Artificial Life & Complex Systems

Lecture 5

-- Complexity and Emergence --

May 26

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Contents

- Complex systems
- Self-organization and emergence
- Power laws
- Self-organized criticality (sandpiles)
- Multi-fractality

Why is this

more like this

than like this

?

Partial Answer

- Multiple scales of organization
- Lots of similar elements/agents at each scale
- No one has the big picture
- No one is in total control
- There is no grand plan
- Every agent acts autonomously and locally
- Specific interactions are mostly local or agent-agent
- Global organization emerges without explicit design

→ **Complex Adaptive Systems**

Emergence

Attempt to a definition:

“The arising of novel and coherent structures, patterns and properties during the process of self-organization in complex systems.” (Goldstein, 1999)

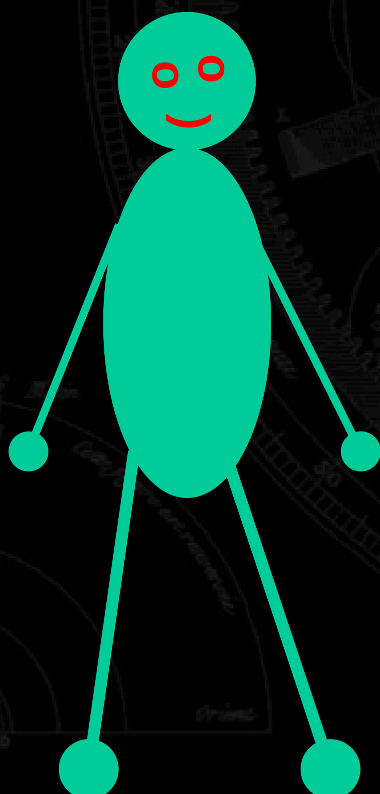
Some complex phenomena associated with water:

- Crystalline ice structures, snowflakes
- Phase transition to steam, boiling
- Whirlpools, vortices, turbulence

- All of these complex phenomena are consequences of the same, simple set of local rules that govern the interaction of molecules of water
- Yet the relation between the molecular level rules and the complex macroscopic phenomena is far from obvious
- This is the essence, and a perfect example, of *emergent phenomena*

Emergence: “Systems” View

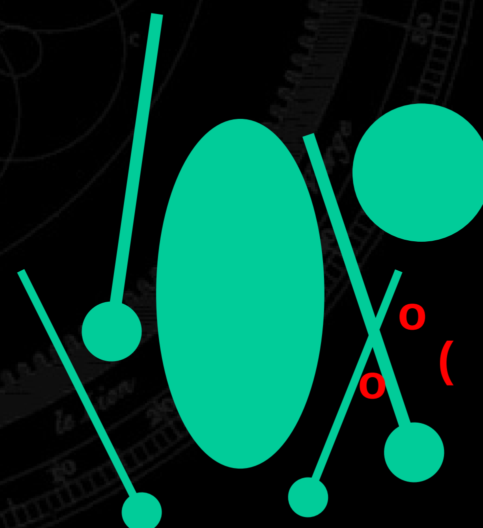
A



A is not the same as B:

A is a *whole* with *emergent properties*

B

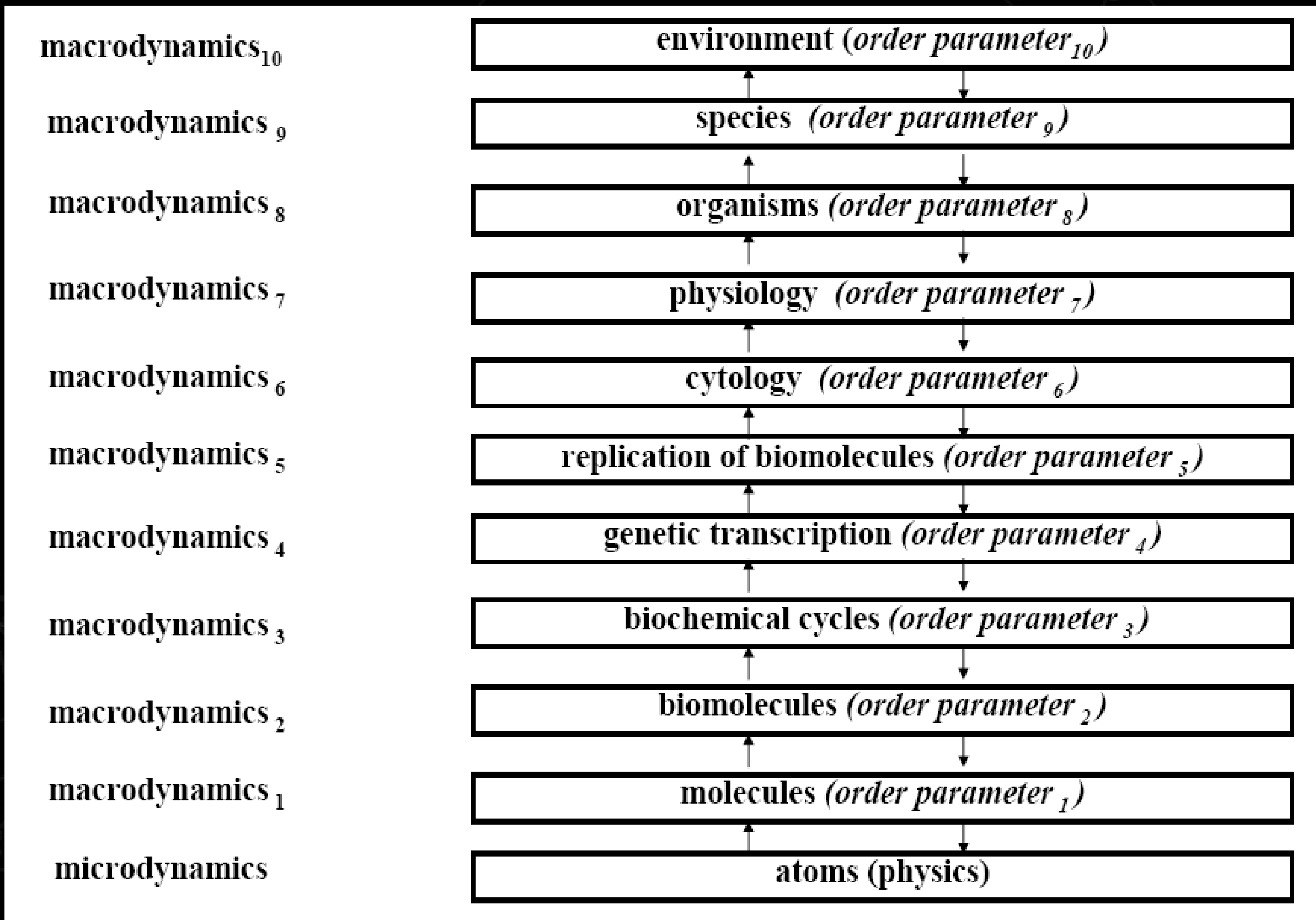


Emergence: Origins

"The whole is something over and above its parts, and not just the sum of them all ..."

(Aristotle, Book H, 1045:8-10)

Emerging Levels in the Hierarchy of Life



Emergence

There is an ongoing, modern interest in emergence within computer models of

- *Simulated neural networks*
  - Modeling a collection of biological neurons, such as the brain
- *Spin glasses*
  - Modeling molecular crystals
- *Cellular automata*
  - Modeling ontogenesis, bacterial growth, etc.
- *Evolutionary algorithms*
  - Modeling phylogenesis, speciation, engineering problems

In all cases, both the model and the system being modeled produce dramatic examples of emergent behavior

Emergence is …

1) … what parts of a system do together that they would not do by themselves, i.e. collective behavior

- How behavior at a larger scale of the system arises from the detailed structure, behavior and relationships on a finer scale

2) … what a system does by virtue of its relationship to its environment that it would not do by itself, i.e. function

- Emergence refers to all the properties that we assign to a system that are really properties of the relationship between a system and its environment

3) … the act or process of becoming an emergent system

Universal Organizational Principles

Let’s talk about scale-invariance ...

Scale-Invariance

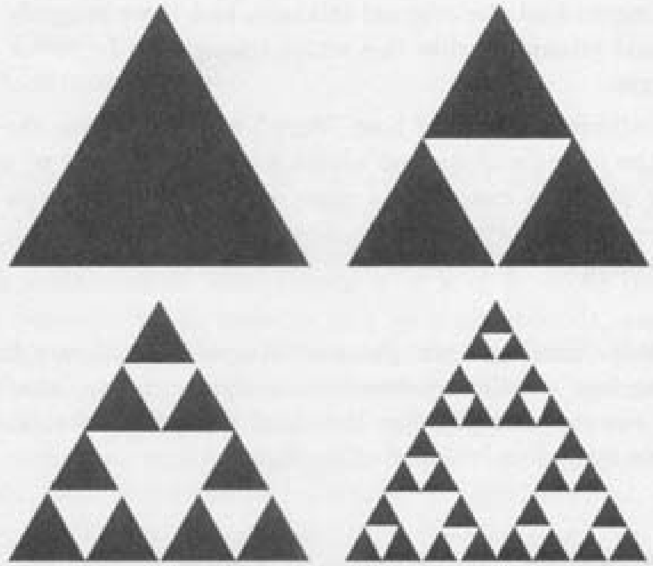


Figure 9.1 Construction of the Sierpinski Triangle.

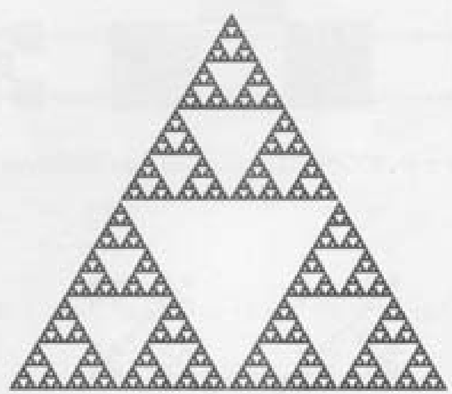
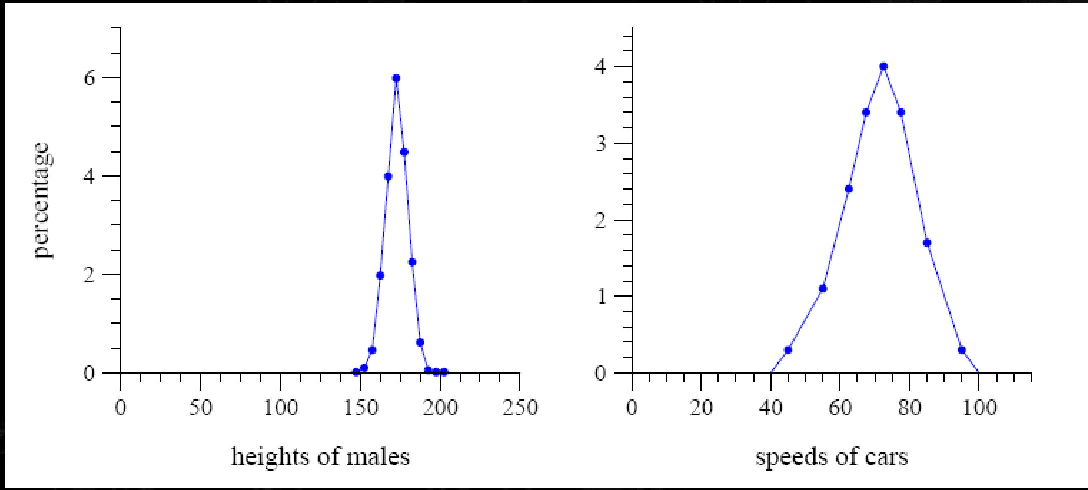


Figure 9.2 The Sierpinski triangle.

Quantities with a Typical Size or Scale

What kind of distribution?



Power Law Distributions

- Zipf
- Pareto
- Power Law

Zipf's Law

The size of the occurrence of a word is inversely proportional to its rank 'r' (occurrence vs. rank):

$$p(r) = Cr^{-\gamma}$$

Pareto's Law

Distribution of income: How many people do have income > x?

