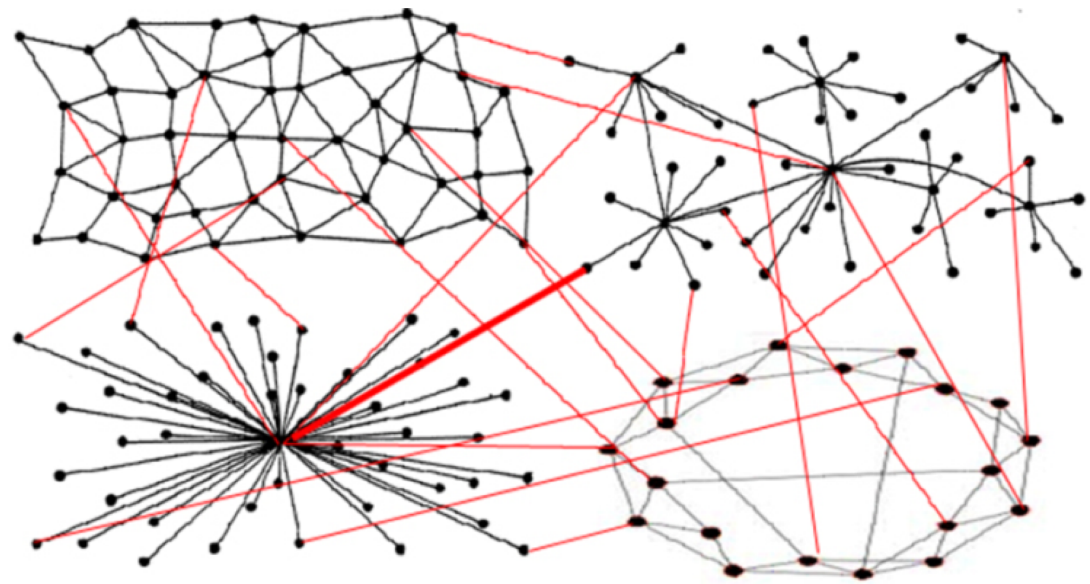
Spatio-Temporal Infrastructure Networks

From single networks to networks of networks

2000-Barabasi

2010





Shlomo Havlin
Bar-Ilan University

multilevel
multilayer
multiplex

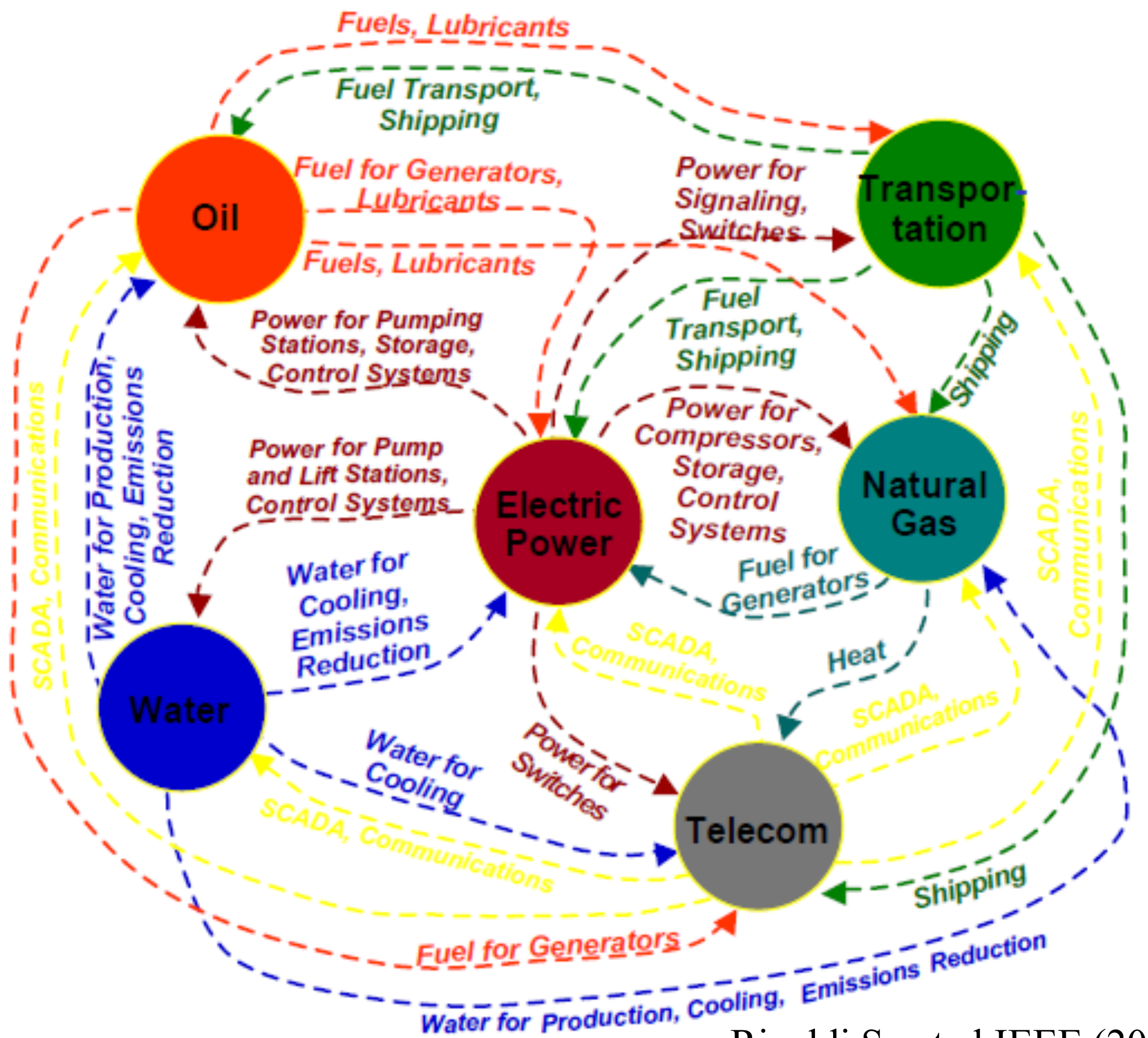
Electric grid,
Communication
Transportation
Services …..

Two types of links:
1. Connectivity
2. Dependency

Protein networks, brain networks-
Different functions can be regarded as different networks
Dependency – nodes in one network depend on nodes in another network to function.

Cascading failures-abrupt transition

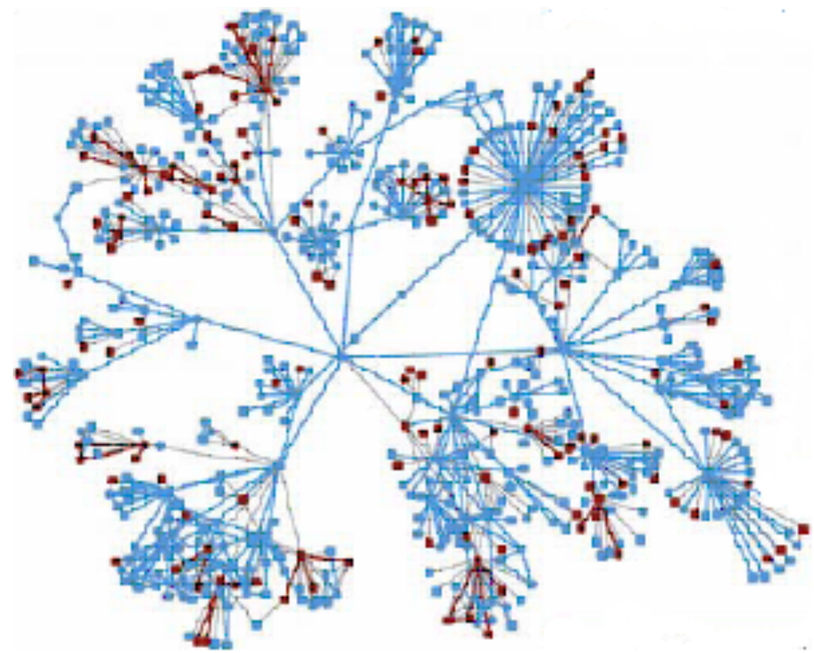
How interdependent are infrastructures?



Rinaldi S, et al IEEE (2001)

Extensive Studies Since 2000 -- Single Networks

- A Network is a structure of N nodes and M edges (or 2M links)
- Called usually graph – in Mathematics
- Complex systems can be described and understood using networks



Internet: nodes represent computers links the connecting cables

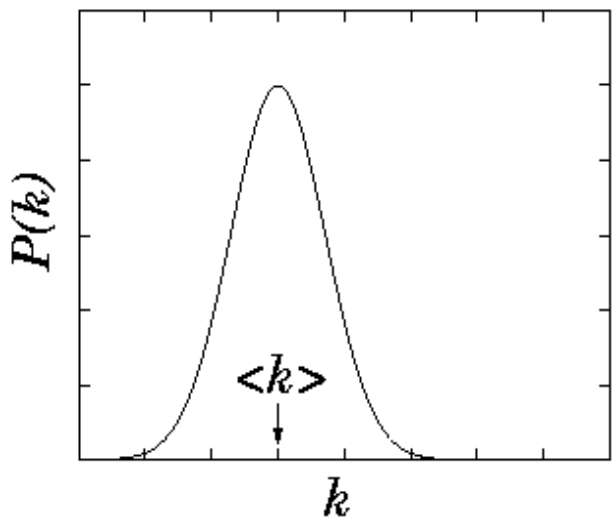
Airline systems: nodes represent airports links their destinations

Climate system: nodes represent locations links similar climate

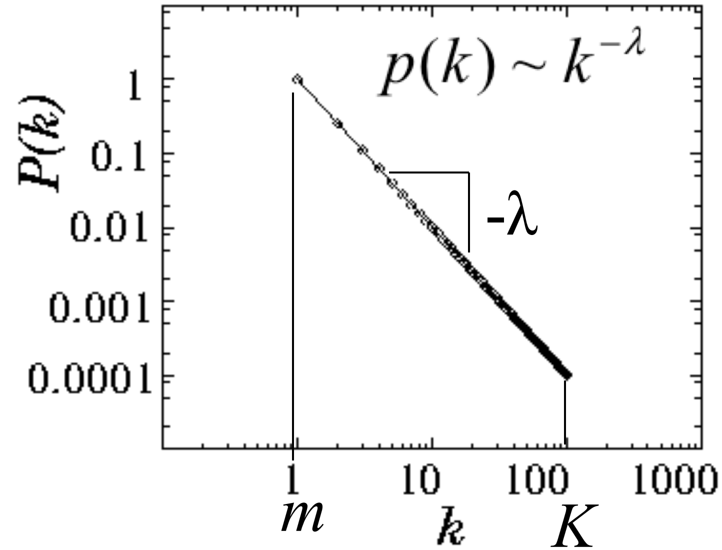
Successful results: Efficient immunization strategies, identifying key players, robustness, climate, physiology, protein networks-function …..

Complex Single Networks- Since 2000

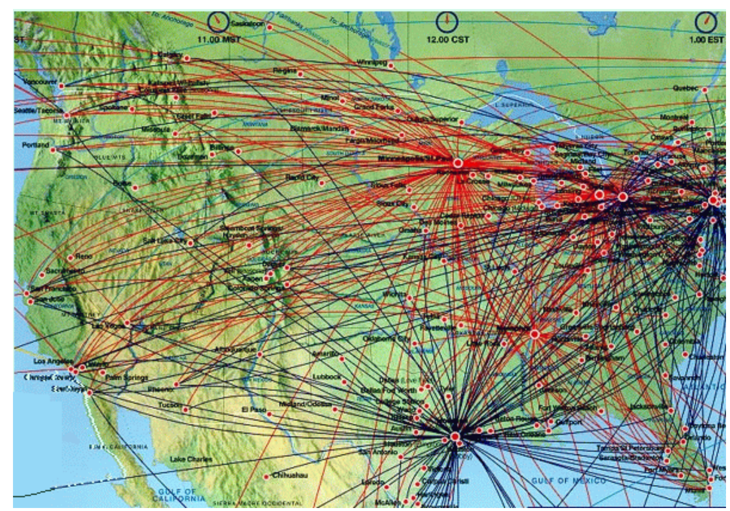
Poisson distribution
(ER - 1959)



Scale-free distribution
(Barabasi –Albert 1999)

