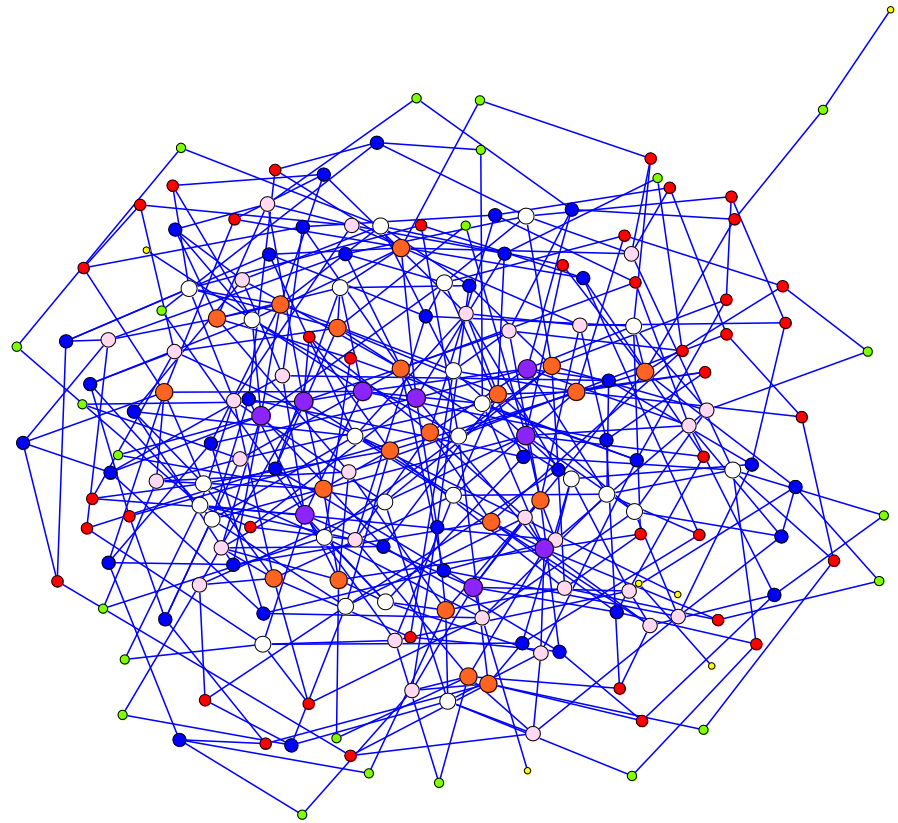




Networkology

The Science and Applications of Networks



INTRODUCTION



Spatial Networks

Temporal Networks

Innovation, Bibliometrics

Evolution of Complex Systems

Particle Physics

Statistical Physics

Science

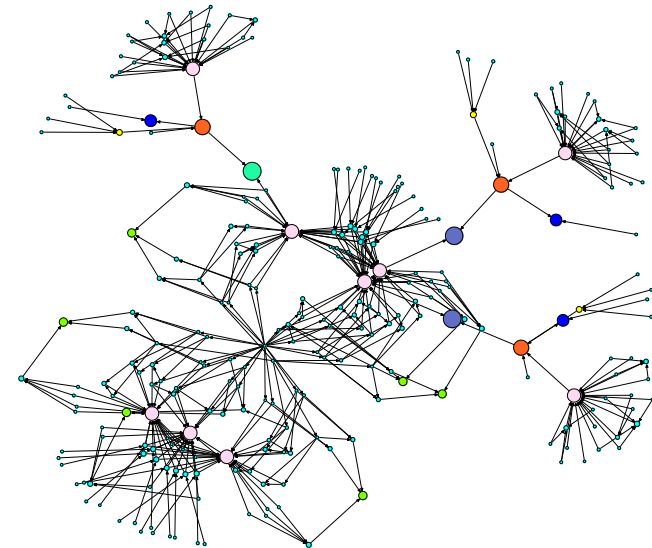
Innovation, Bibliometrics

SoCA Lab,
Science Institute

Complexity is

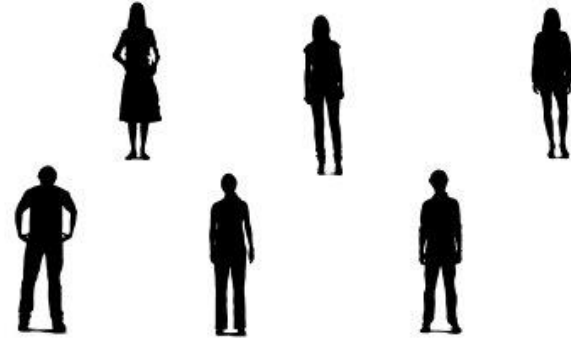
- Interactions occur defined at small, local scales
- Emergence of large scale phenomena
 - Just statistical mechanics applied to new problems?

Networks are part of this wider complexity programme

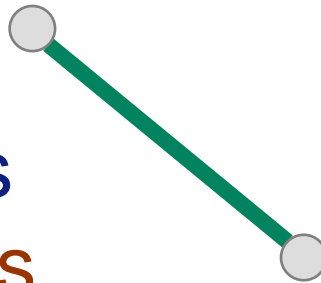


Definition of a Network

- A set of **nodes** 
e.g. people

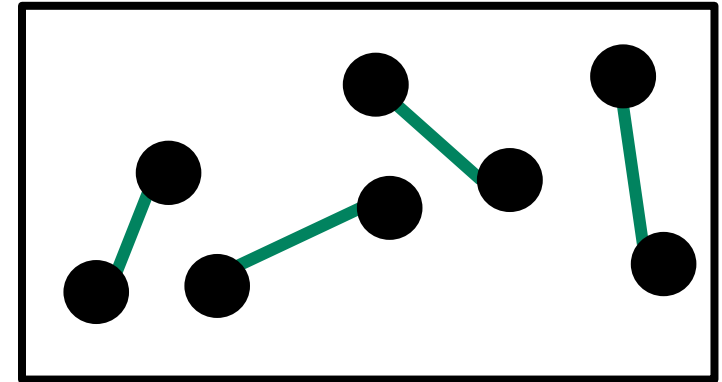


- A set of **edges**
between nodes
e.g. friendships
between people

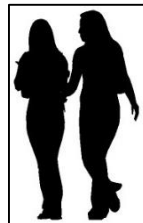


No Need For Network Analysis?

Edges describe bilateral relationships between nodes



Just analyse the **statistics of these pairs** using usual statistical methods



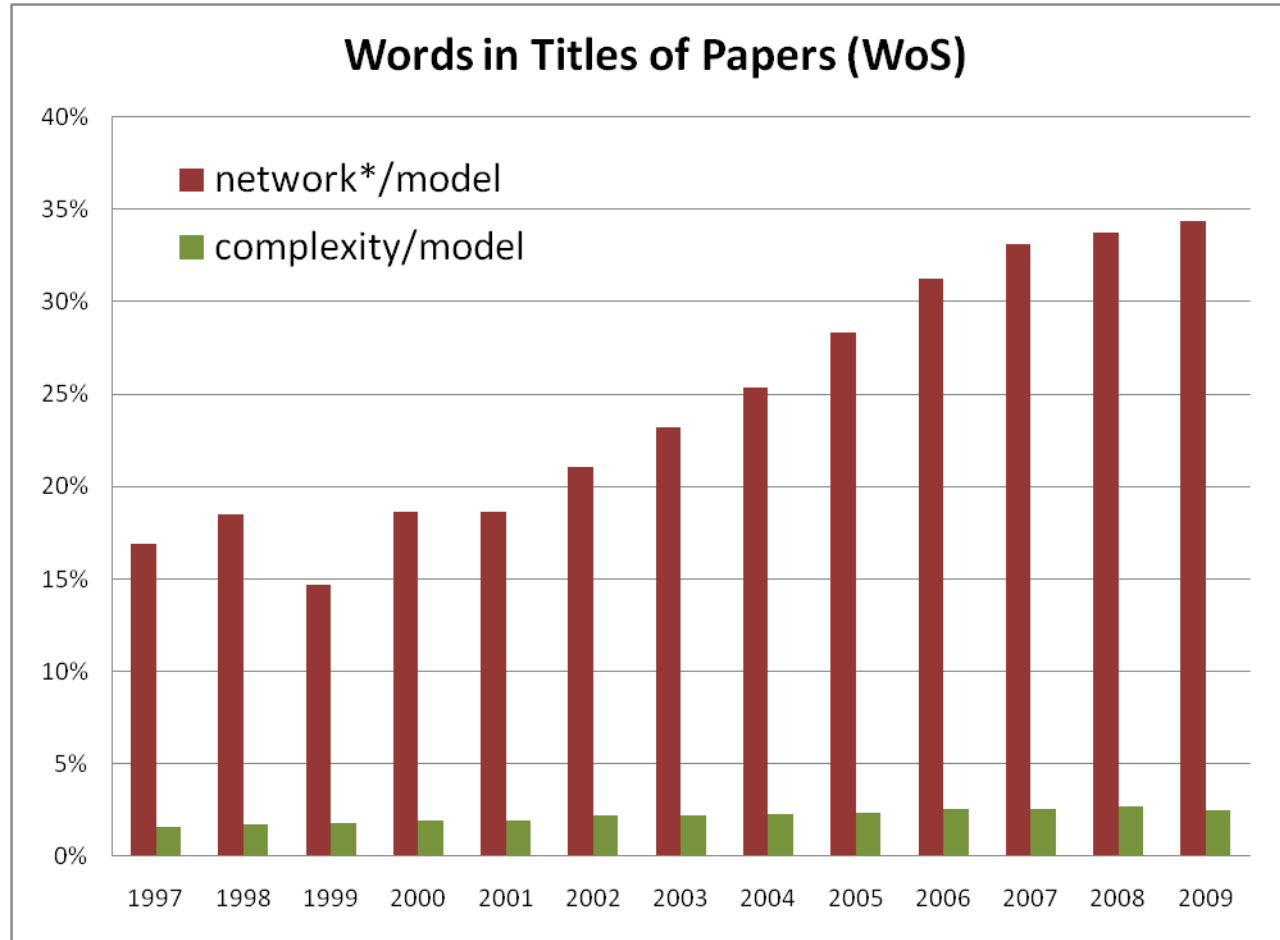
Network Analysis

Adds new insights when large scales are relevant

Networks focus on **WHOLE STRUCTURE**
not just nearest neighbours



Explosion of interest since 1998



Fraction of papers with word starting “NETWORK” in title compared to number of papers with word “MODEL”

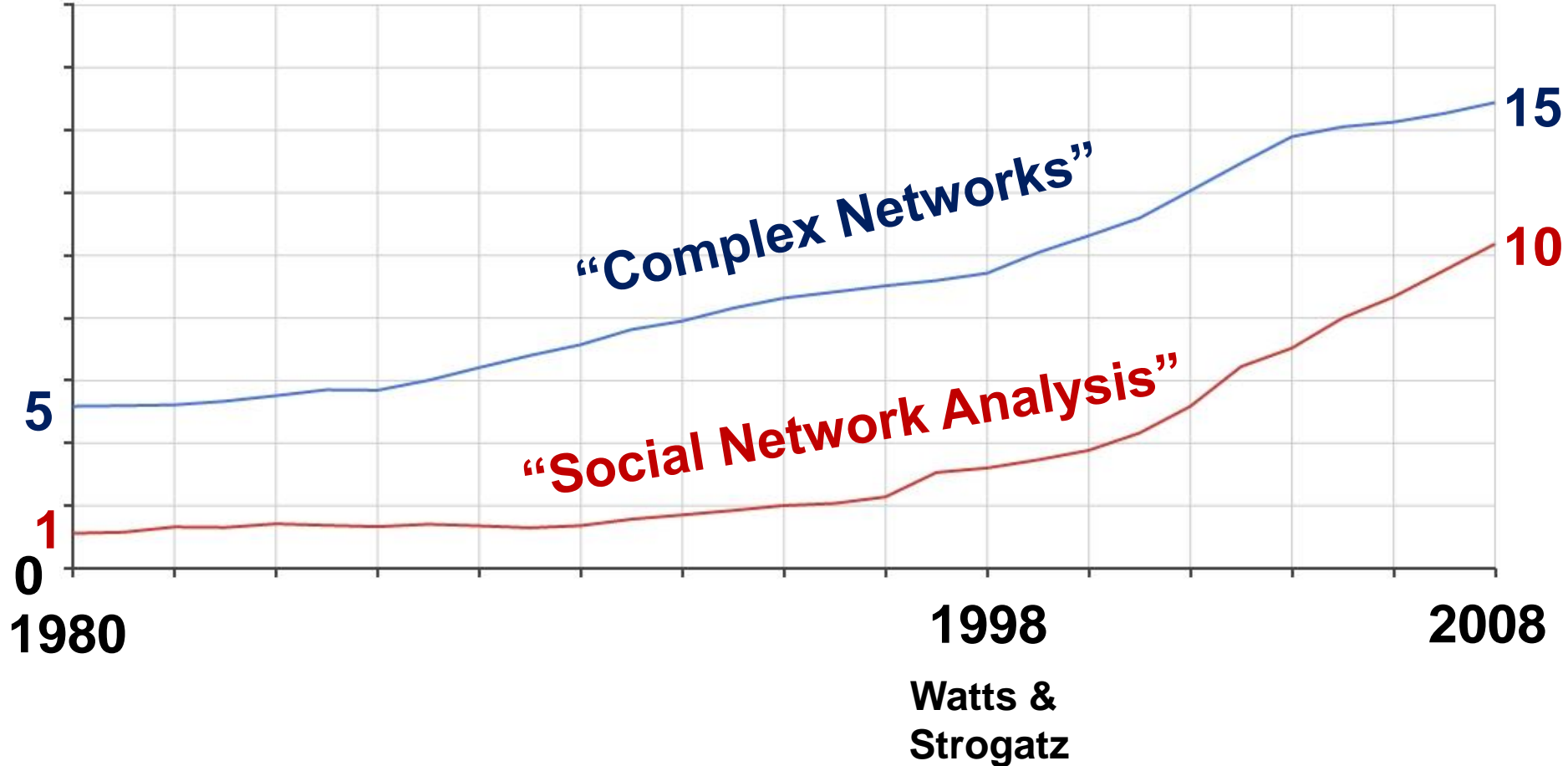


WHY?

Explosion of interest

Percentage of
Google Books
Ngrams
 $\times 10^7$

Google Books Ngram analysis
(case sensitive)

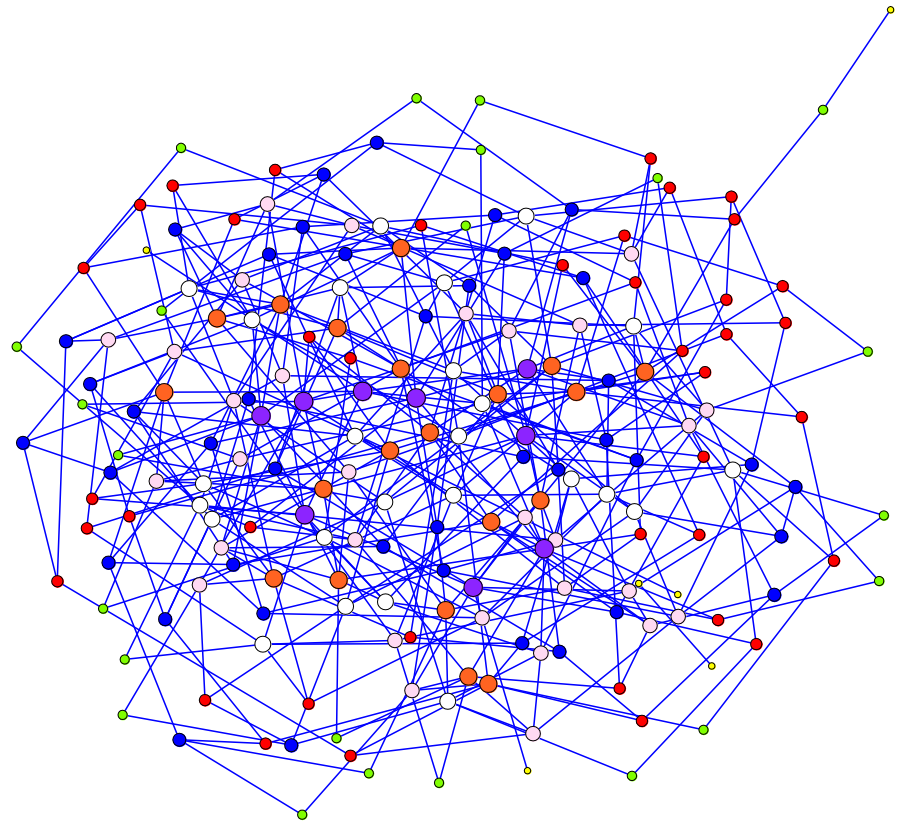


Multidisciplinary Nature of Network Research

Since

- **Mathematics** (Graph Theory, Dynamical Systems) 1930's
- **Physics** (Statistical Physics) 2000's
- **Biology** (Genes, Proteins, Disease Spread, Ecology) 2000's
- **Computing** (Web search and ranking algorithms) 1970's
- **Economics** (Knowledge Exchange in Markets) 1990's
- **Geography** (Transport Networks, City Sizes) 1960's
- **Social Science** (Social Networks) 1960's
- **Archaeology** (Trade Routes) 1970's