A (continuous) random variable X follows a Pareto distribution if it has a cumulative function

$$p[X \geq x] = Cx^{-\beta}$$

Few multi-billionaires, but most people have only a modest income

Power-Law

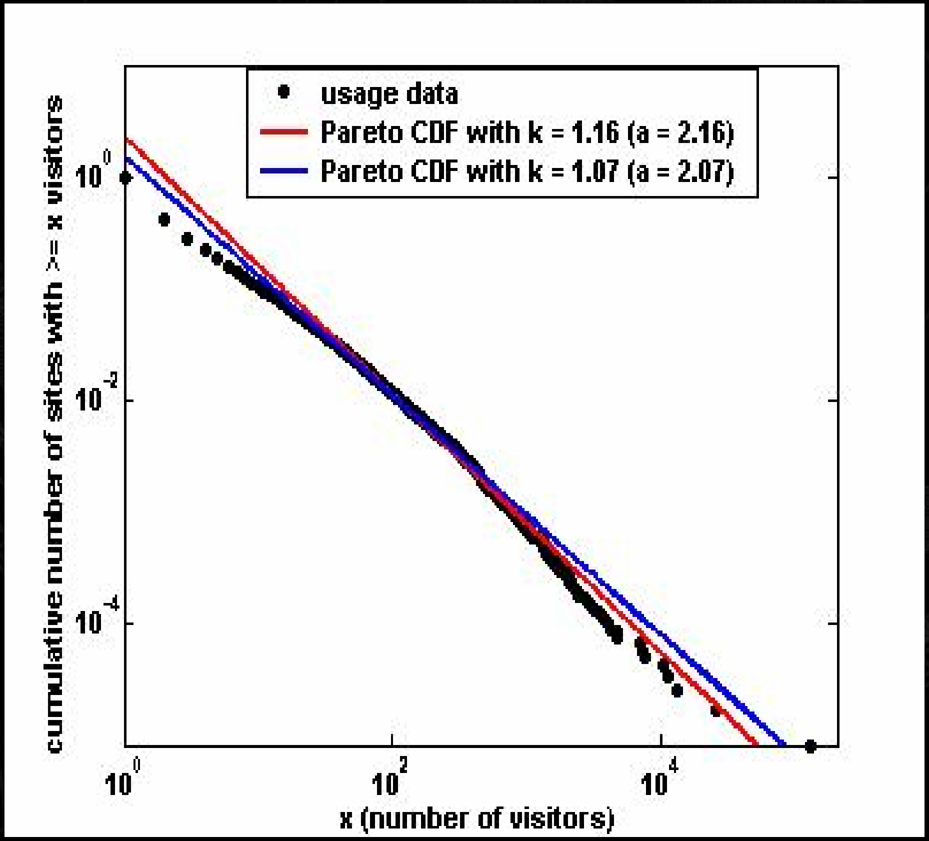
A (continuous) random variable X follows a power-law distribution if it has a density function (where a>1):

$$p(X = x) = Cx^{-(\beta+1)} = Cx^{-a}$$

Cumulative Distribution (Pareto)

Fit a line on the log-log plot of the cumulative distribution

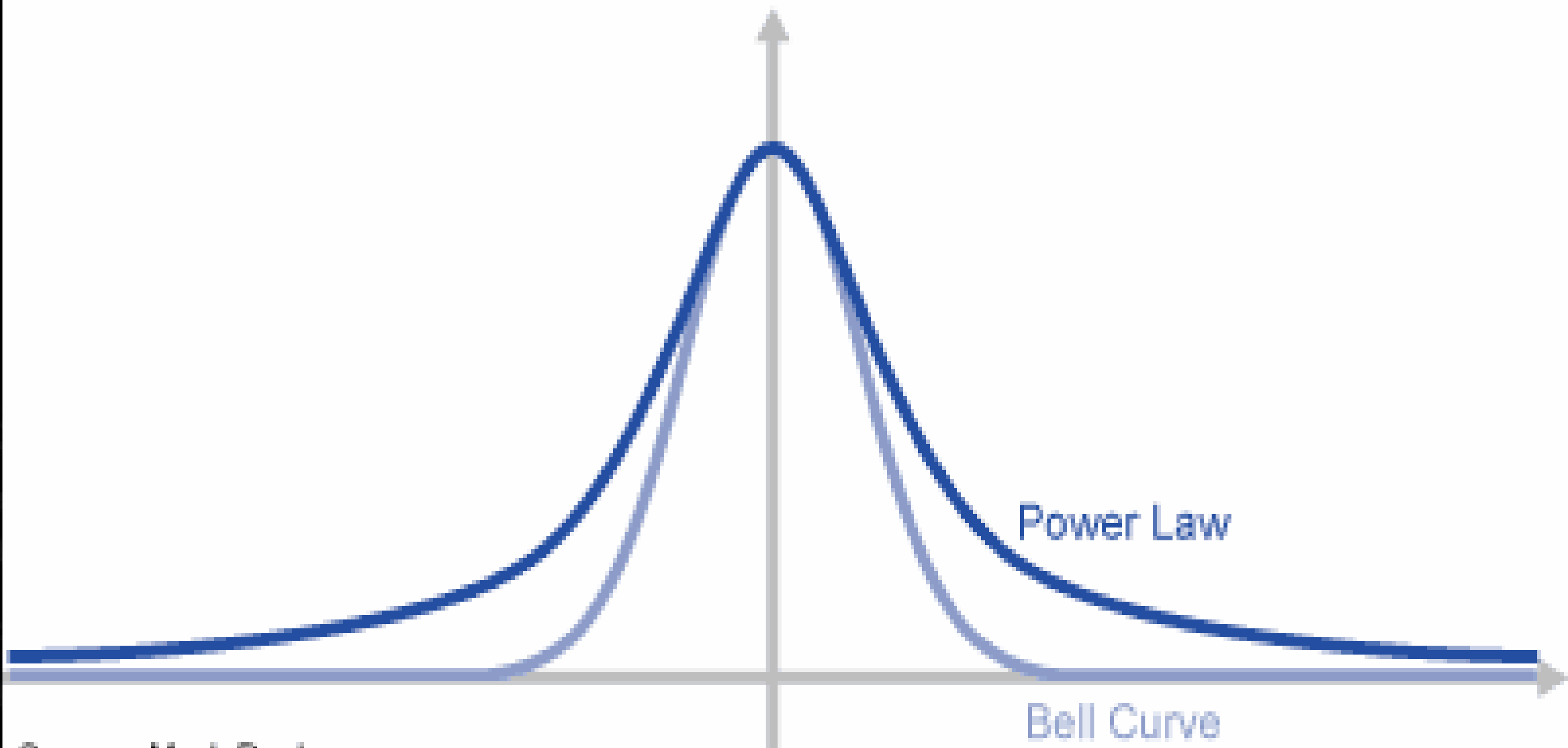
– it also follows a power-law with exponent a = k+1



Power-Law vs. Gaussian Distribution

Exhibit 1:

The Bell Curve vs. the Power Law: The Importance of "Fat Tails"



Source: Mark Buchanan

Power-Law Distributions

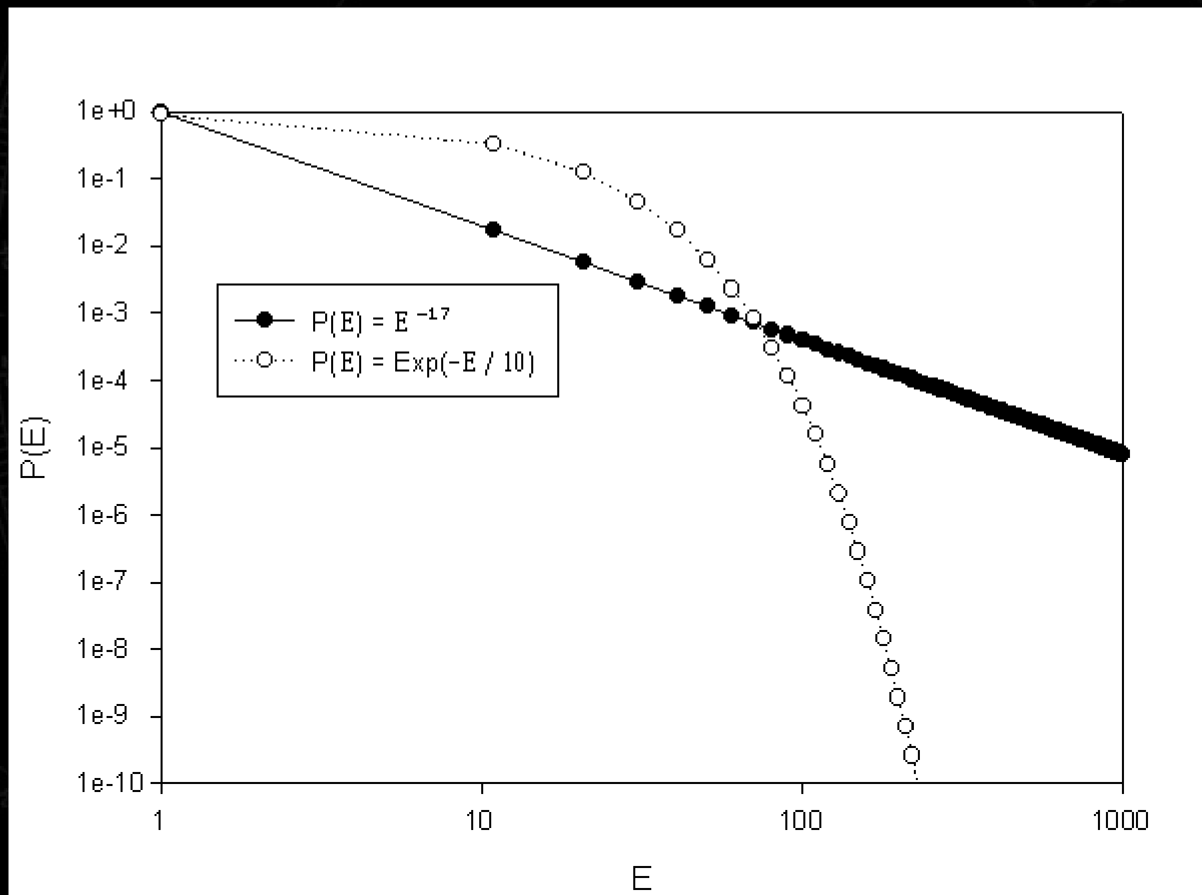
Sometimes called scale-free distributions

Example:

Let's say that files of size 2kB are ¼ as common as files of size 1kB. Switching to measuring size in megabytes we also find that files of size 2MB are ¼ as common as files of size 1MB.

→ Shape of the file-size distribution curve (at least for particular values) does not depend on the scale on which we measure file size

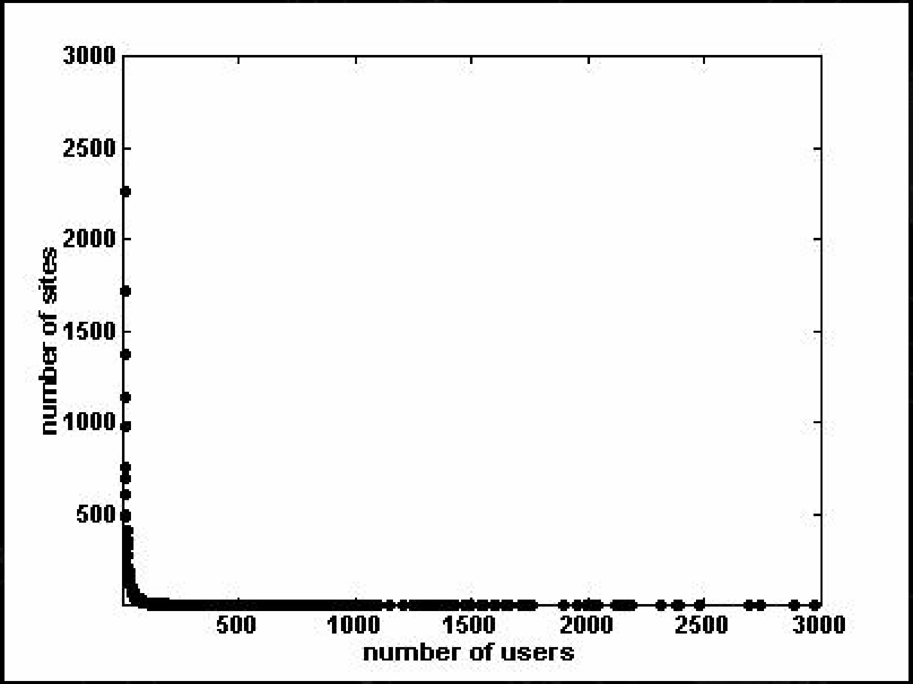
Power-Law and Exponential Distribution



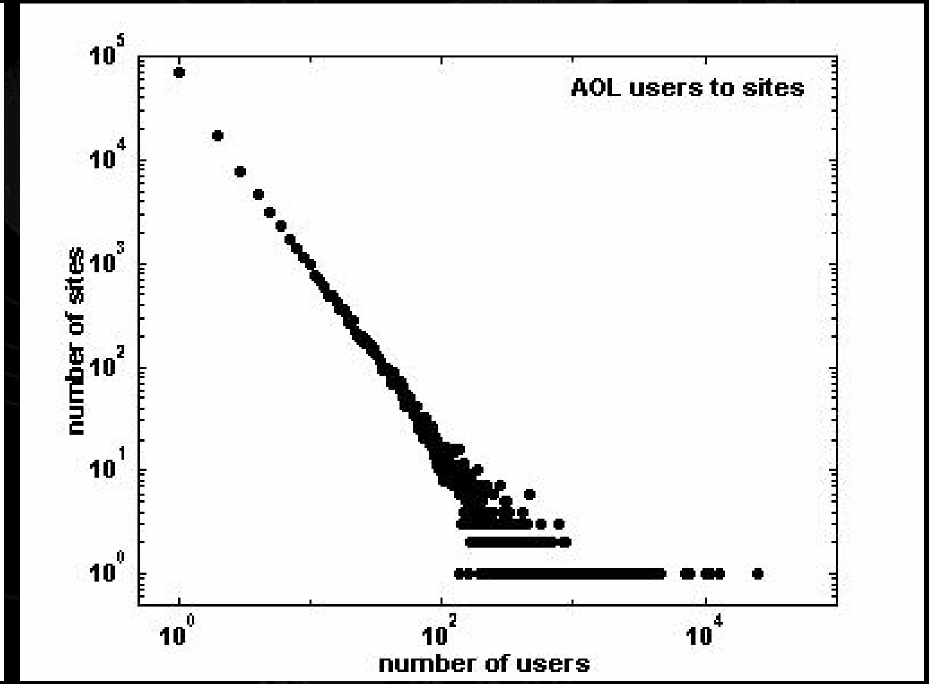
A power-law implies that small occurrences are extremely common, whereas large instances are extremely rare

