Small-world networks

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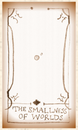
Principles of Complex Systems, Vol. 1 | @pocsvox
CSYS/MATH 300, Fall, 2020

Prof. Peter Sheridan Dodds | @peterdodds

Computational Story Lab | Vermont Complex Systems Center
Vermont Advanced Computing Core | University of Vermont



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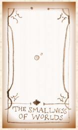

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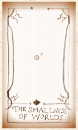
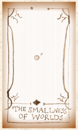
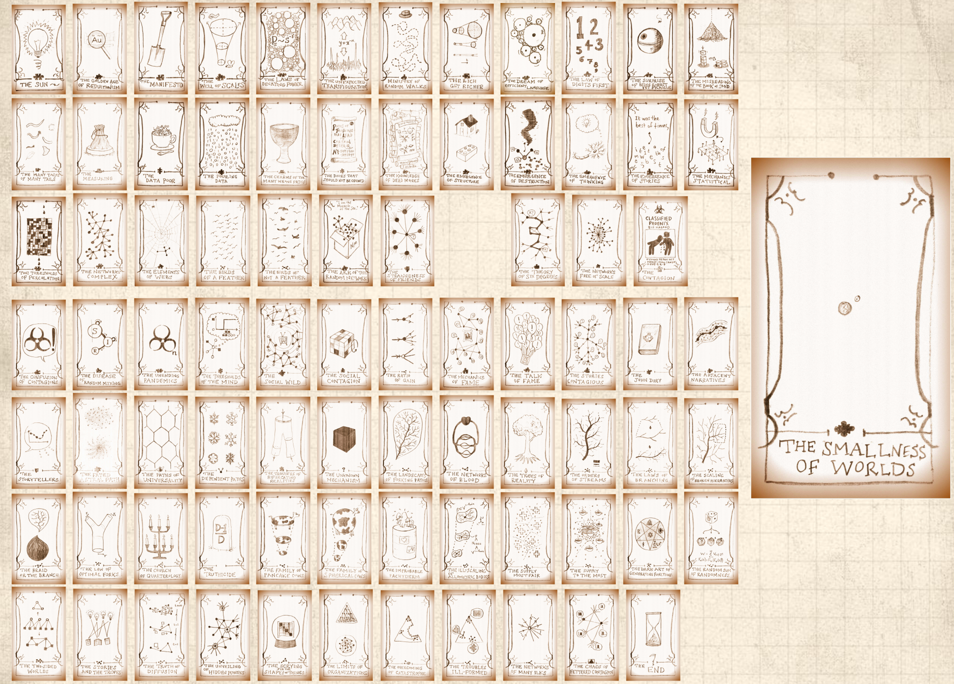


Outline




THE SUN
THE GOLDEN AGE OF REDUCTIONISM
THE MANIFESTO
THE WELL OF SCALES
THE LAWS OF DECAYING POWER
THE UNEXPECTED TRANSFIGURATION
MINISTRY OF RANDOM WALKS
THE RICH GET RICHER
THE DREAM OF EFFICIENT LANGUAGE
THE LAW OF DIGITS FIRST
THE SURPRISE OF BEING ROBUST YET FRAGILE
THE MISREADING OF THE BOOK OF SAND
THE MANY TALES OF MANY TAILS
THE MEASURING
THE DATA POOR
THE POURING DATA
THE CHARMS OF THE MANY WRONG PATHS
THE DOORS THAT SHOULD NOT BE OPENED
THE KNOWLEDGE OF DEAD MONKS
THE EMERGENCE OF STRUCTURE
THE EMERGENCE OF DESTRUCTION
THE EMERGENCE OF THINKING
THE EMERGENCE OF STORIES
THE MECHANICS STATISTICAL
THE THRESHOLDS OF PERCOLATION
THE NETWORKS COMPLEX
THE ELEMENTS OF WEBS
THE BIRDS OF A FEATHER
THE BIRDS OF NOT A FEATHER
THE ARK OF THE RANDOM NETWORK
THE STRANGENESS OF FRIENDS
THE THEORY OF SIX DEGREES
THE NETWORKS FREE OF SCALE
CLASSIFIED
PHOENIX
THE CONTAGION
THE CONFUSION OF CONTAGIONS
THE DISEASE OF RANDOM MIXING
THE UNENDING PANDEMICS
THE THRESHOLDS OF THE MIND
THE SOCIAL WILD
THE SOCIAL CONTAGION
THE RATIO OF GAIN
THE MECHANICS OF FAME
THE TALK OF FAME
THE STORIES CONTAGIOUS
THE JOHN DORY
THE ADJACENT NARRATIVES
THE STORYTELLERS
THE FATED ASTRAL PATH
THE PATHS OF UNIVERSALITY
THE DEPENDENT PATHS
THE TROUSERS OF BIFURCATING REALITIES
THE UNKNOWN MECHANISM
THE LANDSCAPES OF FORKING PATHS
THE NETWORKS OF BLOOD
THE TREES OF REALITY
THE ORDERS OF STREAMS
THE LAWS OF BRANCHING
THE SCALING OF BROKEN HIERARCHIES
THE BRAID OR THE BRANCH
THE LAW OF OPTIMAL FORKS
THE CHURCH OF QUARTEROLOGY
THE TRUTHICIDE
THE FAMILY OF PANCAKE COWS
THE FAMILY OF SPHERICAL COWS
THE IMPROBABLE PACHYDERM
THE ILL-SCALING OF ALLOMETRIC BODIES
THE SUPPLY MOST FAIR
THE SUPPLY TO THE MOST
THE DARK ART OF GENERATING FUNCTIONS
THE RANDOM SUM OF RANDOMNESS
THE TWO-SIDED WORLDS
THE STORIES AND THE TROPES
THE TRUTH OF DIFFUSION
THE UNVEILING OF HIDDEN POWERS
THE SCRYING FOR THE SHAPES OF THINGS
THE LIMITS OF ORGANIZATIONS
THE OVERCOMING OF CATASTROPHE
THE TROUBLES ILL-FORMED
THE NETWORKS OF MANY ILKS
THE CHAOS OF FETTERED CONTAGION
THE END
THE SMALLNESS OF WORLDS