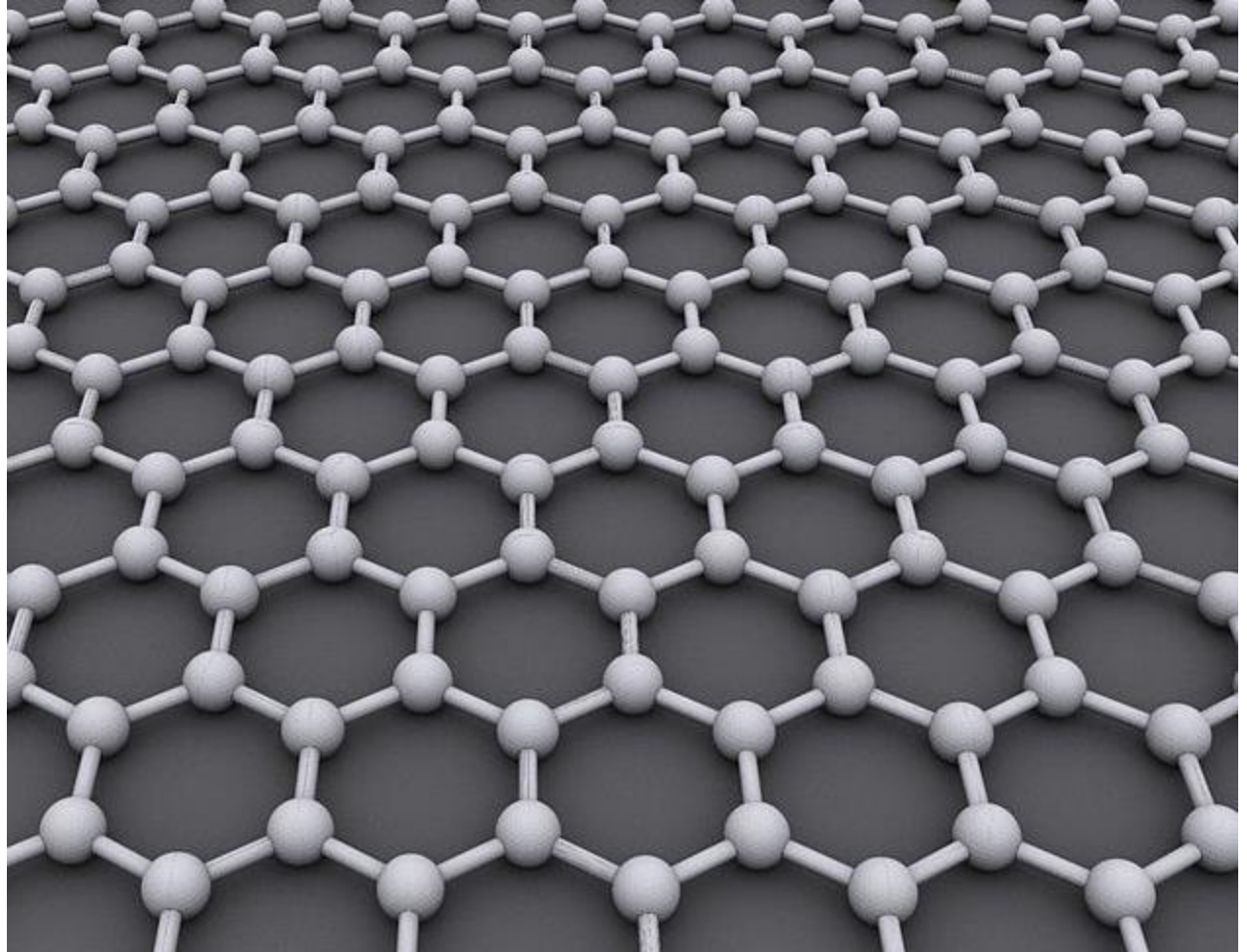




EXAMPLES OF NETWORKS

Traditional Physics networks

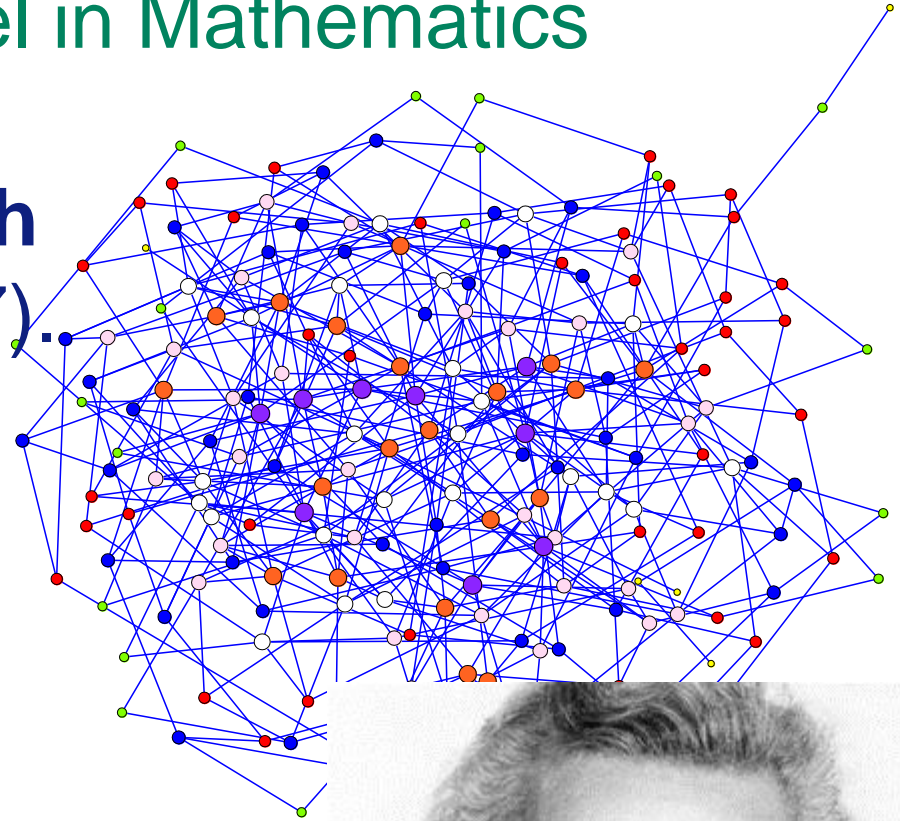
Graphene -
regular
lattice of
atoms in two
dimensions



Traditional Network Model in Mathematics

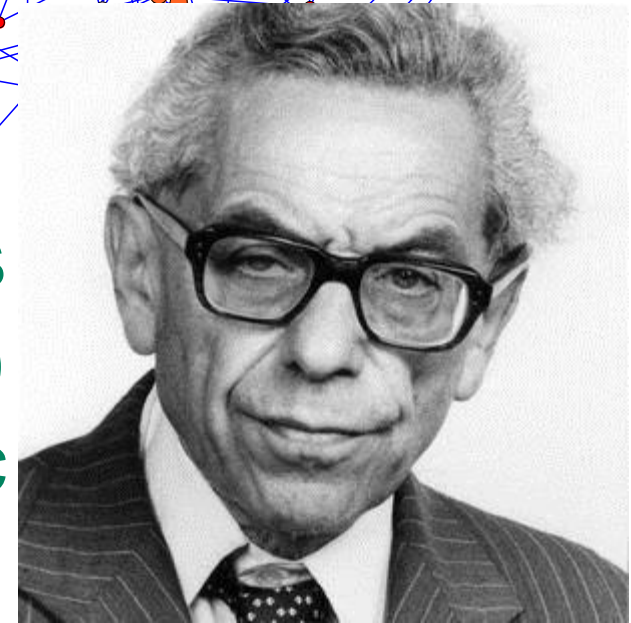
Classical Random graph of Erdős & Reyní (1957)

1. Take **N** nodes,
2. Throw down
 E edges at random



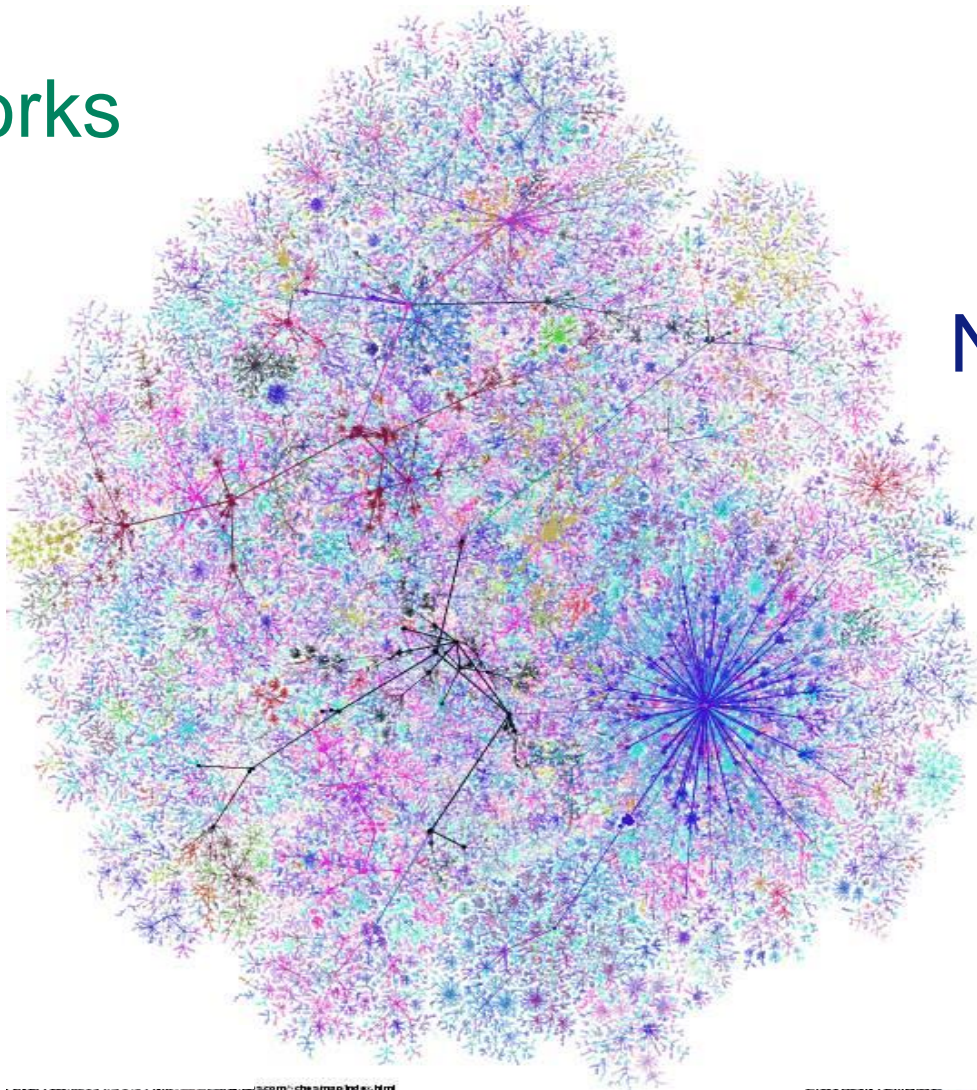
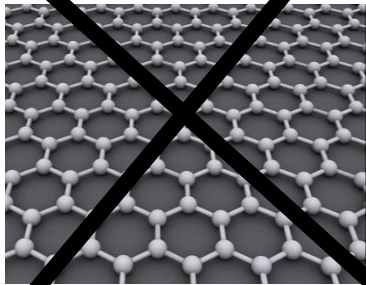
Paul Erdős
(1913-1996)

Itinerant, prolific, eccentric

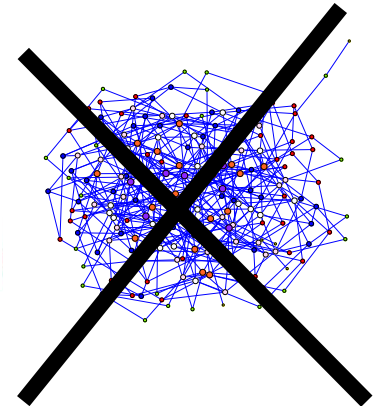


Real Networks

Neither
perfectly
regular like
atoms



Nor perfectly
random like
Classical
Random
graphs



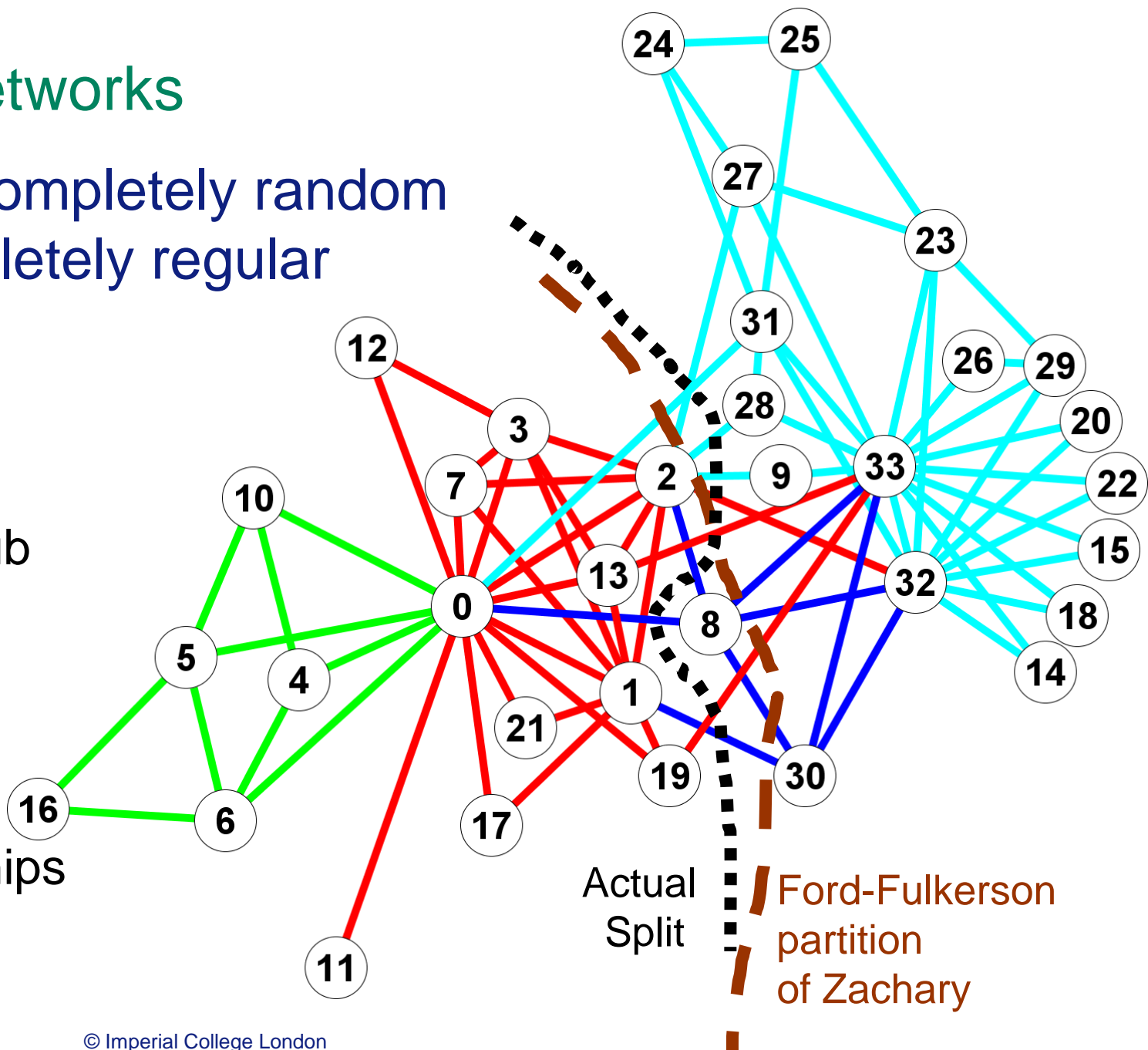
Router Level Map of Internet
[Burch & Cheswick,
Internet Mapping Project]

Social Networks

Neither completely random
nor completely regular

Nodes =
Karate Club
Members

Edges =
Observed
Relationships
ON or
OFF



SocioPhysics?



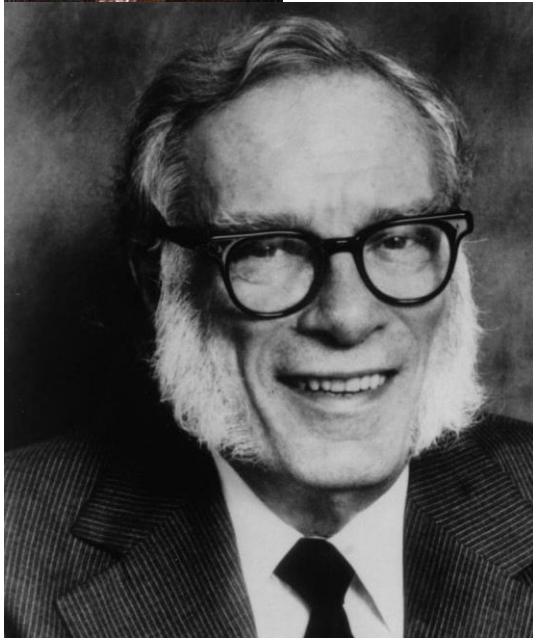
- Thomas Hobbes
'Leviathan' (1651)
- Asimov,
Foundation
Trilogy (1940's+)
- Philip Ball
'Critical Mass'
(2004)



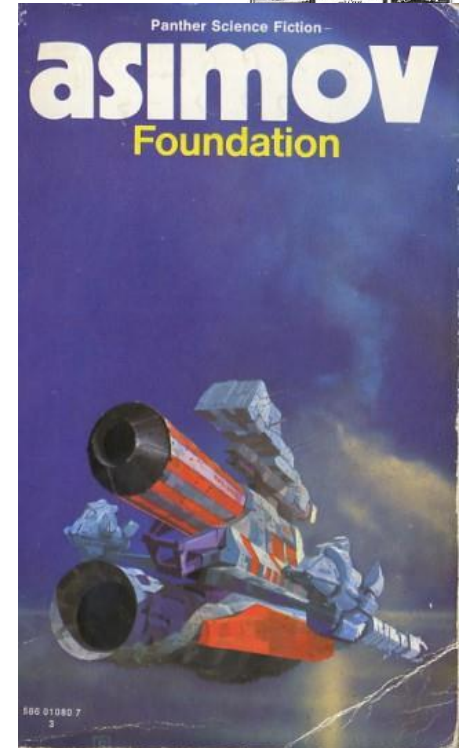
SocioPhysics?



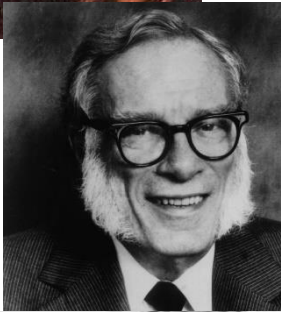
- Thomas Hobbes
'Leviathan' (1651)



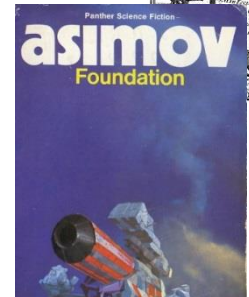
- Asimov,
Foundation
Trilogy (1940's+)
- Philip Ball
'Critical Mass'
(2004)



SocioPhysics?