Measuring Power-Laws

Simple log-log plot gives poor estimate



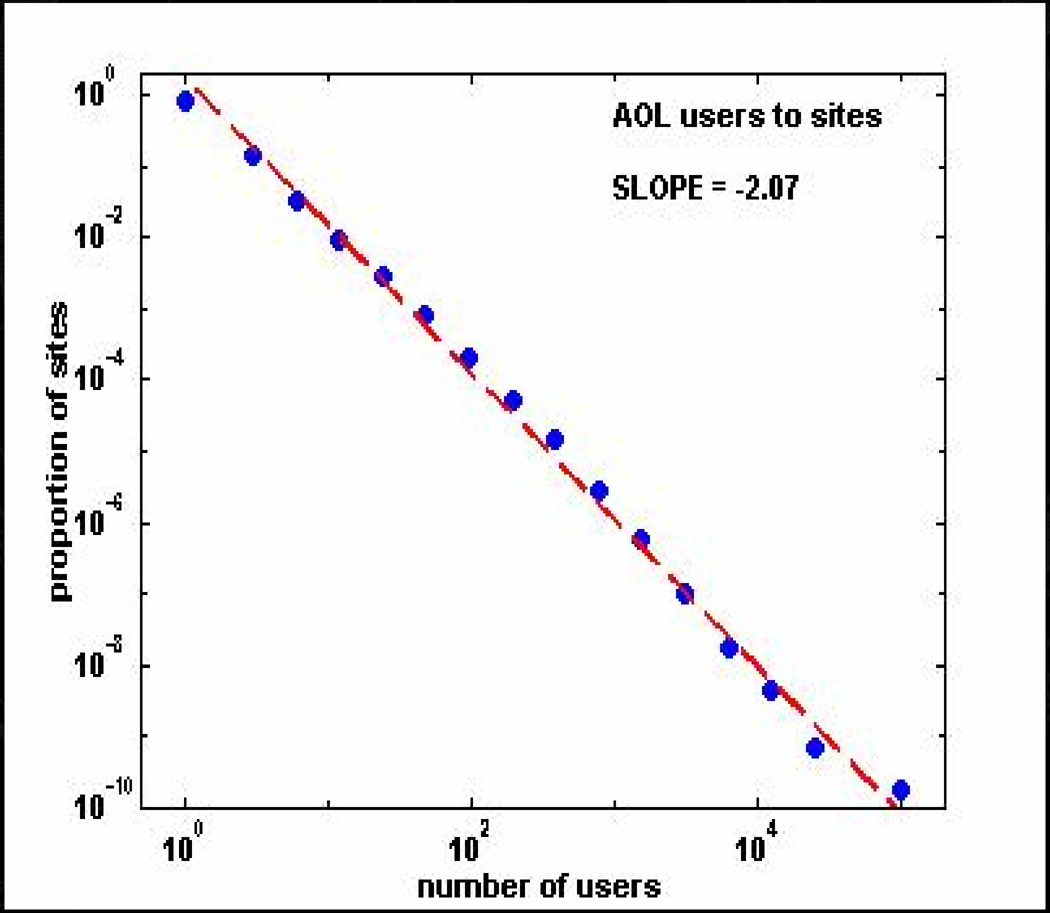
Log-log



Distribution of AOL users' visits to various sites on a December day in 1997

Logarithmic Binning

Tail end is “messy” → bin the observations in bins of exponential width



Power Laws are Ubiquitous

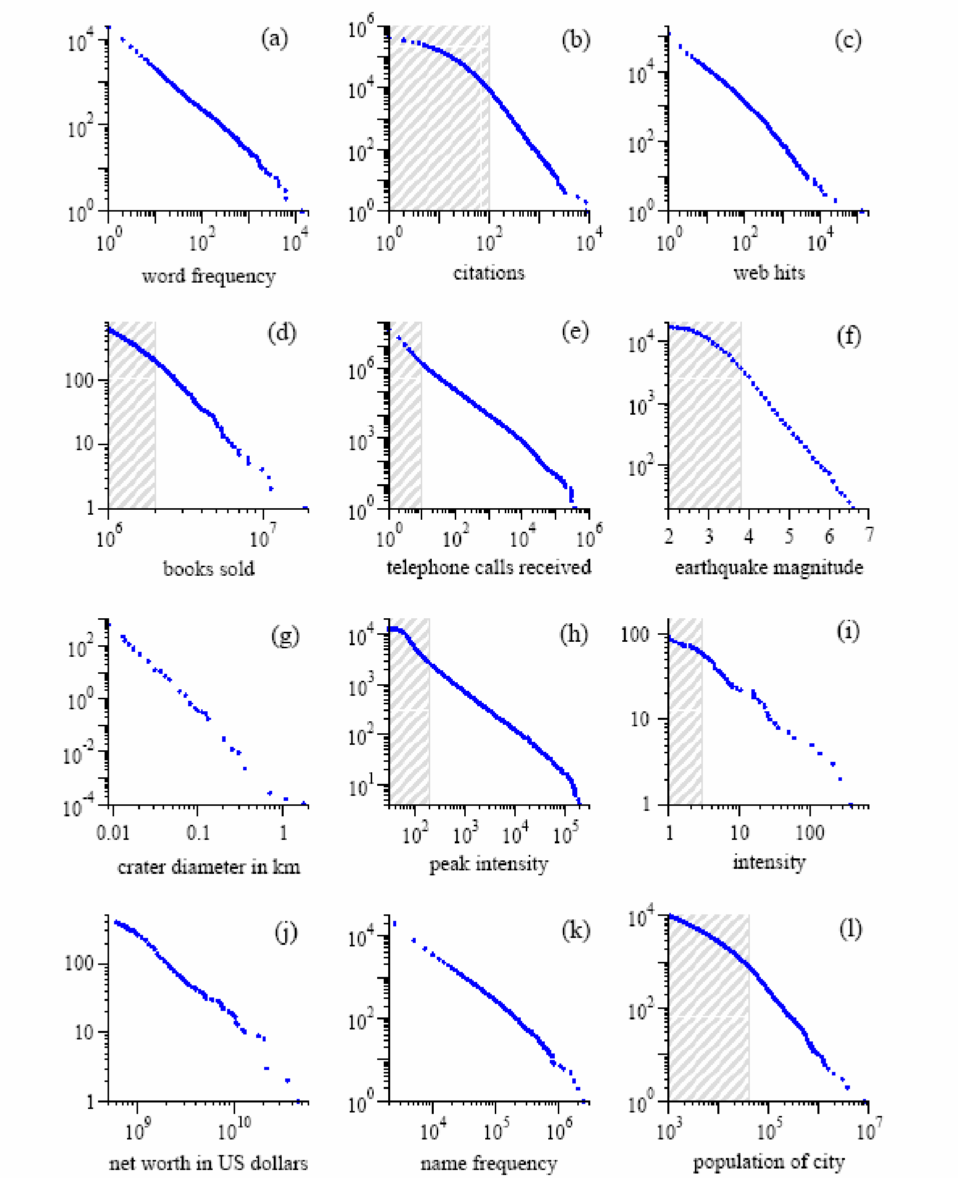
a) Word frequency (“Moby Dick”)
b) Citations of scientific papers (1981-1997)
c) Web hits (during a single day)
d) Copies of book sold (633 books; > 2mio. Copies)
e) Telephone calls (single day; 51 mio. users)
f) Magnitude of earthquakes (Richter magn.; 1910-1992)
g) Diameter of moon craters
h) Intensity of solar flares (1980-1989)
i) Intensity of wars (119 wars; 1816-1980)
j) Wealth of richest people (USA; 2003; Forbes magazine)
k) Frequency of family names
l) Population of cities (USA; 2000)

Power Laws are Ubiquitous

Cumulative distributions

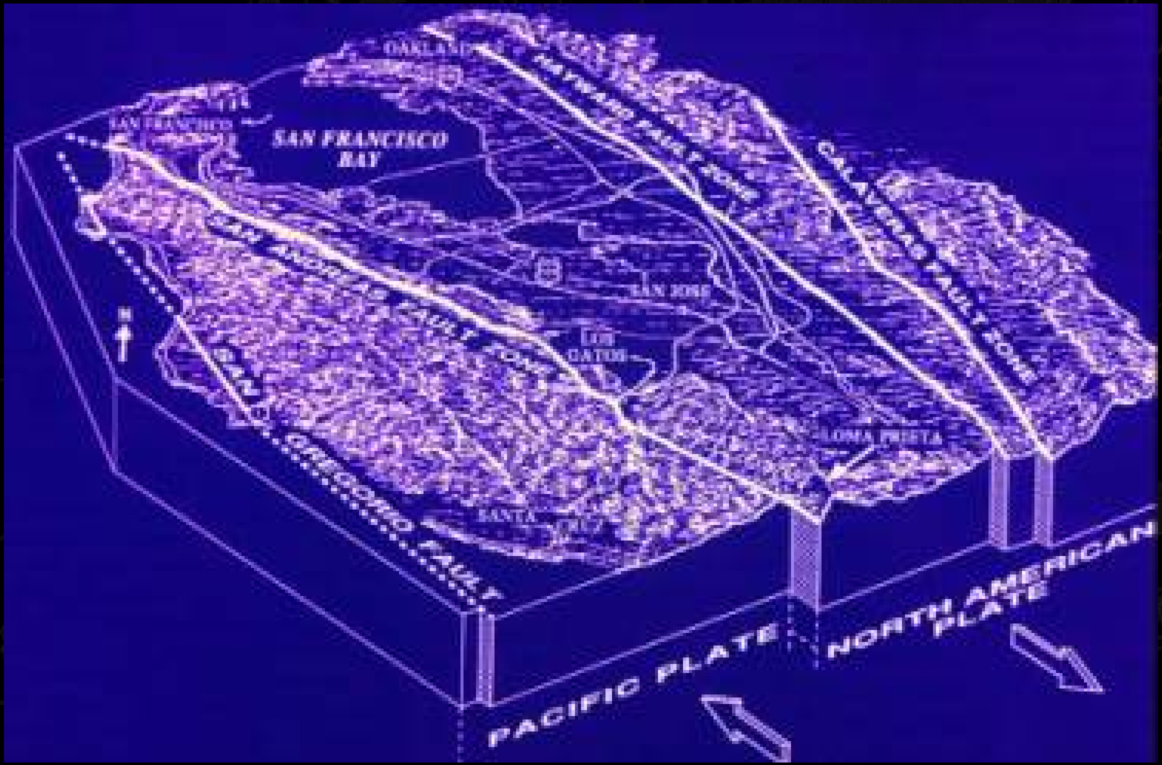
	quantity	minimum $x_{\min}$	exponent α
(a)	frequency of use of words	1	2.20(1)
(b)	number of citations to papers	100	3.04(2)
(c)	number of hits on web sites	1	2.40(1)
(d)	copies of books sold in the US	2 000 000	3.51(16)
(e)	telephone calls received	10	2.22(1)
(f)	magnitude of earthquakes	3.8	3.04(4)
(g)	diameter of moon craters	0.01	3.14(5)
(h)	intensity of solar flares	200	1.83(2)
(i)	intensity of wars	3	1.80(9)
(j)	net worth of Americans	\$600m	2.09(4)
(k)	frequency of family names	10 000	1.94(1)
(l)	population of US cities	40 000	2.30(5)

TABLE I Parameters for the distributions shown in Fig. 4. The labels on the left refer to the panels in the figure. Exponent values were calculated using the maximum likelihood method of Eq. (5) and Appendix B, except for the moon craters (g), for which only cumulative data were available. For this case the exponent quoted is from a simple least-squares fit and should be treated with caution. Numbers in parentheses give the standard error on the trailing figures.



