

Power-Law Size Distributions

Last updated: 2019/08/26, 09:16:18

Principles of Complex Systems | @pocsvox
CSYS/MATH 300, Fall, 2019

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Vermont Advanced Computing Core | University of Vermont



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Zipf's law

Zipf $\Leftrightarrow$ CCDF

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$$P(x) \sim x^{-\delta}$$



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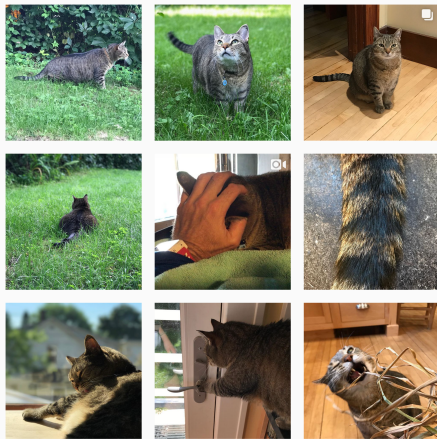
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Two of the many things we struggle with cognitively:

1. Probability.

- Ex. The Monty Hall Problem. 
- Ex. Daughter/Son born on Tuesday. 
(see next two slides; Wikipedia entry here )

2. Logarithmic scales.

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- Ex. The Monty Hall Problem. [↗](#)
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(see next two slides; Wikipedia entry here [↗](#).)

2. Logarithmic scales.

On counting and logarithms:



Listen to Radiolab's 2009 piece:
"Numbers." [↗](#).



Later: Benford's Law [↗](#).

$$P(x) \sim x^{-\gamma}$$

Two of the many things we struggle with cognitively:

1. Probability.

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2. Logarithmic scales.

On counting and logarithms:



Listen to Radiolab's 2009 piece:
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Later: Benford's Law [↗](#).

Also to be enjoyed: the magnificence of the
Dunning-Kruger effect [↗](#)

$$P(x) \sim x^{-\gamma}$$

Homo probabilisticus?

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A parent has two children.

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Simple probability question:

 What is the probability that both children are girls?

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Homo probabilisticus?

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The set up:

 A parent has two children.

Simple probability question:

 What is the probability that both children are girls?

The next set up:

 A parent has two children.

 We know one of them is a girl.

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Simple probability question:

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 1/4 ...

The next set up:

 A parent has two children.

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The next probabilistic poser:

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$$P(x) \sim x^{-\delta}$$

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The next probabilistic poser:

 What is the probability that both children are girls?

 1/3 ...

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Try this one:



A parent has two children.



We know one of them is a girl **born on a Tuesday**.

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Try this one:



A parent has two children.



We know one of them is a girl born on a Tuesday.

Simple question #3:



What is the probability that both children are girls?

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Try this one:



A parent has two children.



We know one of them is a girl born on a Tuesday.

Simple question #3:



What is the probability that both children are girls?

Last:



A parent has two children.

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Try this one:



A parent has two children.



We know one of them is a girl born on a Tuesday.

Simple question #3:



What is the probability that both children are girls?

Last:



A parent has two children.



We know one of them is a girl born on December 31.

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Try this one:



A parent has two children.



We know one of them is a girl born on a Tuesday.

Simple question #3:



What is the probability that both children are girls?

Last:



A parent has two children.



We know one of them is a girl born on December 31.

And ...



What is the probability that both children are girls?

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What is the probability that both children are girls?



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Last:



A parent has two children.



We know one of them is a girl born on December 31.

And ...



What is the probability that both children are girls?



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Money
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Two questions about wealth distribution in the United States:

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Two questions about wealth distribution in the United States:

1. Please estimate the percentage of all wealth owned by individuals when grouped into quintiles.

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Two questions about wealth distribution in the United States:

1. Please estimate the percentage of all wealth owned by individuals when grouped into quintiles.
2. Please estimate what you believe each quintile should own, ideally.

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Two questions about wealth distribution in the United States:

1. Please estimate the percentage of all wealth owned by individuals when grouped into quintiles.
2. Please estimate what you believe each quintile should own, ideally.
3. Extremes: 100, 0, 0, 0, 0 and 20, 20, 20, 20, 20

$$P(x) \sim x^{-\delta}$$



Wealth distribution in the United States:^[13]