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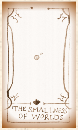
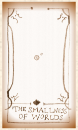


People thinking about people:

How are social networks structured?

- How do we define and measure connections?
- Methods/issues of self-report and remote sensing.



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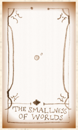
- How does information move through social networks?
- Which rules give the best ‘game of society?’



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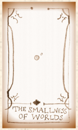
Sociotechnical phenomena and algorithms:

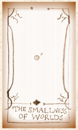
- What can people and computers do together? (google)
- Use Play + Crunch to solve problems. Which problems?



Social Search

A small slice of the pie:

- Q. Can people pass messages between distant individuals using only their existing social connections?



Social Search

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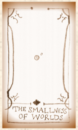
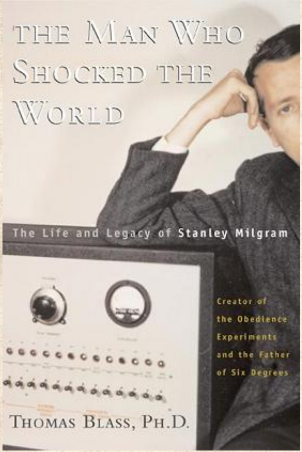
- Q. Can people pass messages between distant individuals using only their existing social connections?
- A. Apparently yes ...

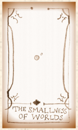


Milgram's social search experiment (1960s)



http://www.stanleymilgram.com

- Target person = Boston stockbroker.
- 296 senders from Boston and Omaha.



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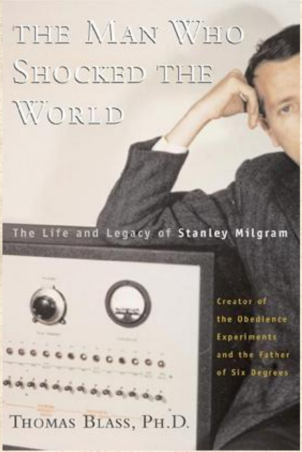

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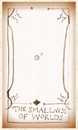
- 20% of senders reached target.
- chain length $\simeq 6.5$.



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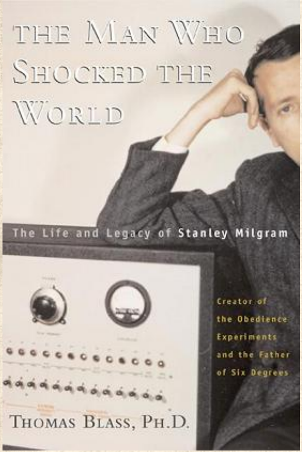

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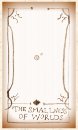
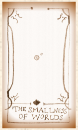
Popular terms:

- The Small World Phenomenon;
- "Six Degrees of Separation."

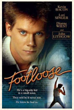


From Frigyes Karinthy's "Chain-links" in "Everything is Different", 1929:

'A fascinating game grew out of this discussion. One of us suggested performing the following experiment to prove that the population of the Earth is closer together now than they have ever been before. We should select any person from the 1.5 billion inhabitants of the Earth–anyone, anywhere at all. He bet us that, using no more than five individuals, one of whom is a personal acquaintance, he could contact the selected individual using nothing except the network of personal acquaintances. For example, "Look, you know Mr. X.Y., please ask him to contact his friend Mr. Q.Z., whom he knows, and so forth."'

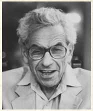


Six Degrees of Kevin Bacon:

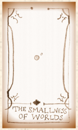


- It's a game: "Kevin Bacon is the Center of the Universe"
- The Oracle of Bacon

Six Degrees of Paul Erdös:



- Academic papers.
- Erdös Number
- Erdös Number Project



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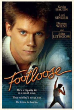

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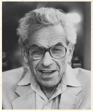

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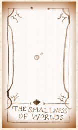

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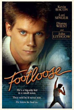

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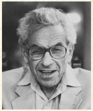

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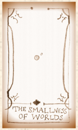

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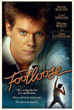

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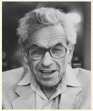

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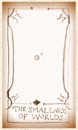
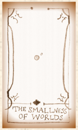
- Natalie Hershlag's (Portman's) EB# = 5 + 2 = 7.