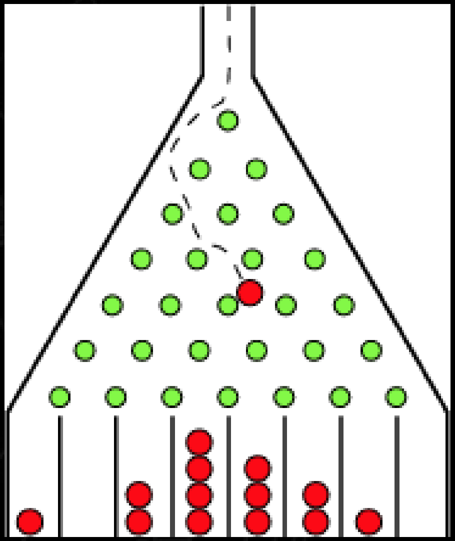
Example: Earthquakes

It is believed that earthquakes result from a stick-slip dynamics involving the Earth’s crust sliding along faults.



Example: Earthquakes

Can we predict earthquake? It is as difficult as predicting the individual ball movement in a Galton Board.

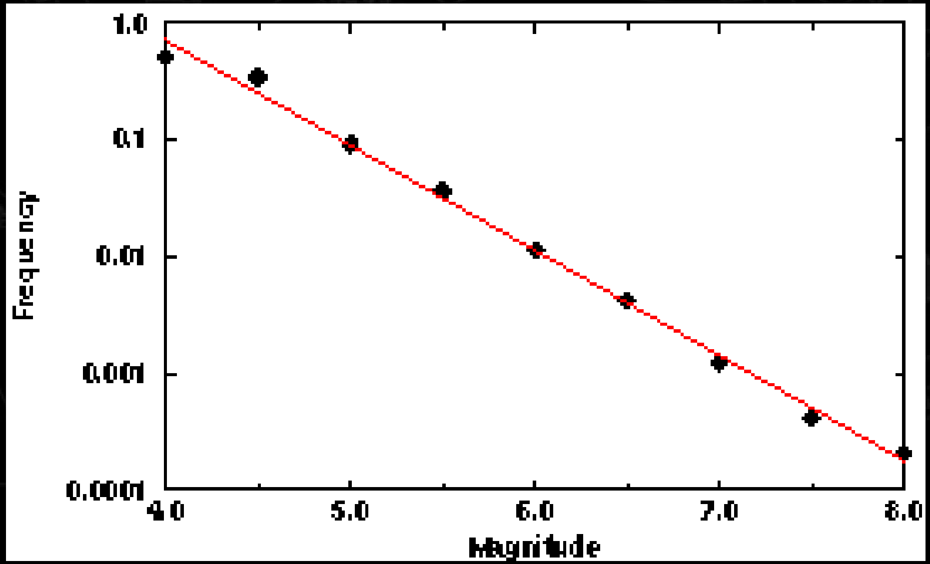


Movement of individual ball cannot be predicted → probabilistic description of the movement of the ball (Gaussian distribution).

Similarly, even though we cannot predict precisely the size of the next earthquake, we can calculate the probability that an earthquake of a given size will occur.

Gutenberg-Richter Law

- Despite of apparent complexity involved in the dynamics of earthquakes, the probability distribution of earthquakes follows a simple distribution function known as the **Gutenberg-Richter law**
- The probability of having an earthquake of energy E is $P(E) = c\ 1/E^{1+B}$, where the exponent B is a universal exponent in the sense that it does not depend on particular geographic area
- On a log-log scale, such power laws appear as straight lines, where the slope is -B: $\log(P(E)) = \log(c) - (1+B)\log(E)$

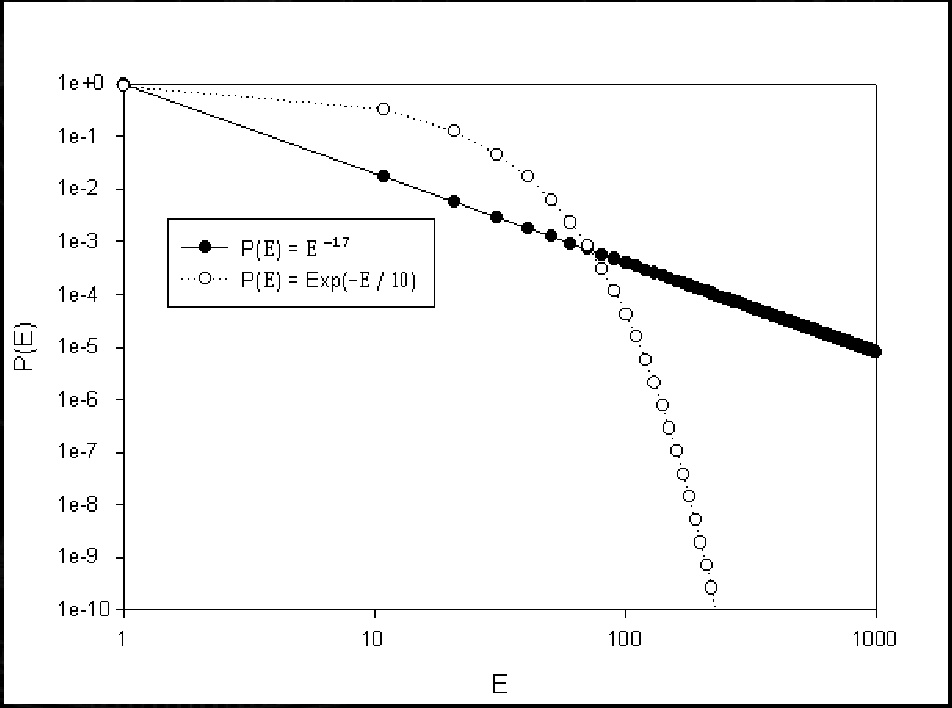


Earthquake Statistics (1995)

Gutenberg-Richter Law

There are more small earthquakes than large ones. But there is no apparent cut-off in the possible size of an earthquake; earthquakes of all sizes are possible.

If the probability distribution were of the form exp(-E/E0), then there would be a well defined cut-off at the energy E0 such that the probability for an earthquake of size E much greater than E0 is exponentially small.



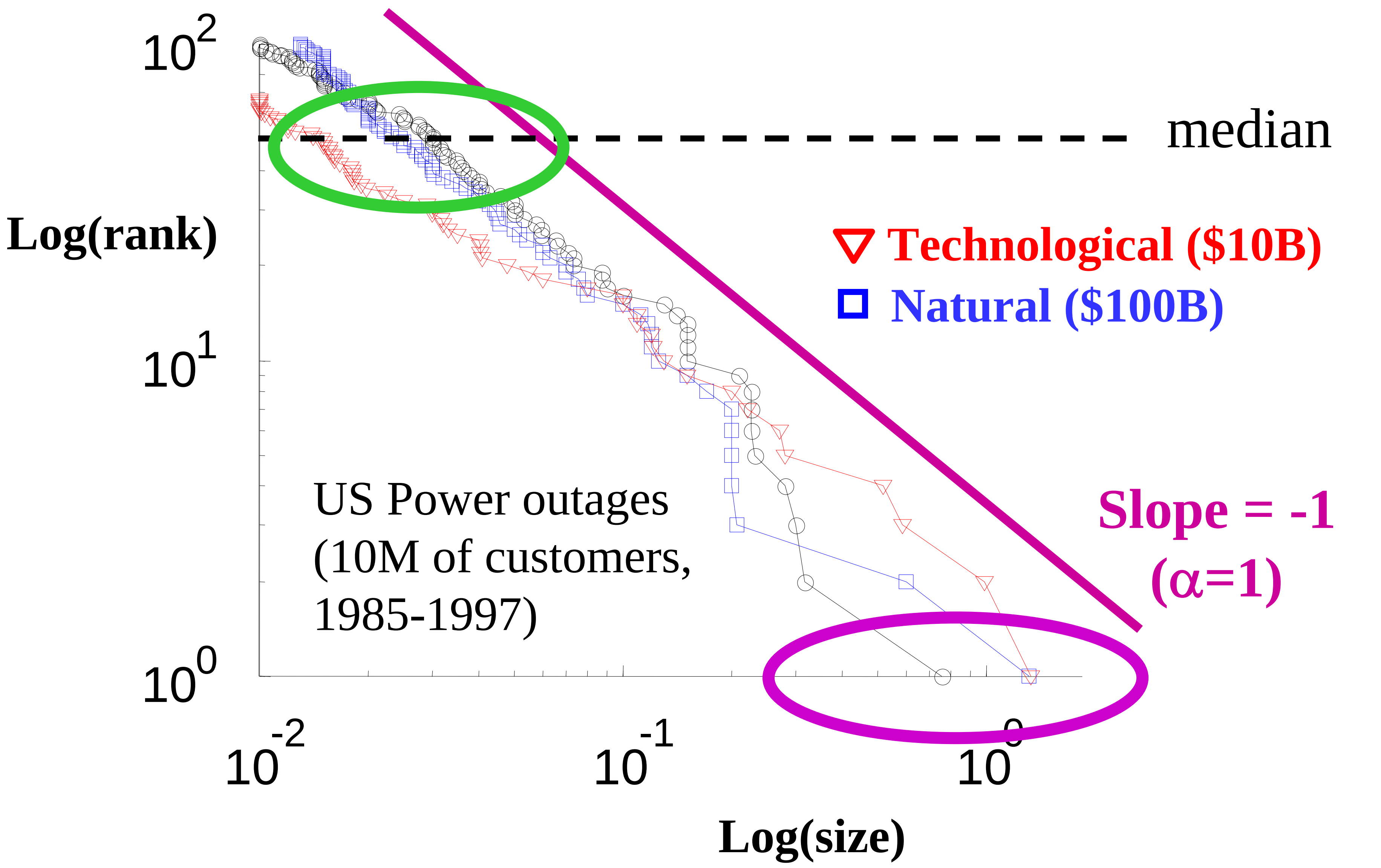
Gutenberg-Richter Law

M	*Energy(TNT)*	*Descriptions*	*Frequency (num/year)*
1~2	30lb ~ 1 ton	Blast at a construction site	
2 1/2	4.6 tons	Smallest felt earthquakes;	>10,0000
3	29 tons		50,000
4	1000 tons	Atomic bomb; sleep awaken	6000
5	32,000 tons	Smallest damaging shocks;	800
6	1 million tons	Hydrogen bomb	120
7	32 million tons		18
8	1 billion tons		1
9	32 billion tons		1~2 in a century

Chile (1960), Alaska(1964), Aceh(2004)

Note: M→M+1 ⇔ E → 32 E

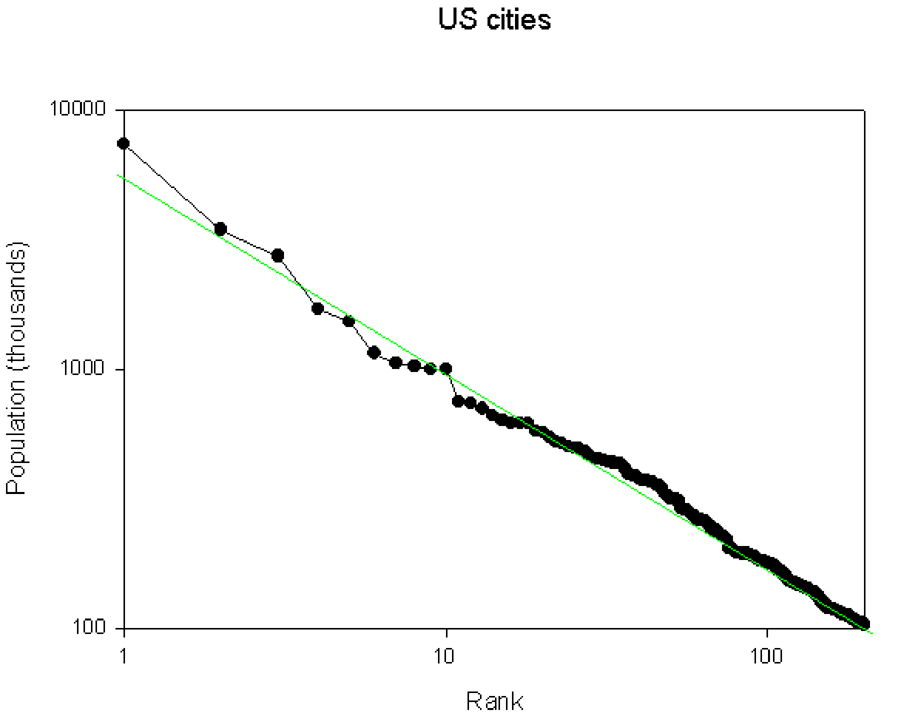
US Power Outages (1985-1997)



Distribution of City Sizes

Data for US cities (g ~ 0.8)
[Source: Oxford University Press]

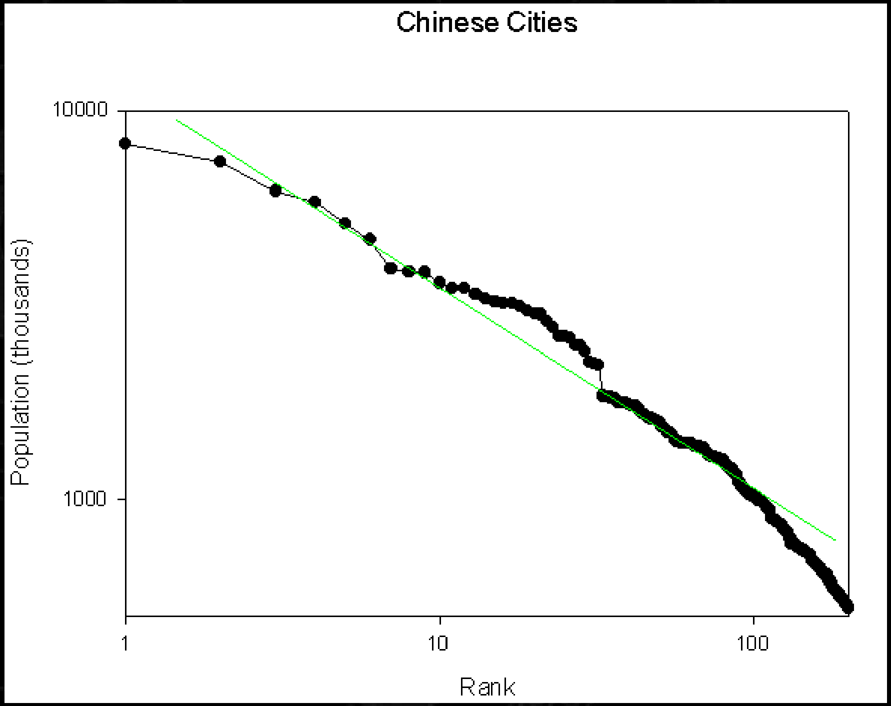
City	Pop. (thousands)	Rank
New York	7333	1
Los Angeles	3449	2
Chicago	2732	3
Houston	1702	4
Philadelphia	1524	5
San Diego	1152	6
Phoenix	1049	7
Dallas	1023	8
San Antonio	999	9
Detroit	992	10
...	...	...