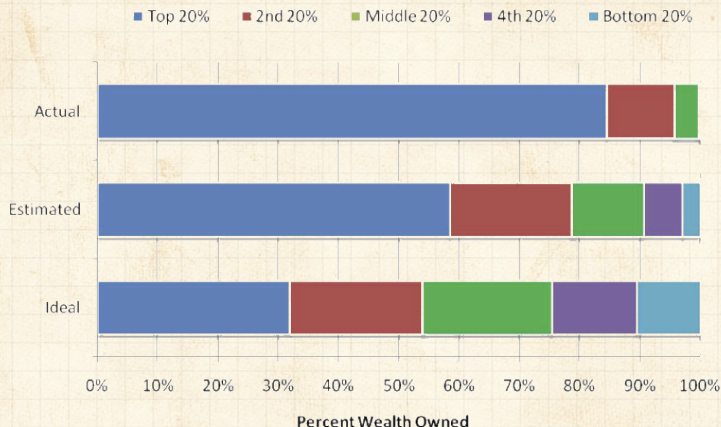


Fig. 2. The actual United States wealth distribution plotted against the estimated and ideal distributions across all respondents. Because of their small percentage share of total wealth, both the “4th 20%” value (0.2%) and the “Bottom 20%” value (0.1%) are not visible in the “Actual” distribution.

“Building a better America—One wealth quintile at a time”
Norton and Ariely, 2011.^[13]

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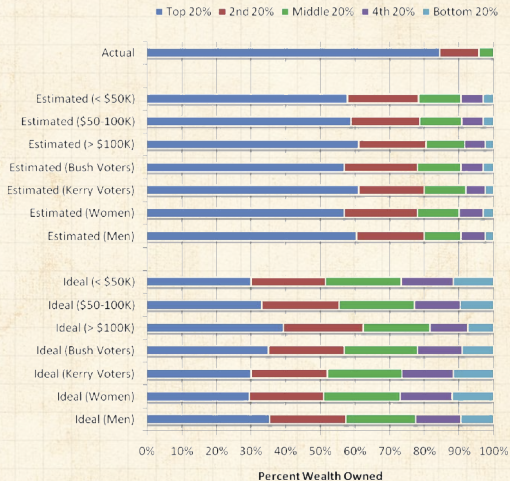


Fig. 3. The actual United States wealth distribution plotted against the estimated and ideal distributions of respondents of different income levels, political affiliations, and genders. Because of their small percentage share of total wealth, both the “4th 20%” value (0.2%) and the “Bottom 20%” value (0.1%) are not visible in the “Actual” distribution.

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The sizes of many systems' elements appear to obey an
inverse power-law size distribution:

$$P(\text{size} = x) \sim c x^{-\gamma}$$

where $0 < x_{\min} < x < x_{\max}$ and $\gamma > 1$.

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 Negative linear relationship in log-log space:

$$\log_{10} P(x) = \log_{10} c - \gamma \log_{10} x$$

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The sizes of many systems' elements appear to obey an **inverse power-law size distribution**:

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where $0 < x_{\min} < x < x_{\max}$ and $\gamma > 1$.

🧱 $x_{\min}$ = lower cutoff, $x_{\max}$ = upper cutoff

🧱 Negative linear relationship in log-log space:

$$\log_{10} P(x) = \log_{10} c - \gamma \log_{10} x$$

🧱 We use base 10 because we are **good people**.

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Power-Law Size Distributions

Usually, only the tail of the distribution obeys a power law:

$$P(x) \sim c x^{-\gamma} \text{ for } x \text{ large.}$$

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Power-Law Size
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Usually, only the tail of the distribution obeys a power law:

$$P(x) \sim c x^{-\gamma} \text{ for } x \text{ large.}$$



Still use term 'power-law size distribution.'

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Usually, only the tail of the distribution obeys a power law:

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Still use term 'power-law size distribution.'



Other terms:



Fat-tailed distributions.



Heavy-tailed distributions.

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Power-Law Size
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Usually, only the tail of the distribution obeys a power law:

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 Still use term 'power-law size distribution.'

 Other terms:

 **Fat-tailed** distributions.

 **Heavy-tailed** distributions.

Beware:

 Inverse power laws aren't the only ones:
lognormals, Weibull distributions, ...

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Many systems have discrete sizes k :



Word frequency

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Many systems have discrete sizes k :

-  Word frequency
-  Node degree in networks: # friends, # hyperlinks, etc.

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Many systems have discrete sizes k :

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Many systems have discrete sizes k :

-  Word frequency
-  Node degree in networks: # friends, # hyperlinks, etc.
-  # citations for articles, court decisions, etc.

$$P(k) \sim c k^{-\gamma}$$

where $k_{\min} \leq k \leq k_{\max}$

-  Obvious fail for $k = 0$.
-  Again, typically a description of distribution's tail.