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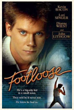

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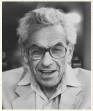

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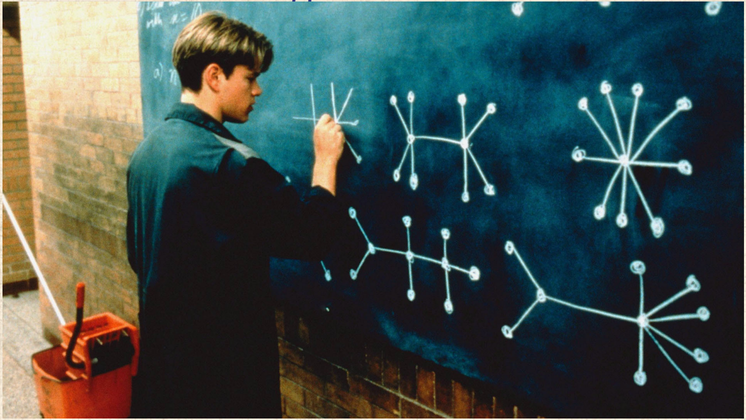
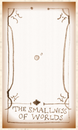
- The EBS# is also a thing: erdosbaconsabbath.com.

Good Will Hunting:



- Boardwork by Dan Kleitman, EB# = 1 + 2 = 3.
- See Kleitman's sidebar in Mark Saul's Movie Review (Notices of the AMS, Vol. 45, 1998.)



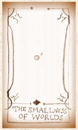
You may already be a winner in NSA's "three-degrees" surveillance sweepstakes!

NSA's probes could cover hundreds of millions of Americans. Thanks, Kevin Bacon.

by **Sean Gallagher** - July 18 2013, 4:00pm EDT

BIG DATA 109

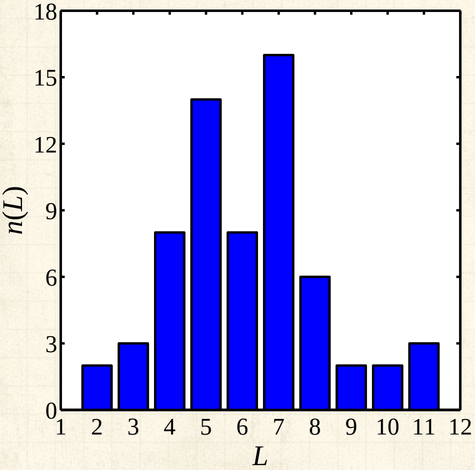
Aurich Lawson



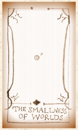
- Many people are within three degrees from a random person …

The problem

Lengths of successful chains:

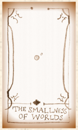


From Travers and Milgram (1969) in Sociometry: [12]
"An Experimental Study of the Small World Problem."



The problem

Two features characterize a social ‘Small World’:



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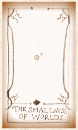

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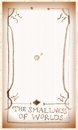

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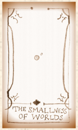

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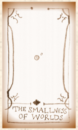
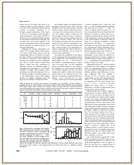
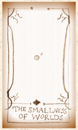


Social Search

Milgram's small world experiment with email:

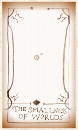


"An Experimental study of Search in Global Social Networks"
Dodds, Muhamad, and Watts,
Science, **301**, 827–829, 2003. [6]



Social search—the Columbia experiment

- 60,000+ participants in 166 countries



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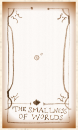

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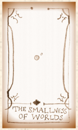

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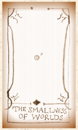

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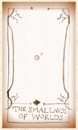

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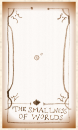

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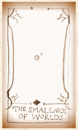

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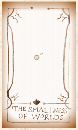

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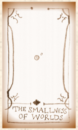
We were lucky and contagious (more later):

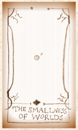
"Using E-Mail to Count Connections", Sarah Milstein, New York Times, Circuits Section (December, 2001)



All targets:

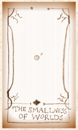
Table S1

Target	*City*	*Country*	*Occupation*	*Gender*	*N*	N_c (%)	r (r_0)	<L>
1	Novosibirsk	Russia	PhD student	F	8234	20(0.24)	64 (76)	4.05
2	New York	USA	Writer	F	6044	31 (0.51)	65 (73)	3.61
3	Bandung	Indonesia	Unemployed	M	8151	0	66 (76)	n/a
4	New York	USA	Journalist	F	5690	44 (0.77)	60 (72)	3.9
5	Ithaca	USA	Professor	M	5855	168 (2.87)	54 (71)	3.84
6	Melbourne	Australia	Travel Consultant	F	5597	20 (0.36)	60 (71)	5.2
7	Bardufoss	Norway	Army veterinarian	M	4343	16 (0.37)	63 (76)	4.25
8	Perth	Australia	Police Officer	M	4485	4 (0.09)	64 (75)	4.5
9	Omaha	USA	Life Insurance Agent	F	4562	2 (0.04)	66 (79)	4.5
10	Welwyn Garden City	UK	Retired	M	6593	1 (0.02)	68 (74)	4
11	Paris	France	Librarian	F	4198	3 (0.07)	65 (75)	5
12	Tallinn	Estonia	Archival Inspector	M	4530	8 (0.18)	63(79)	4
13	Munich	Germany	Journalist	M	4350	32 (0.74)	62 (74)	4.66
14	Split	Croatia	Student	M	6629	0	63 (77)	n/a
15	Gurgaon	India	Technology Consultant	M	4510	12 (0.27)	67 (78)	3.67
16	Managua	Nicaragua	Computer analyst	M	6547	2 (0.03)	68 (78)	5.5
17	Katikati	New Zealand	Potter	M	4091	12 (0.3)	62 (74)	4.33
18	Elderton	USA	Lutheran Pastor	M	4438	9 (0.21)	68 (76)	4.33
Totals					98,847	384 (0.4)	63 (75)	4.05



Social search—the Columbia experiment

- Milgram's participation rate was roughly 75%



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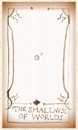
- Email version: Approximately 37% participation rate.



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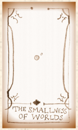

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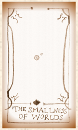
- $\Rightarrow$ 384 completed chains (1.6% of all chains).



Social search—the Columbia experiment

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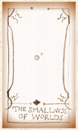

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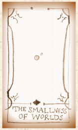

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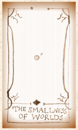

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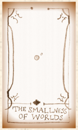
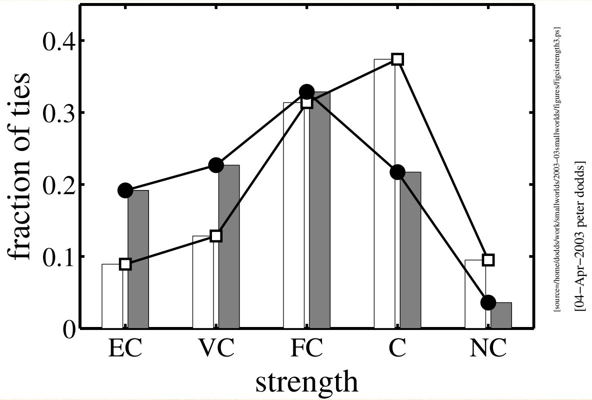
- e.g., $\searrow$ 15% in attrition rate
  $\Rightarrow$ $\nearrow$ 800% in completion rate

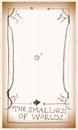


Social search—the Columbia experiment

Comparing successful to unsuccessful chains:

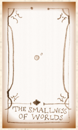
- Successful chains used relatively weaker ties:





Social search—the Columbia experiment

Successful chains disproportionately used:



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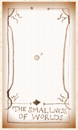

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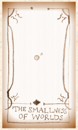

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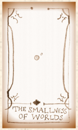

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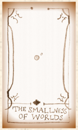

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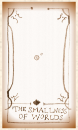

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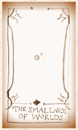

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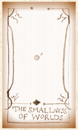

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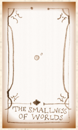
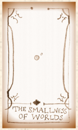
Geography $\rightarrow$ Work



Social search—the Columbia experiment

Senders of successful messages showed little absolute dependency on

- age, gender



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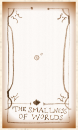

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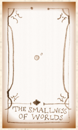

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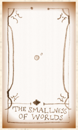

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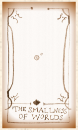

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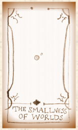
- country of residence
- income
- religion
- relationship to recipient

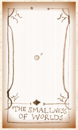
Range of completion rates for subpopulations:
30% to 40%



Social search—the Columbia experiment

Mildly bad for continuing chain:

choosing recipients because “they have lots of friends” or because they will “likely continue the chain.”



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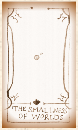

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Why:

- Specificity important

Social search—the Columbia experiment

Mildly bad for continuing chain:

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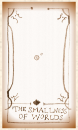
Why:

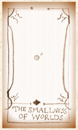
- Specificity important
- Successful links used relevant information. (e.g. connecting to someone who shares same profession as target.)



Social search—the Columbia experiment

Basic results:

- $\langle L \rangle = 4.05$ for all completed chains



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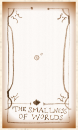

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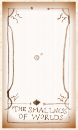

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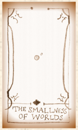

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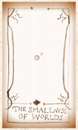

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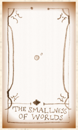
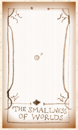
- Milgram: $L_* \simeq 9$



Usefulness:

Harnessing social search:



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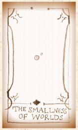

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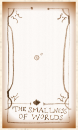

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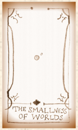

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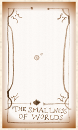

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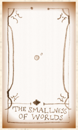

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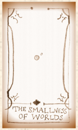

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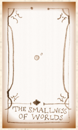
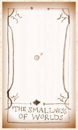
- Must be ‘non-gameable.’