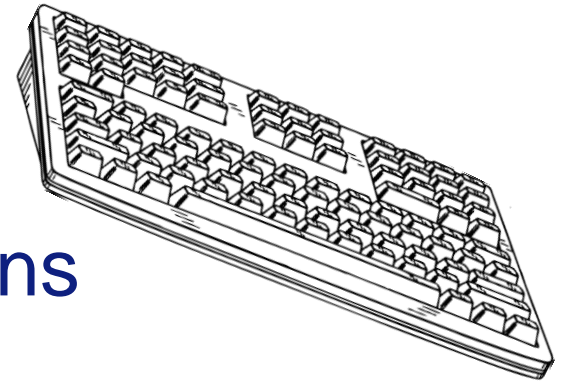


- Thomas Hobbes
'Leviathan' (1651)
- Asimov,
Foundation
Trilogy (1940's+)
- Philip Ball
'Critical Mass'
(2004)

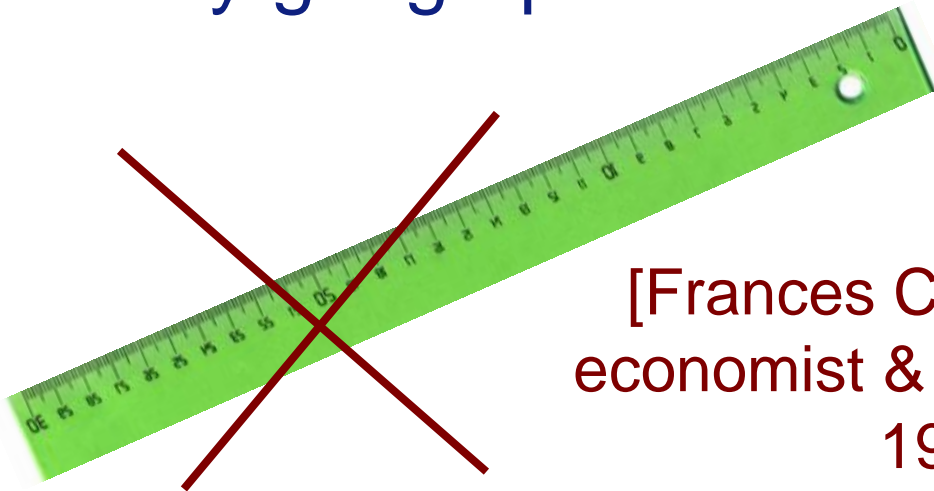


The “Death of Distance”

Modern electronic communications



Links no longer hindered
by geographical distance



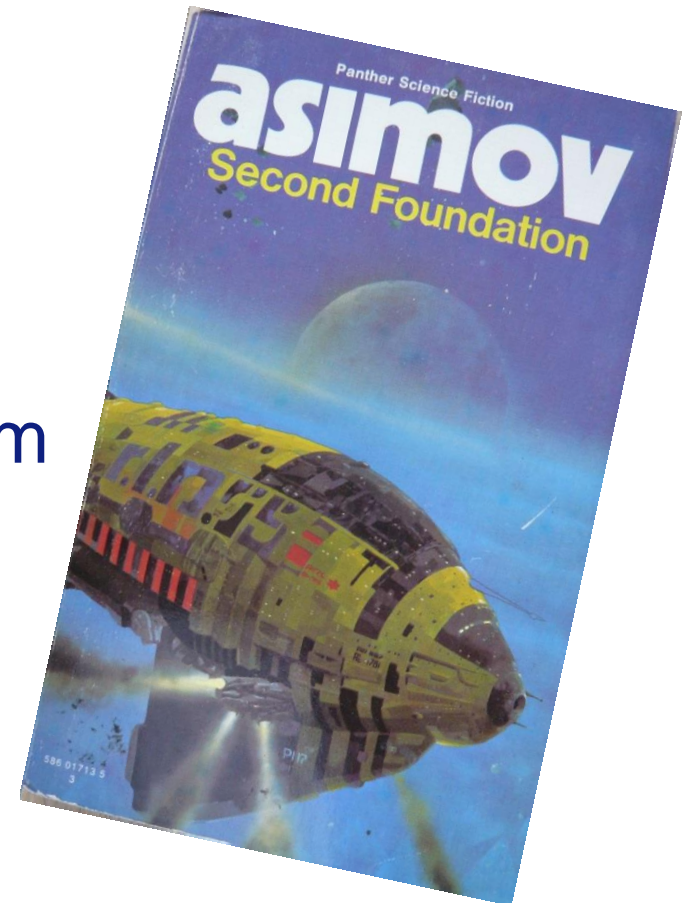
[Frances Cairncross,
economist & journalist,
1995, 1997]



Distance & Space – Geographical or Social?

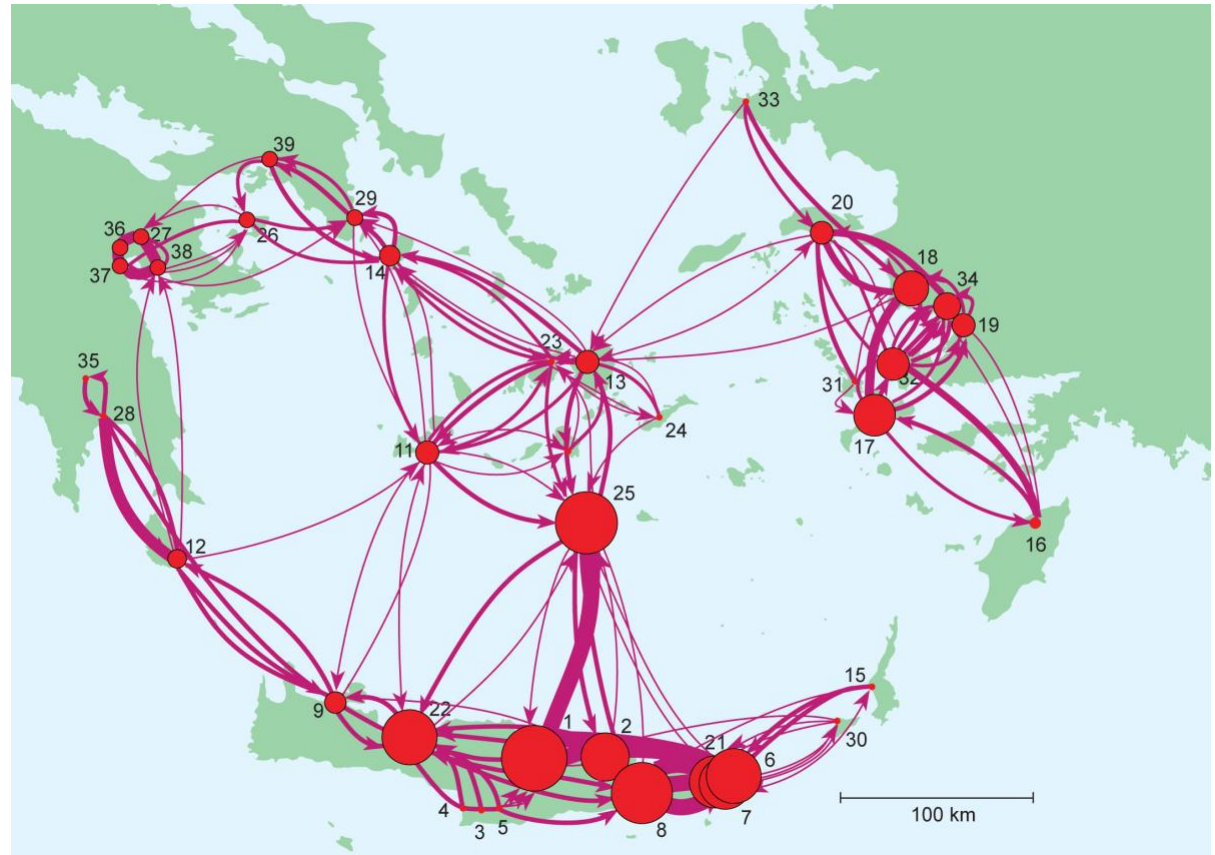
The two foundations lie at
“opposite ends of the galaxy”

- Two ends of a spiral
⇒ **Physical separation**
- Two ends of the political spectrum
⇒ **Social separation**



Physical Networks: Minoan Aegean

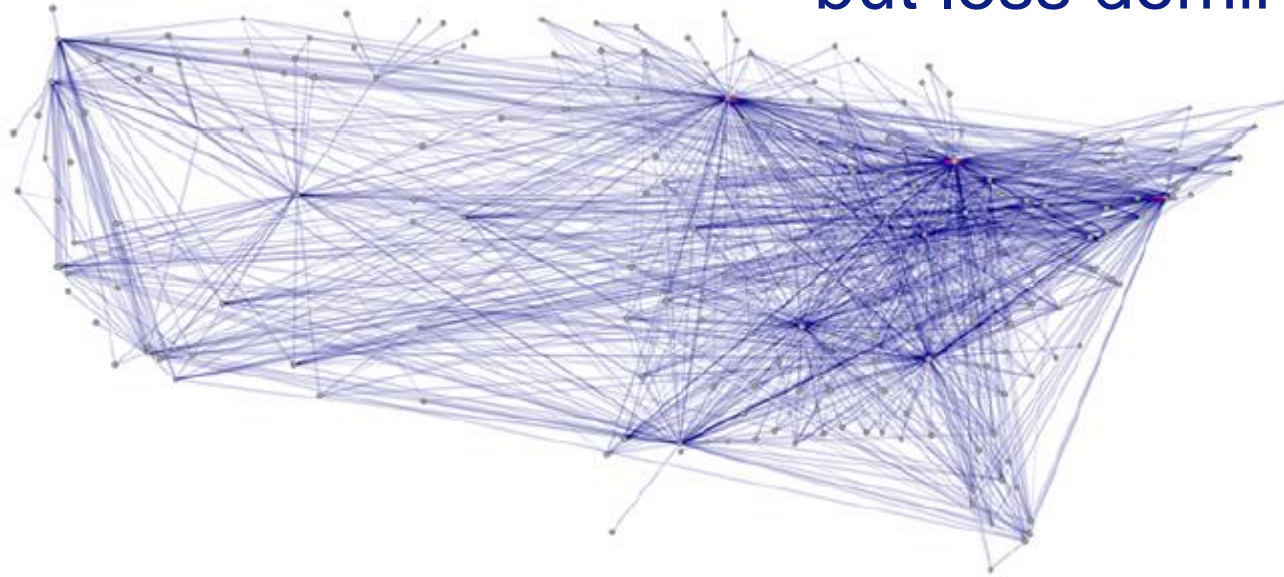
Historical era
geography
dominates



Stochastic network model representing
links in Minoan Aegean (c1500BC)

Transport – Airline Map

Modern era geography still plays a role
but less dominant



nodes = airports, geographical location

Edges= flights from/to, thickness~passengers

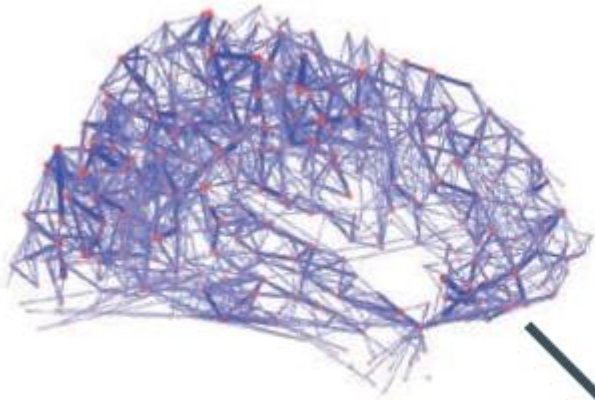
[Holten & van Wijk 2009]

Biological Networks:- Neuroscience

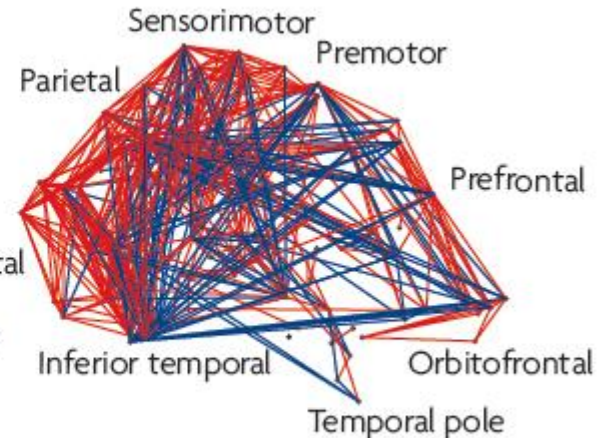
Edges from
anatomy

Edges from
activity

Structural brain network



Functional brain network



4

Graph theoretical analysis

Network Analysis

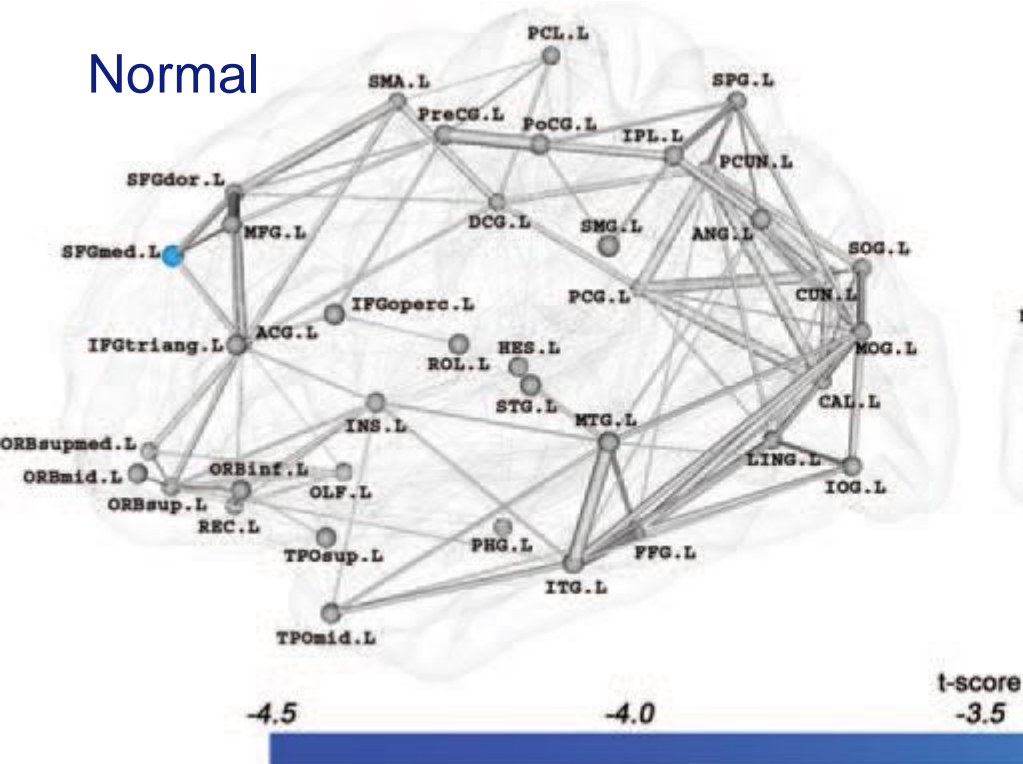
Physical distance
still carries
a cost

[Bullmore & Sporns, 2009]

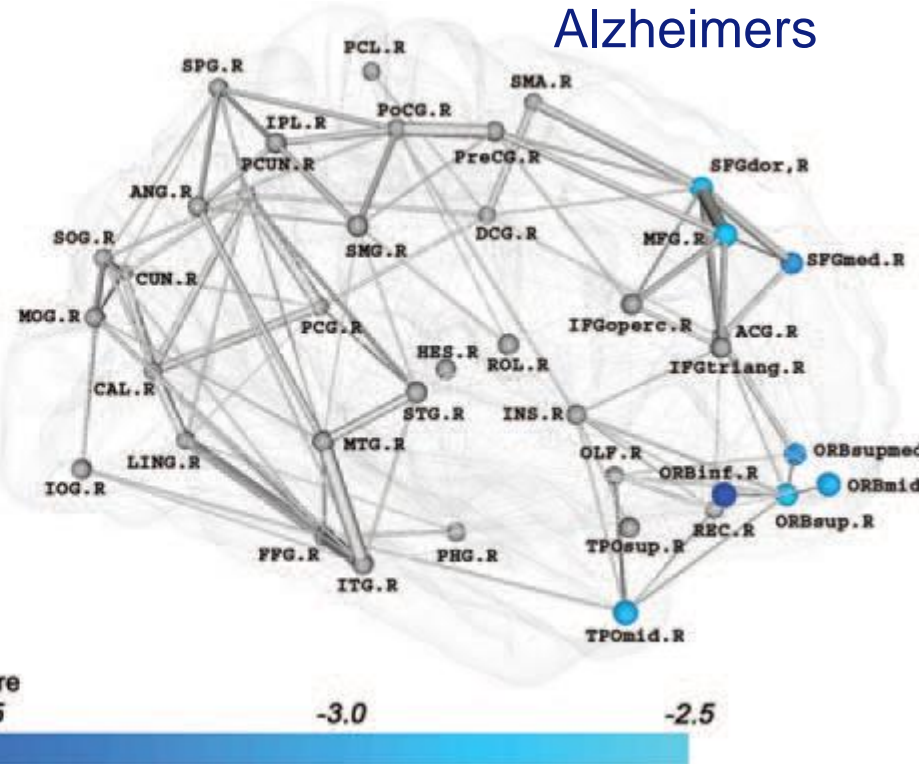
Neuroscience Networks

nodes = Regions,
Edges= Physical connections

Normal



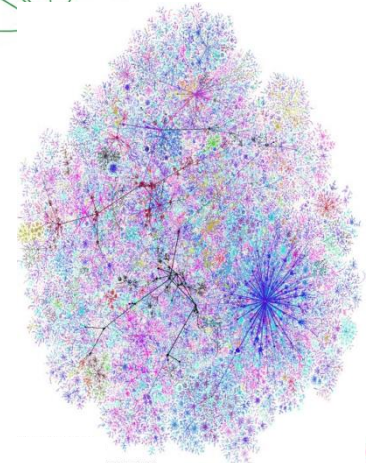
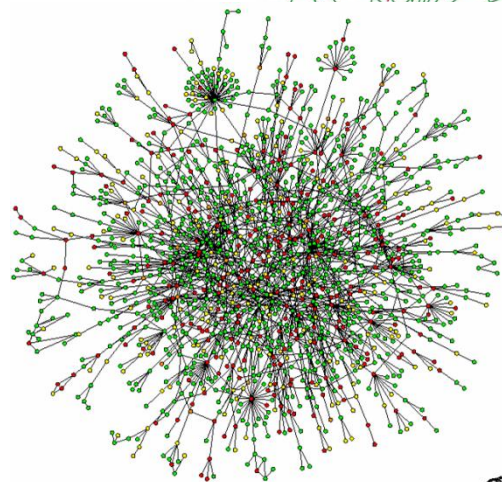
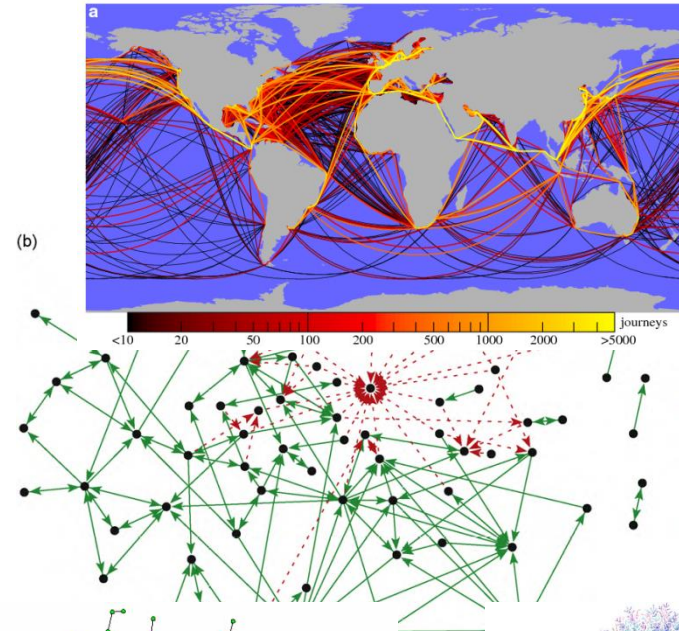
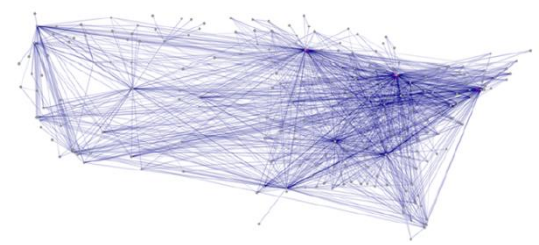
Alzheimers