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Brown Corpus ↗ (~ 10^6 words):

rank	word	% q
1.	the	6.8872
2.	of	3.5839
3.	and	2.8401
4.	to	2.5744
5.	a	2.2996
6.	in	2.1010
7.	that	1.0428
8.	is	0.9943
9.	was	0.9661
10.	he	0.9392
11.	for	0.9340
12.	it	0.8623
13.	with	0.7176
14.	as	0.7137
15.	his	0.6886

rank	word	% q
1945.	apply	0.0055
1946.	vital	0.0055
1947.	September	0.0055
1948.	review	0.0055
1949.	wage	0.0055
1950.	motor	0.0055
1951.	fifteen	0.0055
1952.	regarded	0.0055
1953.	draw	0.0055
1954.	wheel	0.0055
1955.	organized	0.0055
1956.	vision	0.0055
1957.	wild	0.0055
1958.	Palmer	0.0055
1959.	intensity	0.0055

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Jonathan Harris's Wordcount:

A word frequency distribution explorer:

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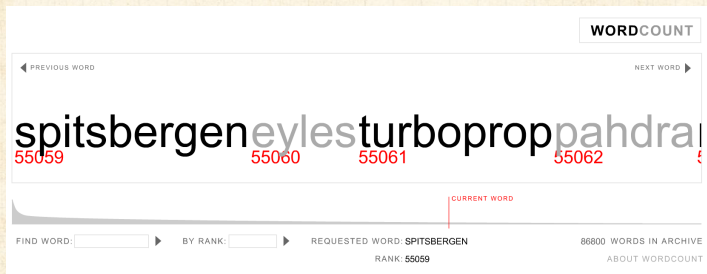
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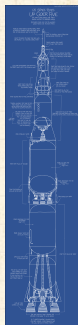
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"Thing Explainer: Complicated Stuff in Simple Words"
by Randall Munroe (2015).^[11]



BOAT THAT GOES UNDER THE SEA

We've always had boats that go under the sea, but in the last few hundred years, we've learned to make ones that come back up.

At first, we used those boats to shoot at other boats, make holes in them, or stick things to them that blew up.

Later, we found a new use for these boats: keeping our city-burning machines hidden, safe, and ready to use if there's a war.

WORLD-ENDING BOAT

The boat shown here carries up to two dozen city-burning war machines. People have added up the power used during the Second World War—all the machines that blew up, all the guns that fired, and all the cities that burned. It's a lot of fire power. Each of these boats carries several times that much.

SPECIAL SEA WORDS

Most of the time, if you call a really big boat a "boat," people who know a lot about boats will get mad at you. But boats that go under the sea are really called "boats."

HEAVY METAL POWER MACHINE

These boats are powered by heavy metal, just like some power buildings. This means they can stay hidden for a long time without running out of power. Any time heavy metal is used for power, people worry about something going wrong. Of course, given what these boats are built for, people worry even more about the idea of one of them working right.

BREATHING STICK

BREATHING STICK
This brings fresh air into the boat, but the boat can also make its own air by breaking water into the parts it's made of. This takes a lot of power, but the boat is powered by heavy metal, so

MIRROR LOOKERS

When the boat is hiding under the sea it can come near the surface and use these sticks with mirrors in them to let the people inside see out of the water.

SOUND LOOKERS

Light can't go far under water, so these boats "see" with sound. The boat makes sound, which hits things and comes back. By listening carefully, the people in the boat can tell what's around them without seeing—just like those skin divers.

SLEEPING ROOMS

The normal people on the boat sleep on either side of the city-burning machines.

Doors for city-burning Officers
Kitchen

EMPTY ROOMS

A while ago, everyone decided the world didn't need so many city-burning machines. This country agreed to turn off four of the two dozen flying machine carriers in each fleet, leaving only twenty

MACHINES FOR BURNING CITIES

Each of these rooms has a flying carrier full of city-burning machines. While hiding under the water, the boats can shoot the machines into space. Any of these boats can send a machine anywhere in the

Machine that makes copies

draws power from fire-water (in case there's a problem with the heavy metal)

MACHINES FOR SHOOTING BOATS

Boats used to carry more guns and machines like this, but boats don't really fight each other anymore.

OTHER BOATS THAT GO UNDER THE SEA

These are some other boats, drawn to show how they are next to the world-ending boat above.

Up goer five 

The statistics of surprise—words:

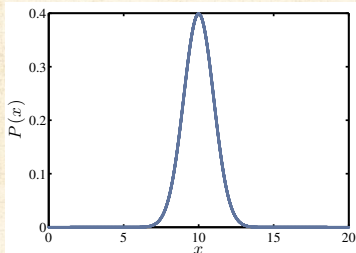
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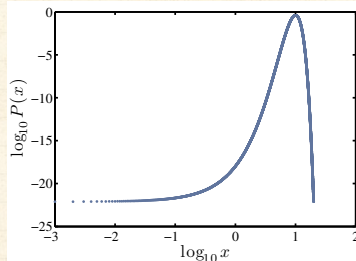
First—a Gaussian example:

$$P(x)dx = \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/2\sigma^2} dx$$

linear:



log-log



mean $\mu = 10$, variance $\sigma^2 = 1$.



Activity: Sketch $P(x) \sim x^{-1}$ for $x = 1$ to $x = 10^7$.