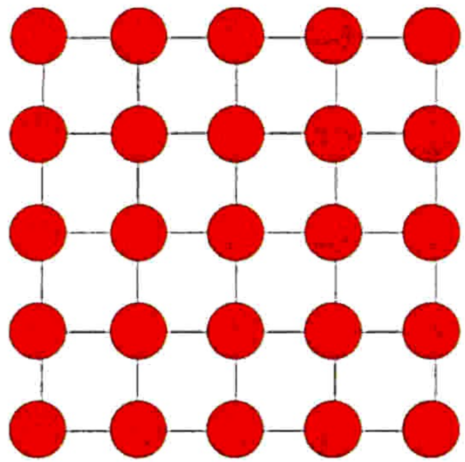


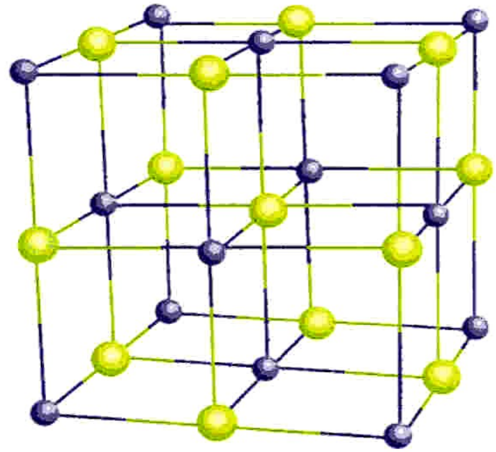
Erdős-Rényi Network



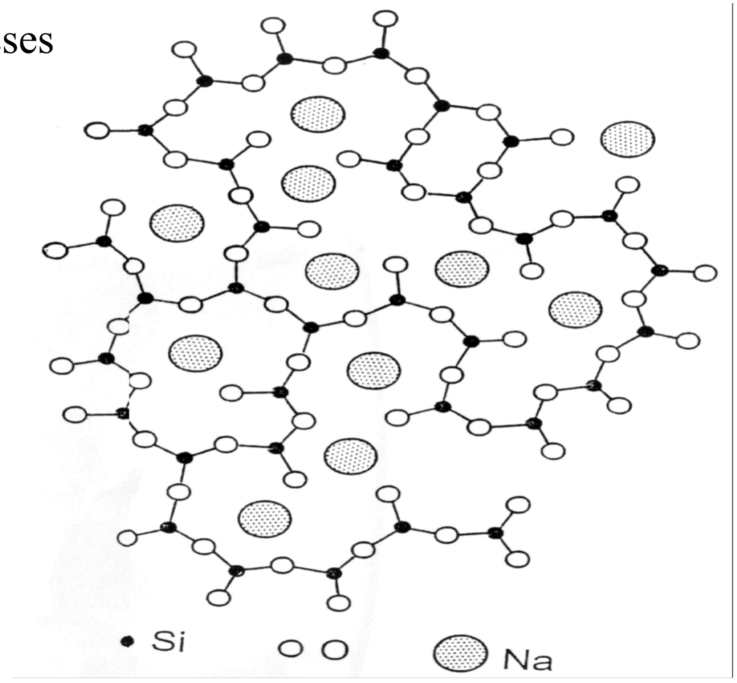
Scale-free Network

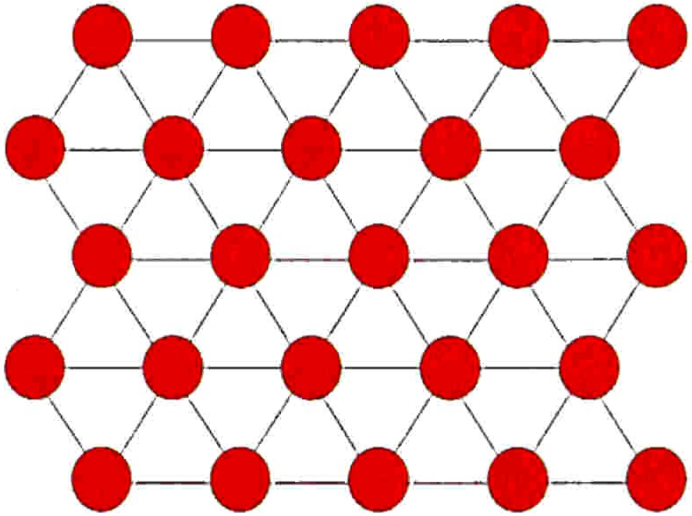
Networks in Physics





glasses



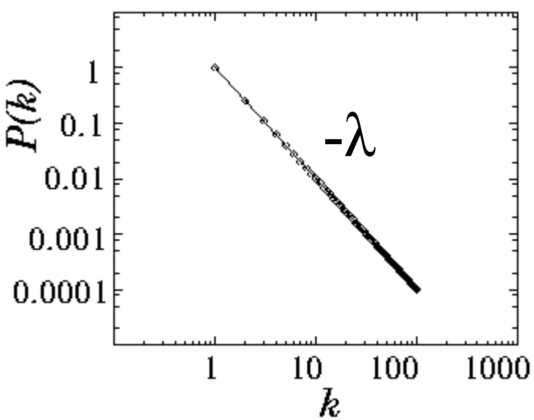


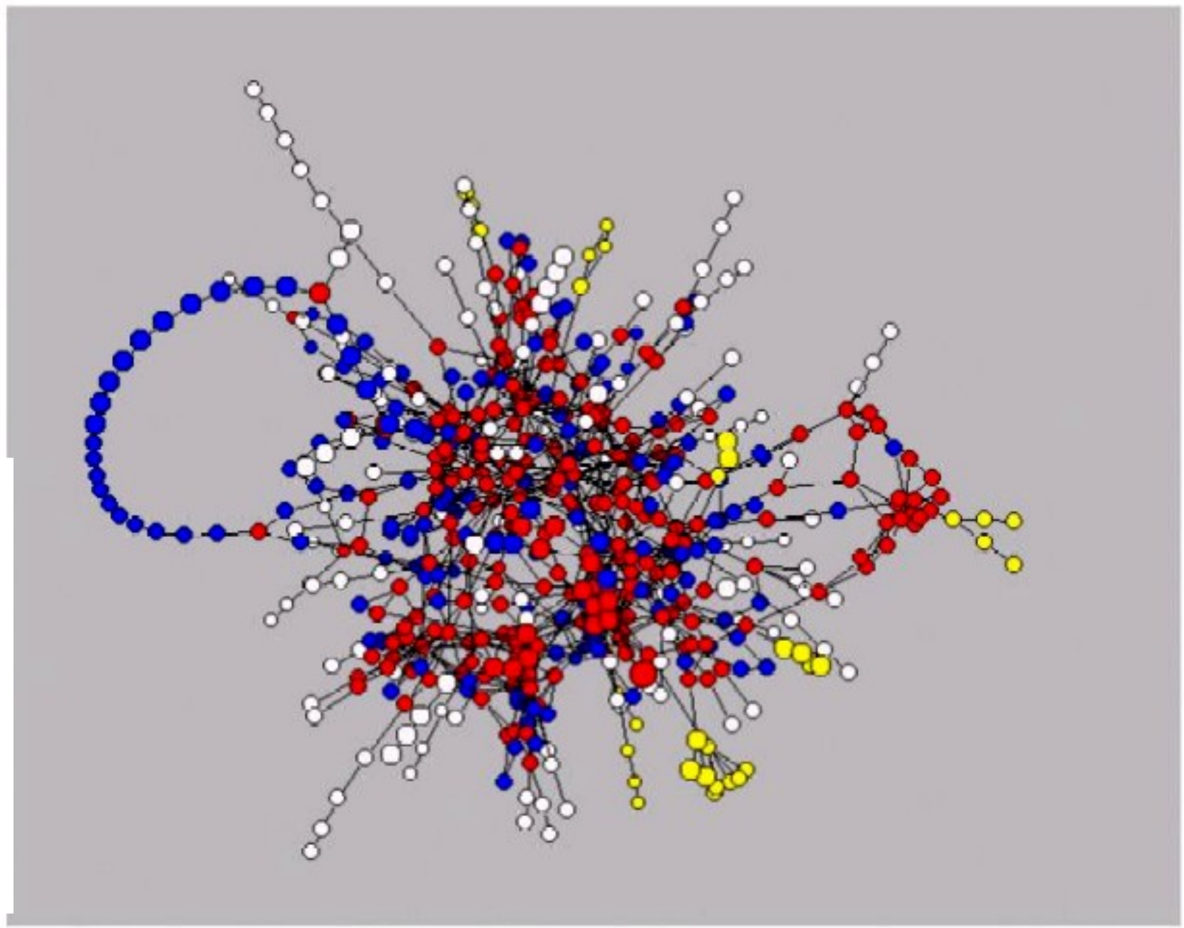
Metabolic Network

Nodes: chemicals (substrates)

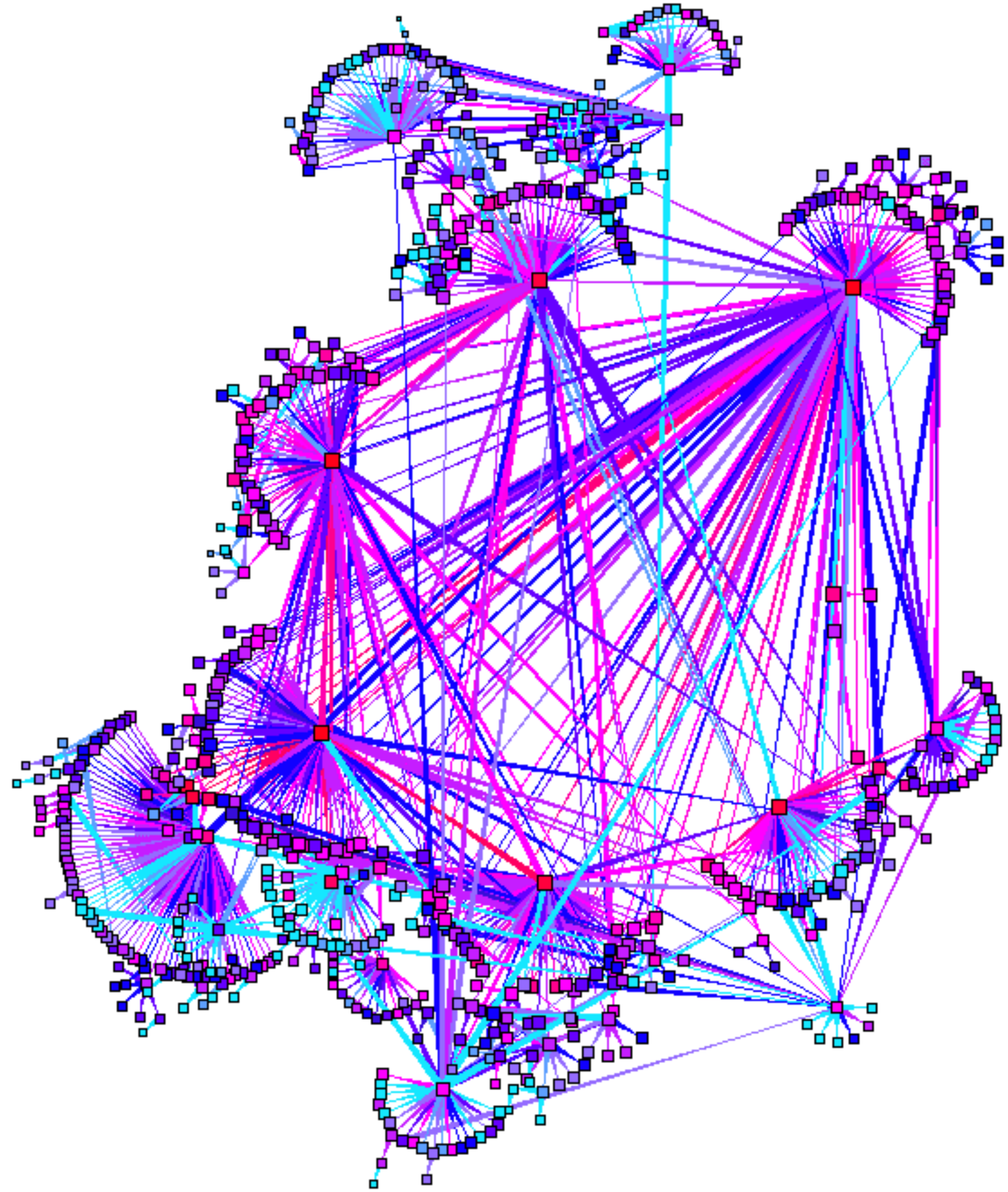
Links: bio-chemical reactions

$$p(k) \sim k^{-\lambda}$$



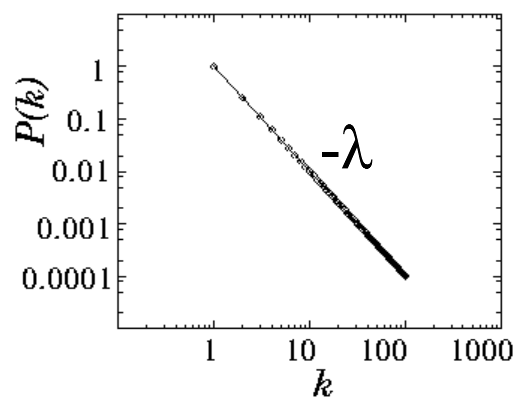


Jeong, Tombor, Albert, Barabasi, Nature (2000)



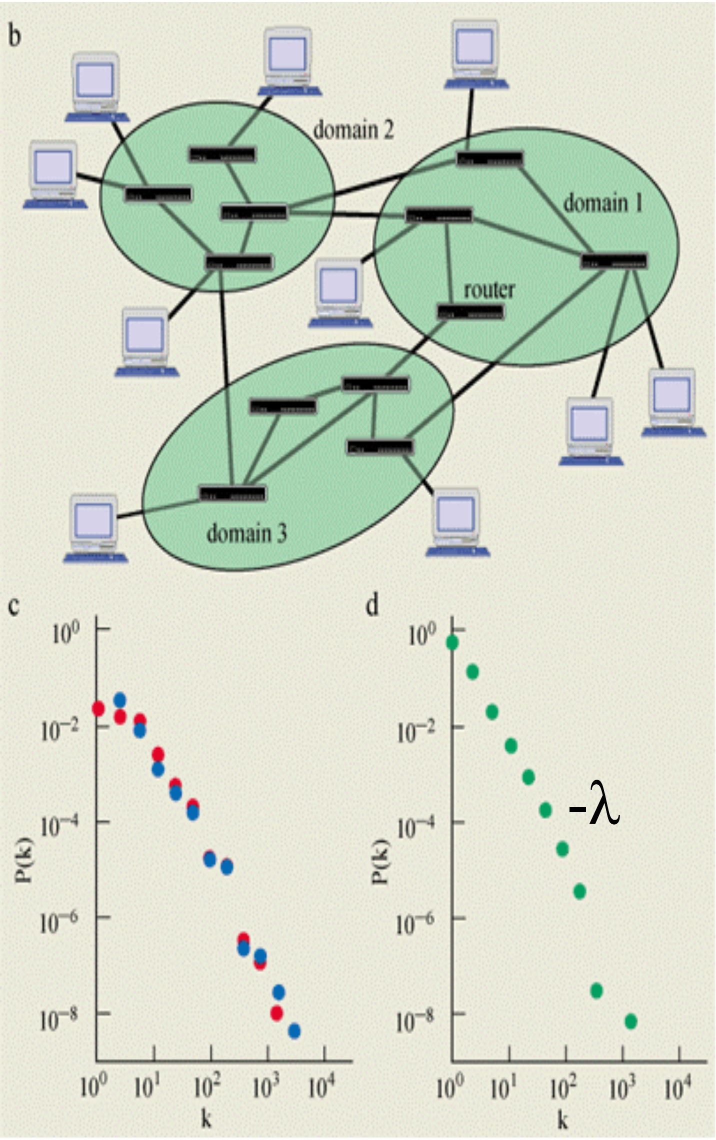
WWW-Network

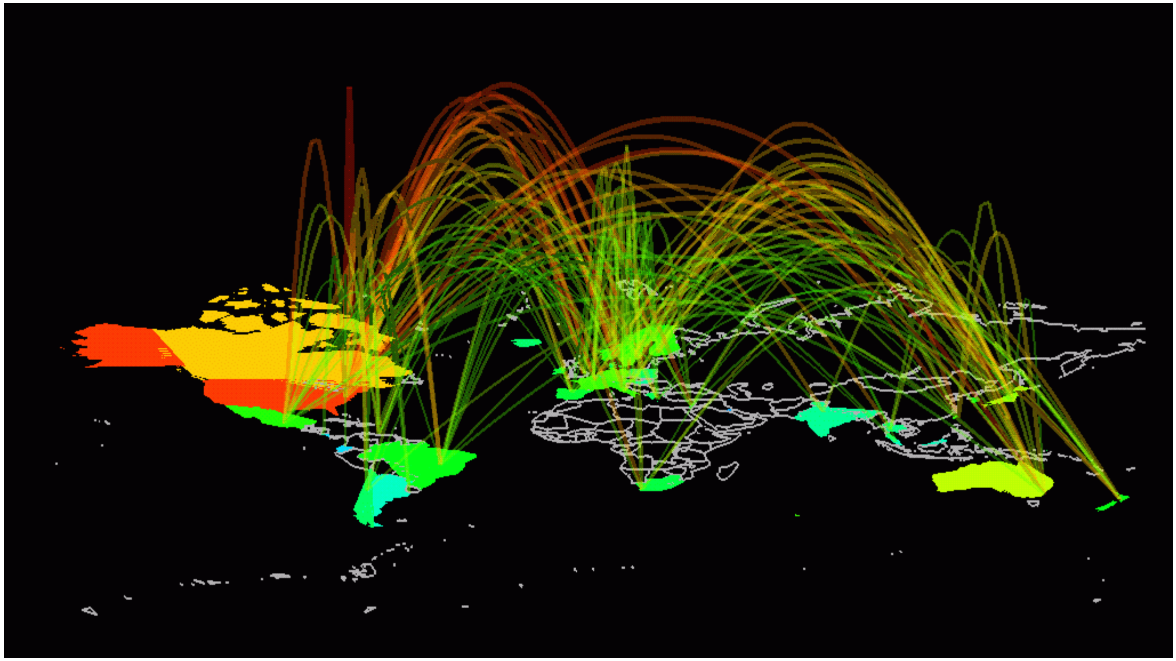
Barabasi et al (1999)