Red balloons:

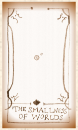
A Grand Challenge:



Red balloons:

A Grand Challenge:

- 1969: The Internet is born (the ARPANET—four nodes!).



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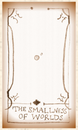

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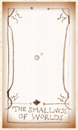

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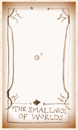

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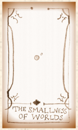

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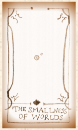

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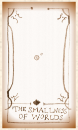

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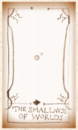

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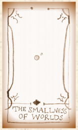

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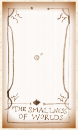

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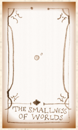

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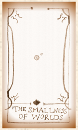

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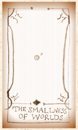

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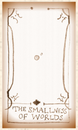

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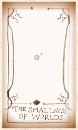

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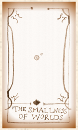

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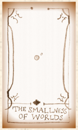

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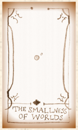
- Max payout = $4000 per balloon.



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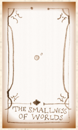

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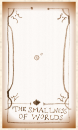

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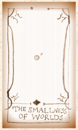

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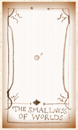

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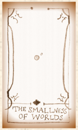

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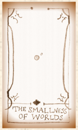
- Worthwhile looking at these competing strategies. [9]



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Finding an errant panda

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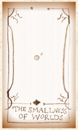
Another neighbor posted a photograph of two zoo workers, one in safari shorts standing on a rooftop, one holding a giant butterfly net. Soon the zoo announced: “Rusty the red panda has been recovered, crated & is headed safely back to the National Zoo!”



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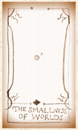

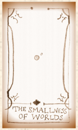

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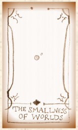
- Motherboard, Vice: One Degree of Separation in the Forever War by Brian Castner (November 11, 2015)

Outline




THE SUN
THE GOLDEN AGE OF REDUCTIONISM
THE MANIFESTO
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THE RICH GET RICHER
THE DREAM OF EFFICIENT LANGUAGE
THE LAW OF DIGITS FIRST
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THE MISREADING OF THE BOOK OF SAND
THE MANY TALES OF MANY TAILS
THE MEASURING
THE DATA POOR
THE POURING DATA
THE CHARMS OF THE MANY WRONG PATHS
THE DOORS THAT SHOULD NOT BE OPENED
THE KNOWLEDGE OF DEAD MONKS
THE EMERGENCE OF STRUCTURE
THE EMERGENCE OF DESTRUCTION
THE EMERGENCE OF THINKING
It was the best of times,
THE EMERGENCE OF STORIES
THE MECHANICS STATISTICAL
THE THRESHOLDS OF PERCOLATION
THE NETWORKS COMPLEX
THE ELEMENTS OF WEBS
THE BIRDS OF A FEATHER
THE BIRDS OF NOT A FEATHER
THE ARK OF THE RANDOM NETWORK
THE STRANGENESS OF FRIENDS
THE SMALLNESS OF WORLDS
THE NETWORKS FREE OF SCALE
CLASSIFIED
PHOENIX
BIO HAZARD
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THE CONFUSION OF CONTAGIONS
THE DISEASE OF RANDOM MIXING
THE UNENDING PANDEMICS
THE THRESHOLDS OF THE MIND
THE SOCIAL WILD
THE SOCIAL CONTAGION
THE RATIO OF GAIN
THE MECHANICS OF FAME
THE TALK OF FAME
THE STORIES CONTAGIOUS
THE JOHN DORY
THE ADJACENT NARRATIVES
THE STORYTELLERS
THE FATED ASTRAL PATH
THE PATHS OF UNIVERSALITY
THE DEPENDENT PATHS
THE TROUSERS OF BIFURCATING REALITIES
THE UNKNOWN MECHANISM
THE LANDSCAPES OF FORKING PATHS
THE NETWORKS OF BLOOD
THE TREES OF REALITY
THE ORDERS OF STREAMS
THE LAWS OF BRANCHING
THE SCALING OF BROKEN HIERARCHIES
THE BRAID OR THE BRANCH
THE LAW OF OPTIMAL FORKS
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THE TRUTHICIDE
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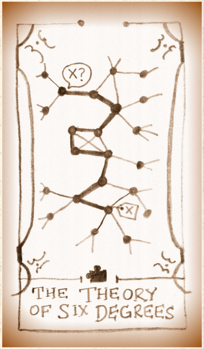
THE CHAOS OF FETTERED CONTAGION
THE END


X?
X
THE THEORY OF SIX DEGREES

The social world appears to be small ...why?

Theory: how do we understand the small world property?