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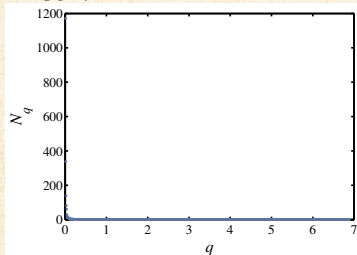
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Raw 'probability' (binned) for Brown Corpus:

linear:



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 q_w = normalized frequency of occurrence of word w (%).

 N_q = number of distinct words that have a normalized frequency of occurrence q .

 e.g, $q_{\text{the}} \simeq 6.9\%$, $N_{q_{\text{the}}} = 1$.



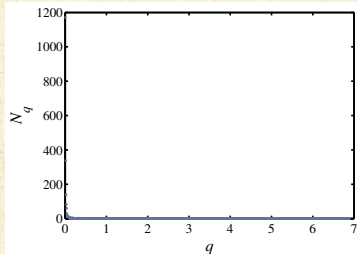
The statistics of surprise—words:

PoCS
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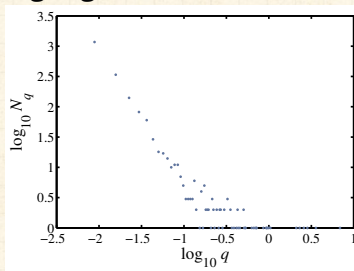
Power-Law Size
Distributions

Raw 'probability' (binned) for Brown Corpus:

linear:



log-log



 q_w = normalized frequency of occurrence of word w (%).

 N_q = number of distinct words that have a normalized frequency of occurrence q .

 e.g, $q_{\text{the}} \simeq 6.9\%$, $N_{q_{\text{the}}} = 1$.

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Wild vs. Mild

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Zipf $\Leftrightarrow$ CCDF

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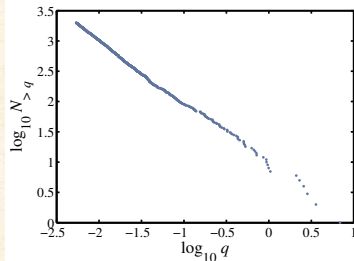
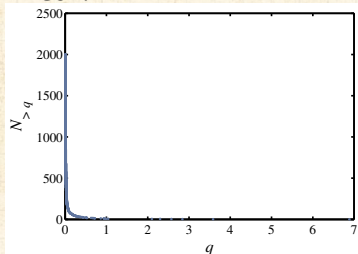
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log-log



Also known as the 'Exceedance Probability.'



My, what big words you have ...

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Power-Law Size
Distributions

Test your vocab

*How many words
do you know?*



 Test  capitalizes on word frequency following a heavily skewed frequency distribution with a decaying power-law tail.

 This Man Can Pronounce Every Word in the Dictionary  (story here )

 Best of Dr. Bailly 

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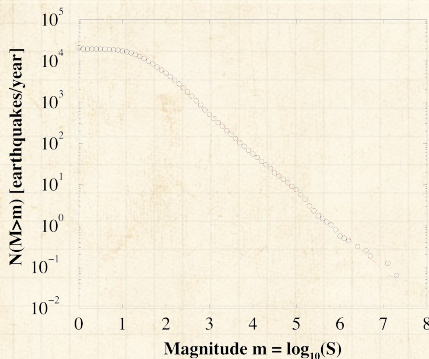


The statistics of surprise:

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Power-Law Size
Distributions

Gutenberg-Richter law



 Log-log plot

 Base 10

 Slope = -1

$$N(M > m) \propto m^{-1}$$

 From **both** the very awkwardly similar Christensen et al. and Bak et al.:

“Unified scaling law for earthquakes” [4, 1]

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The statistics of surprise:

From: "Quake Moves Japan Closer to U.S. and Alters Earth's Spin"  by Kenneth Chang, March 13, 2011, NYT:

'What is perhaps most surprising about the Japan earthquake is how misleading history can be.

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'What is perhaps most surprising about the Japan earthquake is how misleading history can be. In the past 300 years, no earthquake nearly that large—nothing larger than magnitude eight—had struck in the Japan subduction zone. That, in turn, led to assumptions about how large a tsunami might strike the coast.'

"It did them a giant disservice," said Dr. Stein of the geological survey.

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"It did them a giant disservice," said Dr. Stein of the geological survey. That is not the first time that the earthquake potential of a fault has been underestimated.

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"It did them a giant disservice," said Dr. Stein of the geological survey. That is not the first time that the earthquake potential of a fault has been underestimated. Most geophysicists did not think the Sumatra fault could generate a magnitude 9.1 earthquake, ...'