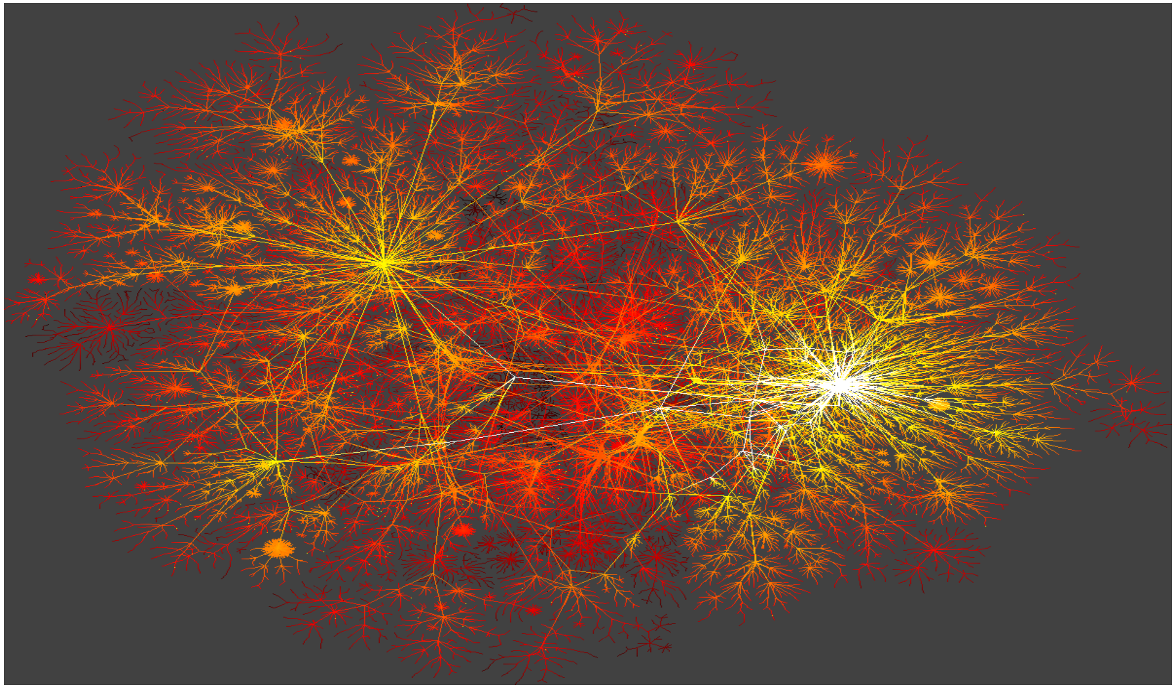


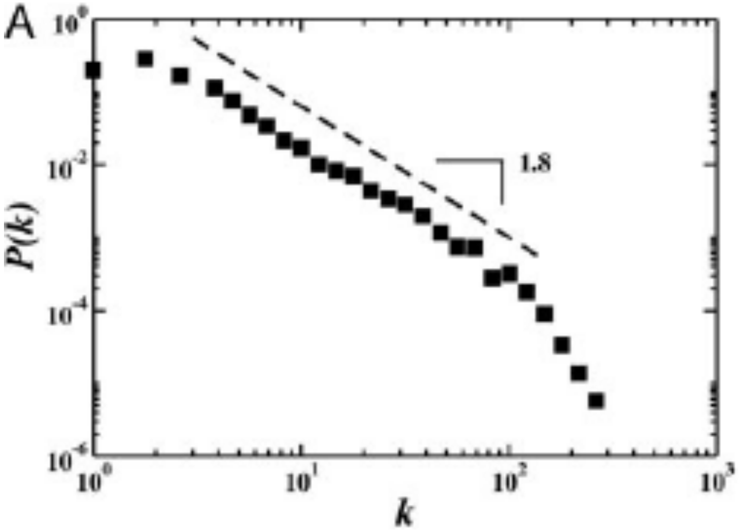
Internet Network

Faloutsos et. al., SIGCOMM '99







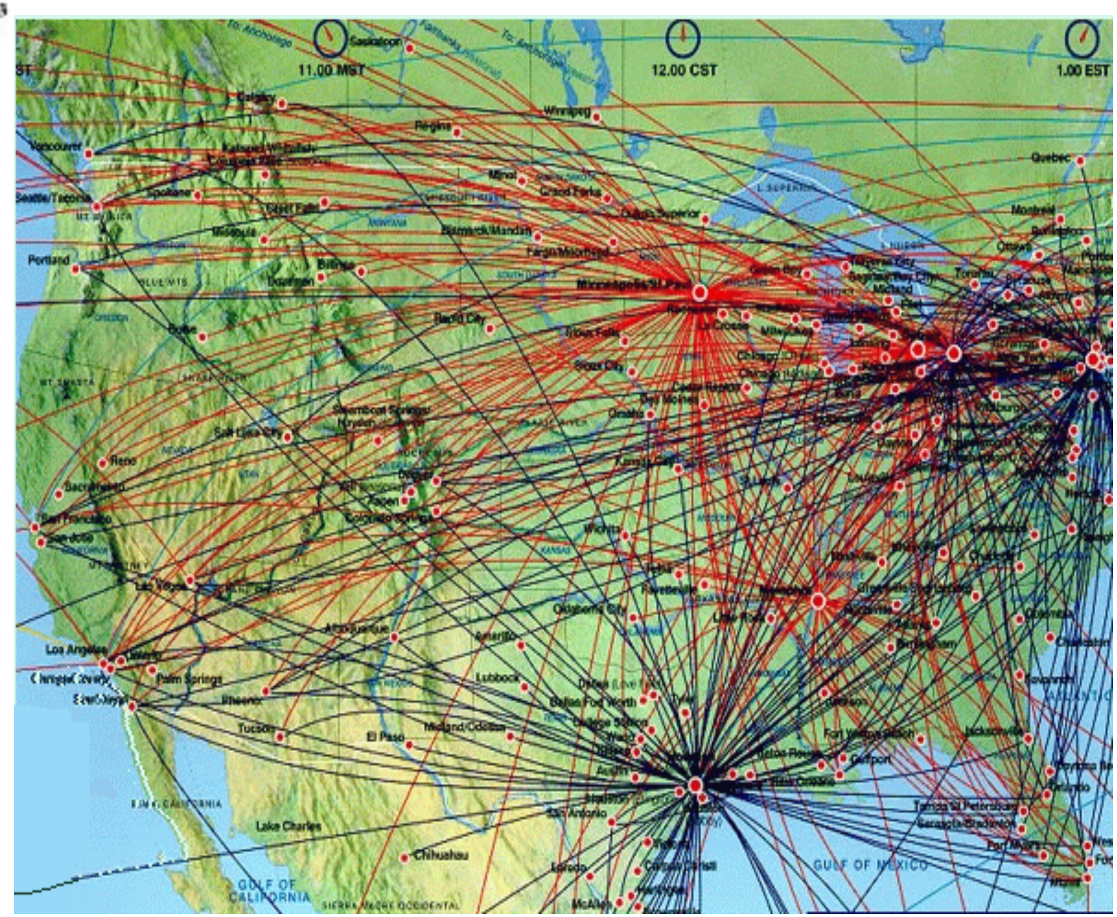


Global Airline Network

Colizza, Vespignani et al PNAS (2006)

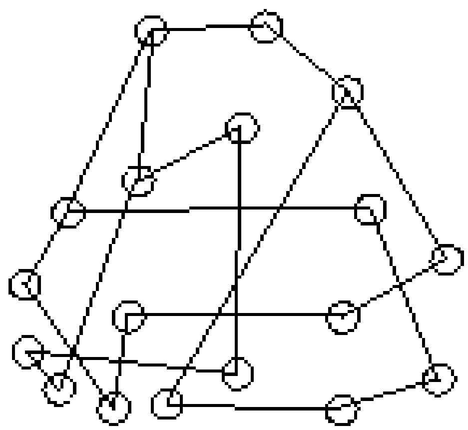
Scale free-degree distribution:

$$p(k) \sim k^{-\lambda}$$



Many real networks are non-Poissonian

Exponential



$$P(k) = e^{-\langle k \rangle} \frac{\langle k \rangle^k}{k!}$$

Classical Erdos-Renyi (1960)

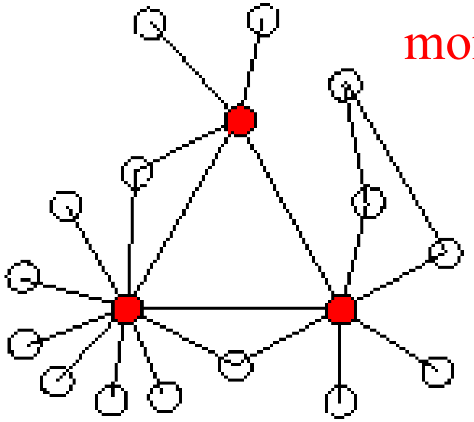
Homogeneous, similar to lattices

$d \sim \log N$-- Small world

$$p_c = 1 - q_c = 1/<k>$$

$$P_\infty = p[1 - \exp(-\langle k \rangle P_\infty)]$$

Scale-free



more robust!!

$$P(k) = \begin{cases} ck^{-\lambda} & m \le k \le K \\ 0 & otherwise \end{cases}$$

Barabasi-Albert (1999)

Heterogeneous-translational symmetry breaks!

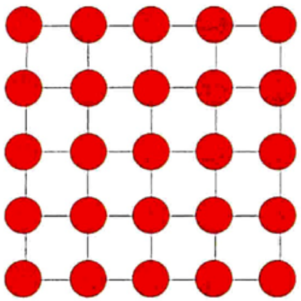
New universality class-many anomalous laws

$e.g.,\quad d \sim \log\log N \;;\; p_c = 0$

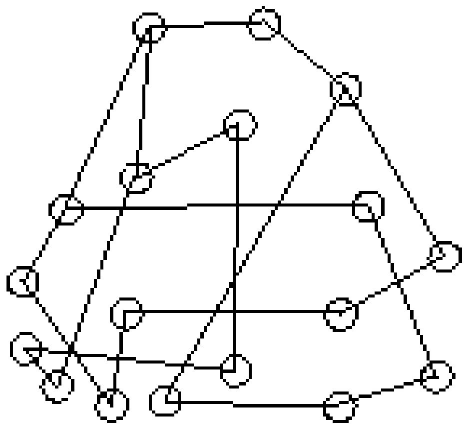
Ultra Small worlds (Cohen and SH, PRL (2003))

Breakthrough in understanding many problems!

Many real networks are non-Poissonian



Exponential



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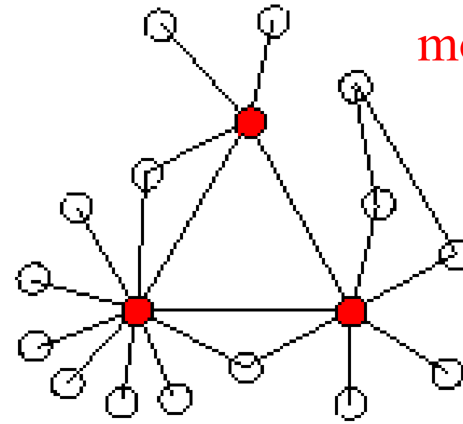
Scale-free



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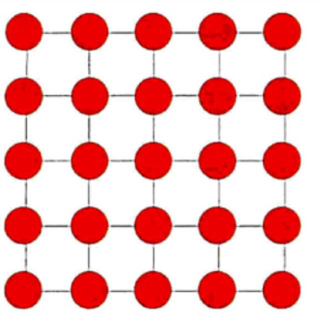
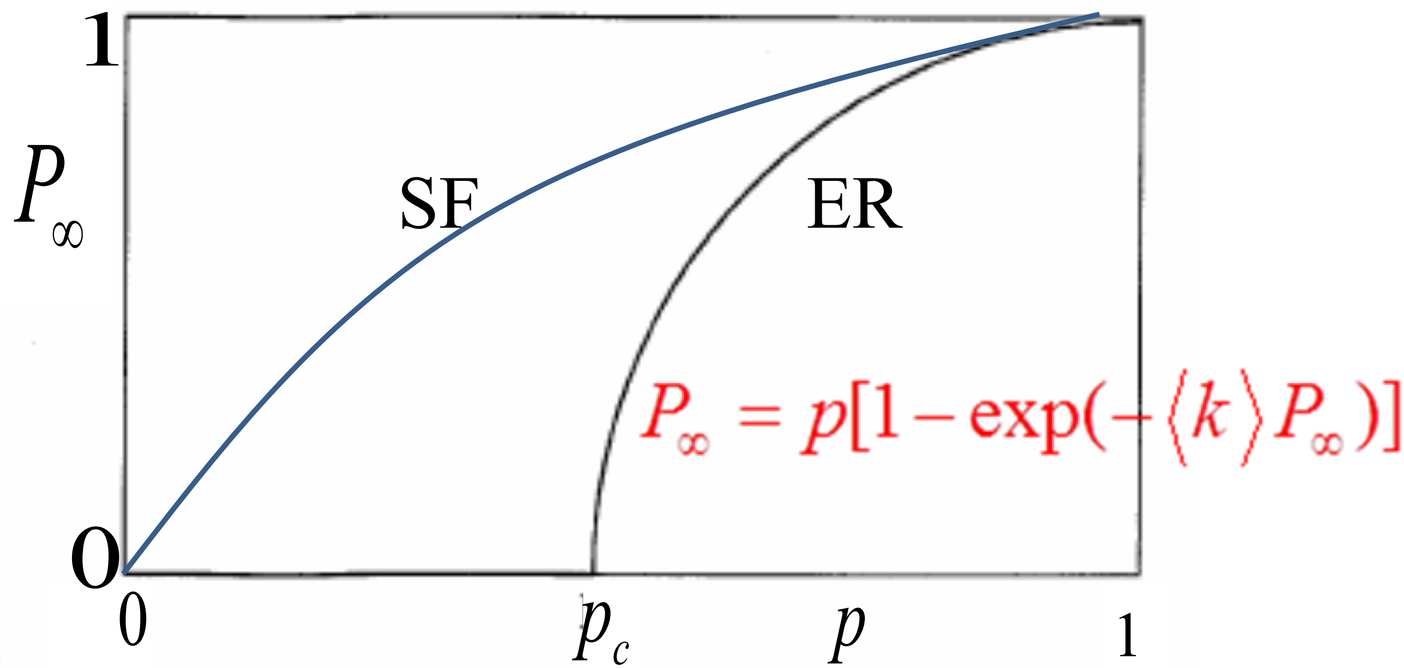


$p_c = 0.593$

Long-range links
More robust!



SF more robust!!

Classical Erdos-Renyi (1960)

Homogeneous, similar to lattices

$d \sim \log N$-- Small world

$p_c = 1 - q_c = 1/<k>$

$P_\infty = p[1-\exp(-\langle k \rangle P_\infty)]$

Barabasi-Albert (1999)

Heterogeneous-translational symmetry breaks!

New universality class-many anomalous laws

e.g., $d \sim \log\log N$; $p_c = 0$

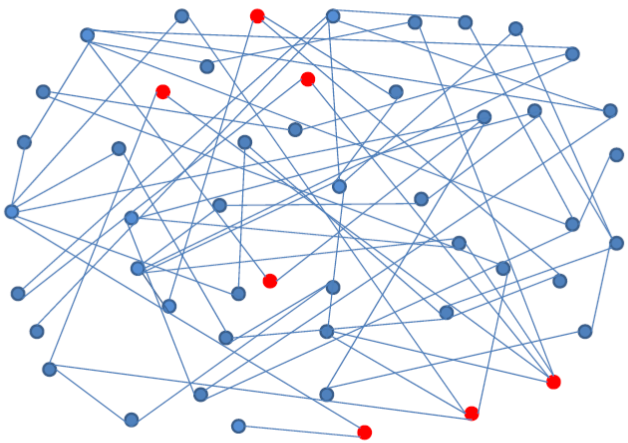
Ultra Small worlds (Cohen and SH, PRL (2003))

Breakthrough in understanding many problems!

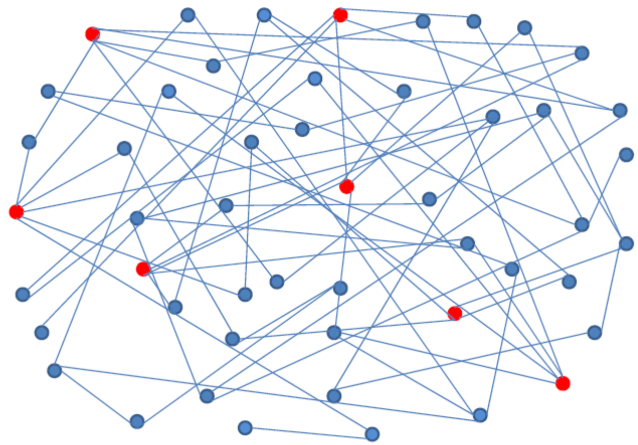
Comparing random, targeted, and equal graph partition strategies

Random scale-free network: N=50; λ=2.5 – immunizing 7 nodes

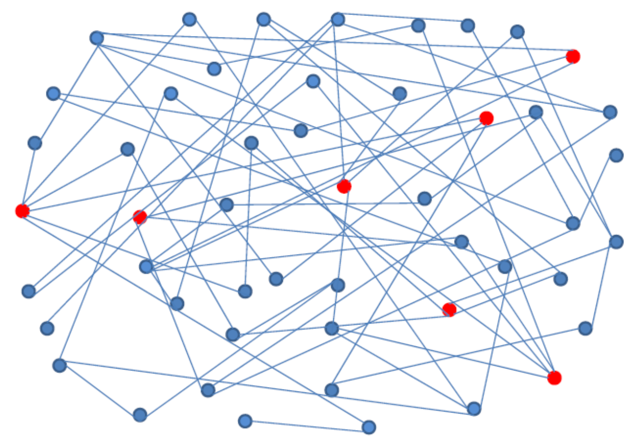
Nodes targeted by random (red)



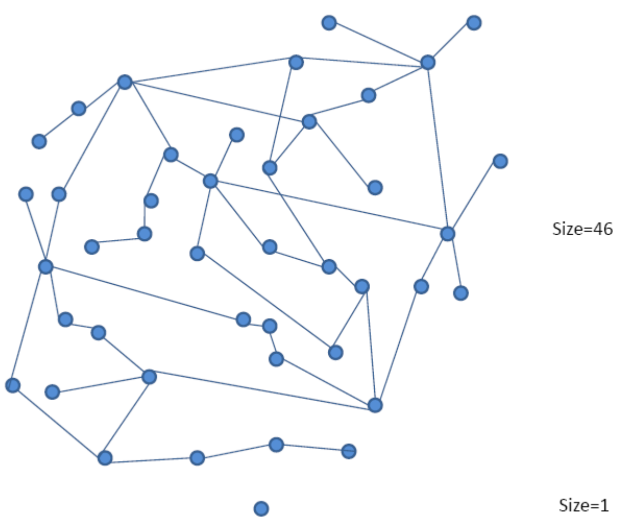
Nodes targeted by High-Degree method (red)



Nodes targeted by GP algorithm (red)



Result (rearranged clusters)



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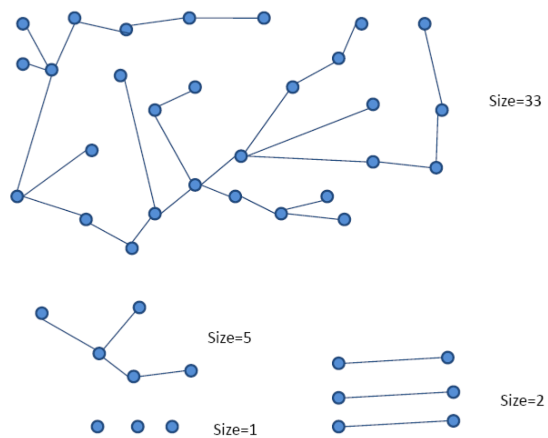

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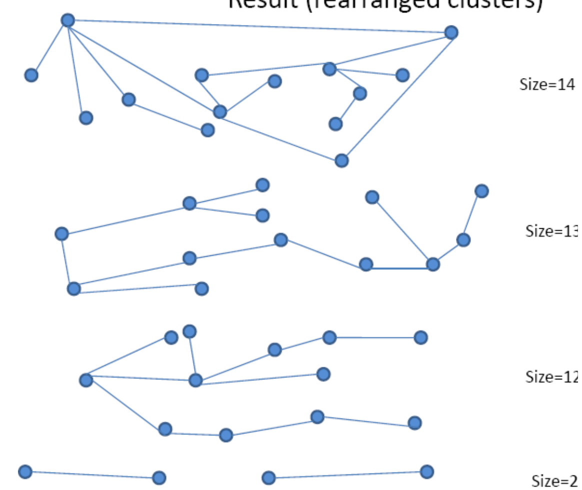


Chen et al, Phys. Rev. Lett. **101**, 058701 (2008)

Best Method

WHAT IS DIFFERENT?