- Connected random networks have short average path lengths:

$$\langle d_{AB} \rangle \sim \log(N)$$

N = population size,

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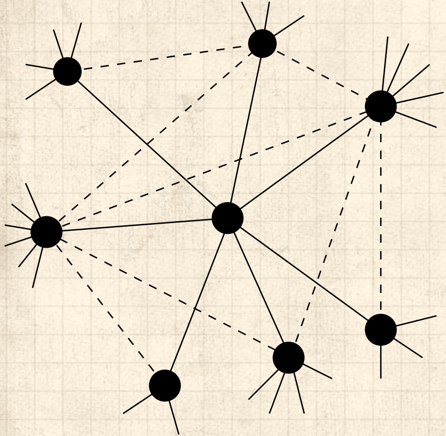
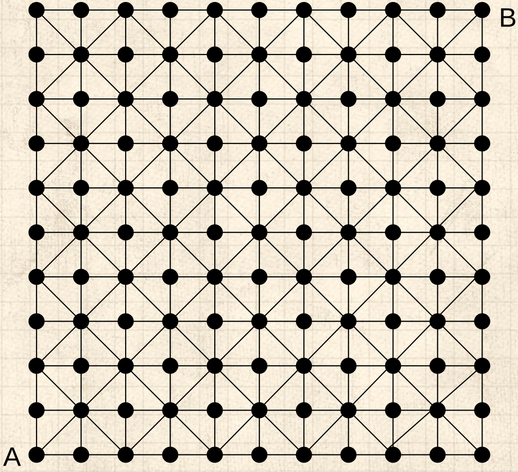
- But: social networks aren't random ...

Simple socialness in a network:



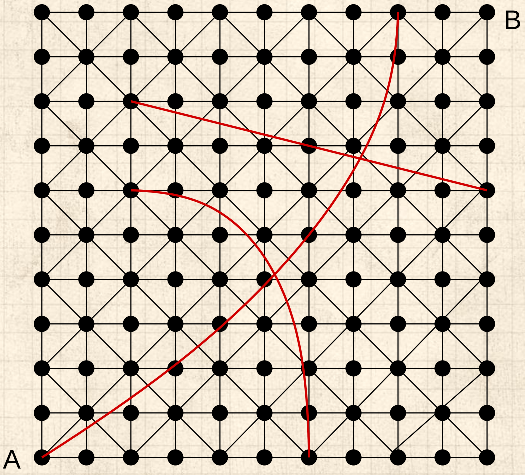
Need "clustering" (your friends are likely to know each other):

Non-randomness gives clustering:



$d_{AB} = 10 \rightarrow$ too many long paths.

Randomness + regularity



Now have $d_{AB} = 3$

$\langle d \rangle$ decreases overall

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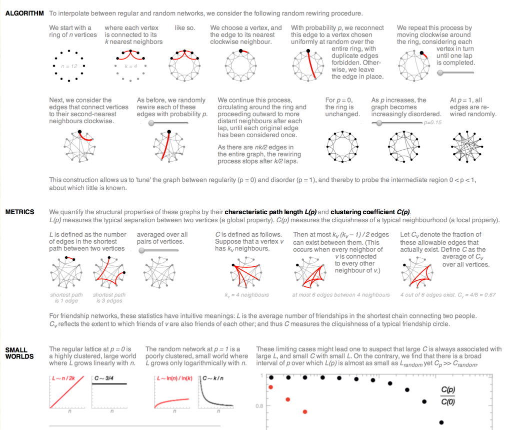
Very weak requirements:

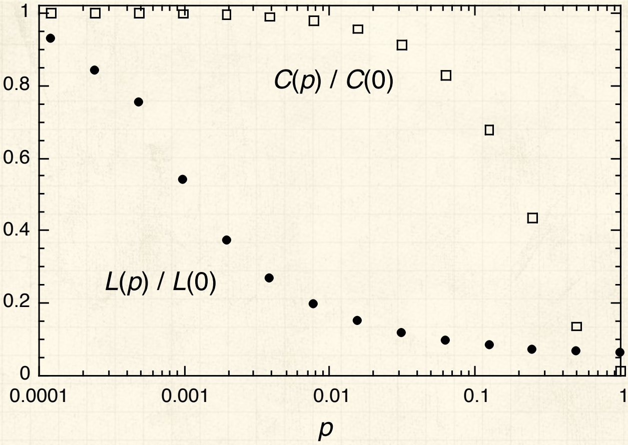
- local regularity + random short cuts

Papers should be apps:



- Bret Victor's Scientific Communication As Sequential Art
- Interactive figures and tables = windows into large data sets (empirical or simulated).

The structural small-world property:



- $L(p)$ = average shortest path length as a function of p
- $C(p)$ = average clustring as a function of p

Previous work—finding short paths

But are these short cuts findable?

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Nope. [8]

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Nodes cannot find each other quickly
with any local search method.

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Need a more sophisticated model ...

Previous work—finding short paths

- What can a local search method reasonably use?

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- How to find things without a map?

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- Need some measure of distance between friends and the target.

Previous work—finding short paths

- What can a local search method reasonably use?
- How to find things without a map?
- Need some measure of distance between friends and the target.

Some possible knowledge:

- Target's identity
- Friends' popularity
- Friends' identities
- Where message has been

Previous work—finding short paths

Jon Kleinberg (Nature, 2000) [8]
"Navigation in a small world."

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Allowed to vary:

1. local search algorithm

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Allowed to vary:

1. local search algorithm
   and
2. network structure.

Previous work—finding short paths

Kleinberg's Network:

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1. Start with regular d-dimensional cubic lattice.