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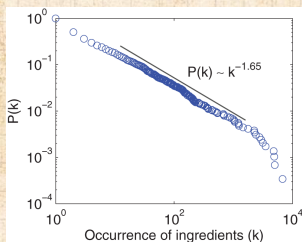
References





"Geography and similarity of regional cuisines in China" ↗

Zhu et al.,
PLoS ONE, **8**, e79161, 2013. [18]



Fraction of ingredients
that appear in at least k
recipes.



Oops in notation: $P(k)$ is
the Complementary
Cumulative Distribution
 $P_{\geq}(k)$

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"On a class of skew distribution functions" ↗

Herbert A. Simon,
Biometrika, **42**, 425–440, 1955. ^[15]



"Power laws, Pareto distributions and Zipf's law" ↗

M. E. J. Newman,
Contemporary Physics, **46**, 323–351,
2005. ^[12]



"Power-law distributions in empirical data" ↗

Clauset, Shalizi, and Newman,
SIAM Review, **51**, 661–703, 2009. ^[5]



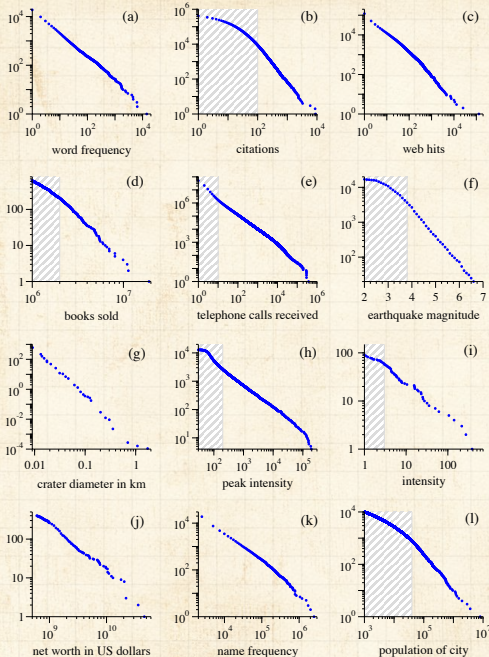


FIG. 4 Cumulative distributions or "rank/frequency plots" of twelve quantities reputed to follow power laws. The distributions were computed as described in Appendix A. Data in the shaded regions were excluded from the calculations of the exponents in Table I. Source references for the data are given in the text. (a) Numbers of occurrences of words in the novel *Moby Dick* by Herman Melville. (b) Numbers of citations to scientific papers published in 1981, from time of publication until June 1997. (c) Numbers of hits on web sites by 60,000 users of the America Online Internet service for the day of 1 December 1997. (d) Numbers of copies of bestselling books sold in the US between 1895 and 1965. (e) Number of calls received by AT&T telephone customers in the US for a single day. (f) Magnitude of earthquakes in California between January 1940 and May 1992. Magnitude is proportional to the logarithm of the maximum amplitude of the earthquake, and hence the distribution obeys a power law even though the horizontal axis is linear. (g) Diameter of craters on the moon. Vertical axis is measured per square kilometre. (h) Peak gamma-ray intensity of solar flares in counts per second, measured from Earth orbit between February 1980 and November 1989. (i) Intensity of wars from 1816 to 1980, measured as battle deaths per 10,000 of the population of the participating countries. (j) Aggregate net worth in dollars of the richest individuals in the US in October 2003. (k) Frequency of occurrence of family names in the US in the year 1990. (l) Populations of US cities in the year 2000.



Size distributions:

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Power-Law Size
Distributions

Some examples:

 Earthquake magnitude (Gutenberg-Richter law ): ^[9, 1] $P(M) \propto M^{-2}$

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 Earthquake magnitude (Gutenberg-Richter law ): ^[9, 1] $P(M) \propto M^{-2}$

 # war deaths: ^[14] $P(d) \propto d^{-1.8}$

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 Earthquake magnitude (Gutenberg-Richter law ): ^[9, 1] $P(M) \propto M^{-2}$

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 Sizes of forest fires ^[8]

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 Sizes of forest fires ^[8]

 Sizes of cities: ^[15] $P(n) \propto n^{-2.1}$

 # links to and from websites ^[2]

 Note: Exponents range in error

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Size distributions:

More examples:

 # citations to papers: ^[6, 7] $P(k) \propto k^{-3}$.

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Size distributions:

More examples:

-  # citations to papers: ^[6, 7] $P(k) \propto k^{-3}$.
-  Individual wealth (maybe): $P(W) \propto W^{-2}$.
-  Distributions of tree trunk diameters: $P(d) \propto d^{-2}$.
-  The gravitational force at a random point in the universe: ^[10] $P(F) \propto F^{-5/2}$. (See the Holtmark distribution  and stable distributions .)

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- # religious adherents in cults: ^[5] $P(k) \propto k^{-1.8 \pm 0.1}$.