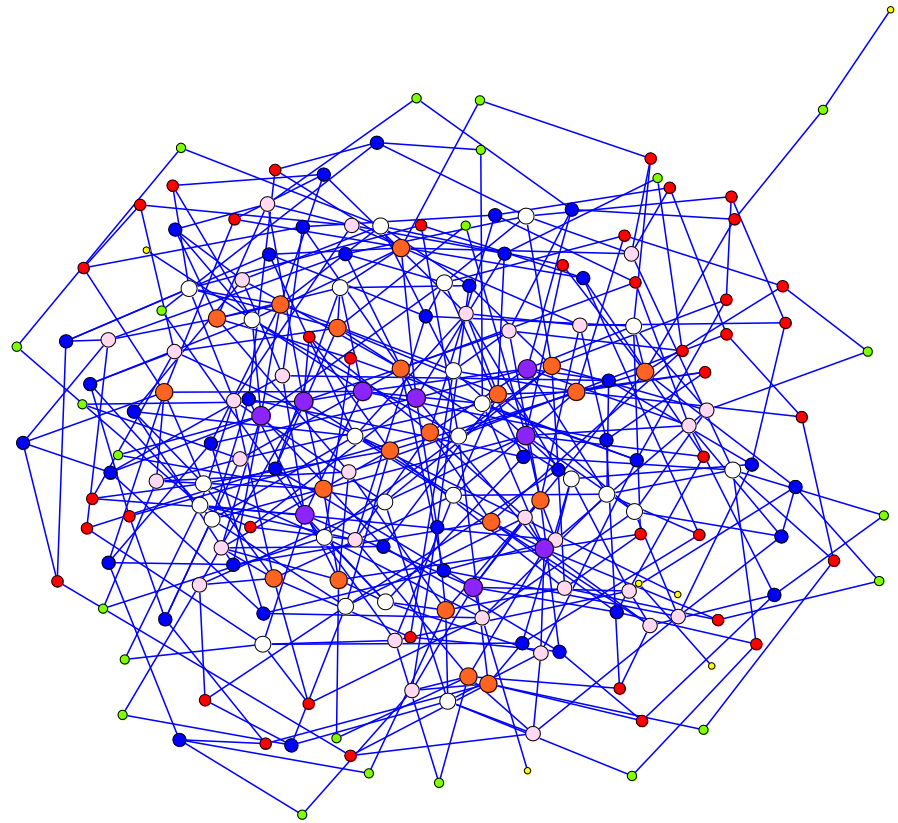


So many networks

Networks are a useful way to describe many different data sets

- Physical links/Hardware based
- Biological Networks
- Social Networks
- Information Networks





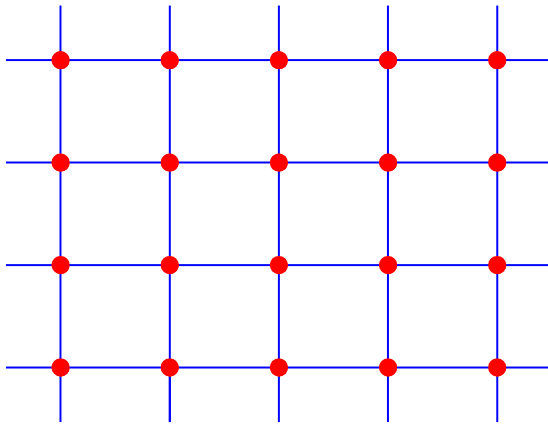
REPRESENTATIONS

Representations

- Data often has a `natural' network
- There is no one way to view this natural network \Rightarrow ***visualisation***
- There are always many different networks representing the same data

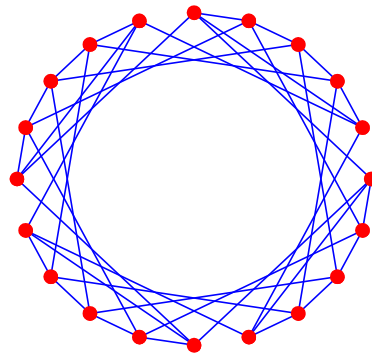
Visualisation – Topology vs Space

In a network the location of a node is defined only by its neighbours \Rightarrow *topology*

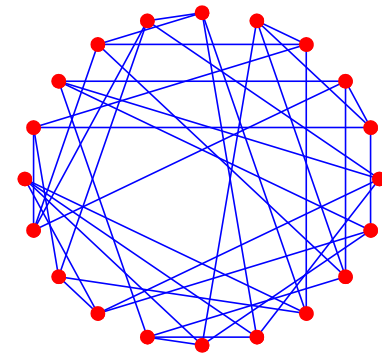


Periodic Lattice

$N=20, E=40$



Same network with nodes arranged in regular order.



Same network with nodes arranged in random order

Identical Networks



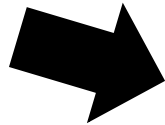
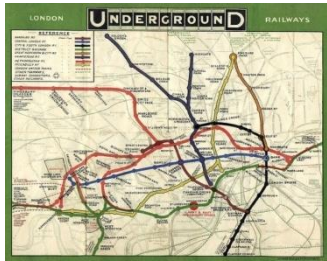
Choose visualisation to reveal spatial structure

Visualisation – Space before Topology



Tube lines laid out in geographical space (1908)

Visualisation – Topology over Space



Modern map
preserves
relationships
between
stations, not
geography



[Derived from Beck 1931]

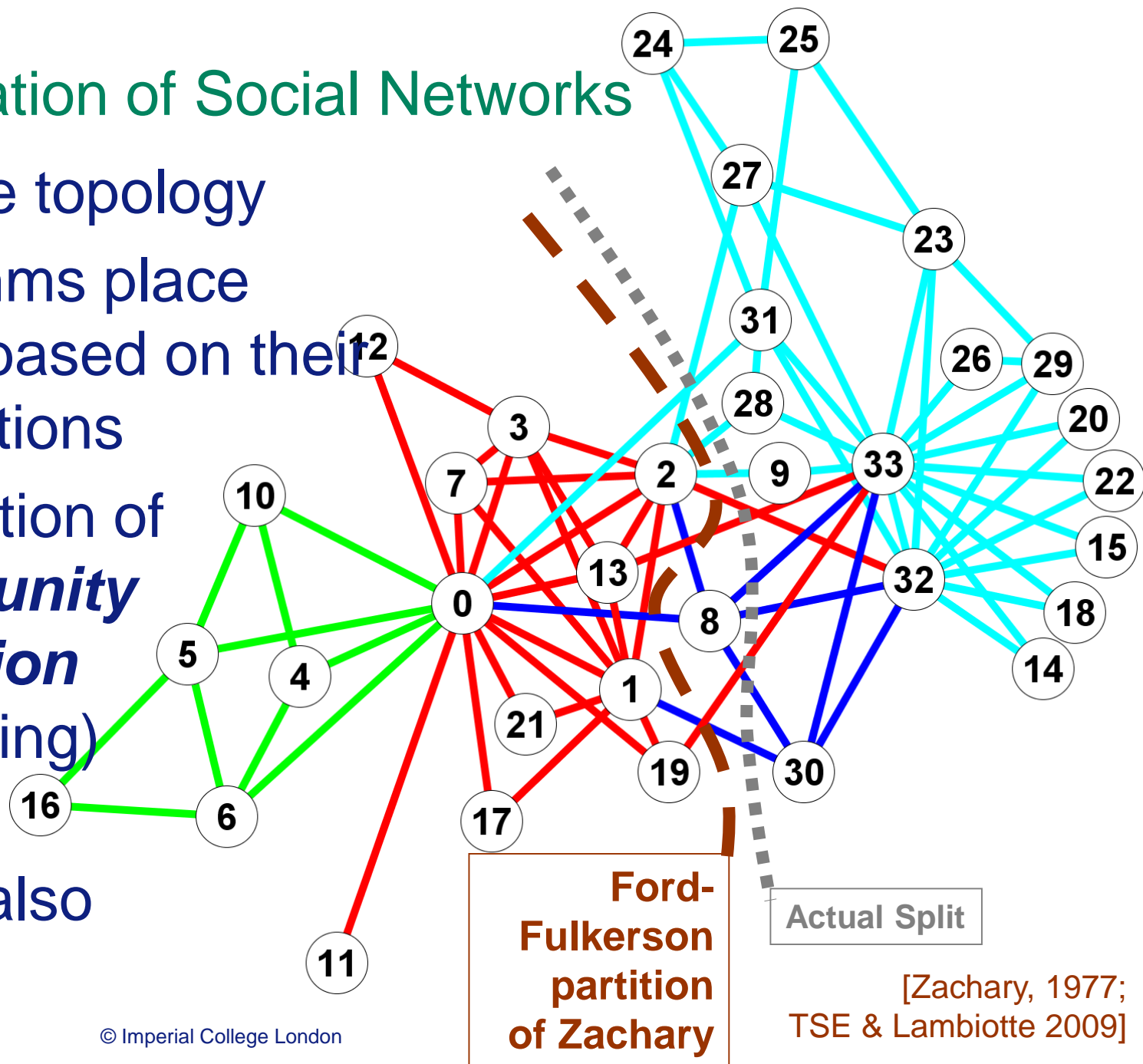
Visualisation – no space, only topology

Most networks are not embedded in any space e.g. social networks

Visualisation of Social Networks

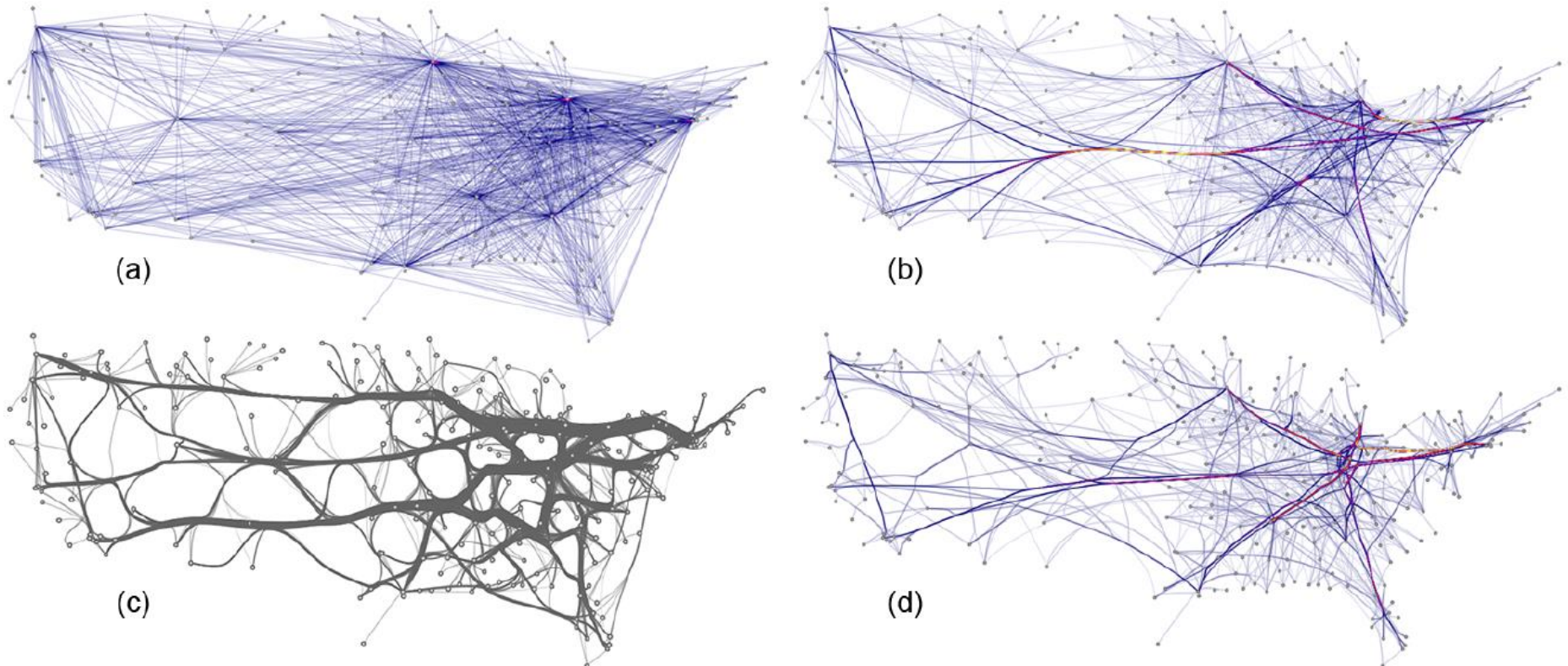
Only have topology

- Algorithms place nodes based on their connections
- Application of **Community Detection** (clustering)
- Edge colour also



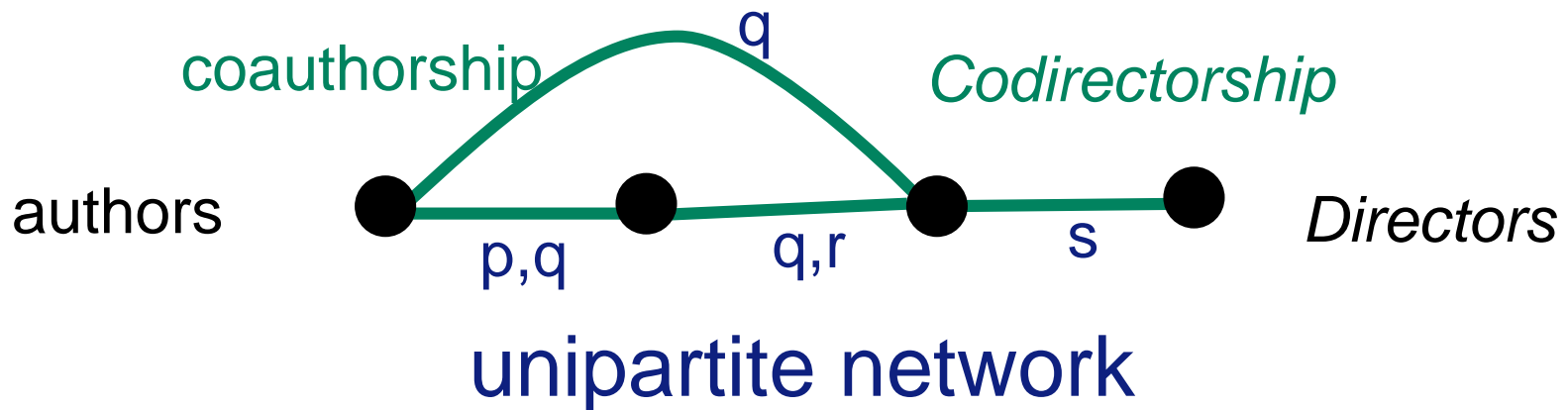
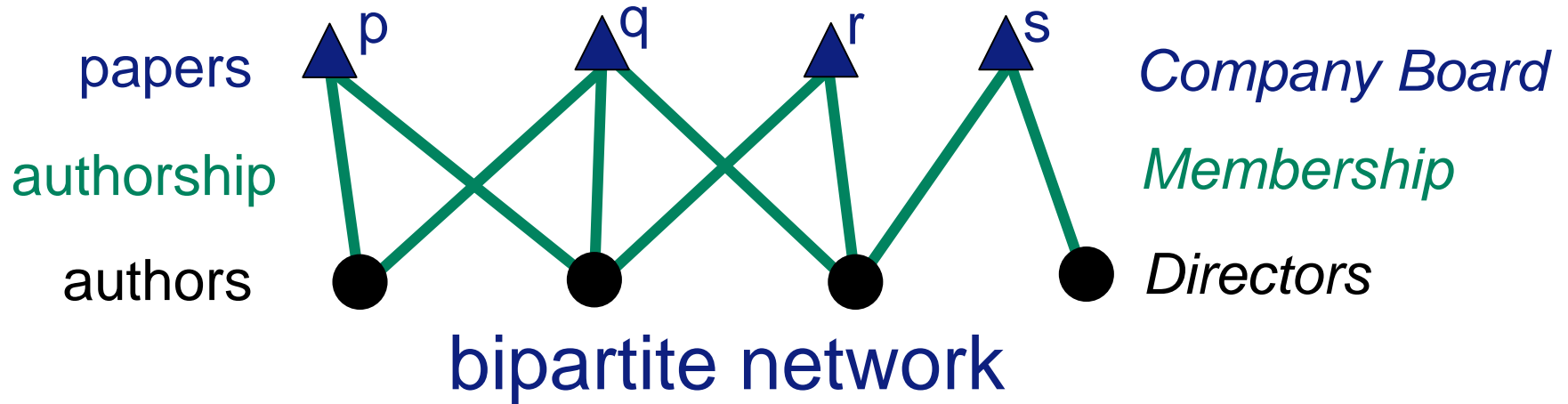
Visualisation

Choosing the right visualisation is a powerful practical tool, and its not just the nodes ...



Same Data, Many Networks

e.g. Co-membership
networks



Network of Streets

Some networks
are embedded
in geographical
space.