Known values of epidemic thresholds:

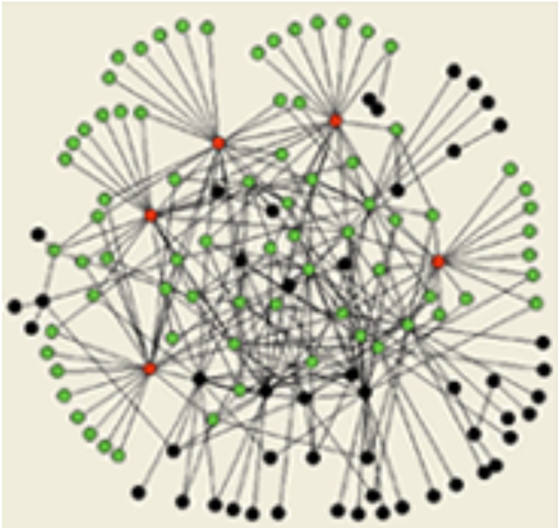
$$q_c = 1 - p_c$$

Infectious disease	**Critical Threshold**
Malaria	99%
Measles	90-95%
Whooping cough	90-95%
Fifths disease	90-95%
Chicken pox	85-90%
Internet	more than 99%

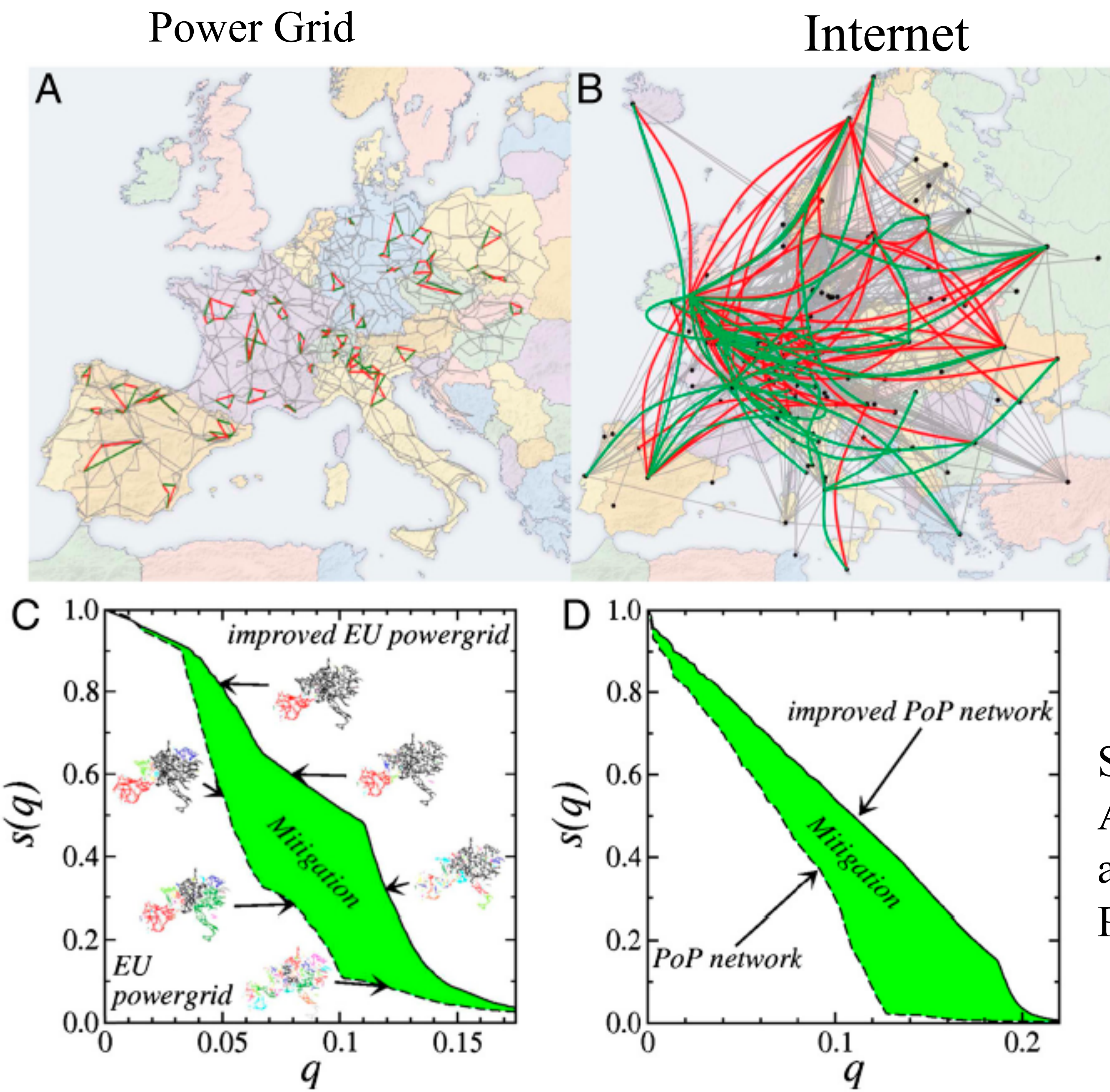
Such immunization thresholds were not understood since they were well above the expected value of percolation in classical random networks:

$$q_c = 1 - p_c = 1 - 1/ < k >$$

This puzzle is solved due to the broad degree distribution (HUBS) of social networks which does not occur in random graphs!



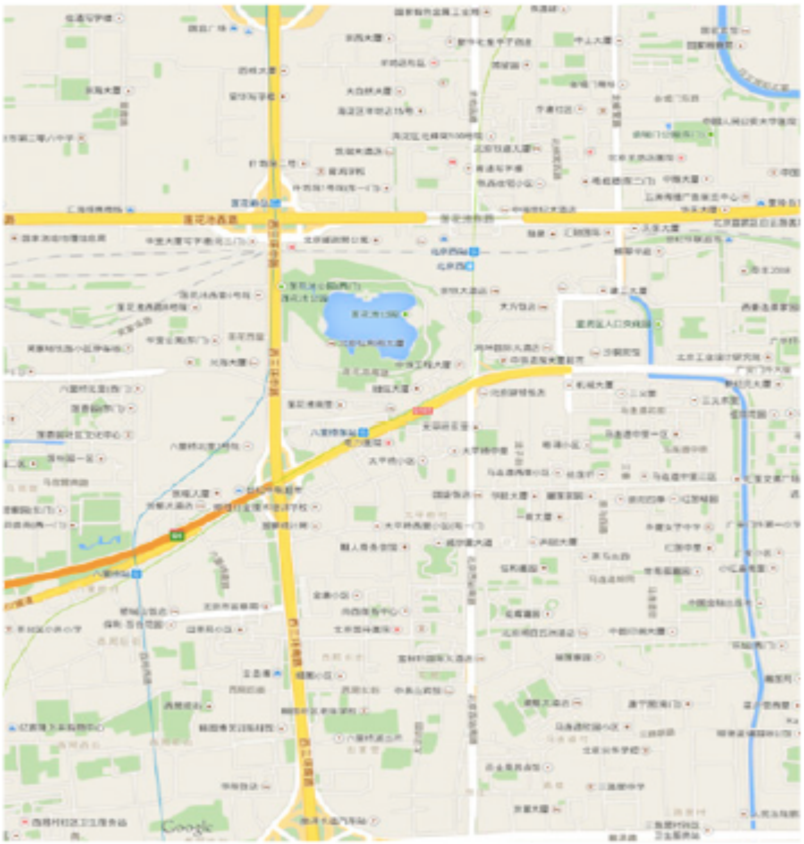
Mitigation of malicious attacks on networks

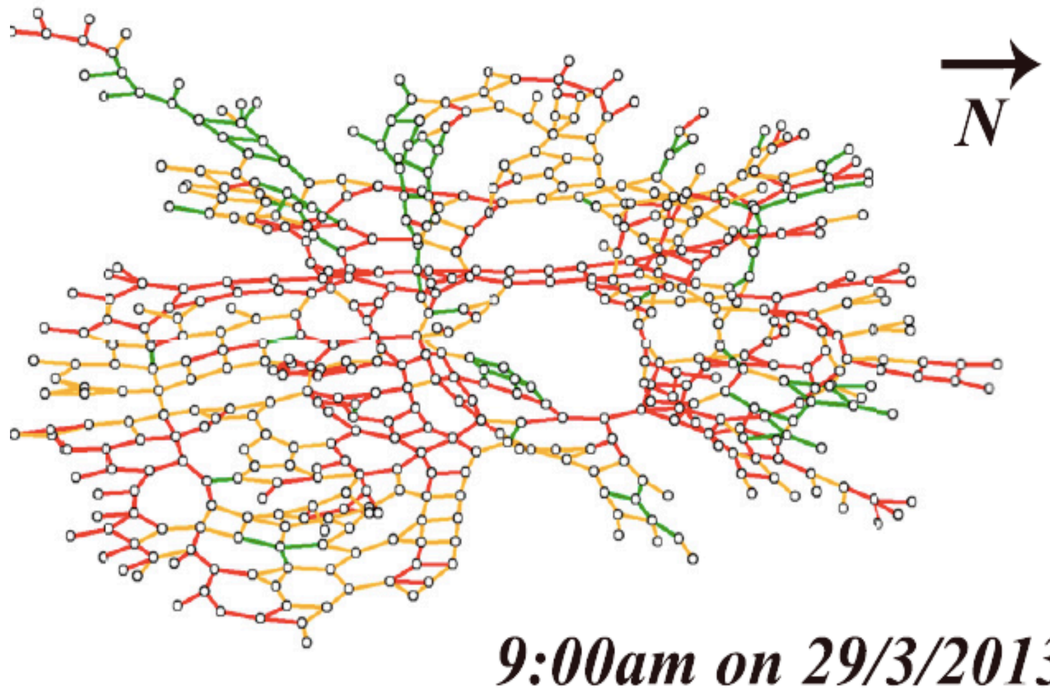


Schneider, Moreira,
Andrade, SH
and Herrmann
PNAS (2011)

Traffic and Network Theory

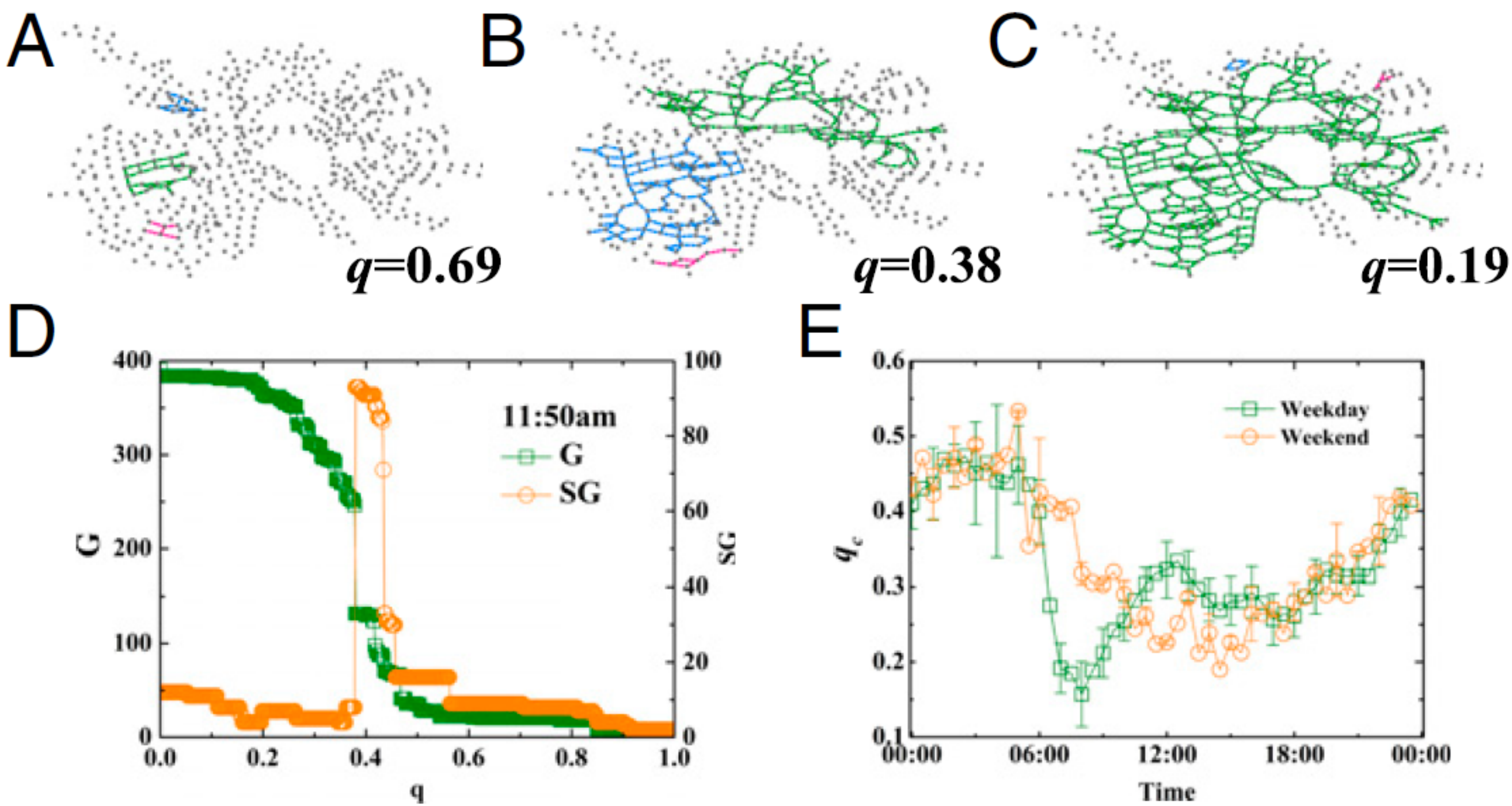
1. Mapping traffic in Beijing as a dynamic network
2. Percolation theory identify bottlenecks





Daqing Li, Bowen Fu, Yungpeng Wang, Guangquan Lu et al, PNAS (2015)

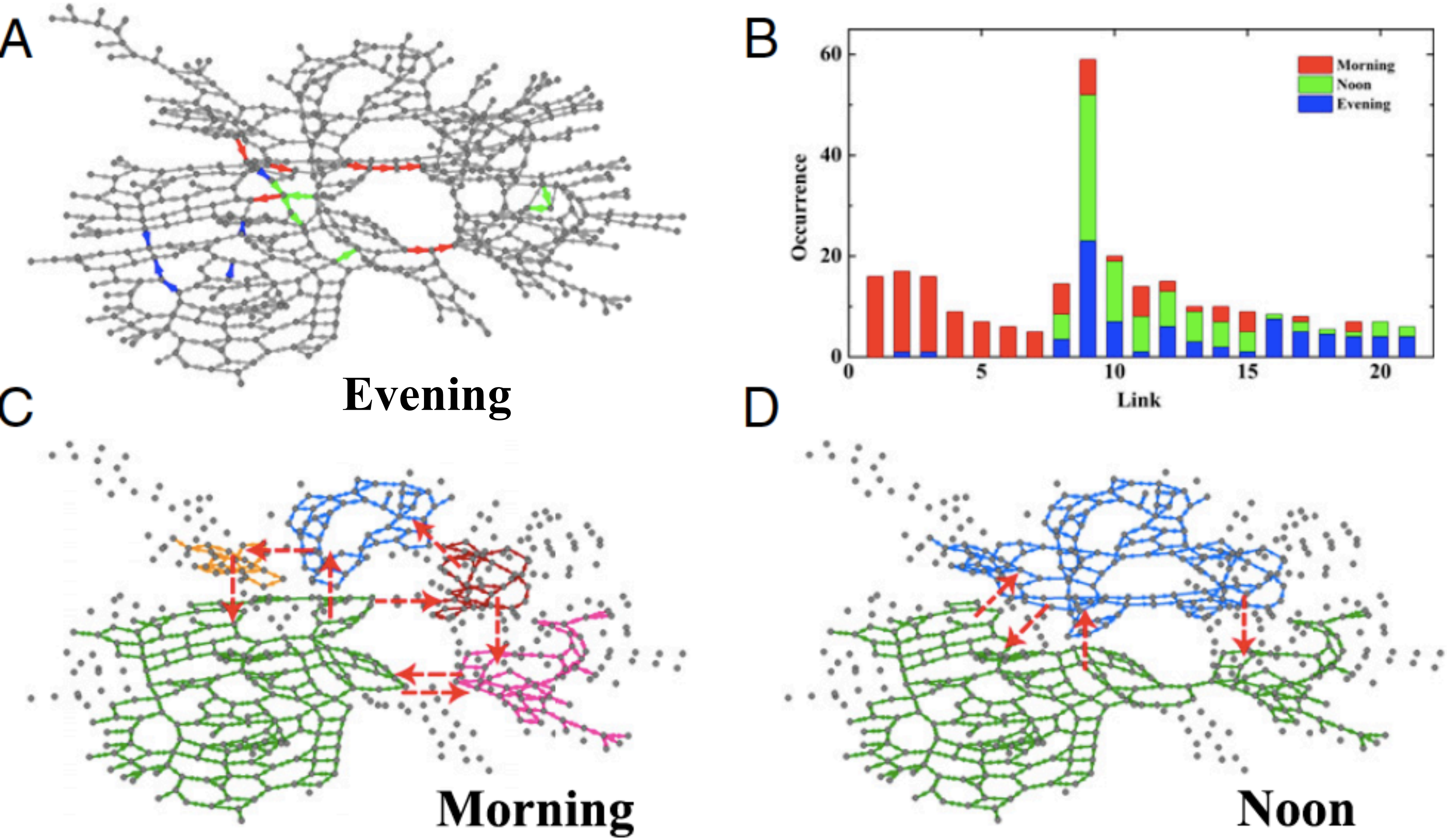
PERCOLATION AND TRAFFIC



Daqing Li et al PNAS, 2015, also (in press,2018)