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Size distributions:

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- # sightings of birds per species (North American Breeding Bird Survey for 2003): ^[5]
 $P(k) \propto k^{-2.1 \pm 0.1}$.
- # species per genus: ^[17, 15, 5] $P(k) \propto k^{-2.4 \pm 0.2}$.



Table 3 from Clauset, Shalizi, and Newman [5]:

Basic parameters of the data sets described in section 6, along with their power-law fits and the corresponding p -values (statistically significant values are denoted in **bold**).

Quantity	n	$\langle x \rangle$	σ	$x_{\max}$	$\hat{x}_{\min}$	$\hat{\alpha}$	n_{tail}	p
count of word use	18 855	11.14	148.33	14 086	7 ± 2	1.95(2)	2958 ± 987	0.49
protein interaction degree	1846	2.34	3.05	56	5 ± 2	3.1(3)	204 ± 263	0.31
metabolic degree	1641	5.68	17.81	468	4 ± 1	2.8(1)	748 ± 136	0.00
Internet degree	22 688	5.63	37.83	2583	21 ± 9	2.12(9)	770 ± 1124	0.29
telephone calls received	51 360 423	3.88	179.09	375 746	120 ± 49	2.09(1)	$102\,592 \pm 210\,147$	0.63
intensity of wars	115	15.70	49.97	382	2.1 ± 3.5	1.7(2)	70 ± 14	0.20
terrorist attack severity	9101	4.35	31.58	2749	12 ± 4	2.4(2)	547 ± 1663	0.68
HTTP size (kilobytes)	226 386	7.36	57.94	10 971	36.25 ± 22.74	2.48(5)	6794 ± 2232	0.00
species per genus	509	5.59	6.94	56	4 ± 2	2.4(2)	233 ± 138	0.10
bird species sightings	591	3384.36	10 952.34	138 705	6679 ± 2463	2.1(2)	66 ± 41	0.55
blackouts ($\times 10^3$)	211	253.87	610.31	7500	230 ± 90	2.3(3)	59 ± 35	0.62
sales of books ($\times 10^3$)	633	1986.67	1396.60	19 077	2400 ± 430	3.7(3)	139 ± 115	0.66
population of cities ($\times 10^3$)	19 447	9.00	77.83	8 009	52.46 ± 11.88	2.37(8)	580 ± 177	0.76
email address books size	4581	12.45	21.49	333	57 ± 21	3.5(6)	196 ± 449	0.16
forest fire size (acres)	203 785	0.90	20.99	4121	6324 ± 3487	2.2(3)	521 ± 6801	0.05
solar flare intensity	12 773	689.41	6520.59	231 300	323 ± 89	1.79(2)	1711 ± 384	1.00
quake intensity ($\times 10^3$)	19 302	24.54	563.83	63 096	0.794 ± 80.198	1.64(4)	$11\,697 \pm 2159$	0.00
religious followers ($\times 10^6$)	103	27.36	136.64	1050	3.85 ± 1.60	1.8(1)	39 ± 26	0.42
freq. of surnames ($\times 10^3$)	2753	50.59	113.99	2502	111.92 ± 40.67	2.5(2)	239 ± 215	0.20
net worth (mil. USD)	400	2388.69	4167.35	46 000	900 ± 364	2.3(1)	302 ± 77	0.00
citations to papers	415 229	16.17	44.02	8904	160 ± 35	3.16(6)	3455 ± 1859	0.20
papers authored	401 445	7.21	16.52	1416	133 ± 13	4.3(1)	988 ± 377	0.90
hits to web sites	119 724	9.83	392.52	129 641	2 ± 13	1.81(8)	$50\,981 \pm 16\,898$	0.00
links to web sites	241 428 853	9.15	106 871.65	1 199 466	3684 ± 151	2.336(9)	$28\,986 \pm 1560$	0.00



We'll explore various exponent measurement techniques in assignments.

power-law size distributions

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Power-Law Size
Distributions

Gaussians versus power-law size distributions:

Mediocristan versus Extremistan

Mild versus Wild (Mandelbrot)

Example: Height versus wealth.

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THE BLACK SWAN



The Impact of the
HIGHLY IMPROBABLE

Nassim Nicholas Taleb



See "The Black Swan" by Nassim Taleb. ^[16]



Terrible if successful framing:
Black swans are not that
surprising ...

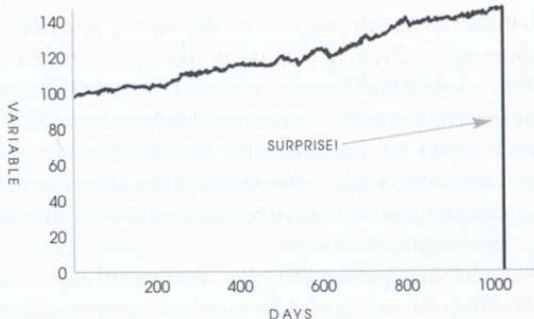


Turkeys ...