Distribution of City Sizes

How about Chinese cities? (g ~ .5)

Cities	Pop. (thousands)	Rank
Shanghai	8206	1
Beijing	7362	2
Hong Kong	6190	3
Tianjin	5804	4
Qingdo	5125	5
Shenyang	4655	6
Guangzhou	3918	7
Wuhan	3833	8
Tai'an	3825	9
Harbin	3597	10



Why is the Zipf exponent for the size distribution of the Chinese cities different from that of the US cities?

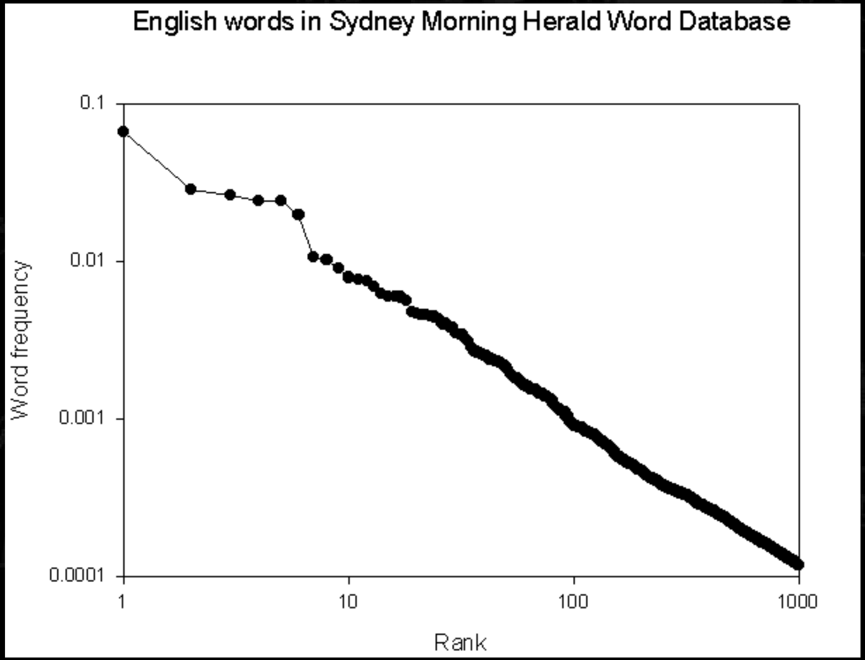
What social-economic dynamics gives rise to the difference?

Zipf's Law: Word Count Distribution

Does the brain operates at the edge of chaos? Genius or a mad man?

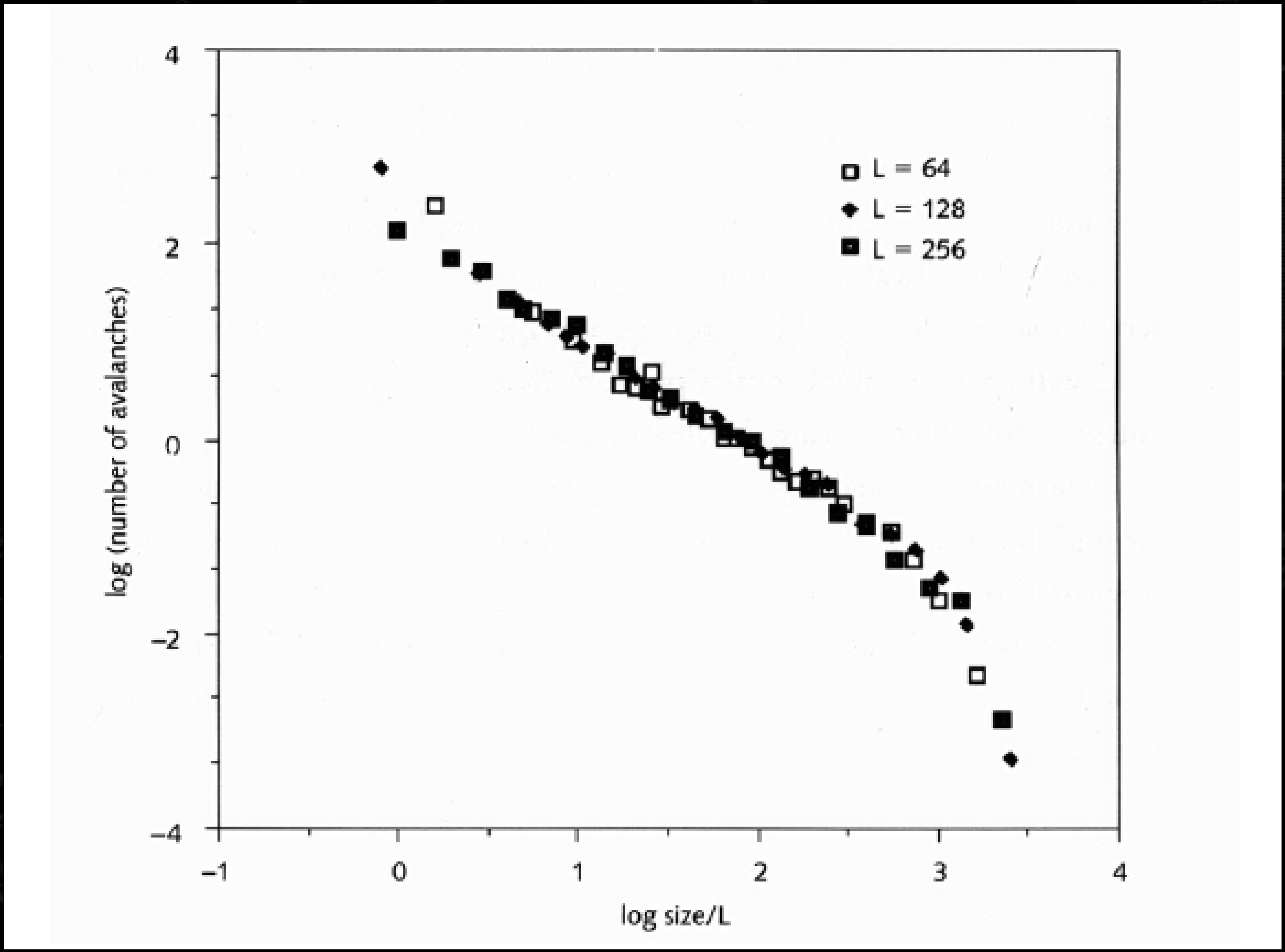
Zipf's law for the Rank - Word Count distribution

Sydney Morning Herald Word Database



Word	Probability	Rank
the	0.0653	1
of	0.0282	2
to	0.0262	3
and	0.0243	4
a	0.0242	5
in	0.0195	6
is	0.0107	7
for	0.0102	8
that	8.9320e-3	9
on	7.8680e-3	10
he	5.9770e-3	16
not	3.9910e-3	26
or	2.5540e-3	39
you	2.3230e-3	45
she	1.5920e-3	63
australian	1.5220e-3	68
her	1.4970e-3	69
million	1.3400e-3	78
him	9.4000e-4	98
market	7.3500e-4	130
think	5.3300e-4	171
computer	1.6300e-4	693

The Game of Life Follows a Power Law!

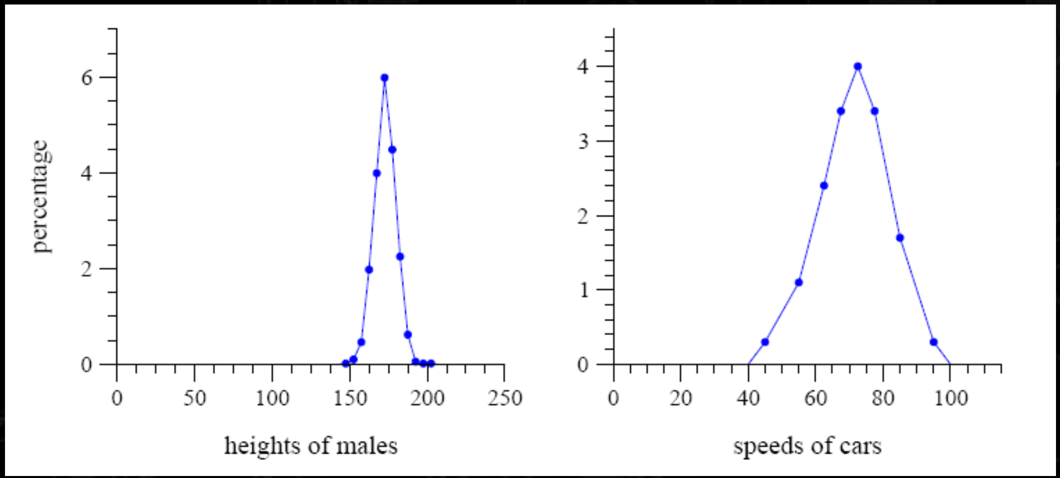


Scale-Invariance of Power Laws

Some properties …

But Not Everything is a Power Law

Quantities with a typical size or scale



But Not Everything is a Power Law

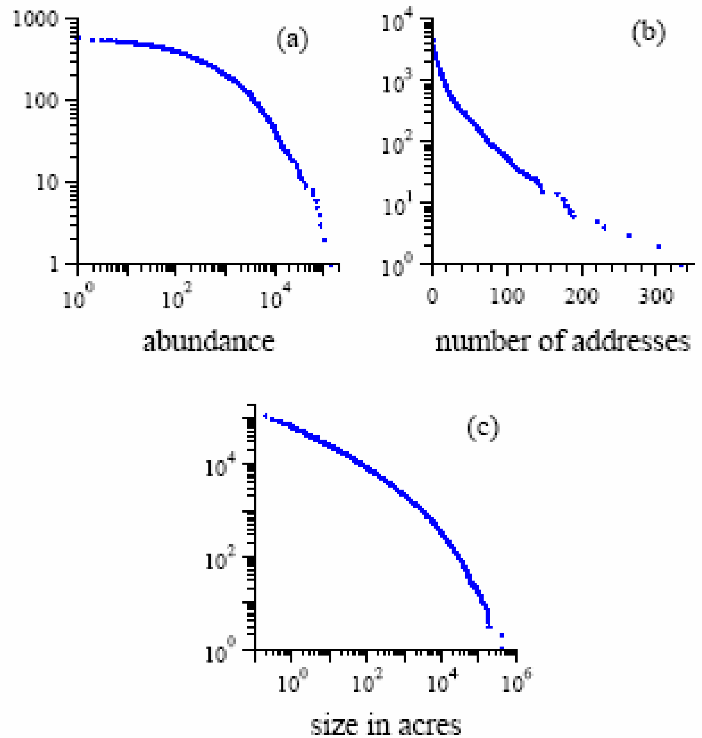


FIG. 5 Cumulative distributions of some quantities whose distributions span several orders of magnitude but that nonetheless do not follow power laws. (a) The number of sightings of 591 species of birds in the North American Breeding Bird Survey 2003. (b) The number of addresses in the email address books of 16 881 users of a large university computer system [34]. (c) The size in acres of all wildfires occurring on US federal land between 1986 and 1996 (National Fire Occurrence Database, USDA Forest Service and Department of the Interior). Note that the horizontal axis is logarithmic in frames (a) and (c) but linear in frame (b).

Divergent Mean (?)