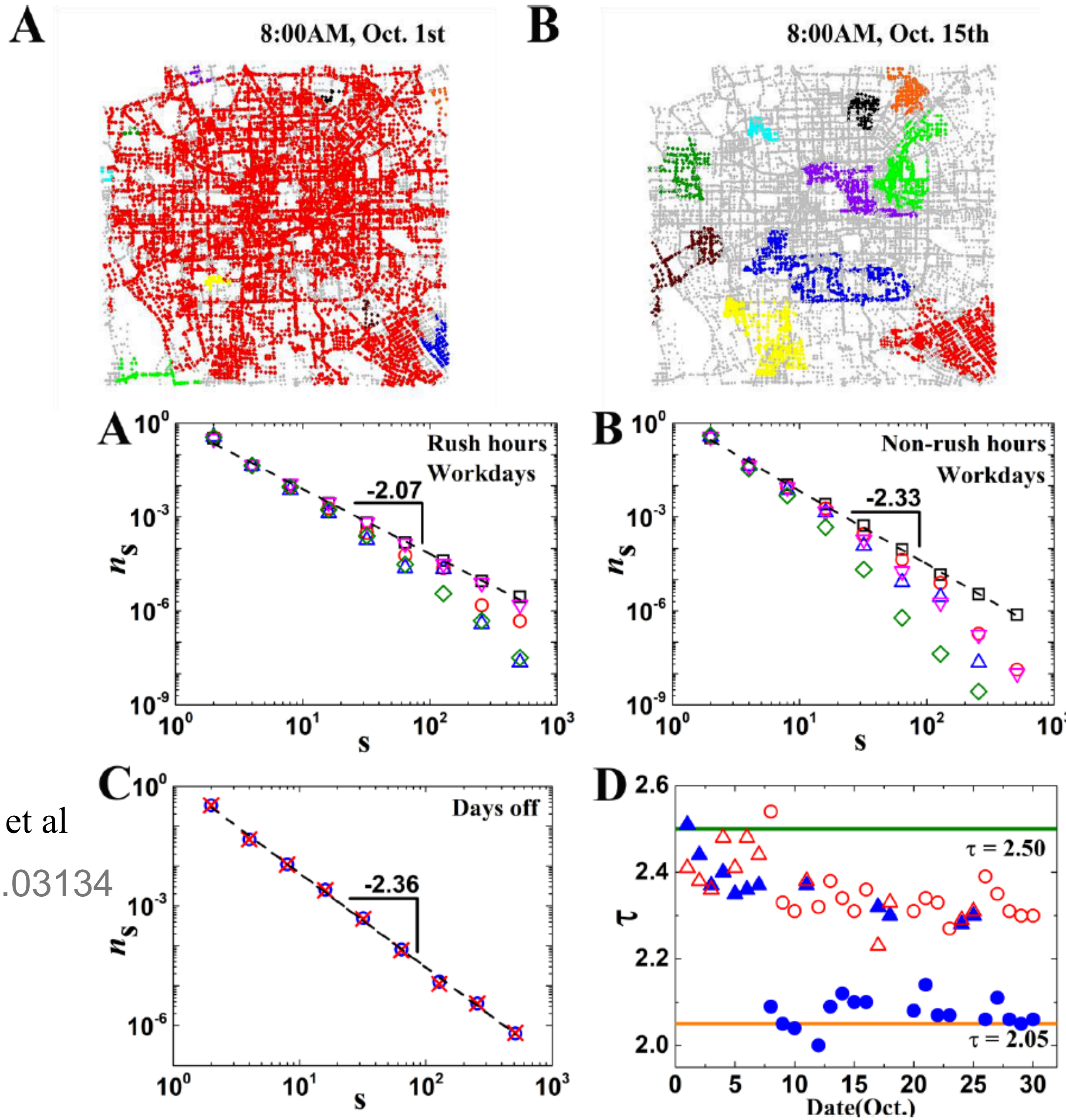
Identifying systematic bottlenecks

DIFFERENT HOURS DIFFERENT BOTTLENECKS



Percolation critical exponents

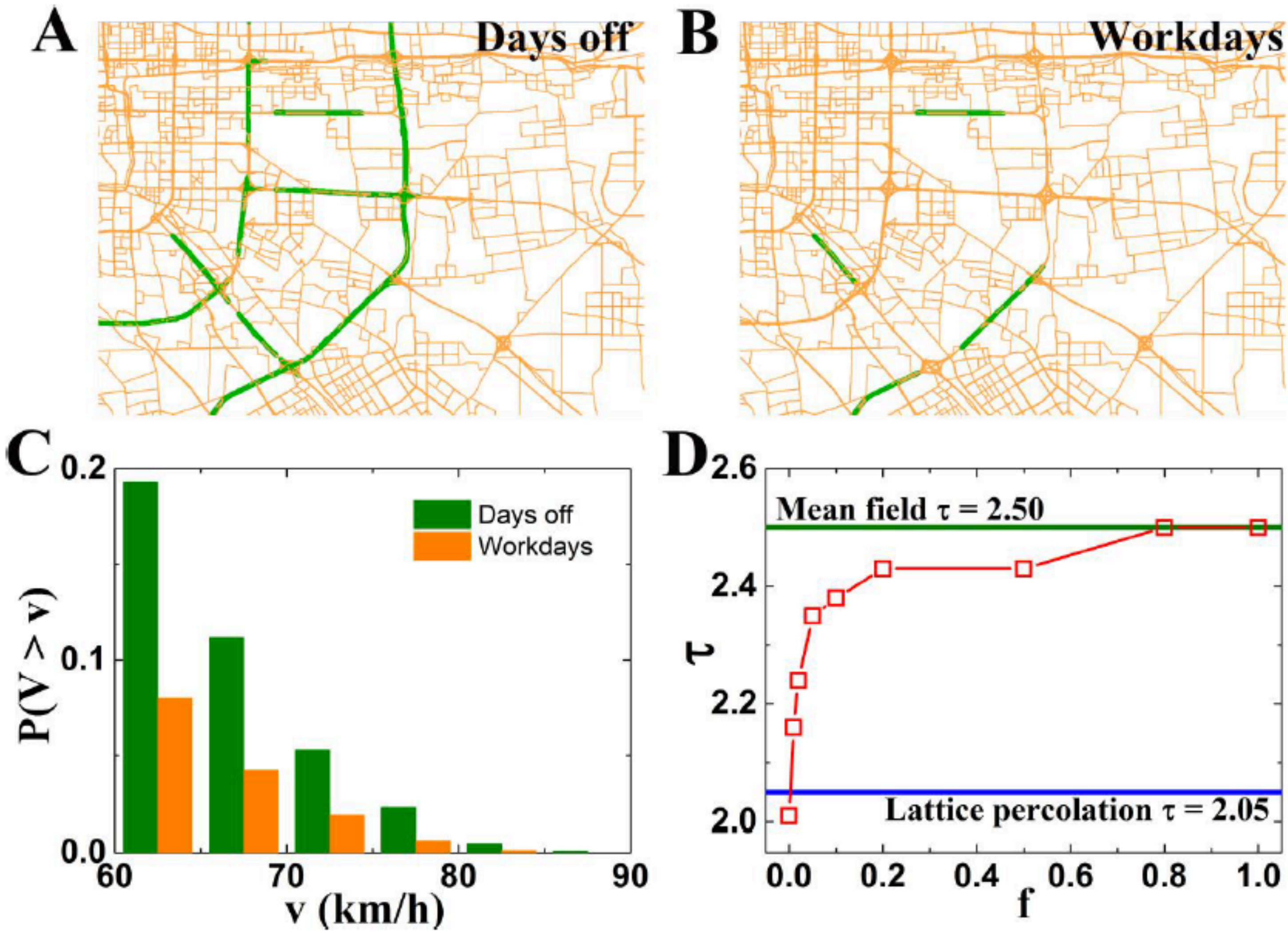
2015



Daqing Li et al

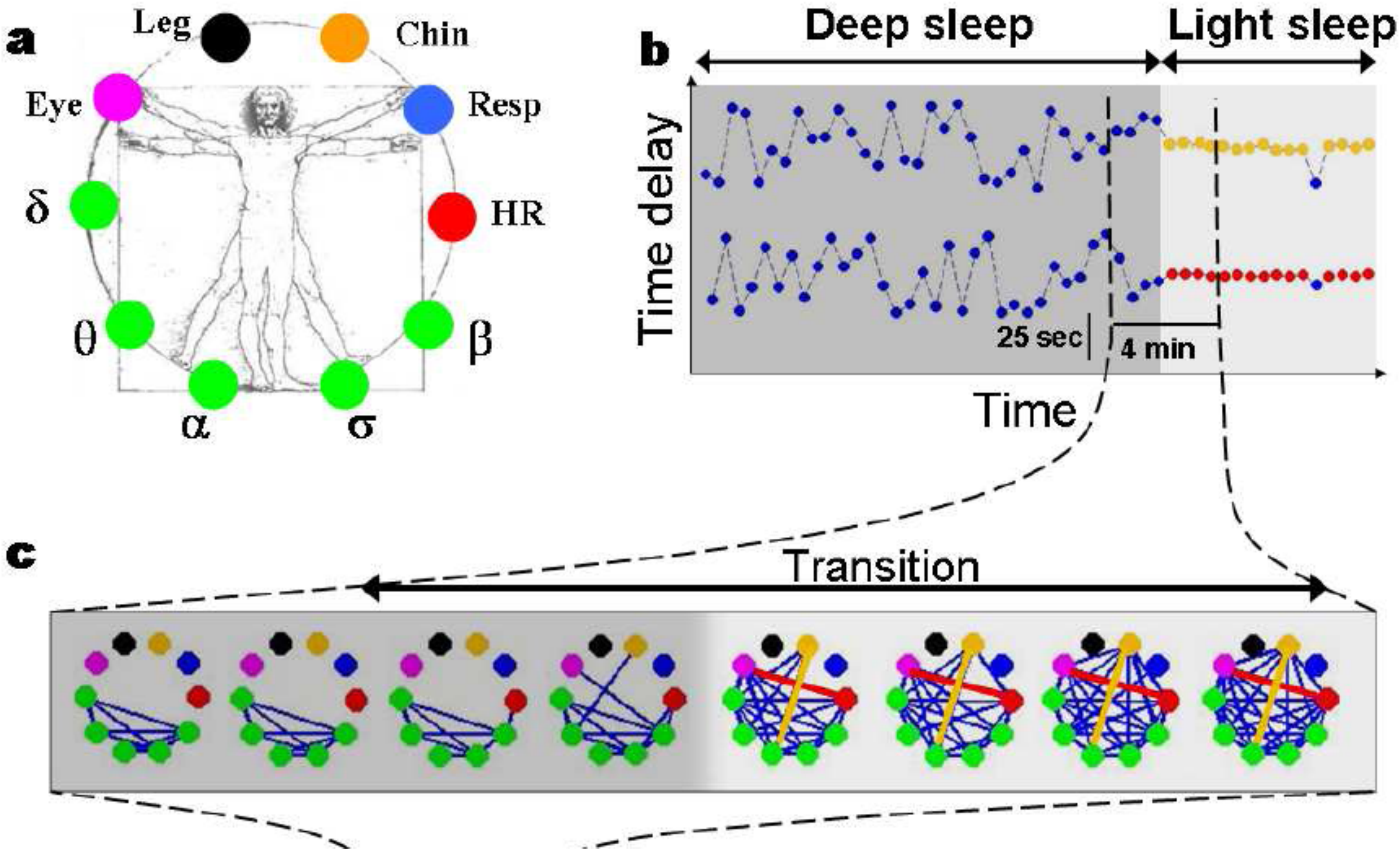
arXiv:1709.03134

Percolation Model



Daqing Li et al
arXiv:1709.03134

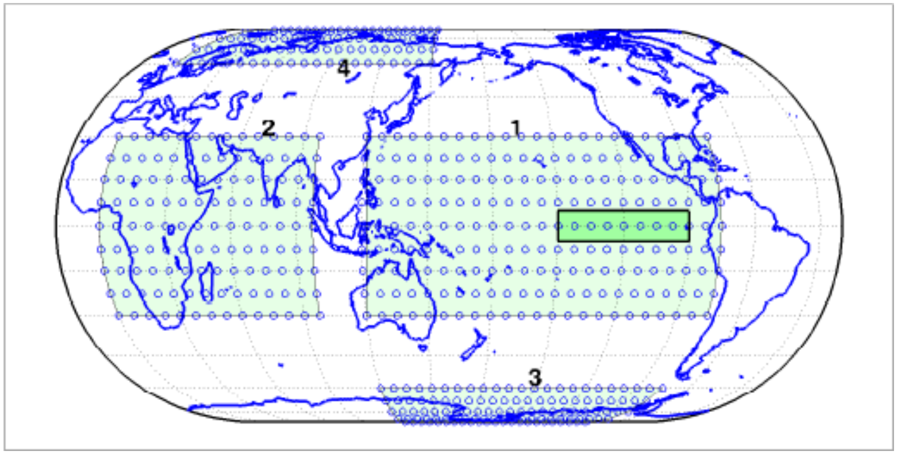
Physiological Networks



Bashan, Ivanov et al, Nature Communication [2012]

Structure and Function

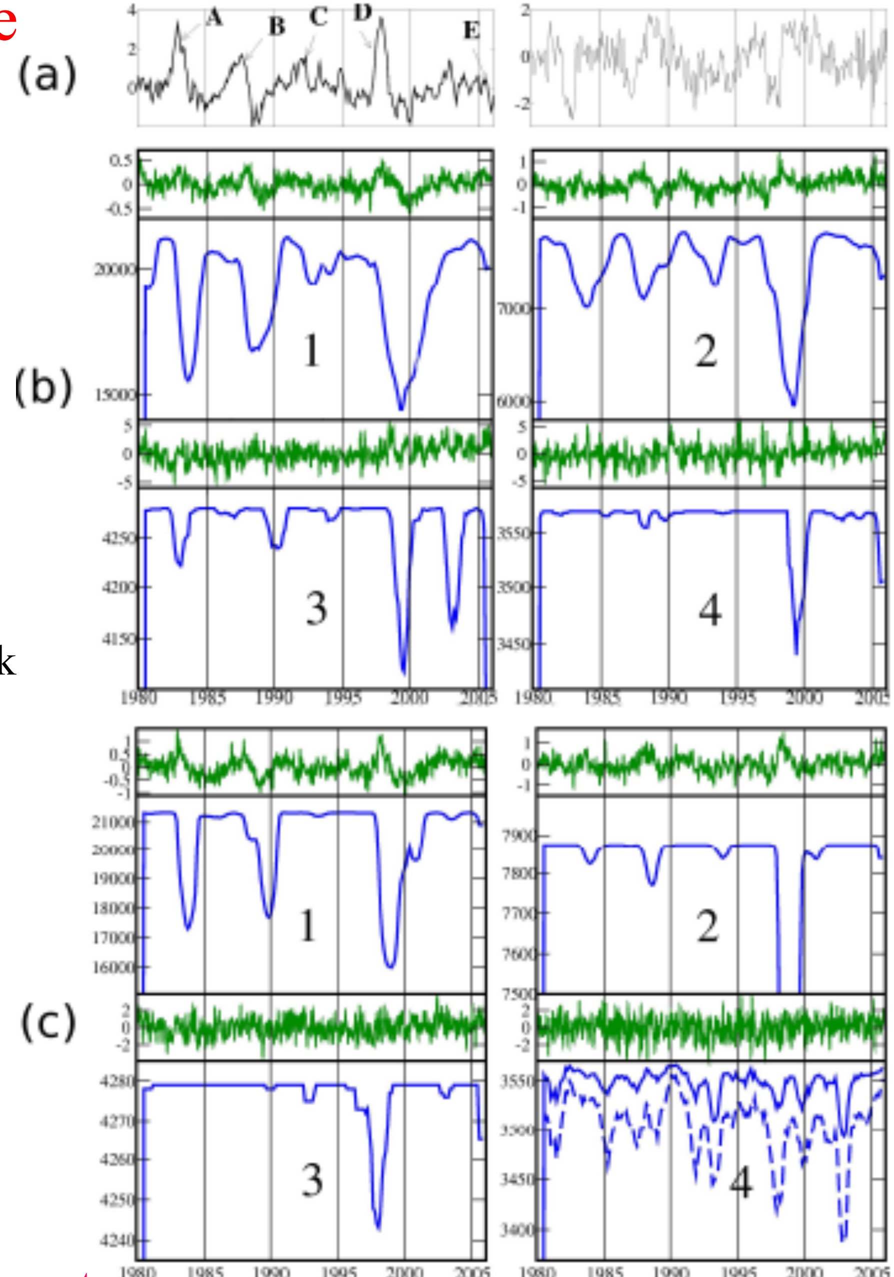
Climate networks are very sensitive to El Nino