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Power-Law Size
Distributions

FIGURE 1: ONE THOUSAND AND ONE DAYS OF HISTORY



A turkey before and after Thanksgiving. The history of a process over a thousand days tells you nothing about what is to happen next. This naïve projection of the future from the past can be applied to anything.

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From "The Black Swan" [16]



Mediocristan/Extremistan

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Mediocristan/Extremistan

 Most typical member is mediocre / Most typical is either giant or tiny

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Mediocristan/Extremistan

- Most typical member is mediocre/Most typical is either giant or tiny
- Winners get a small segment/Winner take almost all effects

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- Most typical member is mediocre/Most typical is either giant or tiny
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- When you observe for a while, you know what's going on/It takes a very long time to figure out what's going on

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- Prediction is easy/Prediction is hard

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- Prediction is easy/Prediction is hard
- History crawls/History makes jumps
- Tyranny of the collective/Tyranny of the rare and accidental

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Size distributions:

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Power-law size distributions are sometimes called Pareto distributions after Italian scholar Vilfredo Pareto.

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Size distributions:

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Pareto noted wealth in Italy was distributed unevenly (80–20 rule; misleading).

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Power-Law Size
Distributions



Power-law size distributions are sometimes called Pareto distributions after Italian scholar Vilfredo Pareto.

-  Pareto noted wealth in Italy was distributed unevenly (80–20 rule; misleading).
-  Term used especially by practitioners of the Dismal Science.

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Devilish power-law size distribution details:

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Power-Law Size
Distributions

Exhibit A:

 Given $P(x) = cx^{-\gamma}$ with $0 < x_{\min} < x < x_{\max}$,
the mean is ($\gamma \neq 2$):

$$\langle x \rangle = \frac{c}{2 - \gamma} (x_{\max}^{2-\gamma} - x_{\min}^{2-\gamma}) .$$

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Insert question from assignment 2 



Devilish power-law size distribution details:

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Power-Law Size
Distributions

Exhibit A:

 Given $P(x) = cx^{-\gamma}$ with $0 < x_{\min} < x < x_{\max}$,
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$$\langle x \rangle = \frac{c}{2 - \gamma} (x_{\max}^{2-\gamma} - x_{\min}^{2-\gamma}).$$

 Mean 'blows up' with upper cutoff if $\gamma < 2$.

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Insert question from assignment 2 



Devilish power-law size distribution details:

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Power-Law Size
Distributions

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 Given $P(x) = cx^{-\gamma}$ with $0 < x_{\min} < x < x_{\max}$,
the mean is ($\gamma \neq 2$):

$$\langle x \rangle = \frac{c}{2 - \gamma} (x_{\max}^{2-\gamma} - x_{\min}^{2-\gamma}).$$

 Mean 'blows up' with upper cutoff if $\gamma < 2$.

 Mean depends on lower cutoff if $\gamma > 2$.

Insert question from assignment 2 

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Devilish power-law size distribution details:

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Power-Law Size
Distributions

Exhibit A:

 Given $P(x) = cx^{-\gamma}$ with $0 < x_{\min} < x < x_{\max}$,
the mean is ($\gamma \neq 2$):

$$\langle x \rangle = \frac{c}{2-\gamma} (x_{\max}^{2-\gamma} - x_{\min}^{2-\gamma}).$$

 Mean 'blows up' with upper cutoff if $\gamma < 2$.

 Mean depends on lower cutoff if $\gamma > 2$.

 $\gamma < 2$: Typical sample is large.

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Power-Law Size
Distributions

Exhibit A:

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 Mean 'blows up' with upper cutoff if $\gamma < 2$.

 Mean depends on lower cutoff if $\gamma > 2$.

 $\gamma < 2$: Typical sample is large.

 $\gamma > 2$: Typical sample is small.

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And in general ...

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Power-Law Size
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Moments:



All moments depend only on cutoffs.

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And in general ...

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Power-Law Size Distributions

Moments:

- ⌘ All moments depend only on cutoffs.
- ⌘ No internal scale that dominates/matters.

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And in general ...

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Power-Law Size
Distributions

Moments:

- ⌘ All moments depend only on cutoffs.
- ⌘ No **internal scale** that dominates/matters.
- ⌘ Compare to a Gaussian, exponential, etc.

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And in general ...