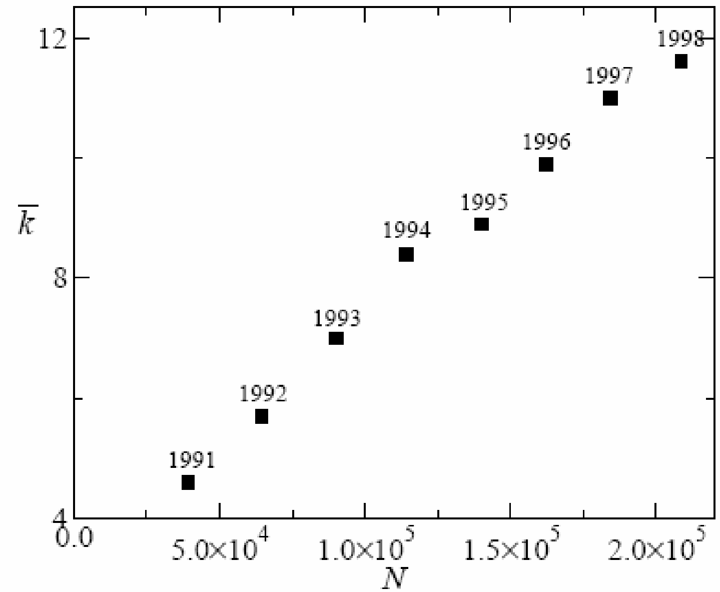


FIG. 3.17. Variation of the mean number of coauthorships (the average degree $\overline{k}$) of the network of coauthorships in neuroscience journals with increasing number of authors, N (according to Barabási, Jeong, Néda, Ravasz, Schubert, and Vicsek 2002).

The 80/20 Rule

Power Law: cumulative distribution is top-heavy

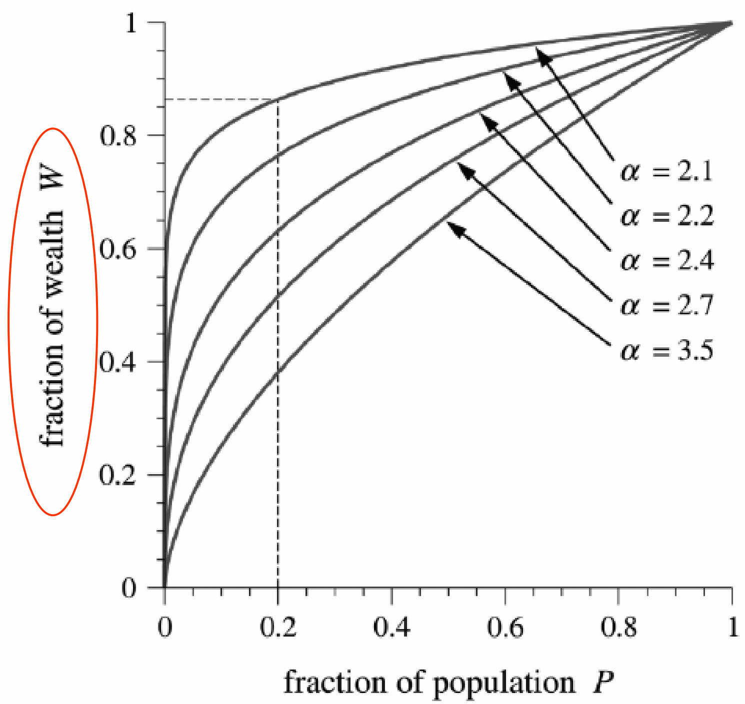


Figure 6. The fraction W of the total wealth in a country held by the fraction P of the richest people, if wealth is distributed following a power law with exponent α. If $\alpha = 2.1$, for instance, as it appears to in the United States (table 1), then the richest 20% of the population hold about 86% of the wealth (dashed lines).

What is the Mechanism behind Power-Laws?

- We have seen that power-laws appear in various natural, or man-made systems
- What are the processes that generate power-laws?
- Is there a “universal” mechanism?

What is the Mechanism behind Power-Laws?

Ideas:

- Cooperative phenomenon of many components, given that system with few degrees of freedom cannot do it
- Must be an open system – closed systems reach an equilibrium
- Could be related to spatial structure
- Could be related to growth (“rich get richer dynamics”)

Universal Mechanisms

Here, we study Self-Organized Criticality

Self-Organized Criticality

PHYSICAL REVIEW A VOLUME 38, NUMBER 1 JULY 1, 1988

Self-organized criticality

Per Bak, Chao Tang, and Kurt Wiesenfeld
Department of Physics, Brookhaven National Laboratory, Upton, New York 11973
(Received 28 August 1987)

We show that certain extended dissipative dynamical systems naturally evolve into a critical state, with no characteristic time or length scales. The temporal "fingerprint" of the self-organized critical state is the presence of flicker noise or $1/f$ noise; its spatial signature is the emergence of scale-invariant (fractal) structure.

What is SOC?

Simple answer: SOC refers to tendency of large dissipative systems to drive themselves to a critical state (at the edge between stability/order and chaos) with a wide range of length and time scales

Self-Organized Criticality

Another potential answer:

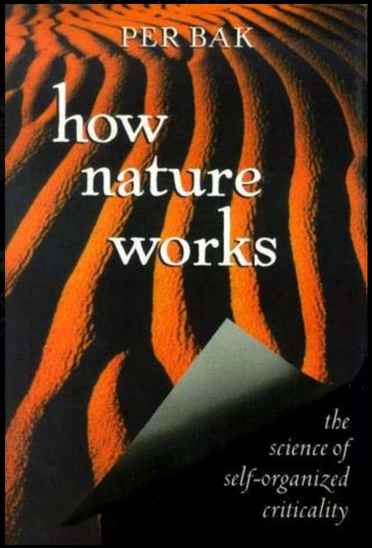
"A critical state at the edge between stability and chaos where complexity is formed by self-organization"

Self-Organized Criticality

Two essential elements:
- self-organization
- criticality

Characteristics:
- The process of self-organization takes place over a long transient period
- The dynamics in this state is intermittent with periods of inactivity separated by well defined bursts of activity or avalanches
- Dissipative systems evolve (autonomously) into a self-organized critical state with no characteristic time or length scales
- The system organise itself exposing the same kind of properties as equilibrium systems at the critical point (for example percolation model)

Explanatory power:
- Distribution of solar flares
- Distribution of earthquake sizes (Gutenberg-Richter law)
- Distribution of initial masses of stars (Salpeter law)
- Distribution of sizes of extinction events (“evolution by jerks”; “punkeek”)



Self-Organization

Self-Organization

"Simple and complex systems exhibit … the spontaneous emergence of order, the occurrence of self-organization." *(S.A. Kaufmann, The Origins of Order)*

"Technological systems become organized by commands from outside, as when human intentions lead to the building of structures or machines. But many natural systems become structured by their own internal processes: these are the self-organizing systems, and the emergence of order within them is a complex phenomenon that intrigues scientists from all disciplines." *(F.E. Yates et al., Self-Organizing Systems: The Emergence of Order)*

Self-Organization: Definition

"Self-organization is a process in which pattern at the global level of a system emerges solely from numerous interactions among the lower-level components of the system. Moreover, the rules specifying interactions among the system's components are executed using only local information, without reference to the global pattern." *(Camezine et al., 2002)*

Self-Organization: Examples

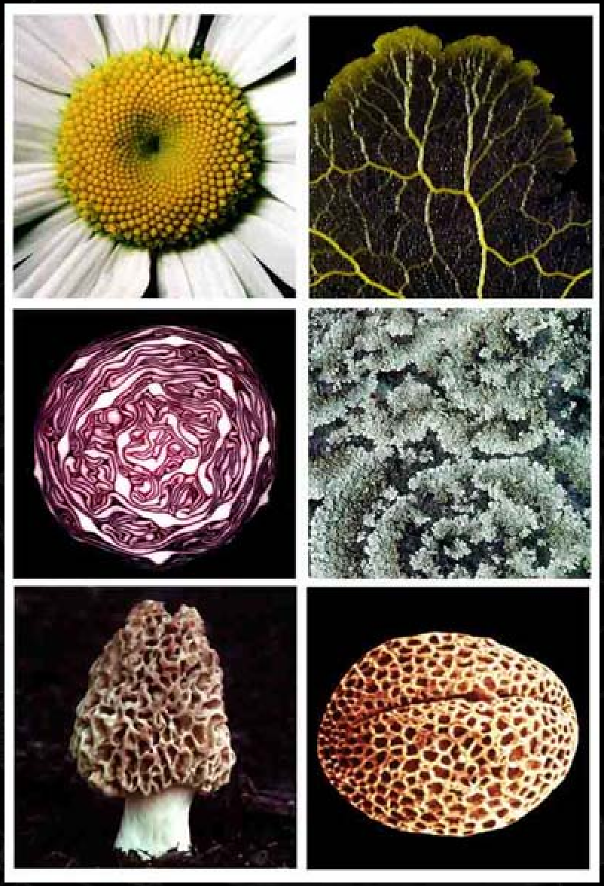
Self-organization refers to a broad range of pattern-formation processes in physical and biological systems

Sand grains assemble into rippled dunes

Chemical reactants forming patterns on seashells

Birds joining together in flocks

Self-Organization: Additional Examples

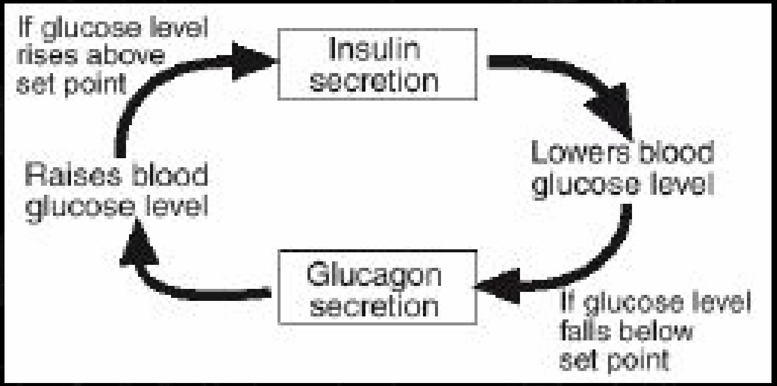


Self-organization: Main Features

- In self-organizing systems, pattern formation occurs through <u>interactions *internal* to the system</u>, without intervention by external directing influences (no leader or director)
- <u>*Local* information</u> only, e.g. nearest neighbors in a fish school, local pheromone concentration, ...
- Self-enhancing pos. <u>feedback</u> + antagonistic neg. feedback
- <u>Random</u> fluctuations and <u>chance</u> heterogeneities act as nucleation centers

Note on Positive Feedback

Negative feedback → homeostasis (e.g. body temperature, blood glucose level)



Positive feedback → promotes generally "negative" changes

For examples: population growth, snowball effect

Exception: Positive feedback may play major role in group activity

- Synchronizing fireflies: "I signal when you signal"
- Infectious quality of yawn or laughter: "I do what you do"

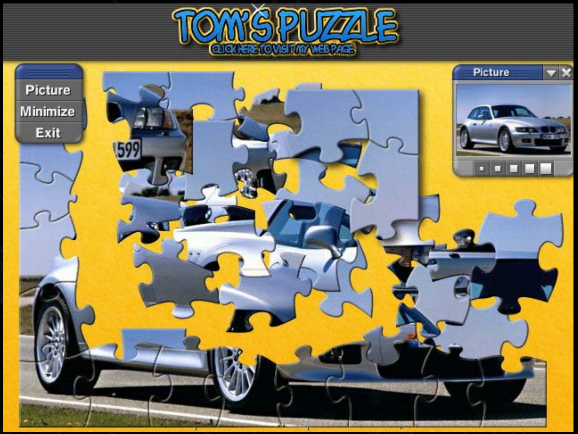
Note on Positive Feedback

Self-enhancing positive feedback coupled with antagonistic negative feedback provides a powerful mechanism for creating structure and pattern in many physical and biological systems involving many coupled components (see morphogenesis and Turing patterns; see new economy of "increasing returns" (Brian Arthur)

Increasing returns: "that which is ahead gets farther ahead" → I.R. generate instabilities, there is no equilibrium as postulated by old-fashioned economy; killer apps which corner the market

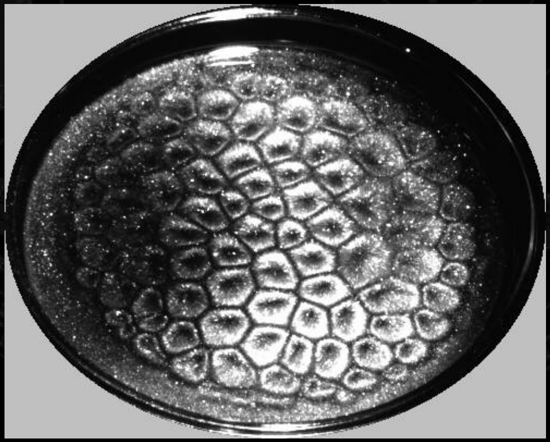
Self-Organization: Some Additional Properties