Sea surface temperature network

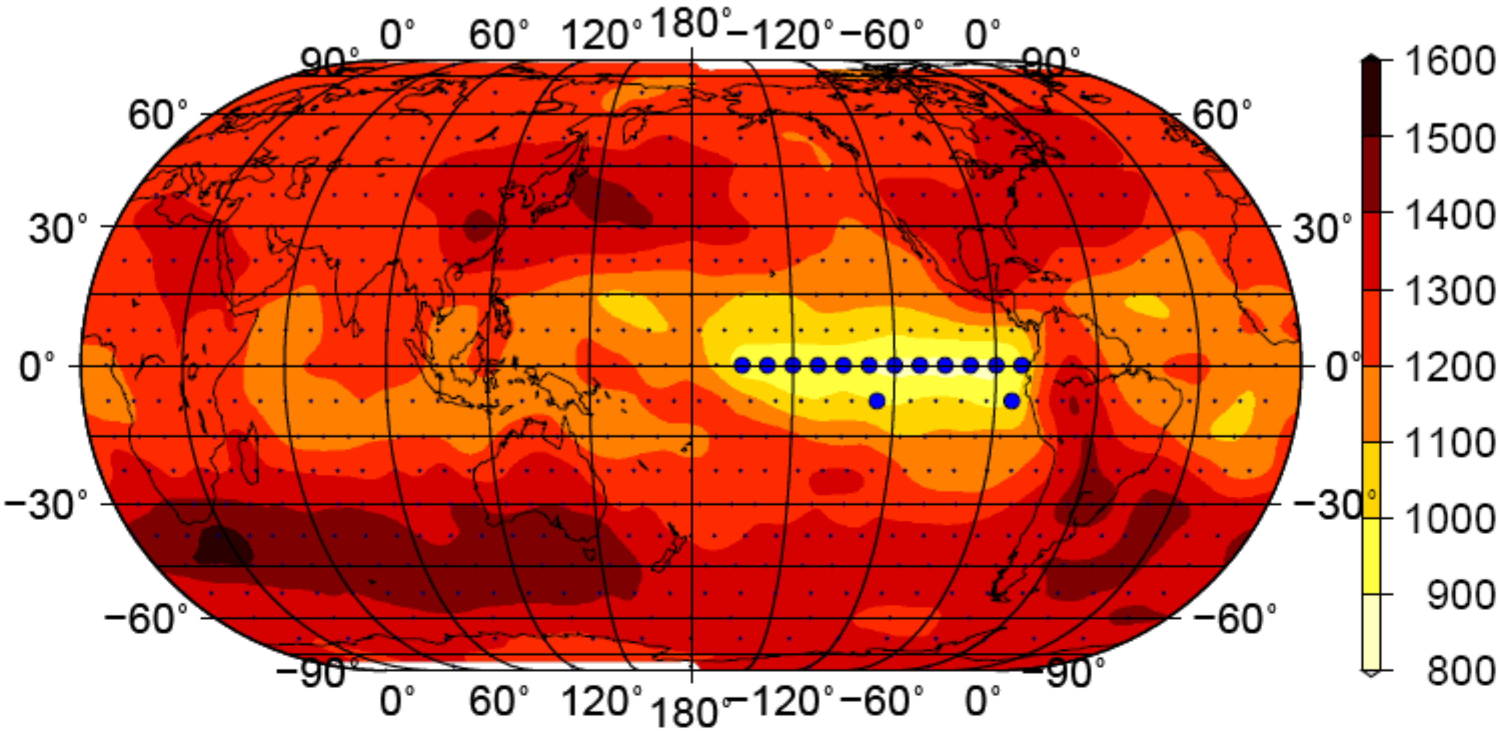
5km height temperature network

Yamasaki, Gozolchiani, SH (PRL 2008, 2011)



Challenge: Porecasting El-Nino and other extreme events
Ludescher et al PNAS (2014, 2015)

EL-NINO BECOMES AUTONOMOUS: ONLY INFUENCE-NOT INFLUENCED

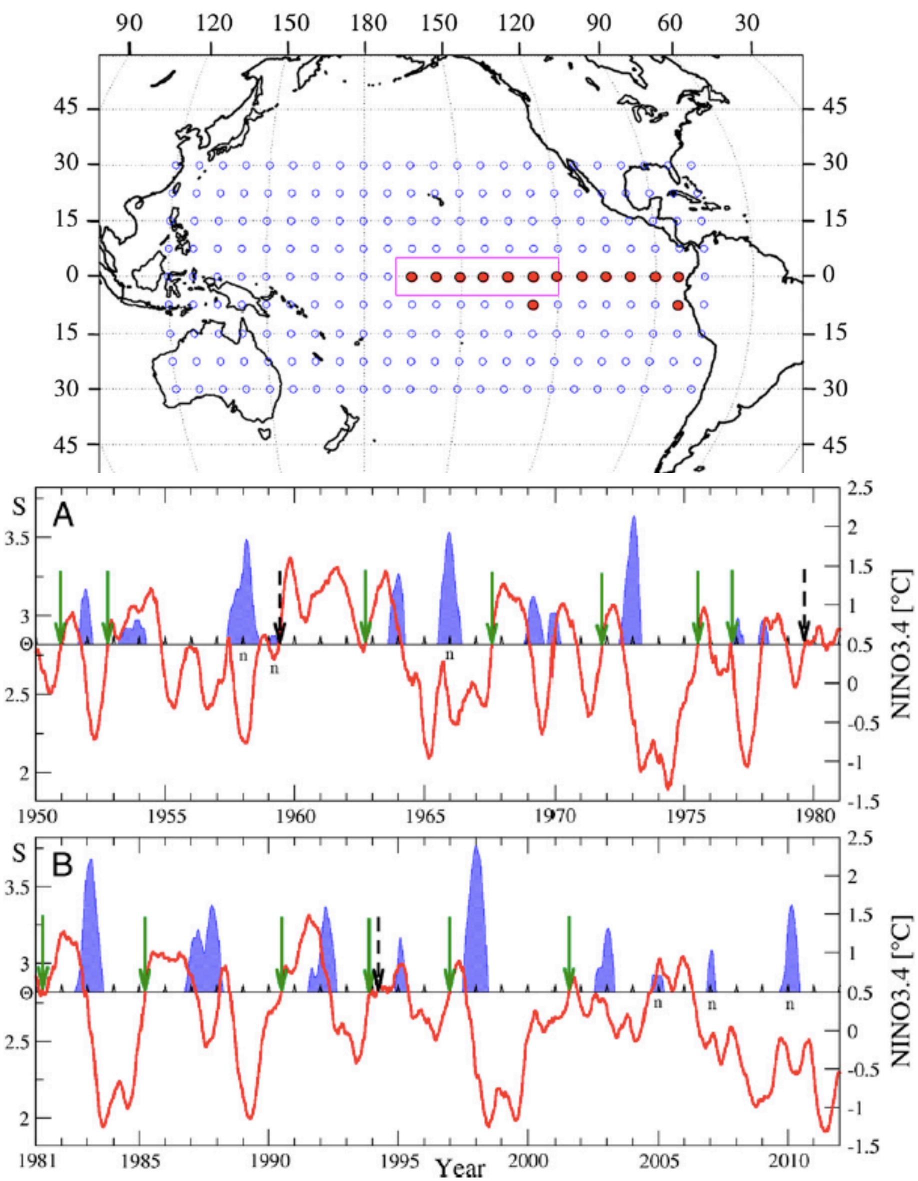


$$\left\langle I_l^y \right\rangle_{y \in El-Nino}$$

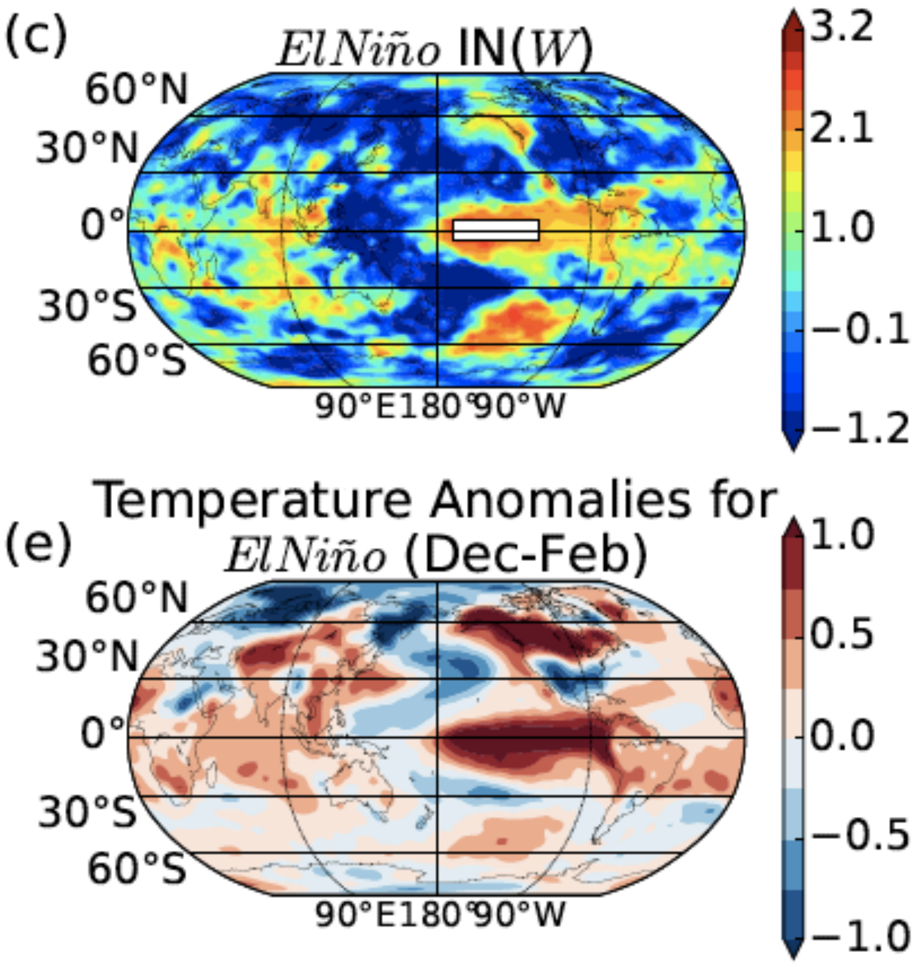
Gozolchiani et al PRL (2011)

VERY EARLY PREDICTION!!! Ludescher et al, PNAS (2014)

Forecasting the onset and global influence



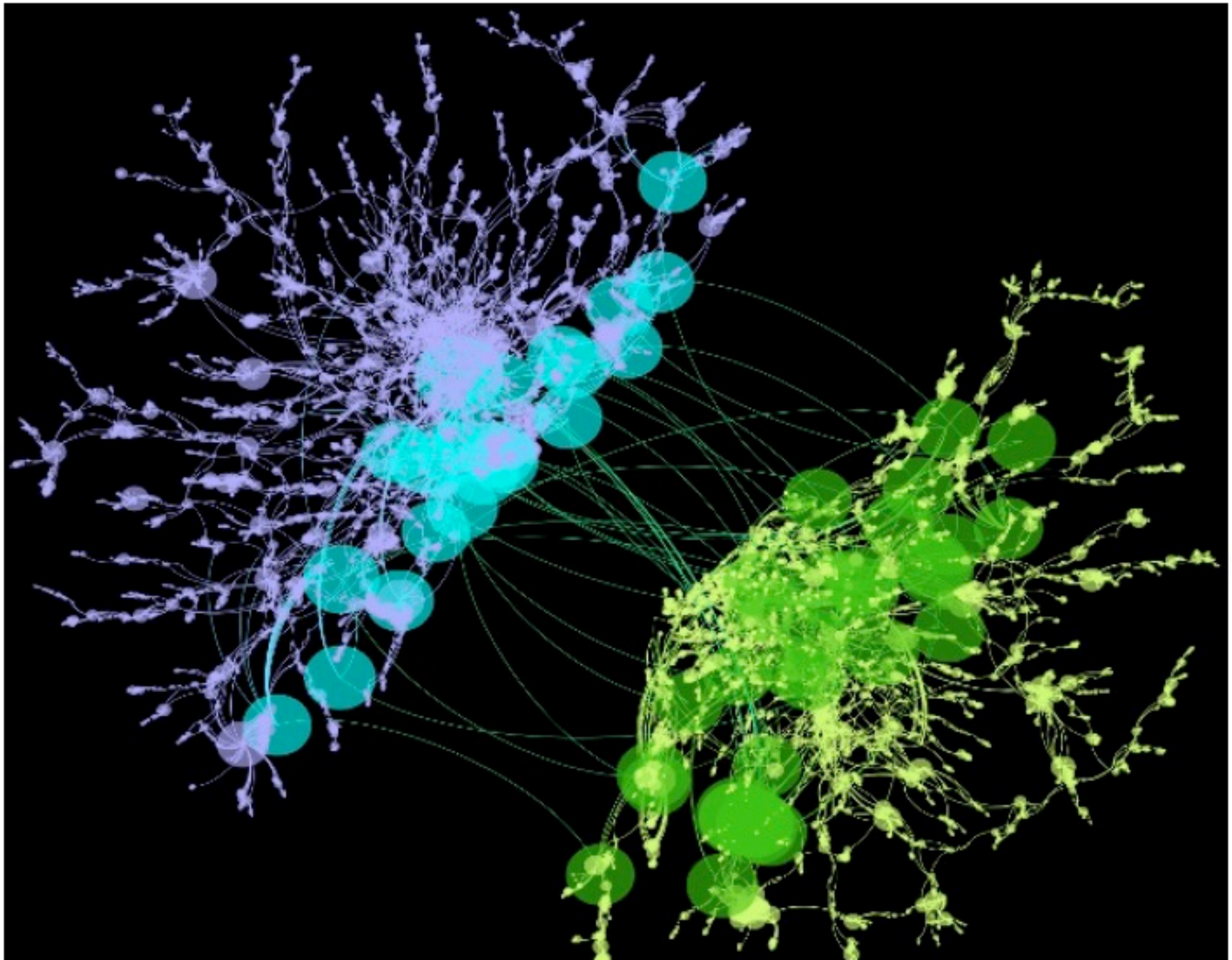
Ludescher et al, PNAS (2013,2014)



Jing-fang Fan et al, PNAS (2017)

Resilience of Networks with Community Structure: External Field Interlinks - Flights between Continents-Back to Physics