This street network
is embedded
in real
two-dimensional
space



Same Data, Many Networks - Line Graphs

nodes =
Intersections

Edges =
Streets



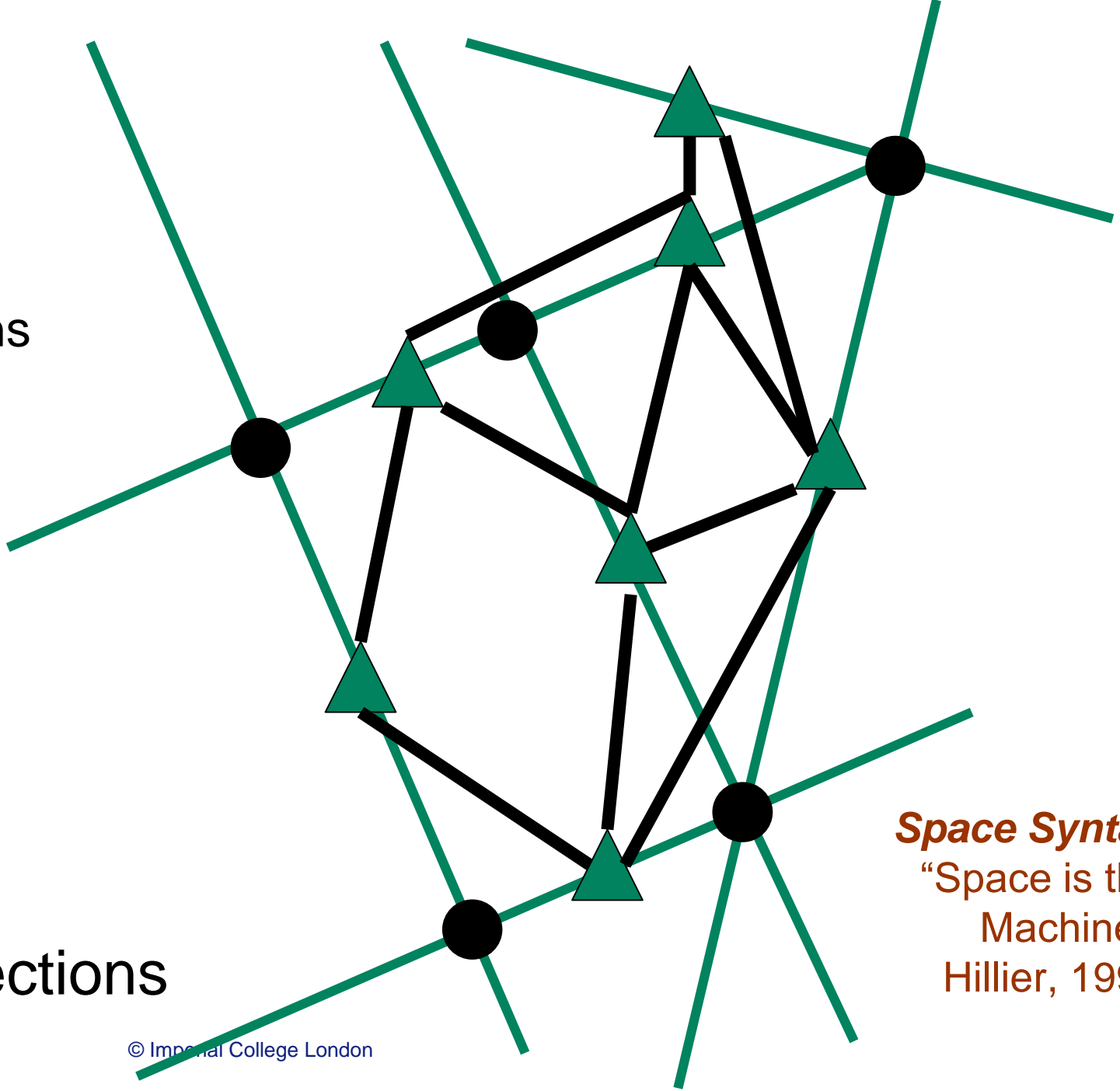
Line Graphs

nodes =
Intersections

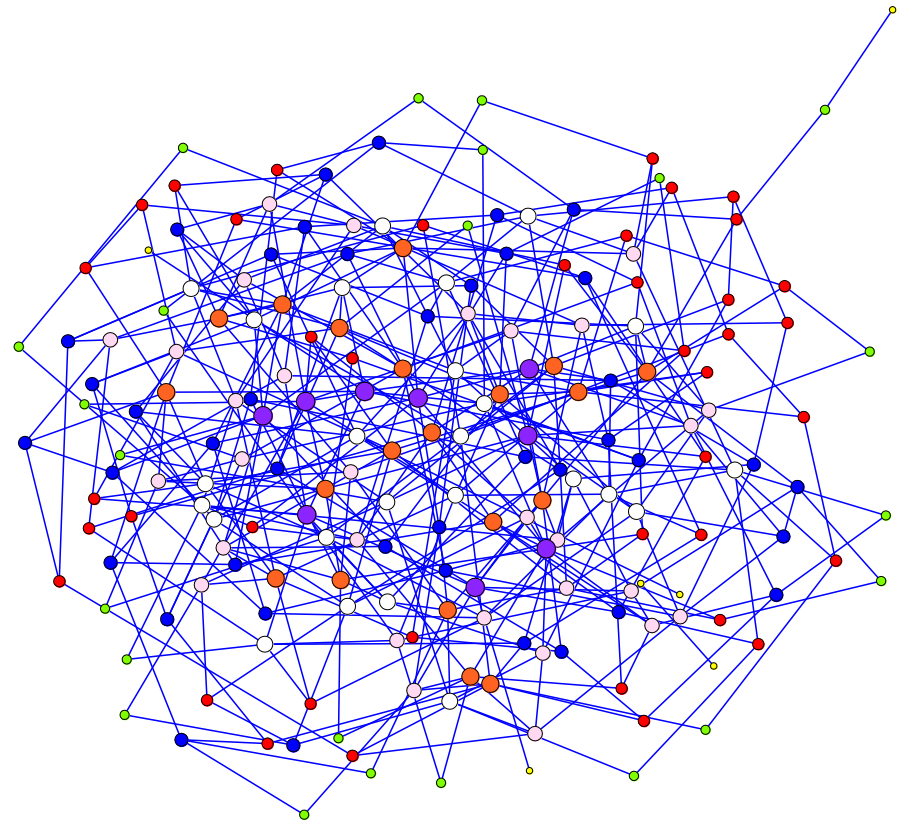
Edges =
Streets

nodes =
Streets

Edges =
Intersections



Space Syntax
“Space is the
Machine”,
Hillier, 1996



THE DIMENSION OF NETWORKS

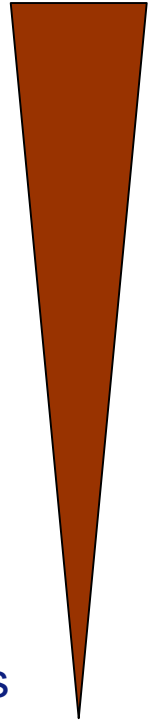
Types of Network – by application

- **Physical links/Hardware based**
 - telephone links, internet hardware, power lines, transport
- **Biological Networks**
 - neural, biochemical, protein, ecological
- **Social Networks**
 - Questionnaires, observation, electronic social networks
- **Information Networks**
 - academic papers, patents, keywords, web pages, artefact networks

Death of Distance?
[Cairncross 1997]

Dimensions

2



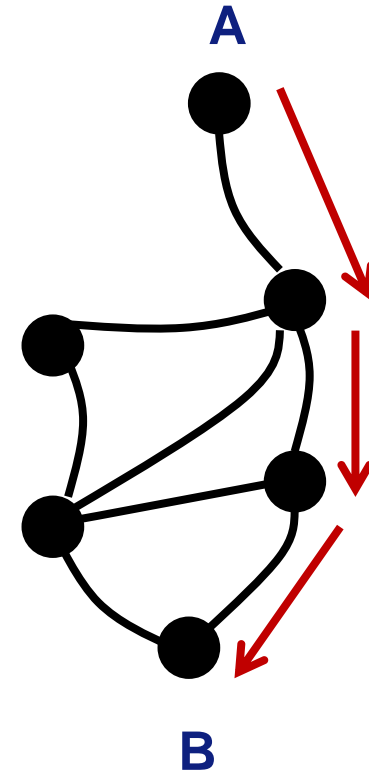
High
Dimension

Length of a Path

The length of a path between two nodes is the number of edges in that path

e.g. The shortest path from A to B has length 3.

There are two such paths of length 3 from A to B and many longer ones.



Dimension

For regular lattice in ***d*** dimensions we find that the shortest path between two points scales with the number of nodes ***N*** as

$$\text{Volume} \sim N = (L)^d$$

Shortest Path Length $L_{\min} \propto (N)^{1/d}$

The length of shortest path between two nodes is the number of edges traversed.

Dimension of Random Graphs

For random graphs we find that the shortest path between two points scales with the number of nodes **N** as

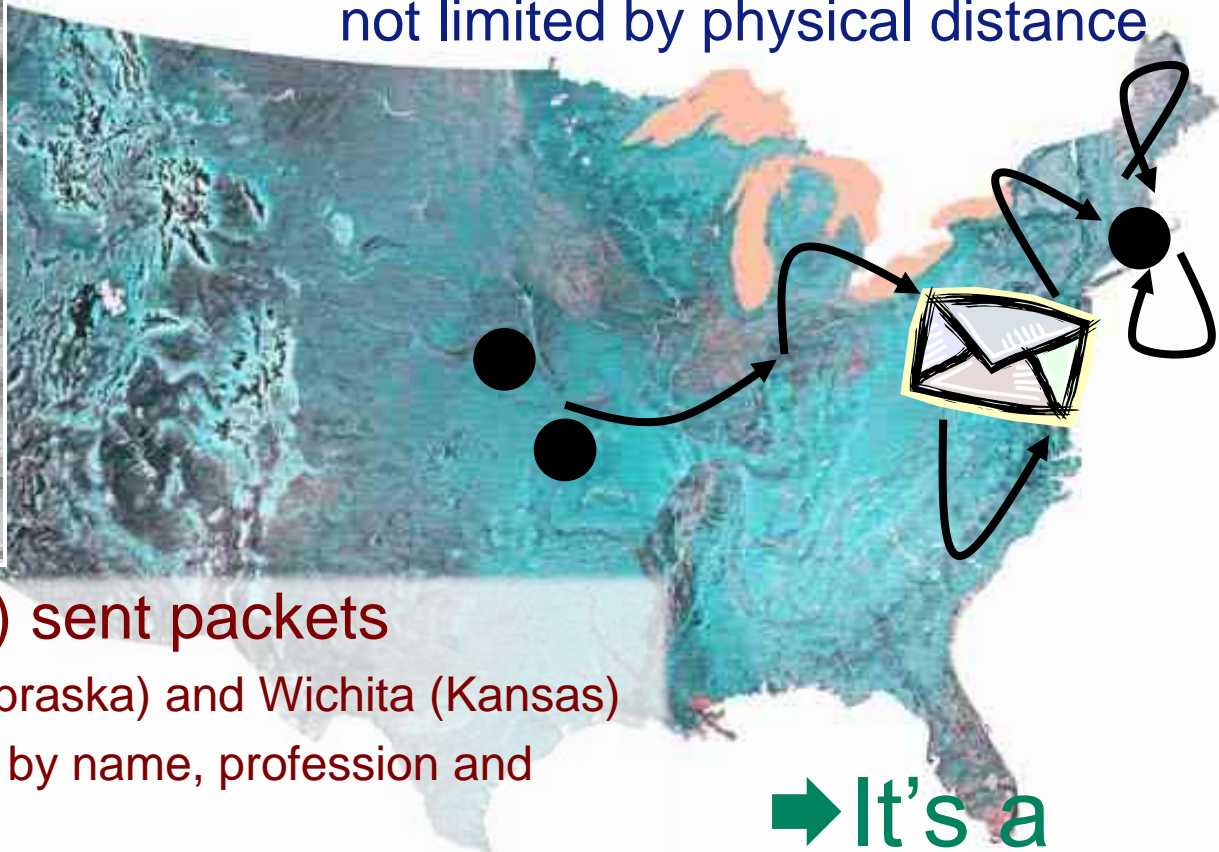
$$L_{\min} \propto \log(N)$$
$$\approx \lim_{d \rightarrow \infty} \left(N^{1/d} \right)$$

Random graphs look like infinite dimensional networks

Social Networks and Small Worlds



- node = Person
- Edges = Friendship
not limited by physical distance

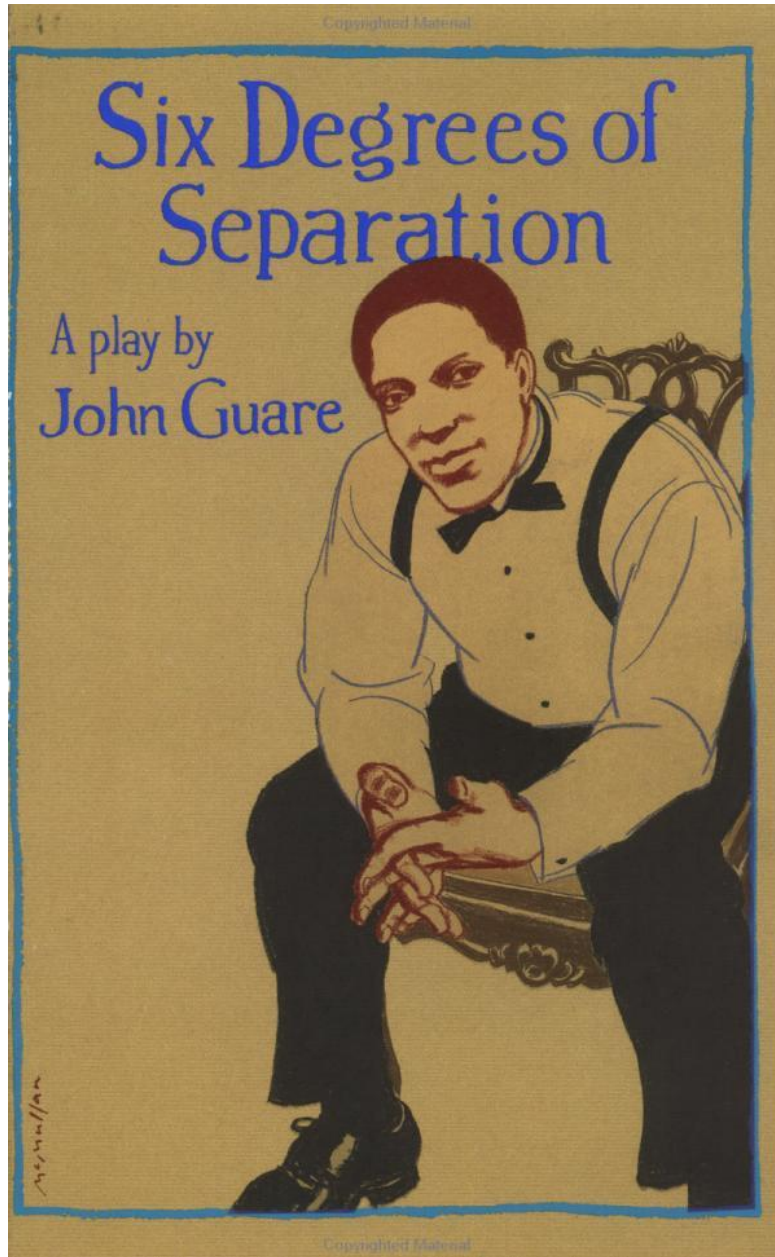


Stanley Milgram (1967) sent packets

- From people in Omaha (Nebraska) and Wichita (Kansas)
- To Cambridge MA specified by name, profession and rough location
- Only swapped between people on first name terms
- Packets which arrived averaged **FIVE intermediaries**

➡ It's a
Small World

Six Degrees of Separation

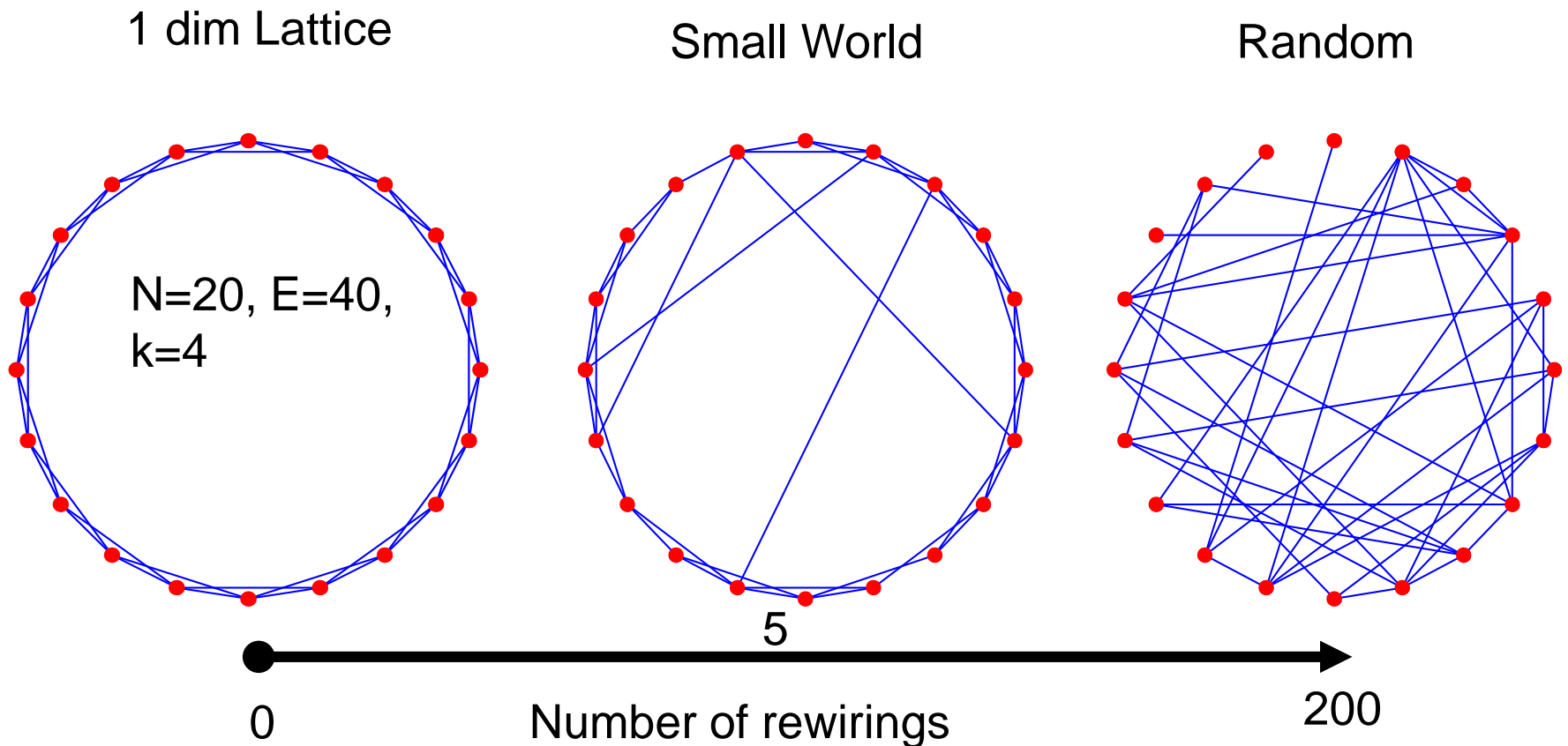


“I read somewhere that everybody on this planet is separated by only six other people. Six degrees of separation.”