Self-organizing systems are <u>dynamic</u>

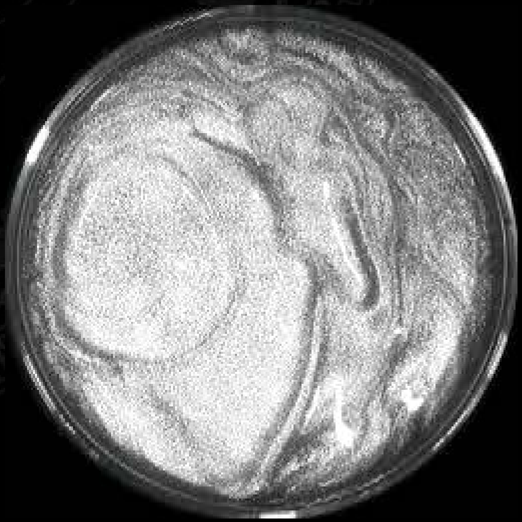


Self-organizing systems exhibit <u>emergent properties</u>

Emergence: process by which a system of interacting subunits acquires <u>qualitatively new properties</u> that cannot be understood as the simple addition of their individual contributions



Benard convection cells



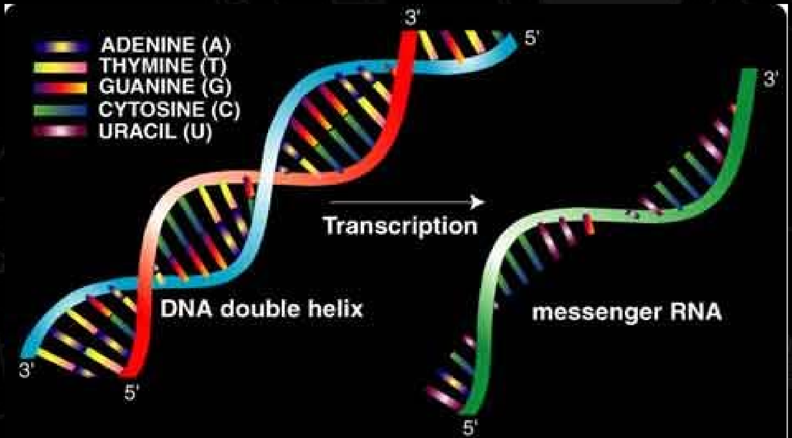
Alternatives to Self-Organization

Systems lacking self-organization can have order imposed on them in many different ways.

Alternative mechanisms of pattern formation:

- *Leader:* well informed leader directs activity through instructions, e.g. orchestra conductor, foreman
- *Blueprints:* group-pattern building is directed by blueprint (representation of spatial and temporal relationships among parts; specifies WHAT is to be built), e.g. crew of construction workers, score for members of orchestra
- *Recipe:* sequential instructions that specify spatial and temporal actions of individual contributions to whole pattern (specifies HOW something is to be built), e.g. soccer team.
- *Template:* guide or mold specifying final pattern, e.g. cookie cutter

Alternatives to Self-Organization



Formation of messenger RNA from a DNA template strand. The strand in blue, the 3'-5' strand is the template strand. The RNA polymerase transcribes the information in this strand . During this transcription, A becomes U, T becomes A, G becomes C and C becomes G.

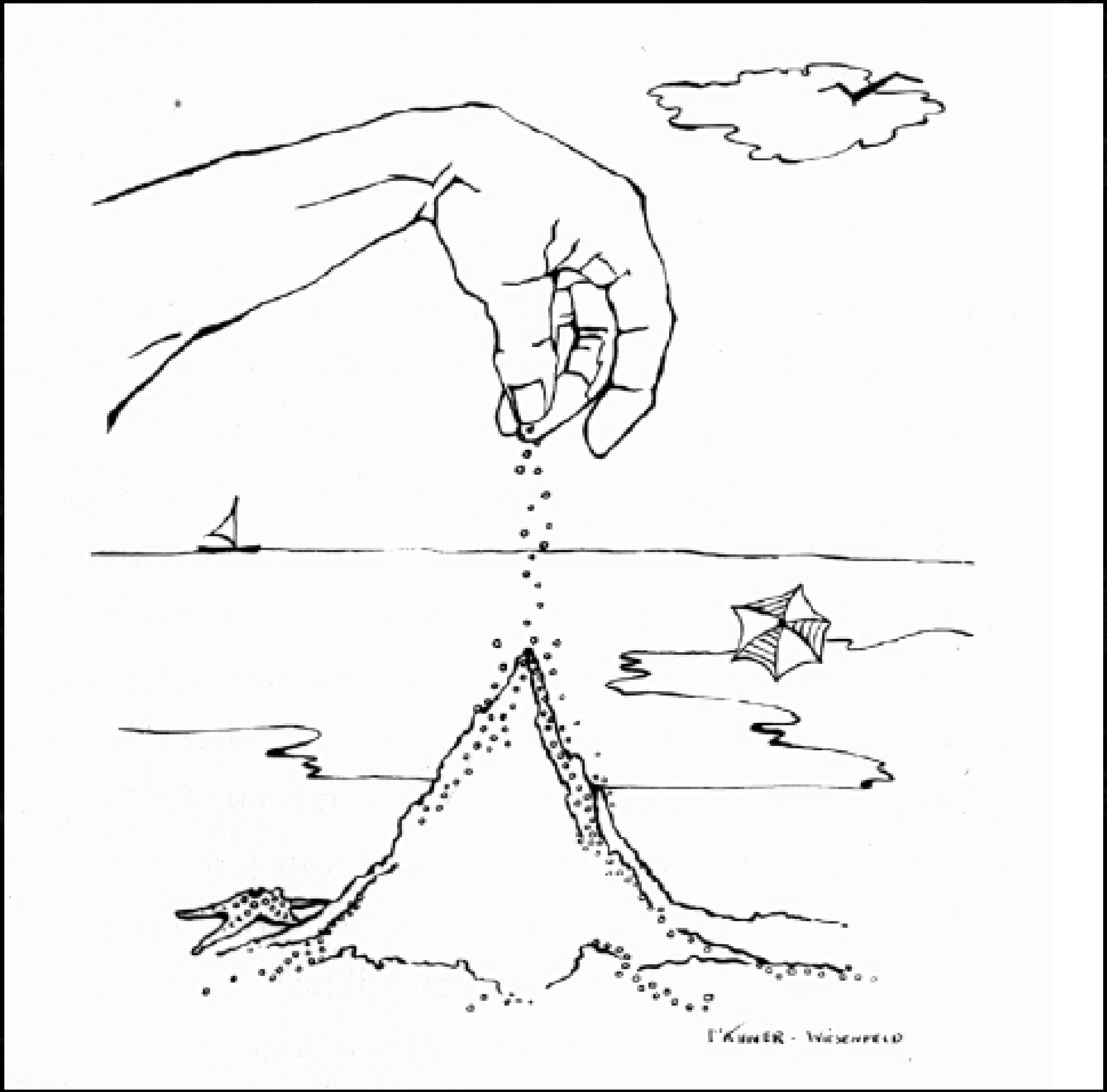
Criticality

- Some systems have only a single macroscopic length-scale, size-scale, or time-scale governing them
- Under particular circumstances (e.g. temperature value) the characteristic scale of the system can diverge
- The precise point for which this happens is called a critical point or phase transition (e.g. melting point of ice)
- Critical means that all of the members of the entire system influence each other, that is, at a critical state the perturbations influence the whole system (even though only the nearest neighbor system components interact directly!)
- Critical phenomena happen at the vicinity of the phase transition: a power-law (scale-free) distribution appears

Self-Organized Criticality

- For systems displaying SOC, the critical state is an <u>attractor for the dynamics</u>
- Such systems self-organize to the critical point, i.e. they alwasy "sit" at the critical point

The Sandpile Model



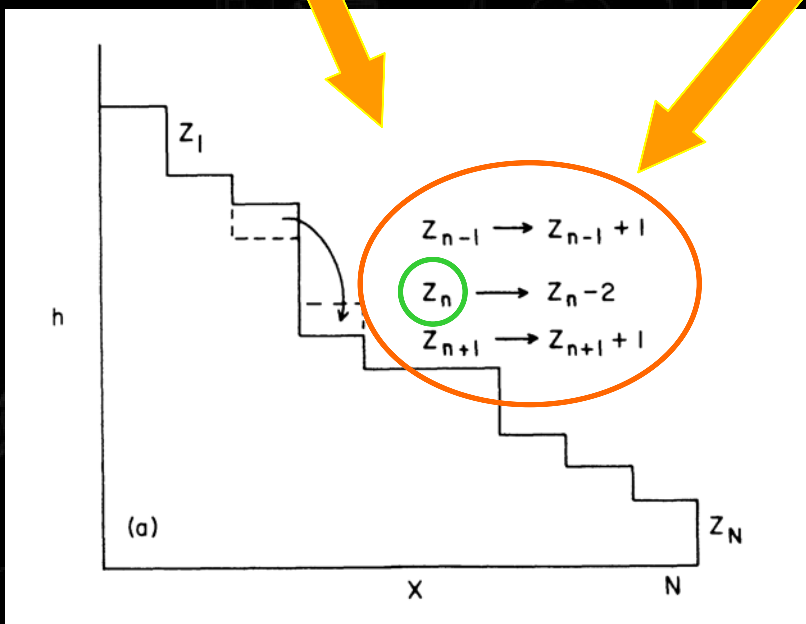
The Sandpile Model

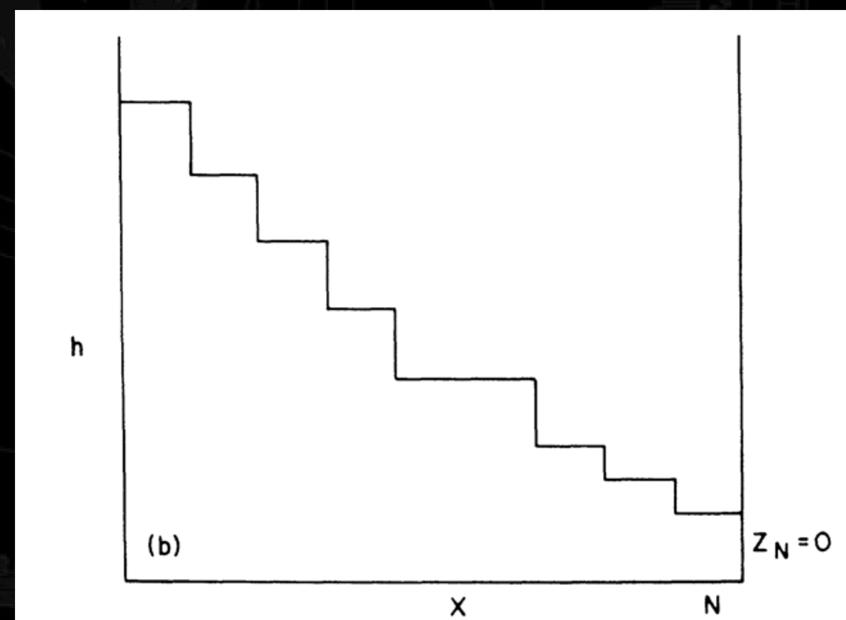
- Adding sand slowly to a flat pile will result only in some local rearrangement of particles
- Local interactions: The individual grains, or *degrees of freedom*, do not interact over large distances
- Phase transition: Continuing the process will result in the slope increasing to a critical value where an additional grain of sand gives rise to avalanches of any size, from a single grain falling up to the full size of the sand pile
- Global behavior: The pile can no longer be described in terms of local degrees of freedom, but only a holistic description in terms of one sandpile will do
- Scale-free: The distribution of avalanches follows a power law

Sandpile Model: 1-D Case (Linear Lattice)

- z(n) represent height difference: h(n)-h(n+1), where ‘n’ is the site
- rule 1: (adding of sand)
- rule 2: (tumbling) if z(n)>zc then one unit of sand tumbles to the lower level

nonlinear discretized diffusion eq.