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$$p_{ij} \propto {x_{ij}}^{-\alpha}.$$

- $\alpha = 0$: random connections.
- α large: reinforce local connections.
- $\alpha = d$: connections grow logarithmically in space.

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Theoretical optimal search:

- “Greedy” algorithm.

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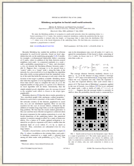
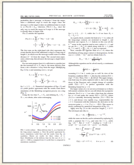
But: social networks aren't lattices plus links.

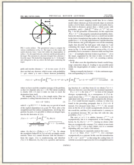
Advances for understanding Kleinberg's model:



"Kleinberg Navigation in Fractal Small World Networks"
Roberson and ben-Avraham,
Phys. Rev. E, **74**, 017101, 2006. [10]



"Asymptotic behavior of the Kleinberg model"
Carmi et al.,
Phys. Rev. Lett., **102**, 238702, 2009. [4]



"Extended navigability of small world networks: Exact results and new insights"
Cartoza and De Los Rios,
Phys. Rev. Lett., **2009**, 238703, 2009. [5]

Previous work—finding short paths

- If networks have hubs can also search well: Adamic et al. (2001) [1]

$$P(k_i) \propto k_i^{-\gamma}$$

where k = degree of node i (number of friends).

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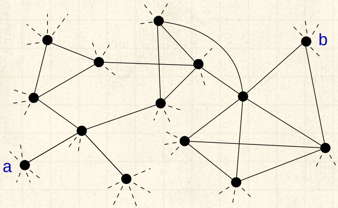
- Basic idea: get to hubs first (airline networks).
- But: hubs in social networks are limited.

Outline

The problem

If there are no hubs and no underlying lattice, how can search be efficient?



Which friend of a is closest to the target b?

What does 'closest' mean?

What is 'social distance'?

Models

One approach: incorporate identity.

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Identity is formed from attributes such as:

- Geographic location
- Type of employment
- Religious beliefs
- Recreational activities.

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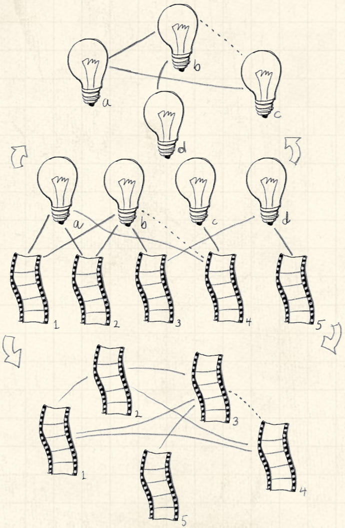
Groups are formed by people with at least one similar attribute.

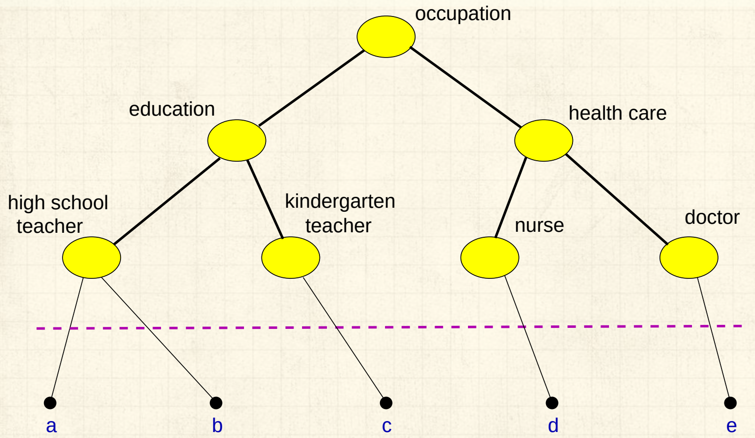
Attributes ⇔ Contexts ⇔ Interactions ⇔ Networks.

Bipartite affiliation structures:



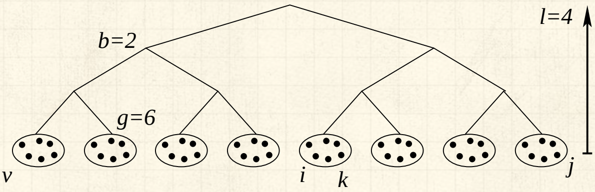
- Many real-world networks have an underlying multi-partite structure.
  - Stories-tropes.
  - Boards and directors.
  - Films-actors-directors.
  - Classes-teachers-students.
  - Upstairs-downstairs.
- Unipartite networks may be induced or co-exist.

Social distance—Context distance



Models

Distance between two individuals x_{ij} is the height of lowest common ancestor.



$x_{ij} = 3$, $x_{ik} = 1$, $x_{iv} = 4$.

Models

Individuals are more likely to know each other the closer they are within a hierarchy.

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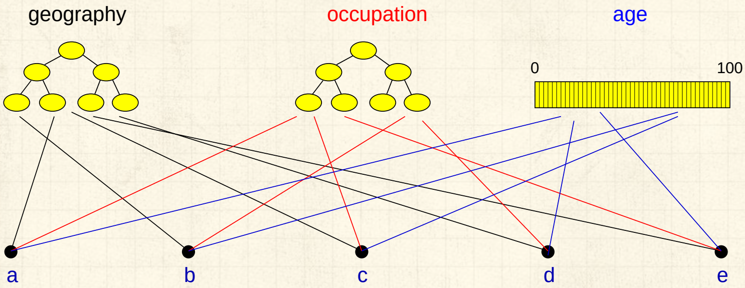
- α large: local connections.