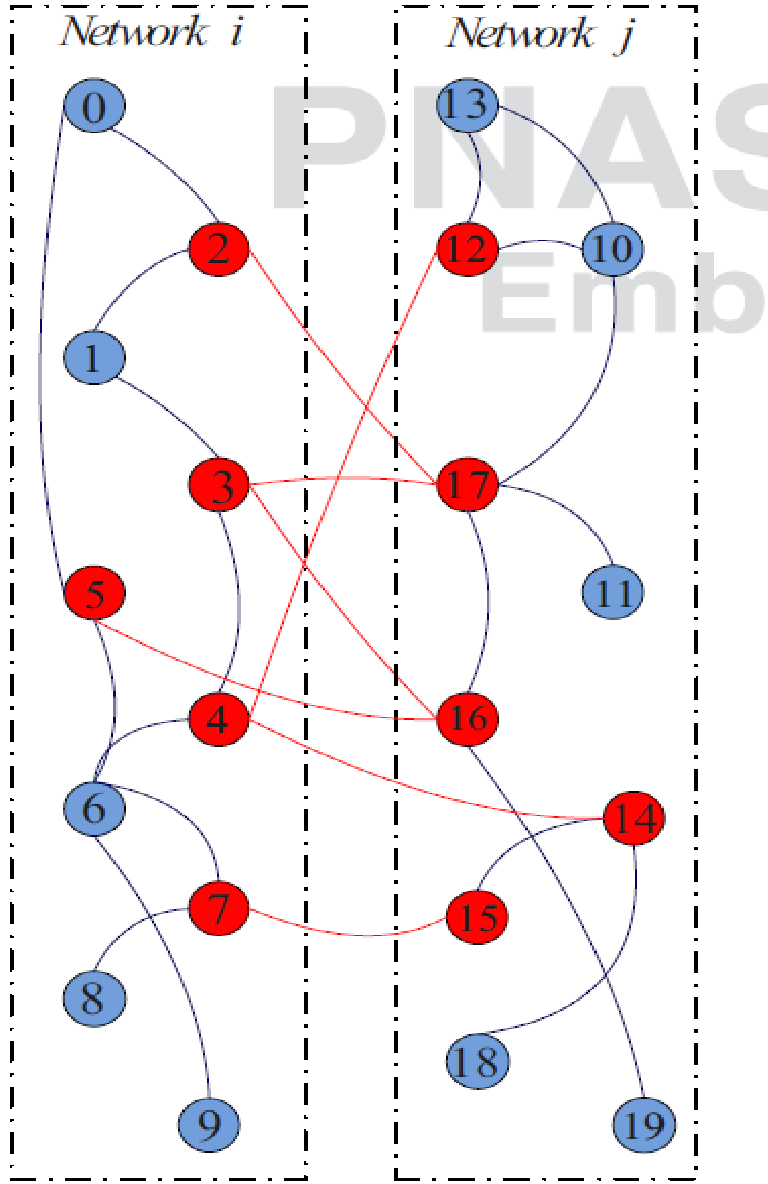
A



Network Model

A fraction *r* of nodes are interconnected nodes

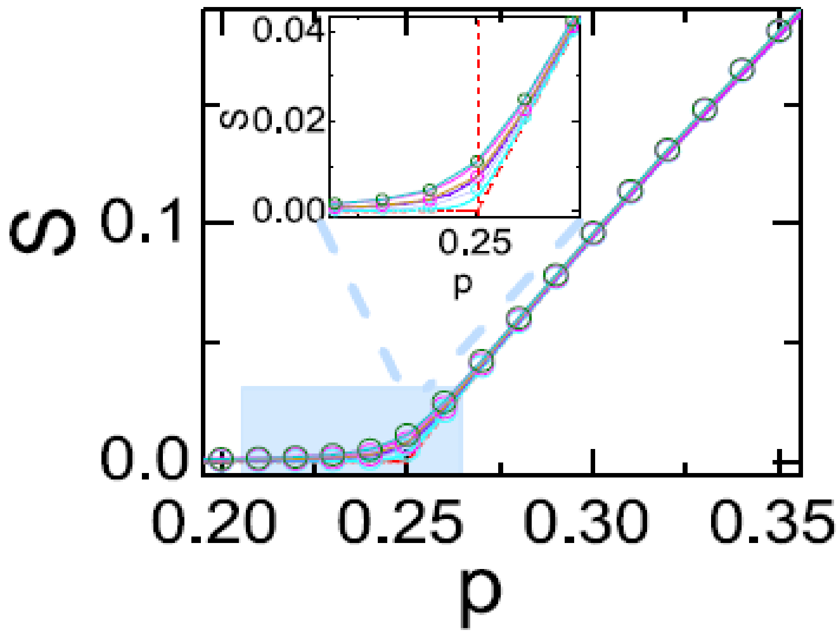
r=0.5

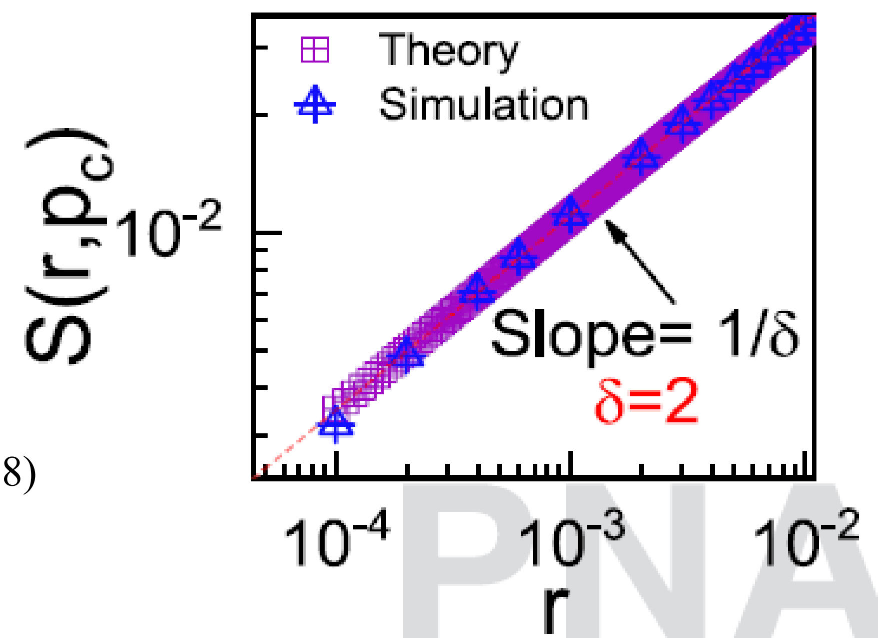


Scaling with field *r*

The field *r* removes the transition
Like magnetic field in spin system

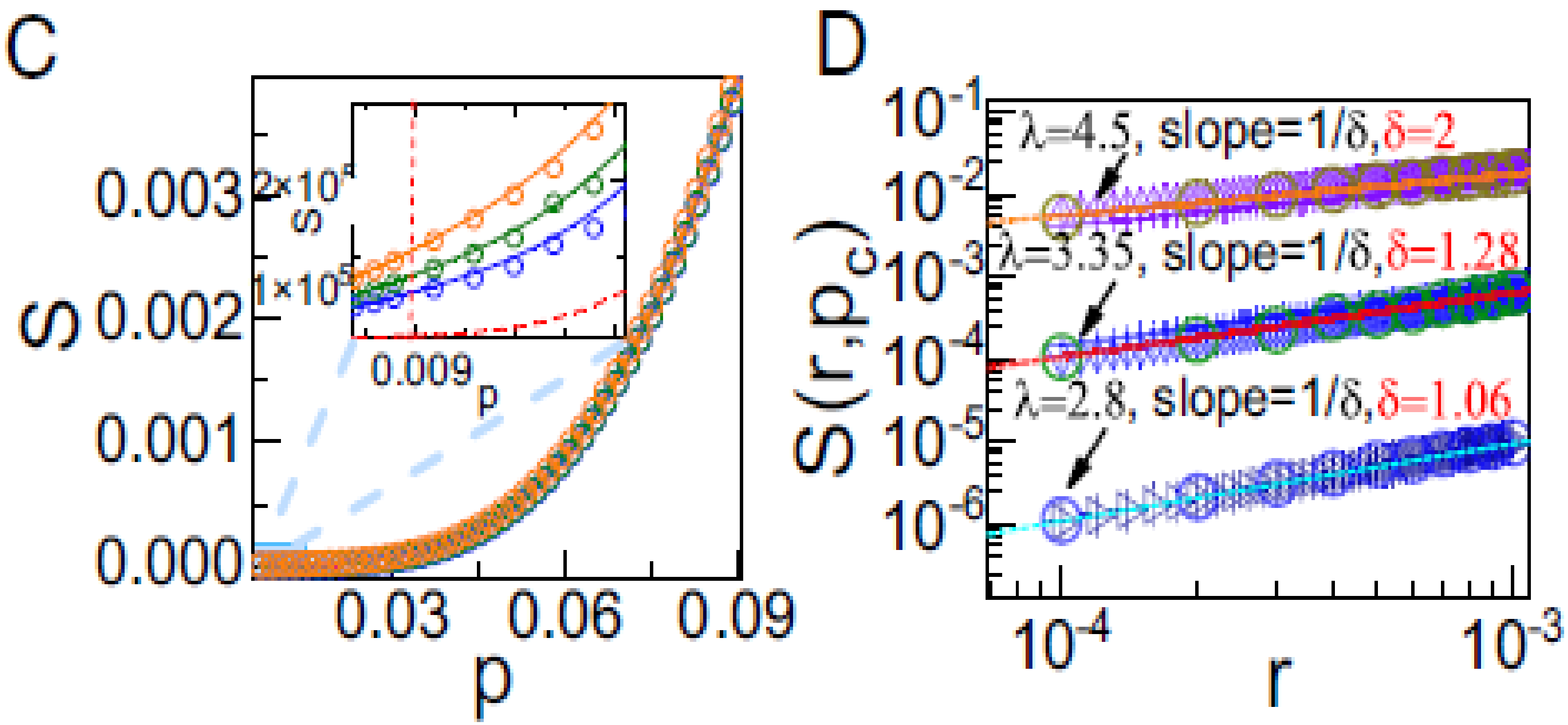
$$S(p_c, r) \sim r^{1/\delta}$$





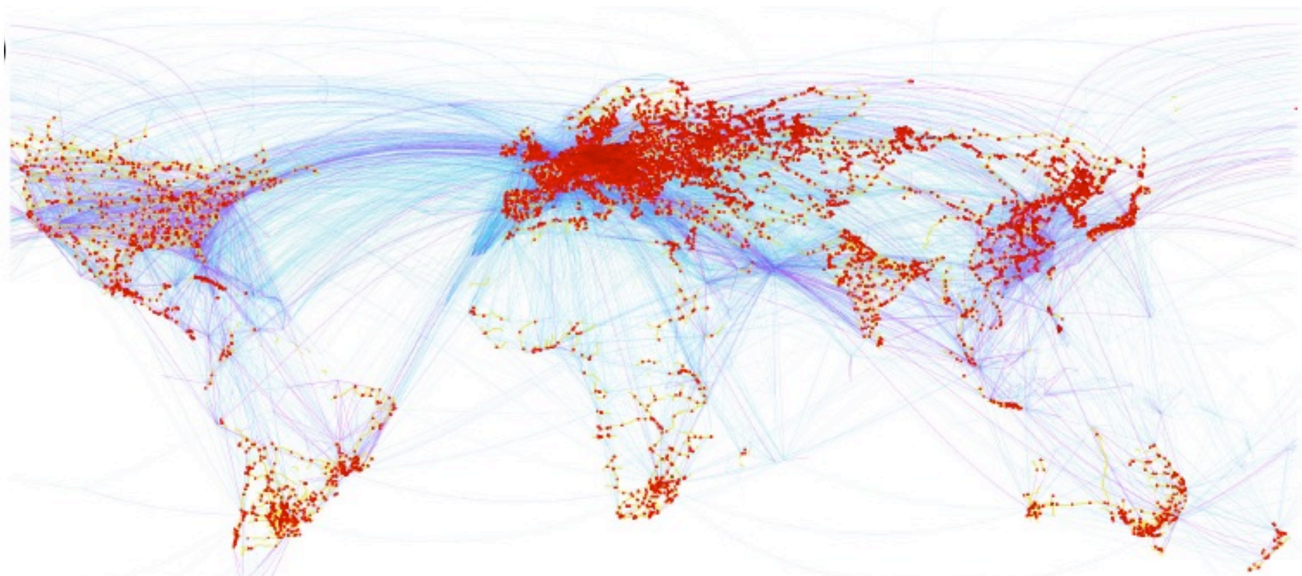
G. Dong et al PNAS 201801588, (2018)
arXiv:1805.01032