Six Degrees of Separation,
John Guare (1990)

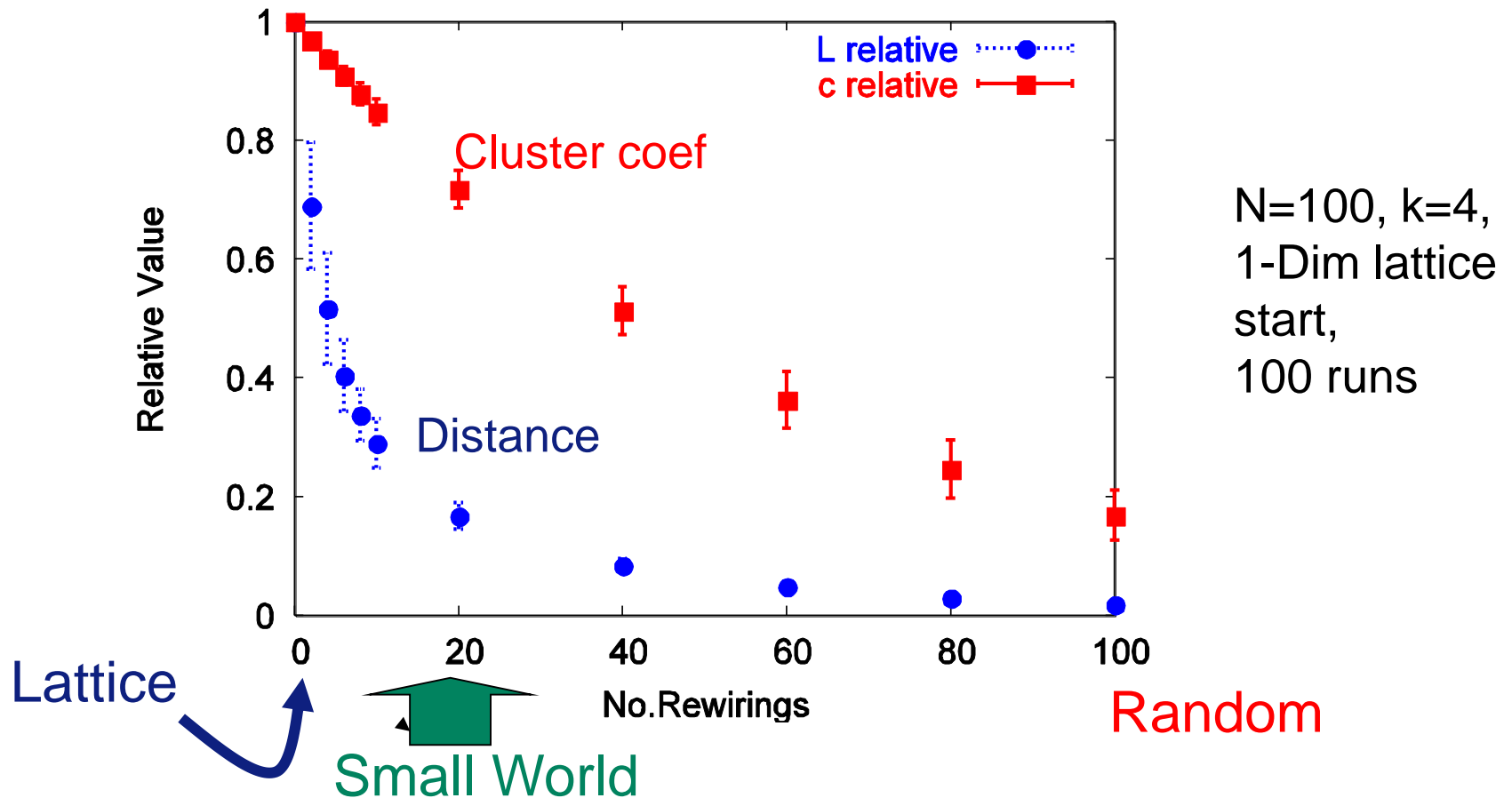
Watts and Strogatz's Small World Network (1998)

Start with regular lattice, pick random edge and move it to link two new nodes chosen at random.



Clustering and Length Scale in WS network

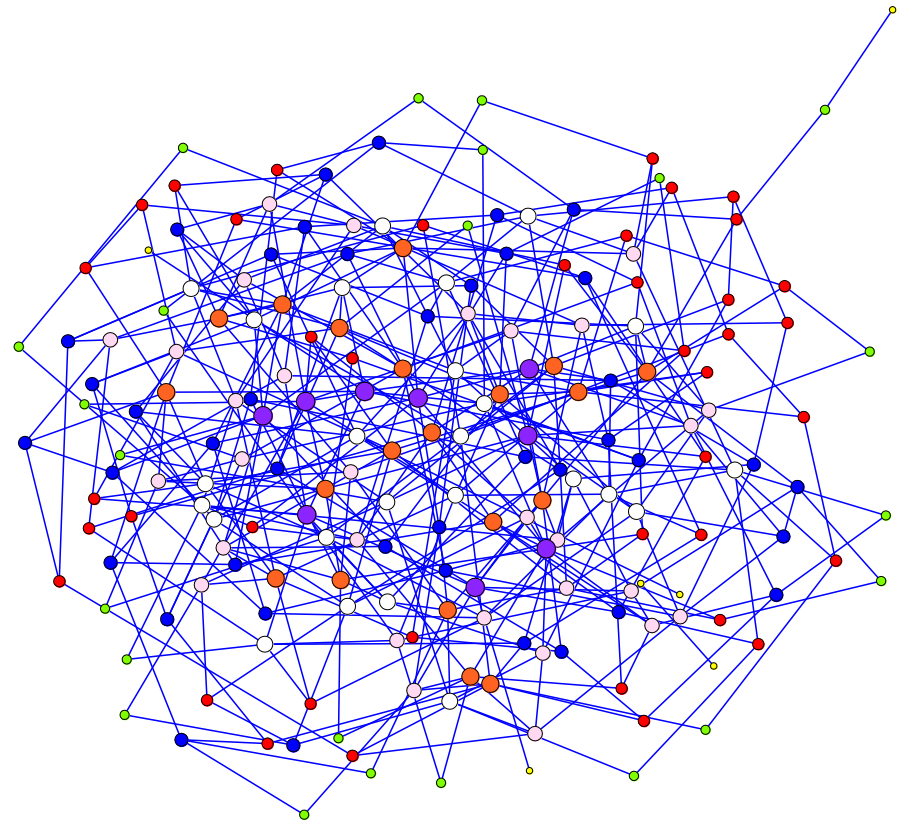
Find **Small World networks** with short distances of random network, local structure (clustering) like a lattice



Real Network Summary

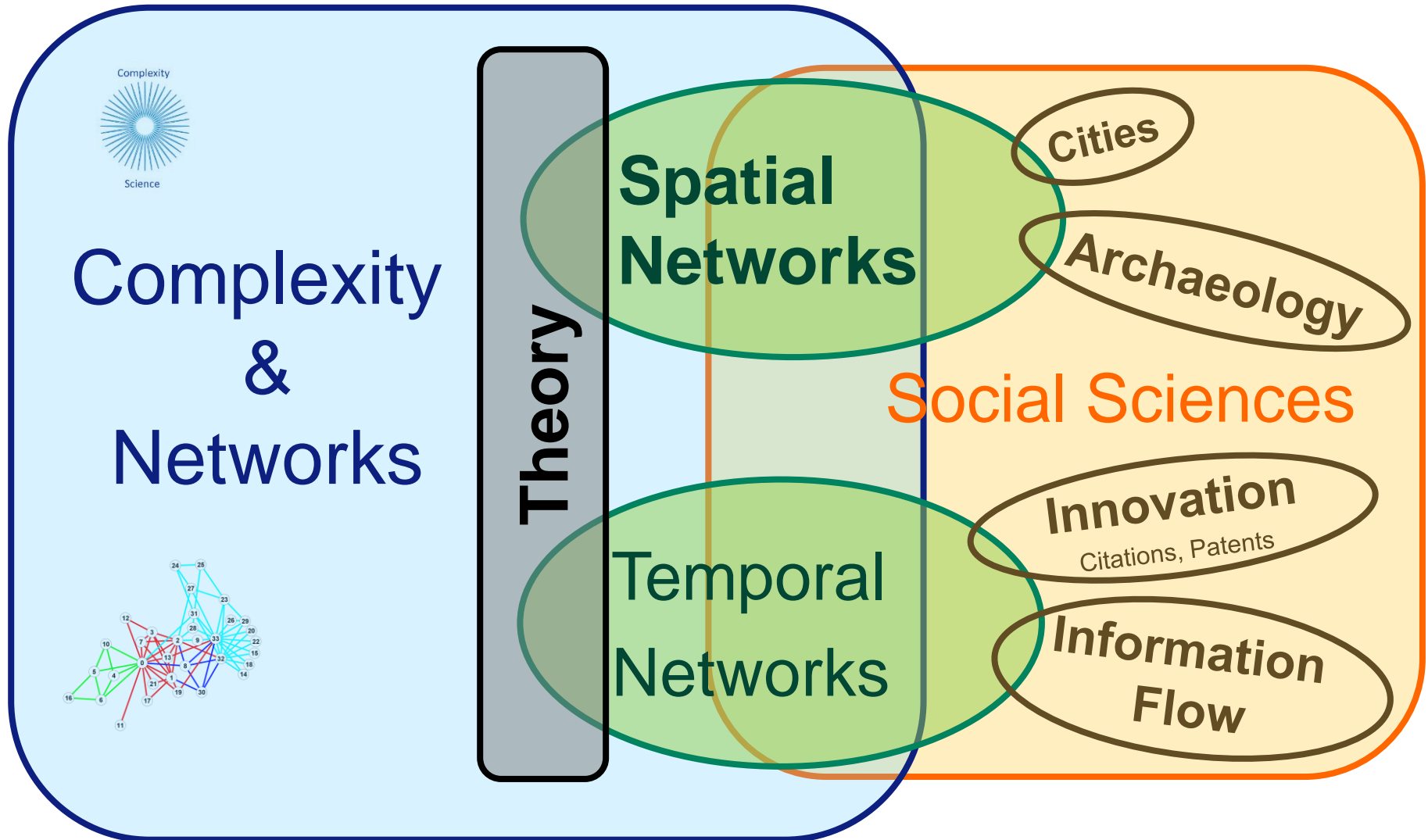
Real Networks have a lot of structure yet are not perfectly regular

- Short distances common like random graphs
- Local structure like regular lattice common
- Many have hubs – a few nodes have a large fraction of edges
 - fat tails for degree distributions, **Scale-Free networks**



TIM EVANS' CURRENT RESEARCH

Tim Evans' Current Research (2015)



Basic Philosophy

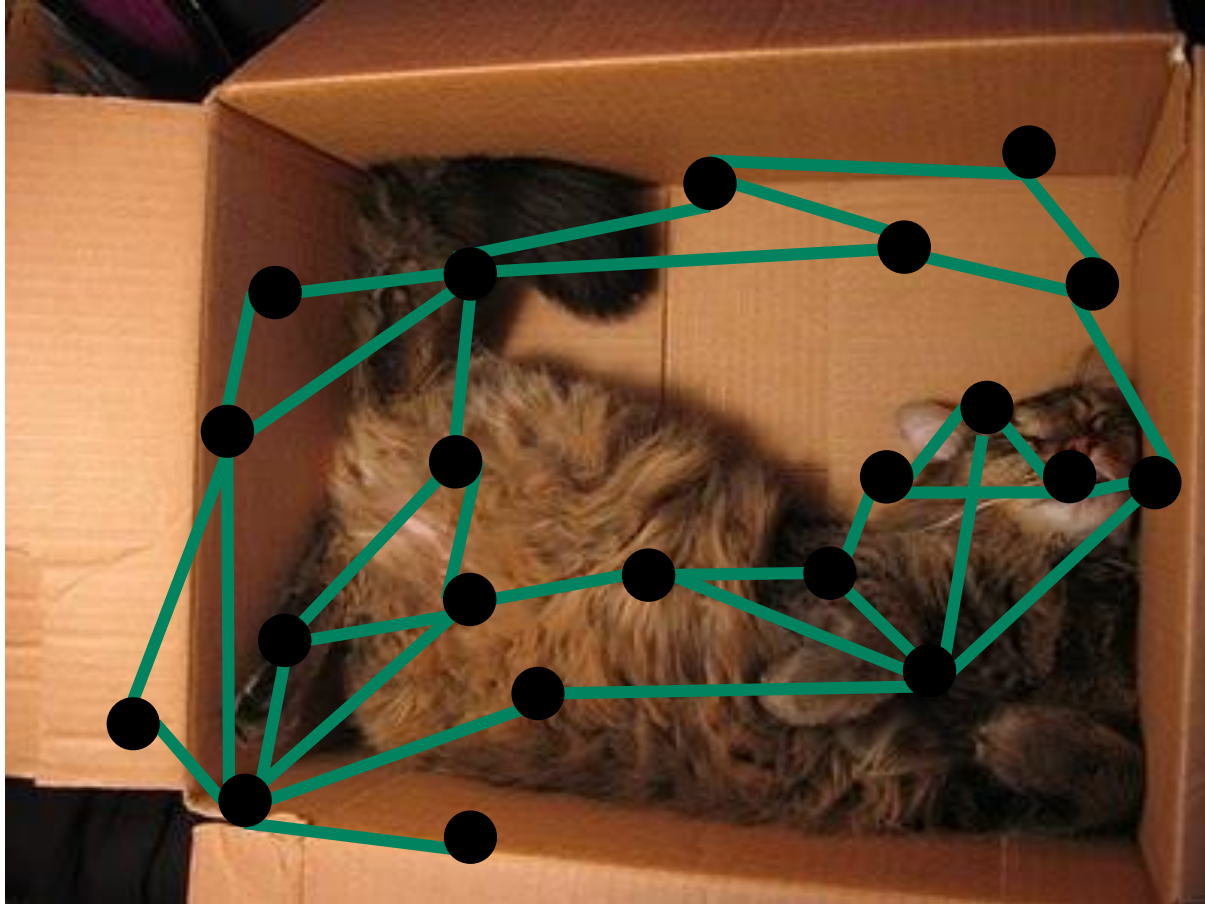
Measurements on a network must be adapted to take account of all constraints

e.g.

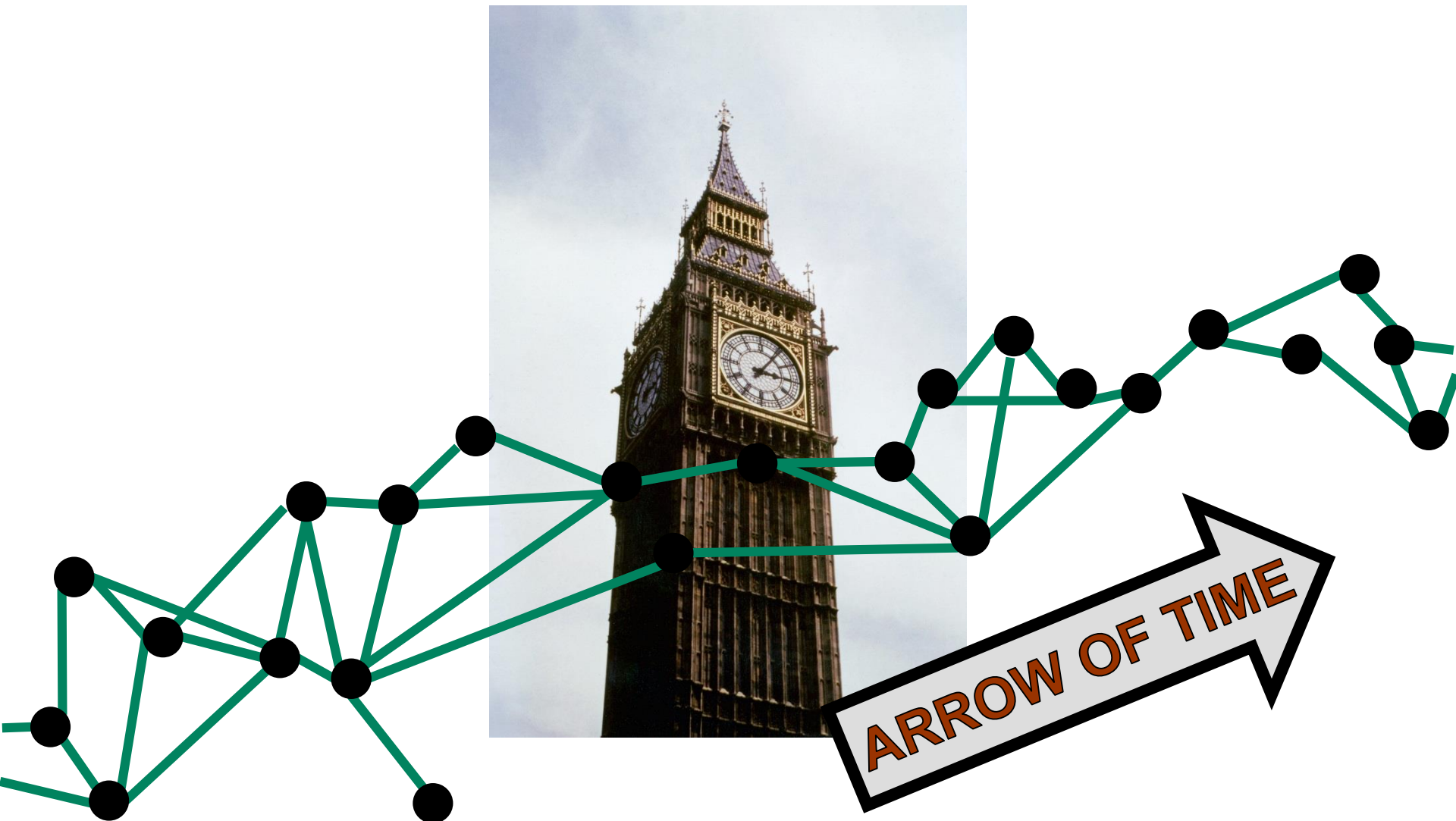
- **in-degree** and **out-degree** used when we have *directed* graphs
- Use **strength** not degree for *weighted* graphs