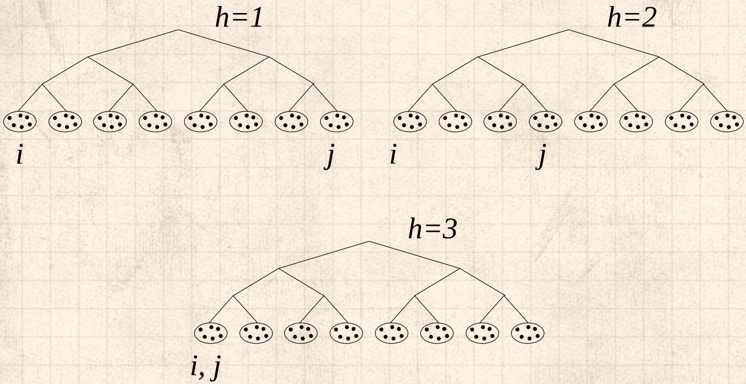
Models

Generalized affiliation networks



- Blau & Schwartz [2], Simmel [11], Breiger [3], Watts *et al.* [13]; see also Google+ Circles.

The model



$\vec{v}_i = [1\ 1\ 1]^T$, $\vec{v}_j = [8\ 4\ 1]^T$

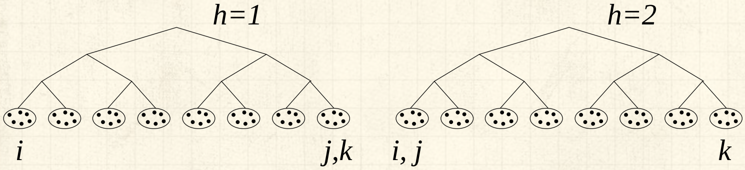
$x^1_{ij} = 4,\ x^2_{ij} = 3,\ x^3_{ij} = 1.$

Social distance:

$$y_{ij} = \min_h x^h_{ij}.$$

The model

Triangle inequality doesn't hold:



$$y_{ik} = 4 > y_{ij} + y_{jk} = 1 + 1 = 2.$$

The model

- Individuals know the identity vectors of

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  1. themselves,

The model

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- Individuals know the identity vectors of
  1. themselves,
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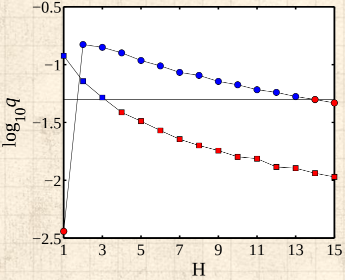
  3. the target.
- Individuals can estimate the social distance between their friends and the target.
- Use a greedy algorithm + allow searches to fail randomly.

The model-results—searchable networks

$\alpha = 0$ versus $\alpha = 2$ for $N \simeq 10^5$:



$q \geq r$

$q < r$

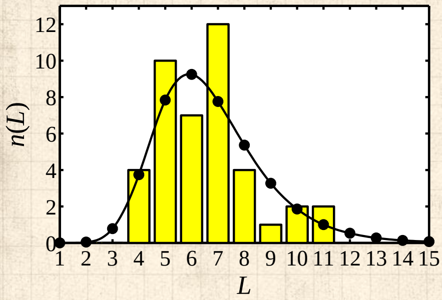
$r = 0.05$

q = probability an arbitrary message chain reaches a target.

- A few dimensions help.
- Searchability decreases as population increases.
- Precise form of hierarchy largely doesn't matter.

The model-results

Milgram's Nebraska-Boston data:



Model parameters:

- $N = 10^8$,
- $z = 300$, $g = 100$,
- $b = 10$,
- $\alpha = 1$, $H = 2$;

- $\langle L_{\text{model}} \rangle \simeq 6.7$
- $L_{\text{data}} \simeq 6.5$

Social search—Data

Adamic and Adar (2003)

- For HP Labs, found probability of connection as function of organization distance well fit by exponential distribution.

Social search—Data

Adamic and Adar (2003)

- For HP Labs, found probability of connection as function of organization distance well fit by exponential distribution.
- Probability of connection as function of real distance $\propto 1/r$.

Social Search—Real world uses

- Tags create identities for objects
- Website tagging: bitly.com
- (e.g., Wikipedia)
- Photo tagging: flickr.com
- Dynamic creation of metadata plus links between information objects.
- Folksonomy: collaborative creation of metadata

Social Search—Real world uses

Recommender systems:

- Amazon uses people's actions to build effective connections between books.

Social Search—Real world uses

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- Conflict between 'expert judgments' and tagging of the hoi polloi.

Outline

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- Bare networks are typically unsearchable.

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- Improved social network models.
- Construction of peer-to-peer networks.
- Construction of searchable information databases.

Neural reboot (NR):

Food-induced happiness

https://www.youtube.com/watch?v=vC8gJ0_9o4M?rel=0

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