Scaling with field *r* in scale free modules

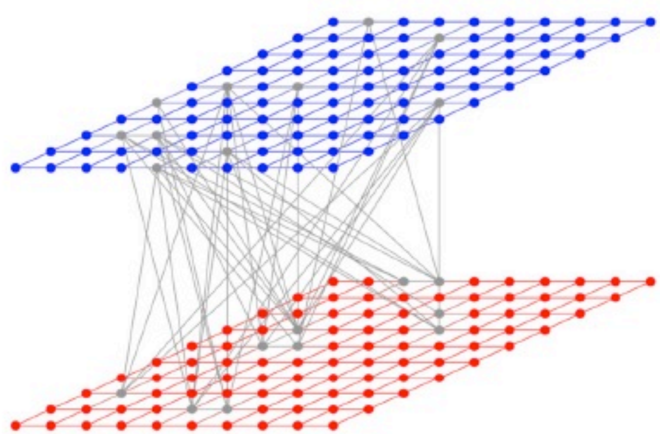


G. Dong et al PNAS (2018)
arXiv:1805.01032

Scaling with field r in spatially embedded modules

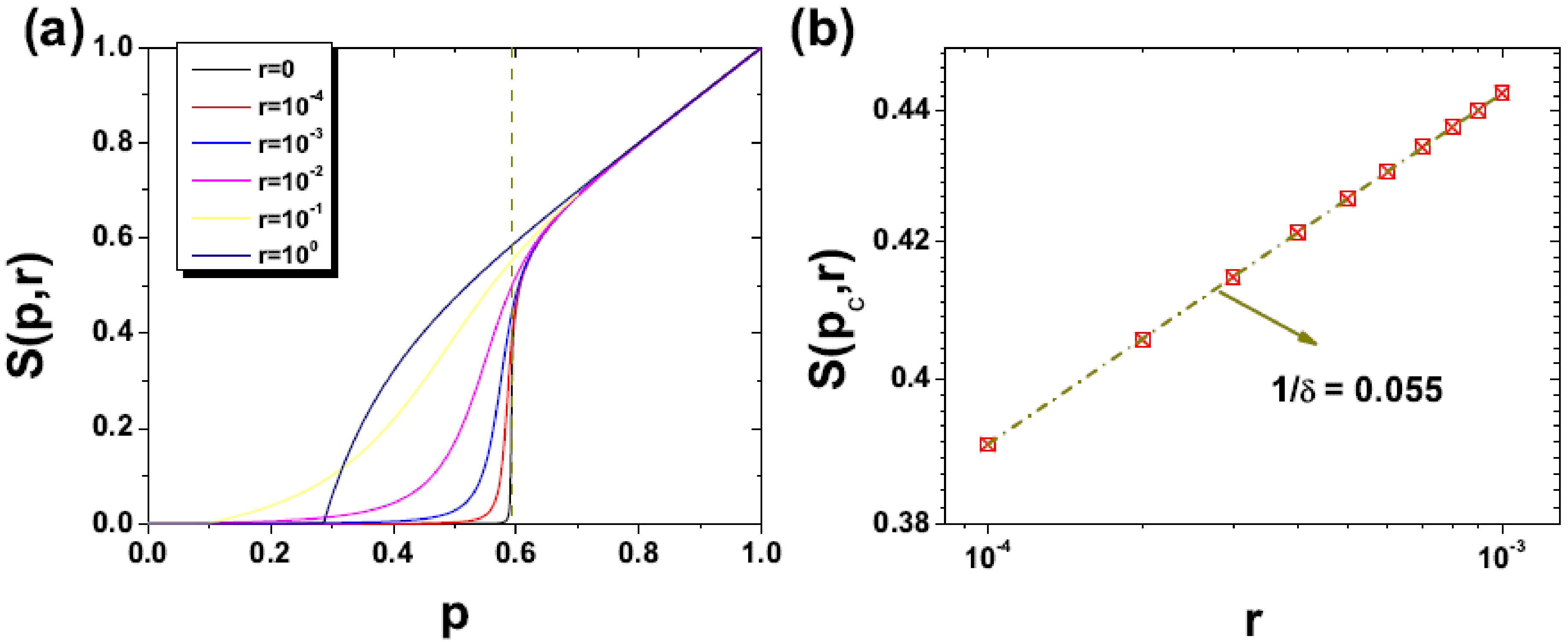


Trains and Flights between Europe and North America



Fan et al arXiv:1806.00756

Scaling with field *r* in spatially embedded modules

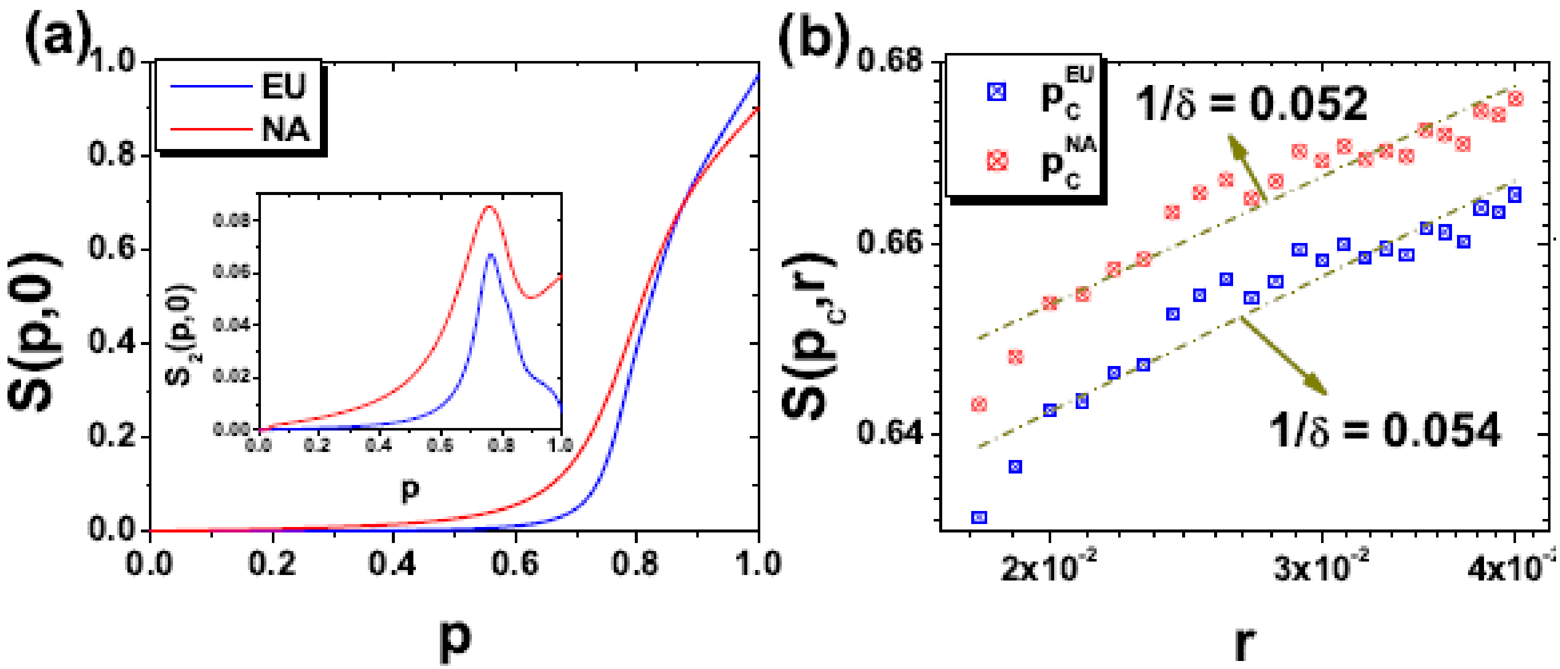


$$S(p_c, r) \sim r^{1/\delta},$$

Fan et al
arXiv preprint arXiv:1806.00756

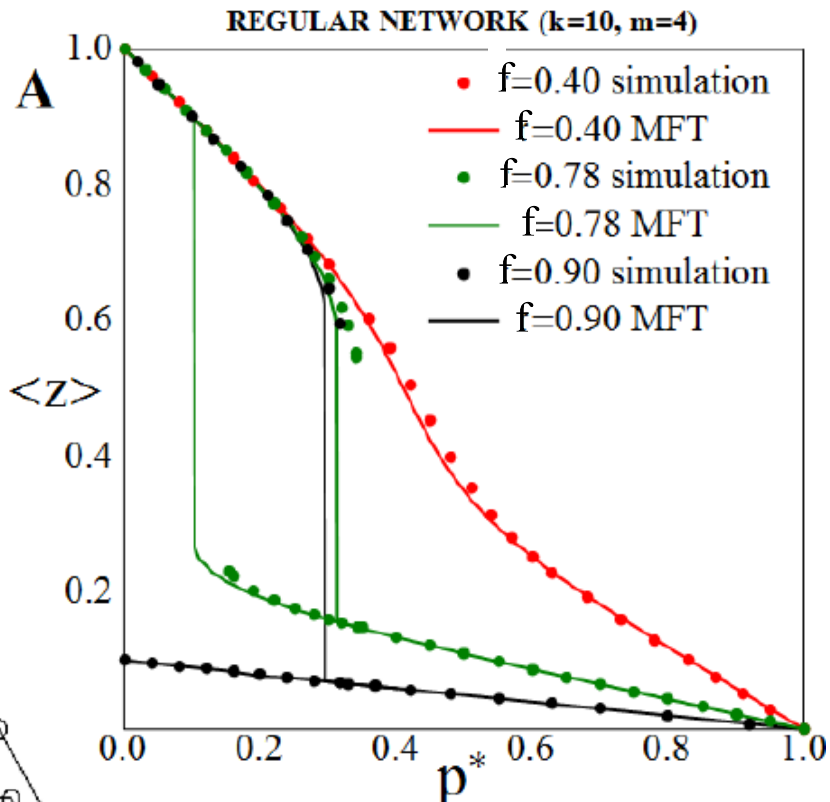
Scaling with field *r* in real spatially embedded modules

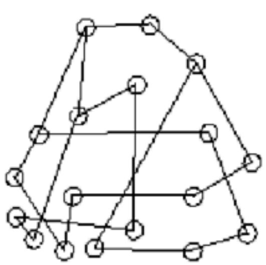
Trains and Flights between Europe and North America

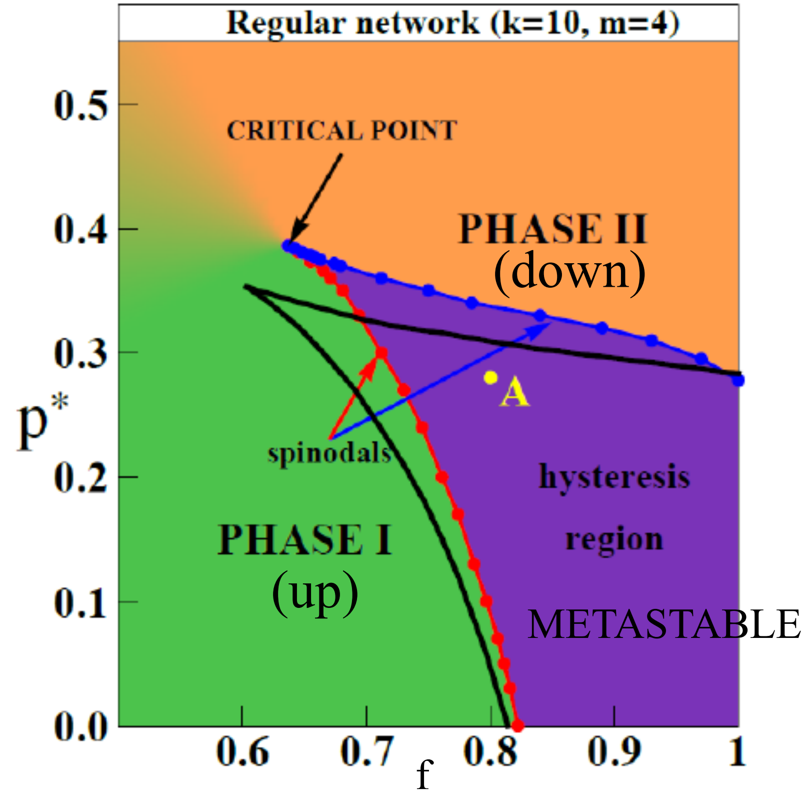


Fan et al arXiv:1806.00756

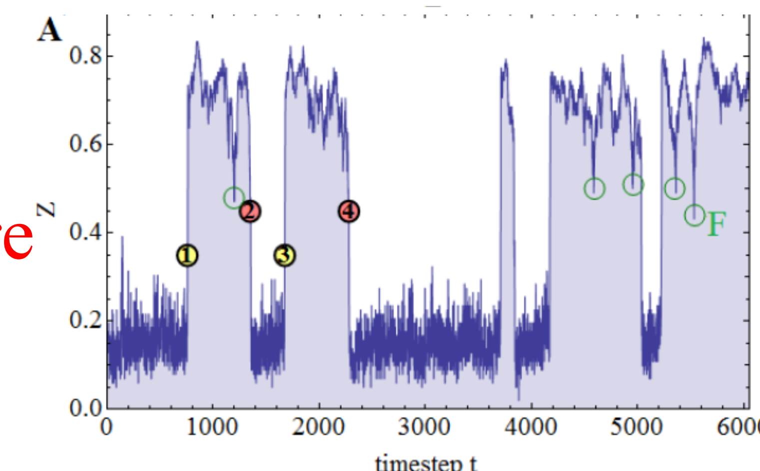
Introducing Recovery-Single Networks







Spontaneous Recovery and Failure



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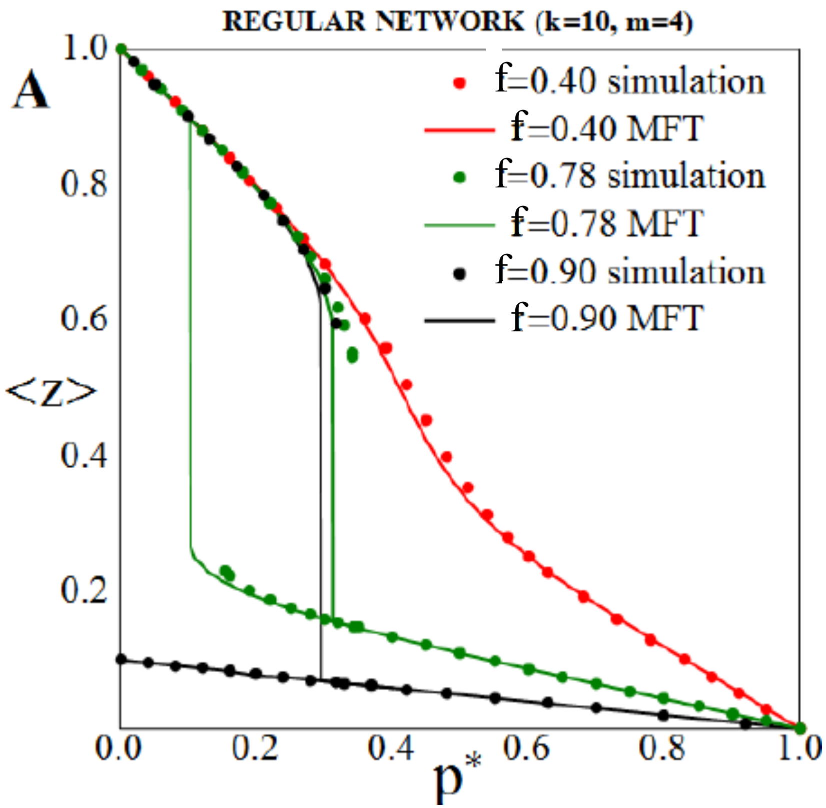
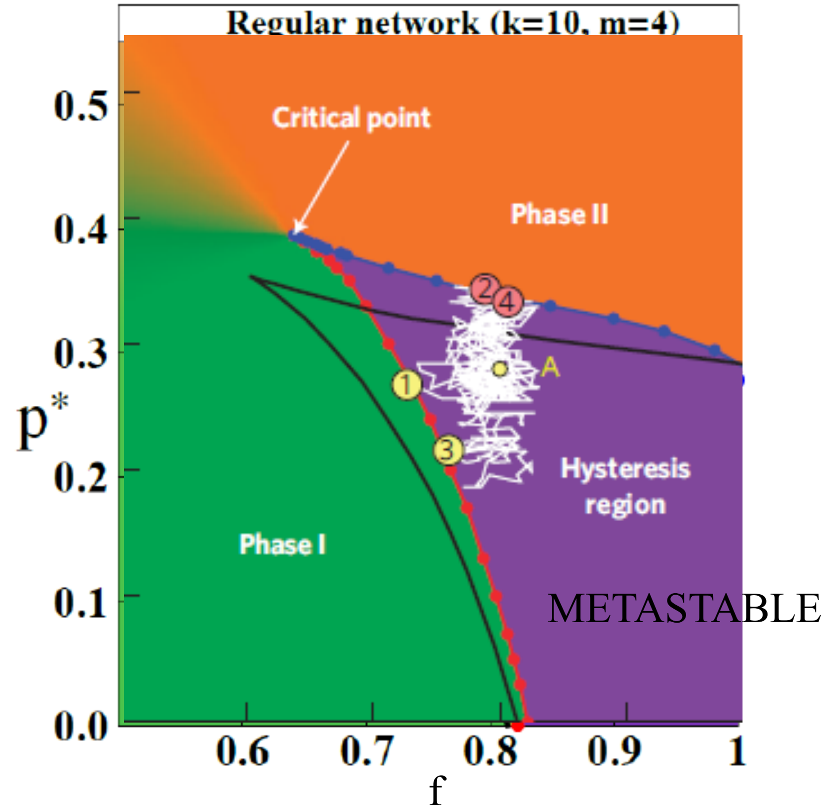
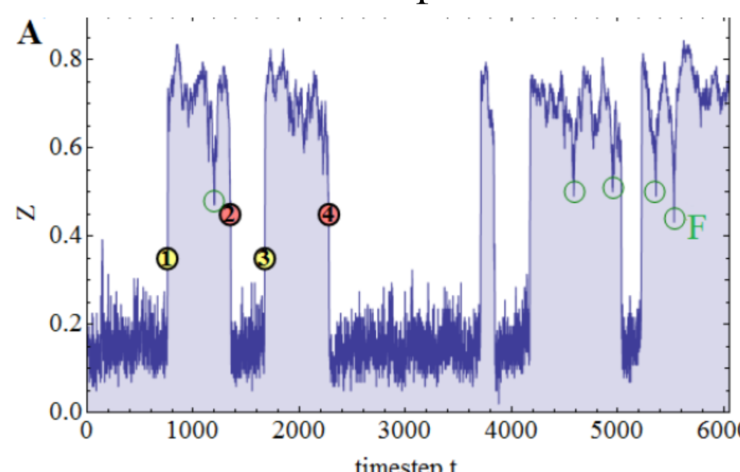
Introducing Recovery-Single Networks







Diffusion of a SYSTEM in phase space

Spontaneous Recovery and Failure

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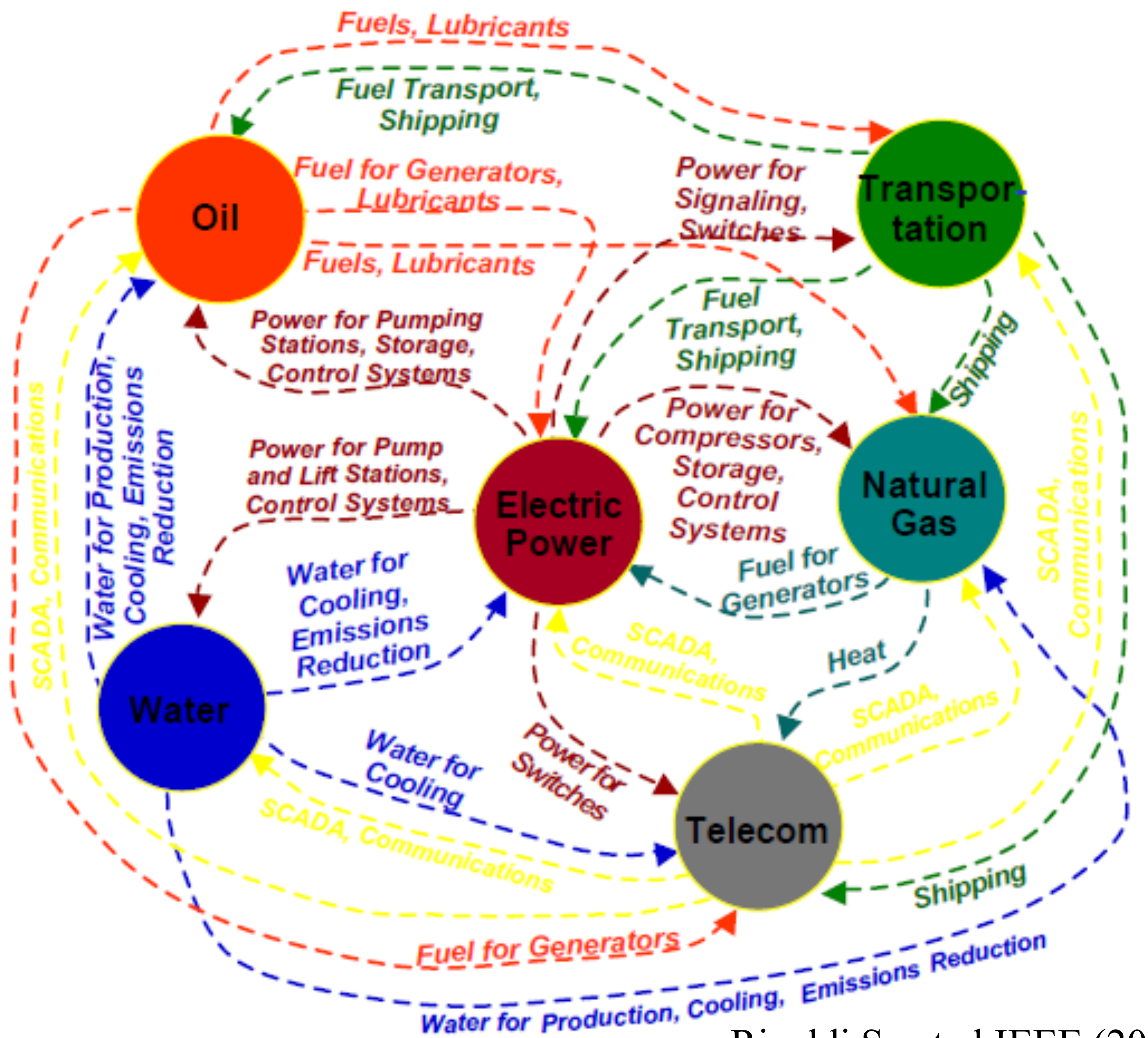
How interdependent are infrastructures?



Rinaldi S, et al IEEE (2001)