Spatial Constraints



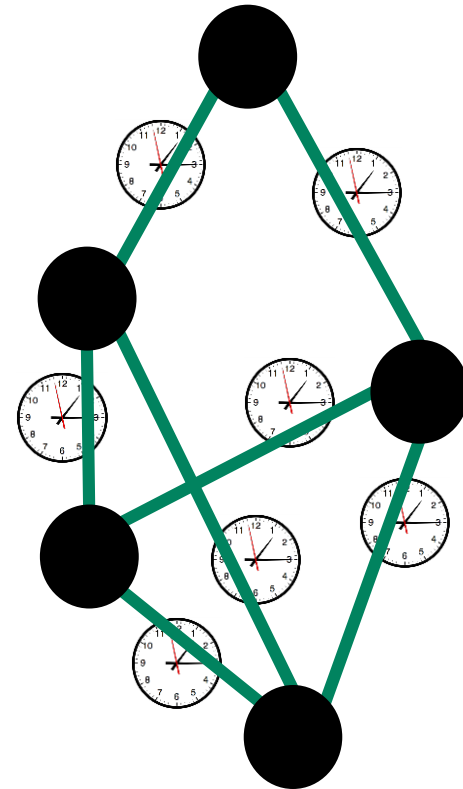
TimeE and Networks



Timed Edges

Communication Networks

- Email
- Phone
- Letters

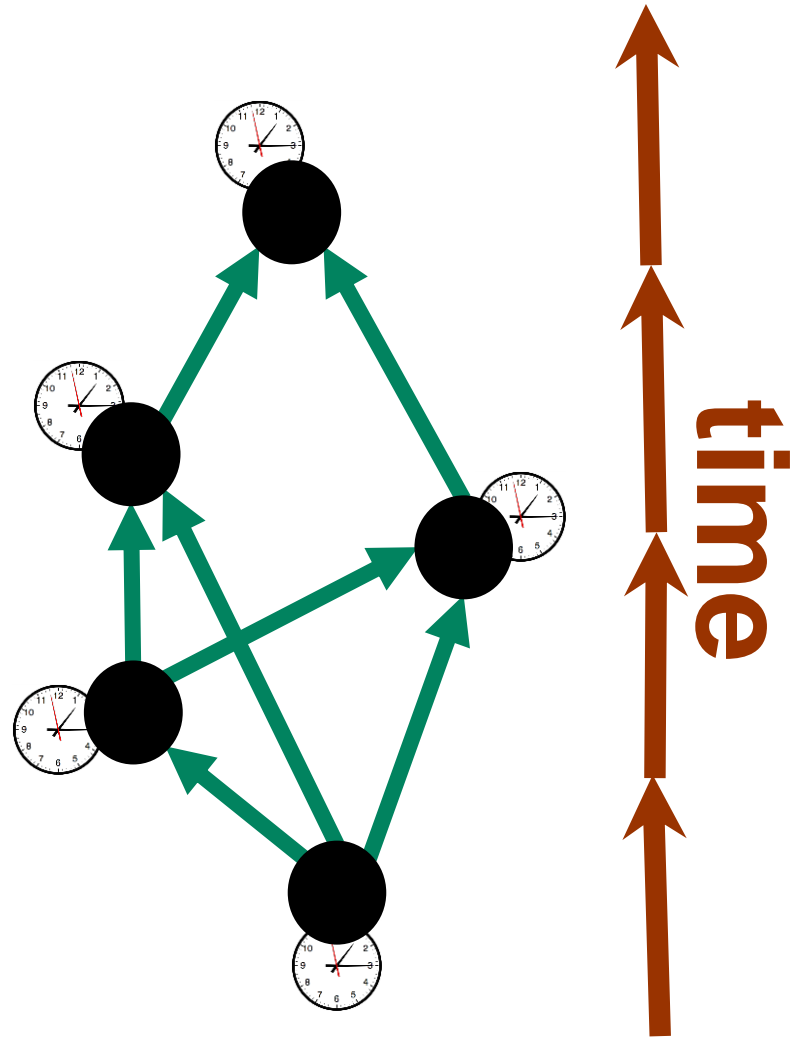


e.g. see [Holme, Saramäki, 2012]

Timed nodes

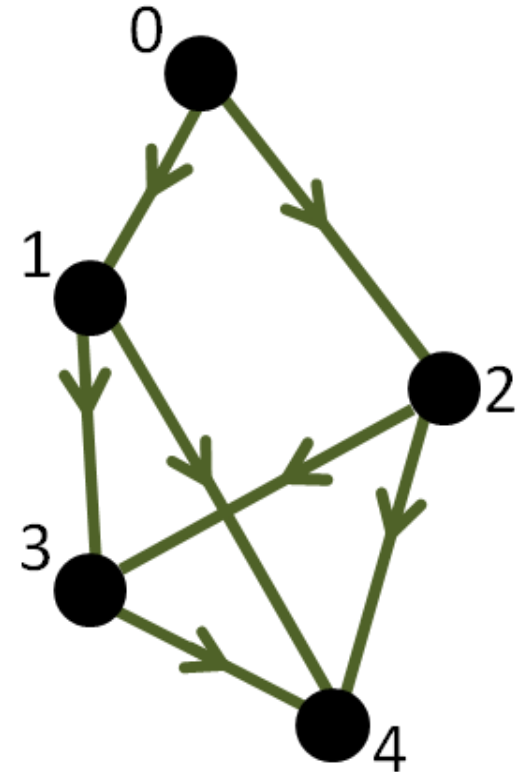
Each node represents an event occurring at one time

- ⇒ Time constrains flows
- ⇒ Edges point in one direction only
- ⇒ No Loops



DAG – Directed Acyclic Networks

- Citation Graphs
- Patents
- Court Judgements
- Physical Flow
 - Raw materials to finished goods
- Logical Flow
 - Spreadsheets
 - All Maths
- Space-Time
 - Causal Set approach to quantum gravity [Dowker 2004]

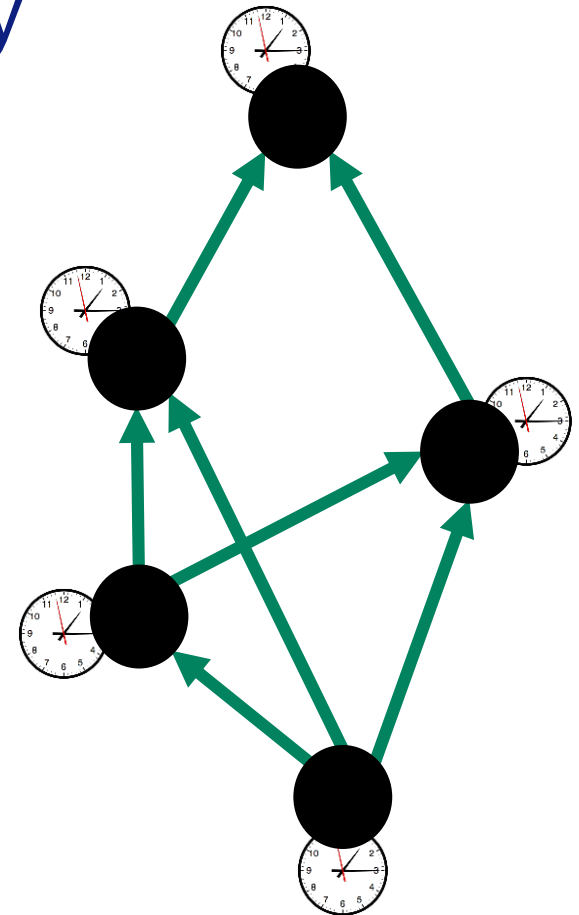


Innovations

Each node represents a discovery

- Patent
- Academic Paper
- Law Judgment

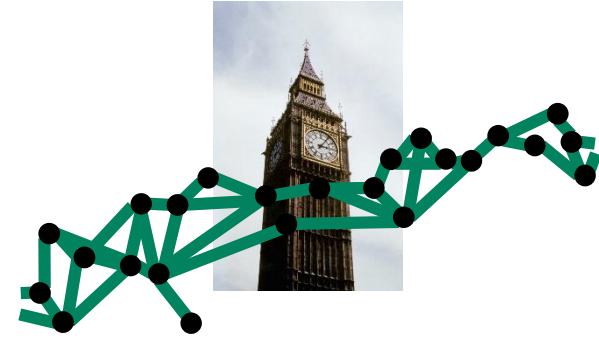
Information is now **copied** from one node to all connected events in the future



Different process from a random walk

Similar to epidemics but different network

TimeE and Networks



- Transitive Reduction
- Dimension

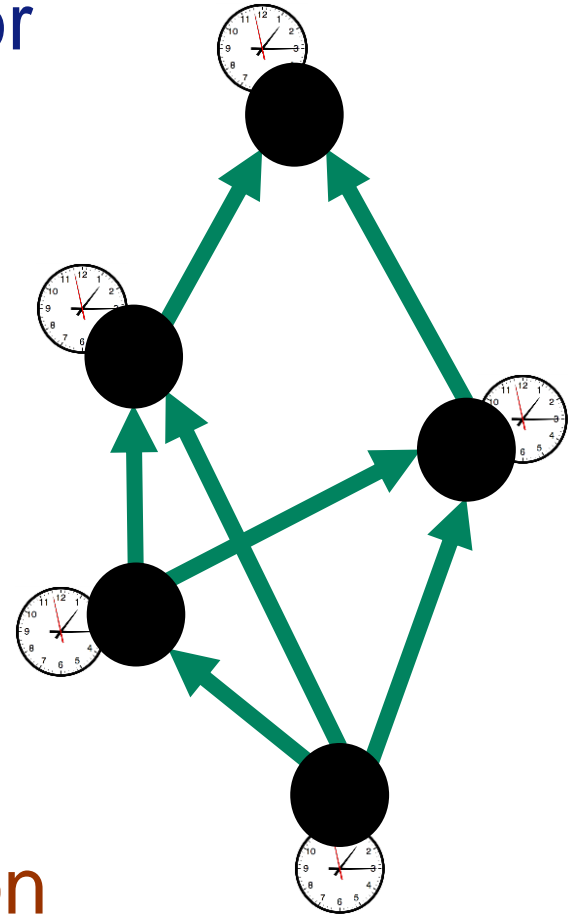
Transitive Reduction

Remove all edges not needed for causal links

- Uniquely defined because of causal structure

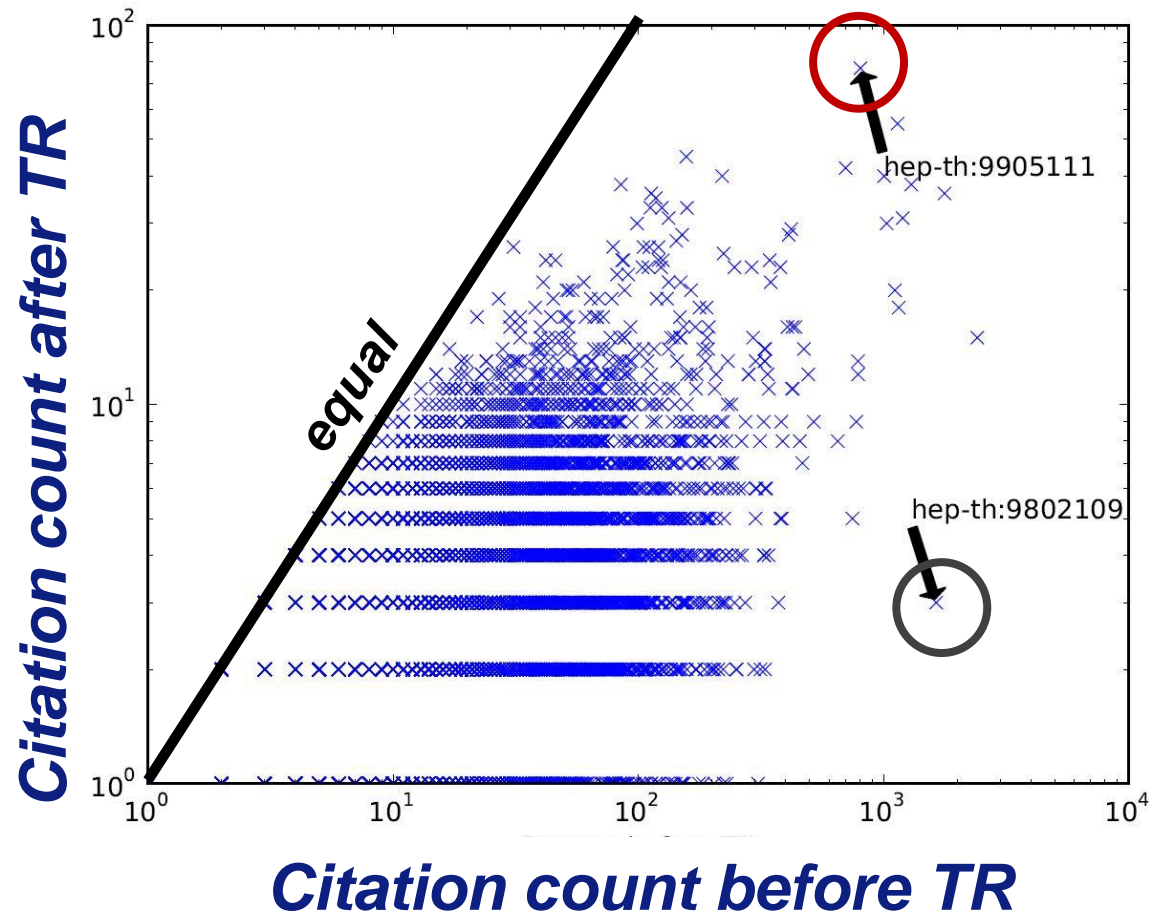
Conjecture:

This removes unnecessary
or indirect influence on innovation



arXiv paper repository

Winner (806 → 77)



**Loser
(1641 → 3)**

Transitively Reducing a Citation Network

- The Transitively Reduced citation network has the same causal structure as the original data.
 - Information can still flow
- Transitive Reduction removes **~80%** edges
 - Simkin & Roychowdury 2002; Goldberg, Anthony, TSE 2015
- **Conjecture:** the edges in Transitive Reduced citation network are the most useful.

Winner and Losers

- ‘Winners’ = papers whose citation rank increases after Transitive Reduction
 - ⇒ Most useful to many different areas
 - ⇒ More impact
- ‘Losers’ = papers that drop relative to others after Transitive Reduction
 - ⇒ papers cited within a narrow group
 - ⇒ Less impact

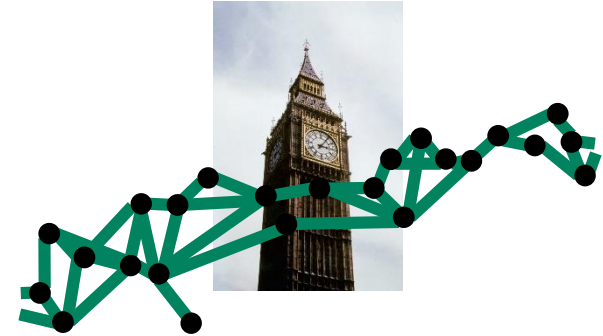
Citation Counts

Citations of academic papers not always made for good reasons

- Cite your own paper
- Cite a standard paper because everyone does
- Copy a citation from another paper
(80%? [Simkin and Roychowdhury 2003])