Sand leaves the pile on the right-hand side only

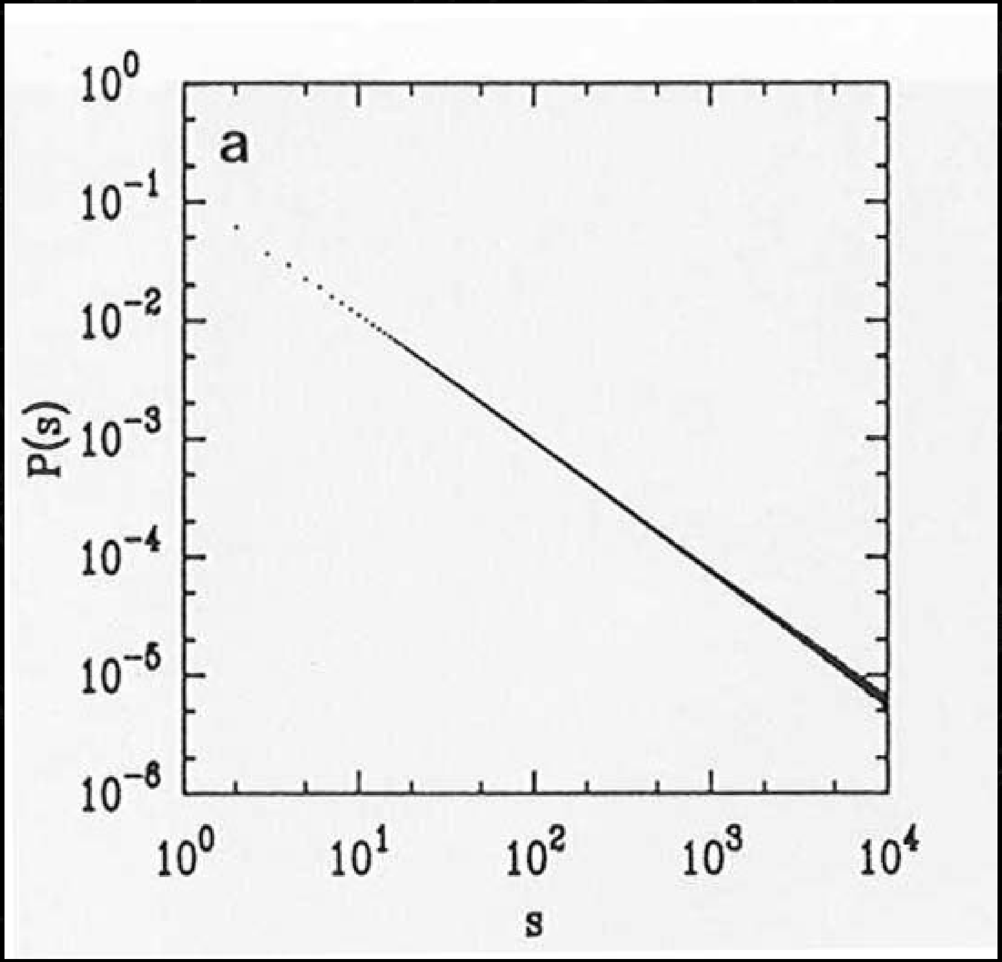
Sand cannot leave the pile

Sandpile Model: 1-D Case

- Minimally stable state or critical state: almost all of the slopes are at the critical point $z(n) = 2$
- Model is essentially a CA where the state of the discrete variable $z(n)$ at time $t+1$ depends on the state of variable (and its neighbors) at time t

Sandpile Model: Power Law Distribution ☺

Distribution of size of events follows a power law



Sandpile Model: 2-D Case

- 2-D cellular automaton with LxL sites
- Integer variables *z(x,y)* on each site *(x,y)* represent the local sandpile slope
- Two rules:
  - **1) add sand**
  - **2) tumble grains**
- When $z(x,y)>z_c$, then a grain is transferred from the unstable site to each 4 neighboring site (von Neumann neighborhood)
- A toppling may initiate a chain reaction, where the total number of topplings is a measure of the size of an avalanche

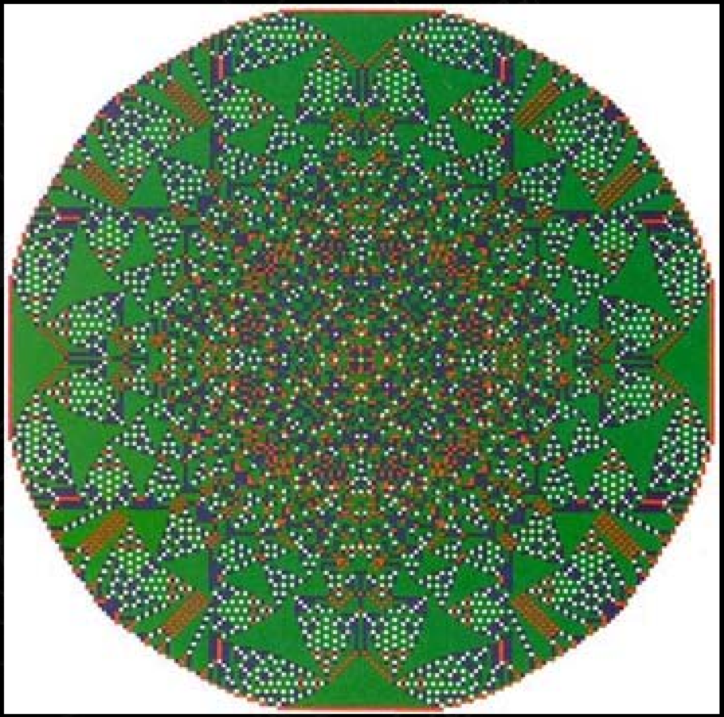


Figure: after 49152 grains dropped on a single site (fractals anyone?)

Sandpile Model: 2-D Case

Repeat until termination

  Select a random x and y

  Let $Z(x,y) \rightarrow Z(x,y)+1$

  Repeat until no $Z(x,y) = 4$

    For all (x,y)

      If $Z(x,y) = 4$ then

        $Z(x,y) \rightarrow Z(x,y)-4$

      and

        $Z(x \pm 1, y) \rightarrow Z(x \pm 1, y)+1$

        $Z(x, y \pm 1) \rightarrow Z(x, y \pm 1)+1$

$Z(x,y)$ no. of grains at position x, y

$Z(2,1) = 2$

1	2	0	2	3
2	3	2	3	0
1	2	3	3	2
3	1	3	2	1
0	2	2	1	2

Sandpile Model: 2-D case

adding of one sand grain: $Z(3,3) \to Z(3,3) + 1$

1	2	0	2	3
2	3	2	3	0
1	2	3	3	2
3	1	3	2	1
0	2	2	1	2

Sandpile Model: 2-D case

1	2	0	2	3
2	3	2	3	0
1	2	4	3	2
3	1	3	2	1
0	2	2	1	2

Sandpile Model: 2-D case

1	2	0	2	3
2	3	2	3	0
1	2	4	3	2
3	1	3	2	1
0	2	2	1	2

Sandpile Model: 2-D case

1	2	0	2	3
2	3	3	3	0
1	3	0	4	2
3	1	4	2	1
0	2	2	1	2

Sandpile Model: 2-D case

1	2	0	2	3
2	3	3	3	0
1	3	0	4	2
3	1	4	2	1
0	2	2	1	2

Sandpile Model: 2-D case

1	2	0	2	3
2	3	3	4	0
1	3	2	0	3
3	2	0	4	1
0	2	3	1	2

Sandpile Model: 2-D case

1	2	0	2	3
2	3	3	4	0
1	3	2	0	3
3	2	0	4	1
0	2	3	1	2

Sandpile Model: 2-D case

1	2	0	3	3
2	3	4	0	1
1	3	2	2	3
3	2	1	0	2
0	2	3	2	2

Sandpile Model: 2-D case

1	2	0	3	3
2	3	4	0	1
1	3	2	2	3
3	2	1	0	2
0	2	3	2	2

Sandpile Model: 2-D case

1	2	1	3	3
2	4	0	1	1
1	3	3	2	3
3	2	1	0	2
0	2	3	2	2

Sandpile Model: 2-D case

1	2	1	3	3
2	4	0	1	1
1	3	3	2	3
3	2	1	0	2
0	2	3	2	2

Sandpile Model: 2-D case

1	3	1	3	3
3	0	1	1	1
1	4	3	2	3
3	2	1	0	2
0	2	3	2	2

Sandpile Model: 2-D case

1	3	1	3	3
3	1	1	1	1
2	0	4	2	3
3	3	1	0	2
0	2	3	2	2

Sandpile Model: 2-D case

1	3	1	3	3
3	1	1	1	1
2	0	4	2	3
3	3	1	0	2
0	2	3	2	2

Sandpile Model: 2-D case

1	3	1	3	3
3	1	2	1	1
2	1	0	3	3
3	3	2	0	2
0	2	3	2	2

Sandpile Model: 2-D case

Time for NetLogo!

Sandpile: Results

If *s* is the number of grains in the cluster, the size of avalanches is distributed according to *P(s) ~ s^a*.

Figure shows a log-log plot of the distribution of the avalanche sizes *s* (number of topplings in an avalanche), *P* is the probability distribution

Intuitively: “small avalanches occur more often than big ones.”

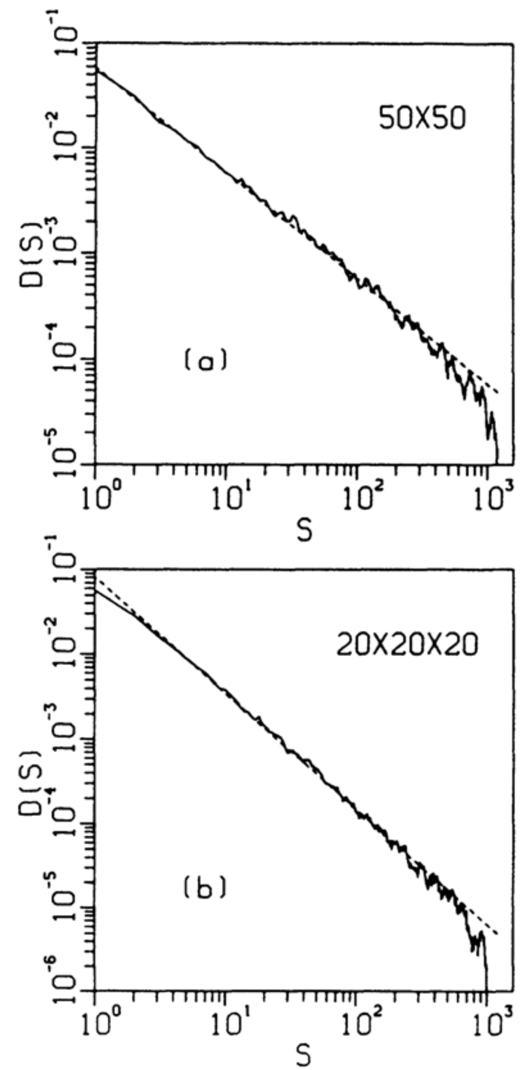


FIG. 3. Distribution of cluster sizes at criticality in two and three dimensions computed as described in the text. The data have been coarse grained. (a) 50×50 array, averaged over 200 samples. The dashed line is a straight line with slope -1.0; (b) $20\times 20\times 20$ array, averaged over 200 samples. The dashed straight line has a slope -1.37.

Sandpile: Results

Because of the power law, the initial state was actually remarkably correlated although it seemed at first featureless

For random distribution of z's (pile heights), one would expect the chain reaction of an avalanche to be either

- Subcritical (small avalanche)
- Supercritical (exploding avalanche with collapse of the entire system)

Power law indicates that the reaction is precisely critical, i.e. the probability that the activity at some site branches into more than one active site, is balanced by the probability that the activity dies

Self-Organized Criticality: Consequences

- Avalanches always occur in complex systems
- Catastrophes in complex systems are inevitable! This includes man-made <u>complex systems</u>, such as aeroplanes, power plants, stock exchange

Source: University Of Warwick
Date: February 22, 2001

More on: Nuclear Energy, Physics, Quantum Physics, Electricity, Energy Technology, Solar Energy

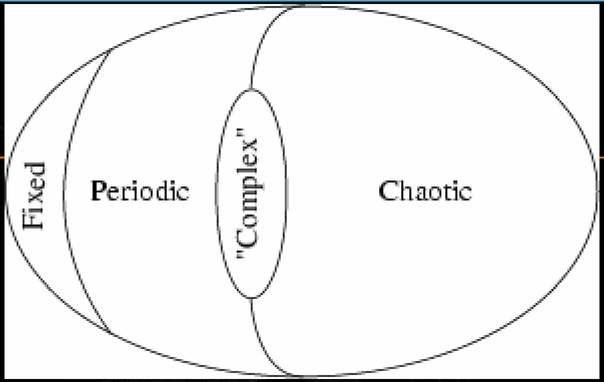
Simple Sandpile Model Helps Solve Problems Of Fusion Power

Science Daily — A team of physicists from the University of Warwick, and the EURATOM/UKAEA fusion research programme at the Culham Science Centre, have found a new simple and elegant way of using the science of 'sandpiles' to achieve a clear model of how a fusion plasma 'self organises' itself into a superstable state - a crucial key to power generation from fusion plasma.

This result is important because it demonstrates a comparatively simple link between space, astrophysical, and fusion plasmas and their overall confinement properties, and is a clear and welcome example of the unity of physics.

Nuclear fusion harnesses the same processes that generate the sun's energy - plasma fusion. This plasma gas is too hot to be contained by a conventional vessel so magnetic fields, shaped like a US donut (tokamak), are used. Temperatures hotter than the centre of the sun have been sustained for tens of seconds in a plasma volume of tens of cubic metres but the challenge is then to keep this small artificial sun burning and confined in its magnetic bottle.

Chaos vs. Complexity



Chaos

- Chaos is unpredictable though deterministic
- Chaos is extremely sensitive to initial conditions
- Chaos has no memory and cannot evolve
- The transition into a chaotic state can be estimated

Complexity

- Chaos is not complexity
- Complex behavior is neither linear nor uncorrelated
- Complexity is found at the border of stability and chaos
- The common mechanism of complex systems can be simulated by simple models (SOC)