Transitive reduction removes poor citations

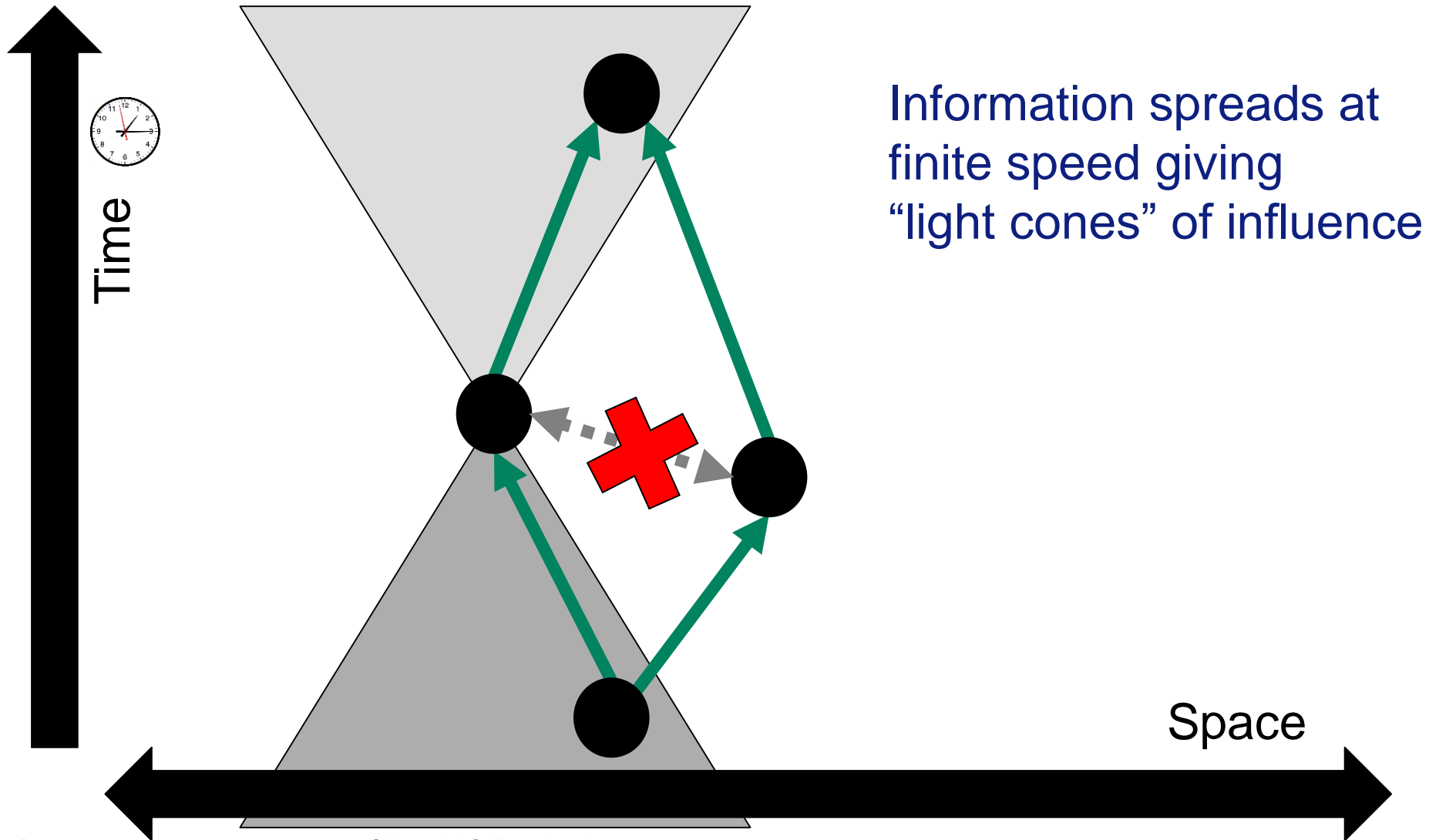
TimeE and Networks



- Transitive Reduction
- Space-Time Dimension

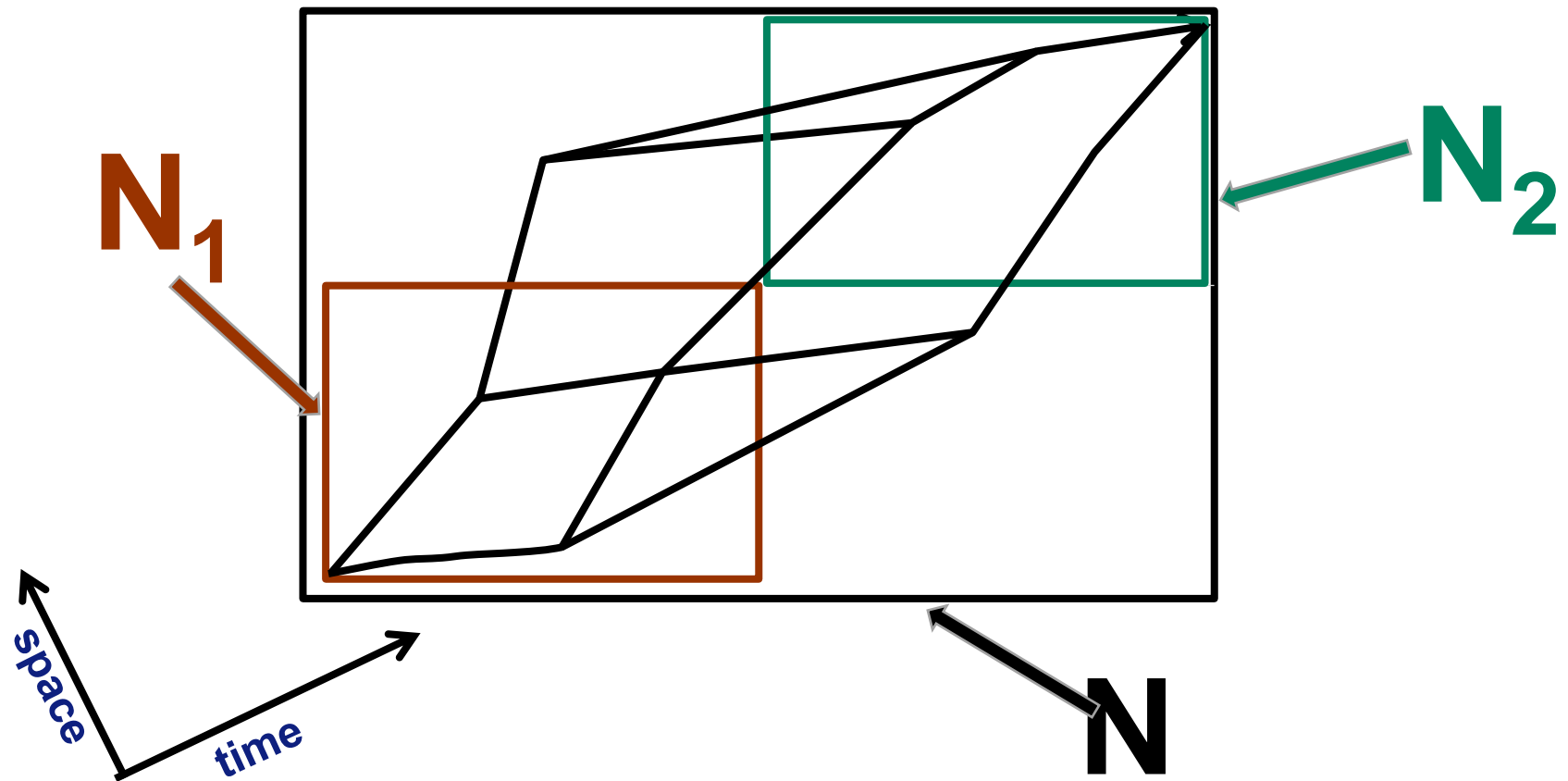
Space-Time

Minkowski
space-time

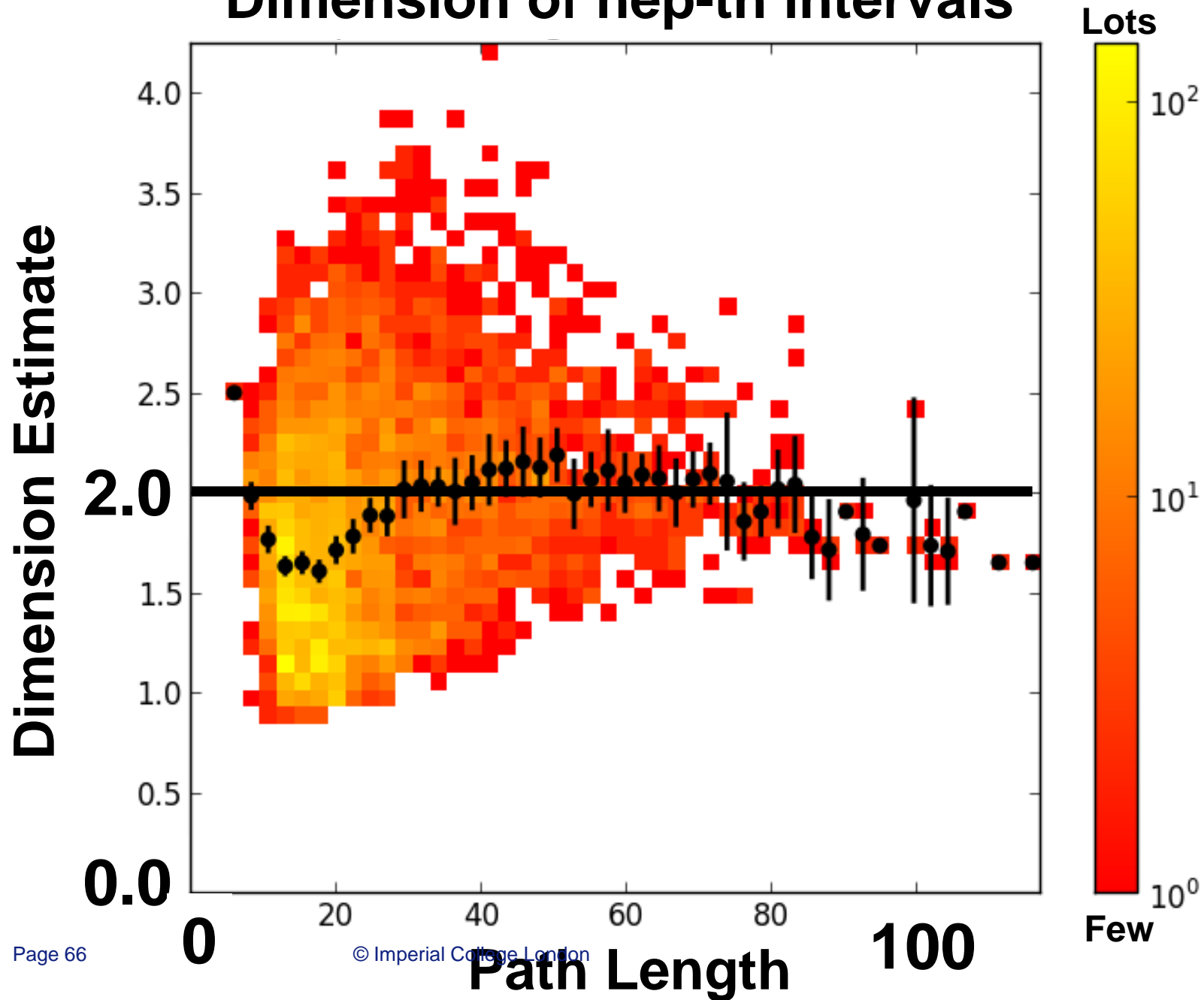


Midpoint Scaling Dimension

- We should expect to see $N_1 \approx N_2 \approx N \times 2^{-d}$



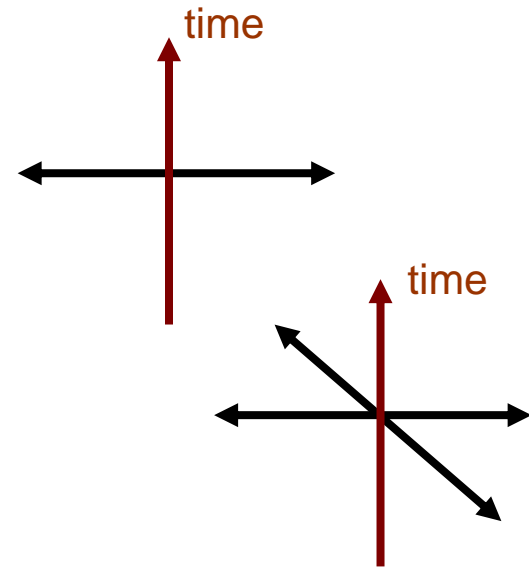
Dimension of hep-th intervals



What does this tell us?

For two different dimension measures on two **arXiv** subsets:

- **hep-th** has dimension 2
 - 1 time, 1 “topic direction”
- **hep-ph** has dimension 3
 - 1 time, 2 “topic directions”



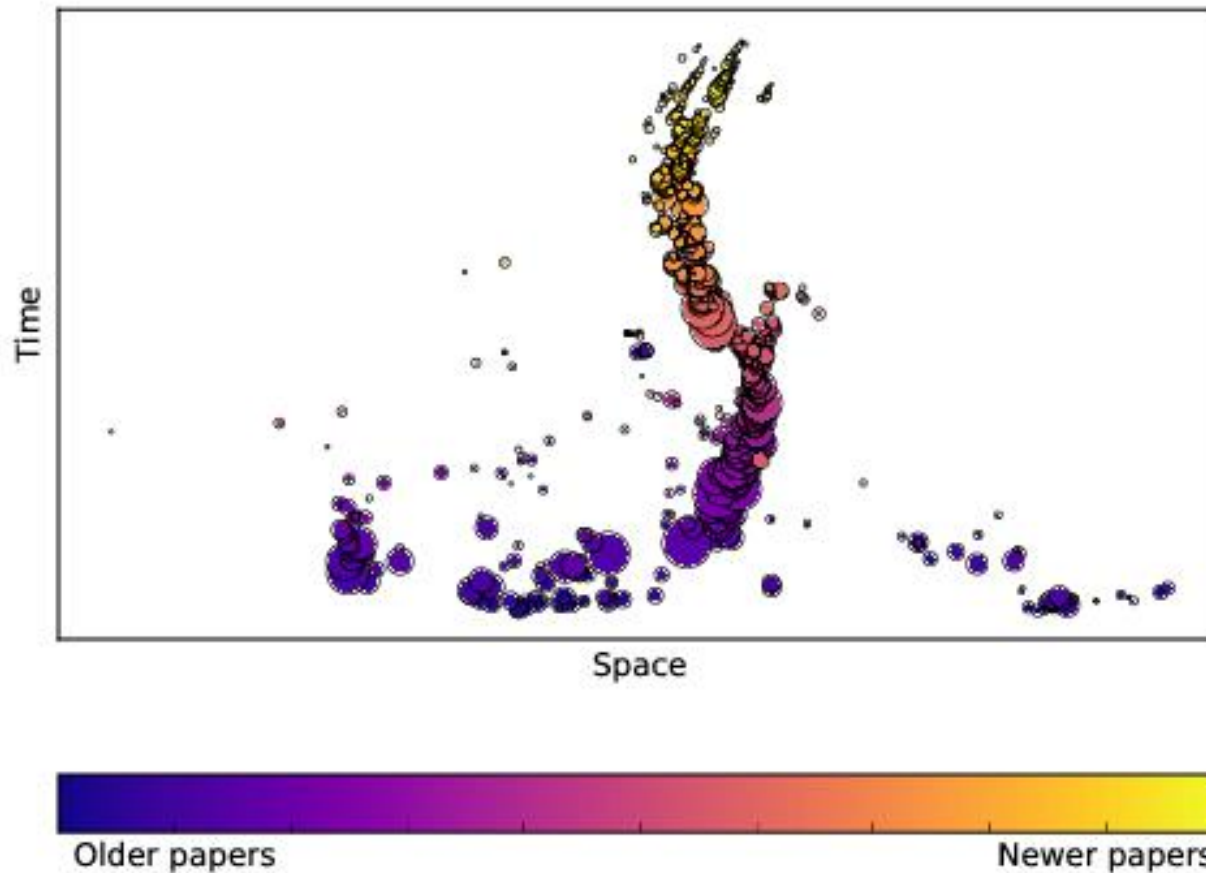
Dimension of a DAG gives a new insight into differences between research topics

Dimensions

Data	Dimension
hep-th (String Theory)	2
hep-ph (Particle Physics)	3
quant-ph (quantum physics)	3
astro-ph (astrophysics)	3.5
US Patents	>4
US Supreme Court Judgments	3 (short times), 2 (long times)

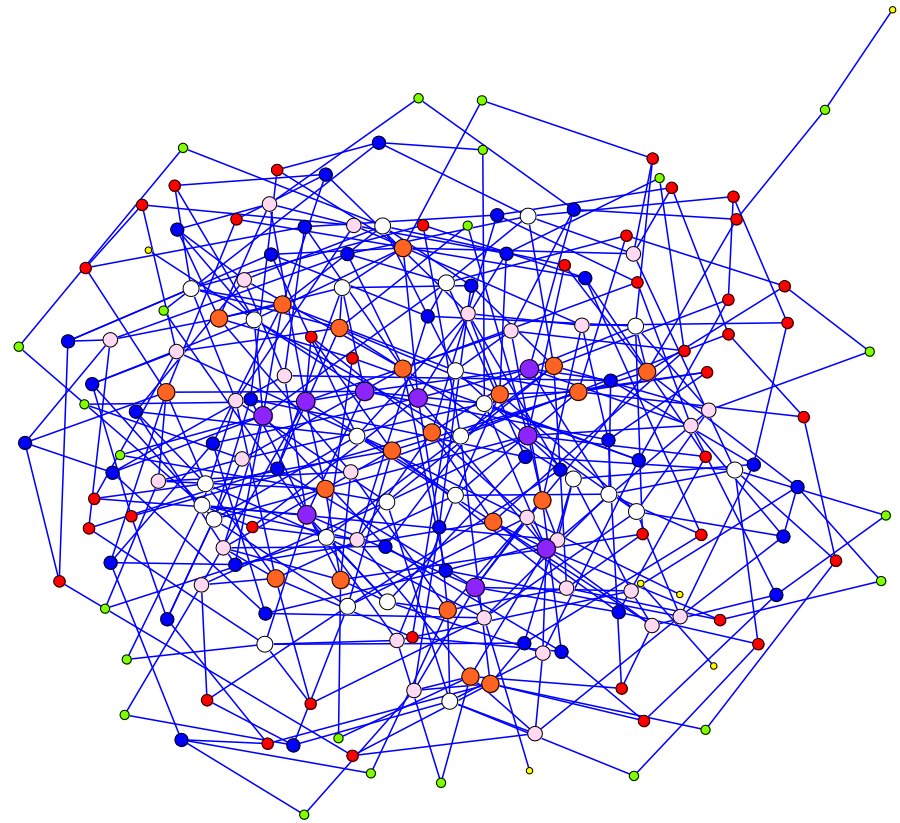
String theory appears to be a narrow field

Embedding hep-th papers



Future Directions: DAG Temporal Networks

- Refine existing measures
- Interpretation of measures
 - Social science input
- Develop practical citation network tools
- Applications other than citation networks
- Theoretical models and Mathematical results
 - Connections to directed percolation
 - Connections to work in partially ordered sets



NETWORK SCIENCE

What is “Network Science”?

- Based on analysis through networks
 - Graphs, hypergraphs
- Part of wider studies in complexity
 - Local interactions produce emergent phenomena
- Not new
 - Social Network Analysis since 50's
 - Mathematical graph theory since Euler in 1735
- New aspect is Information Age
 - Large data sets and their analysis now possible
- Multidisciplinary
 - Communication difficult between fields

Does “Network Science” really exist?

Possible criticisms:-

- No coherent definition
- Too broad to be a single area
- New name for old work = ***Hype***
- Too early to say
- No need to define a new field

[“Network Science”, nap.edu, 2005]

Are networks providing new insights?

- Another approach to statistical analysis and data mining
- Sometimes this is a better way to analyse
 - Gives new questions e.g. Small world definition
 - Gives new answers e.g. Small world models
- Brings the tools of Complexity
 - Scaling

Complexity

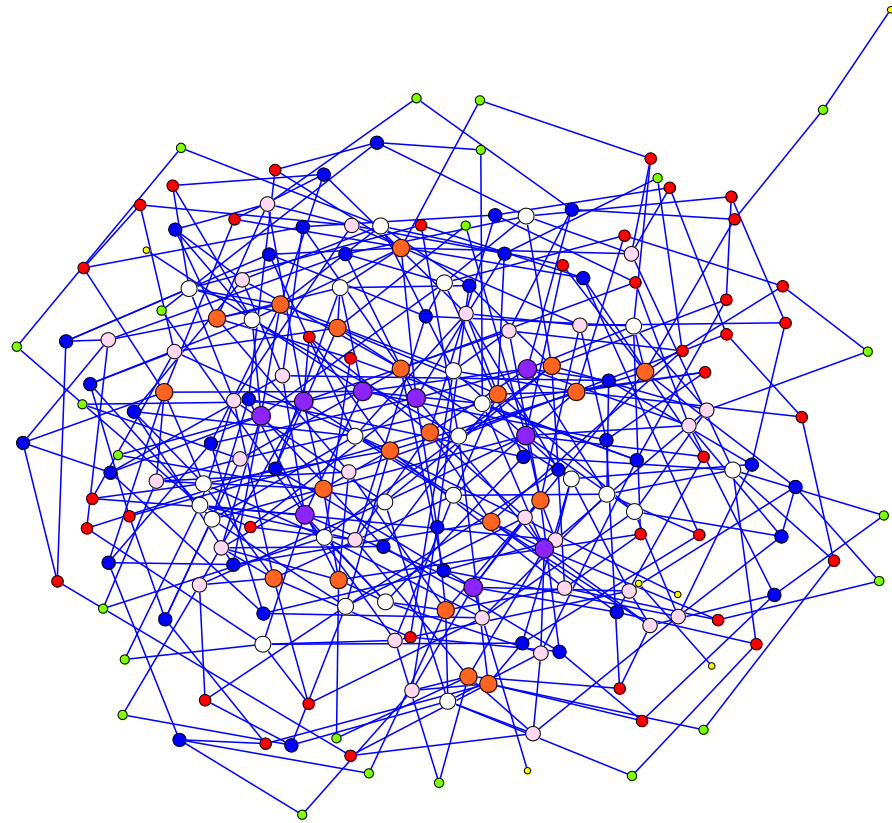


Science

Social & Cultural Analytics Lab,
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netplexity

THANKS



See netplexity.org
or search for *Tim Evans Networks*

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