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Moments:

- ⌘ All moments depend only on cutoffs.
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For many real size distributions: $2 < \gamma < 3$

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Power-Law Size
Distributions

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For many real size distributions: $2 < \gamma < 3$

- ☎ mean is finite (depends on lower cutoff)

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Power-Law Size
Distributions

Moments:

- 🧱 All moments depend only on cutoffs.
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For many real size distributions: $2 < \gamma < 3$

- 🧱 mean is finite (depends on lower cutoff)
- 🧱 σ^2 = variance is 'infinite' (depends on upper cutoff)

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For many real size distributions: $2 < \gamma < 3$

- ⌘ mean is finite (depends on lower cutoff)
- ⌘ σ^2 = variance is 'infinite' (depends on upper cutoff)
- ⌘ Width of distribution is 'infinite'

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Moments:

- ☎ All moments depend only on cutoffs.
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For many real size distributions: $2 < \gamma < 3$

- ☎ mean is finite (depends on lower cutoff)
- ☎ σ^2 = variance is 'infinite' (depends on upper cutoff)
- ☎ Width of distribution is 'infinite'
- ☎ If $\gamma > 3$, distribution is less terrifying and may be easily confused with other kinds of distributions.

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Standard deviation is a mathematical convenience:

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Standard deviation is a mathematical convenience:

 Variance is nice analytically ...

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Standard deviation is a mathematical convenience:



Variance is nice analytically ...



Another measure of distribution width:

$$\text{Mean average deviation (MAD)} = \langle |x - \langle x \rangle| \rangle$$

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Standard deviation is a mathematical convenience:

- 🧱 Variance is nice analytically ...
- 🧱 Another measure of distribution width:

$$\text{Mean average deviation (MAD)} = \langle |x - \langle x \rangle| \rangle$$

- 🧱 For a pure power law with $2 < \gamma < 3$:

$\langle |x - \langle x \rangle| \rangle$ is finite.

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- 🧱 But MAD is mildly unpleasant analytically ...

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Standard deviation is a mathematical convenience:

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- 🧱 For a pure power law with $2 < \gamma < 3$:

$$\langle |x - \langle x \rangle| \rangle \text{ is finite.}$$

- 🧱 But MAD is mildly unpleasant analytically ...
- 🧱 We still speak of infinite 'width' if $\gamma < 3$.

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How sample sizes grow ...

Given $P(x) \sim cx^{-\gamma}$:

 We can show that after n samples, we expect the largest sample to be¹

$$x_1 \gtrsim c' n^{1/(\gamma-1)}$$

[Insert question from assignment 4](#) 

[Insert question from assignment 6](#) 

¹Later, we see that the largest sample grows as n^ρ where ρ is the Zipf exponent

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How sample sizes grow ...

Given $P(x) \sim cx^{-\gamma}$:

- ✉ We can show that after n samples, we expect the largest sample to be¹

$$x_1 \gtrsim c' n^{1/(\gamma-1)}$$

- ✉ Sampling from a finite-variance distribution gives a much slower growth with n .

[Insert question from assignment 4](#) 

[Insert question from assignment 6](#) 

¹Later, we see that the largest sample grows as n^ρ where ρ is the Zipf exponent

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How sample sizes grow ...

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Given $P(x) \sim cx^{-\gamma}$:

 We can show that after n samples, we expect the largest sample to be¹

$$x_1 \gtrsim c' n^{1/(\gamma-1)}$$

 Sampling from a finite-variance distribution gives a much slower growth with n .

 e.g., for $P(x) = \lambda e^{-\lambda x}$, we find

$$x_1 \gtrsim \frac{1}{\lambda} \ln n.$$

[Insert question from assignment 4](#) 

[Insert question from assignment 6](#) 

¹Later, we see that the largest sample grows as n^ρ where ρ is the Zipf exponent

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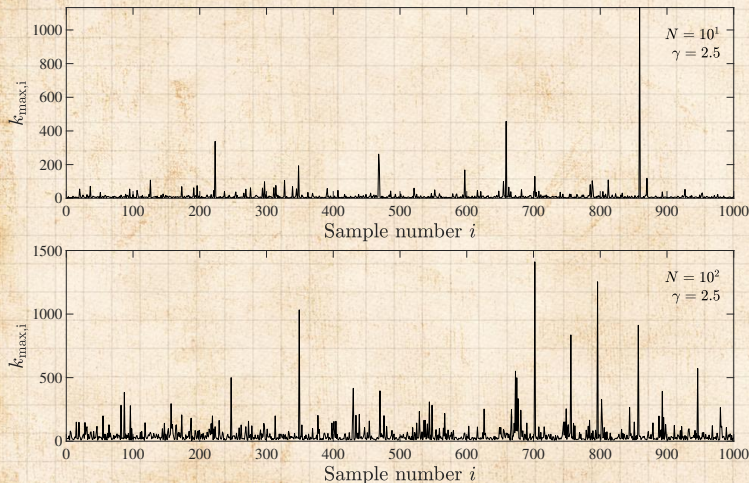
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 $\gamma = 5/2$, maxima of N samples, $n = 1000$ sets of samples:



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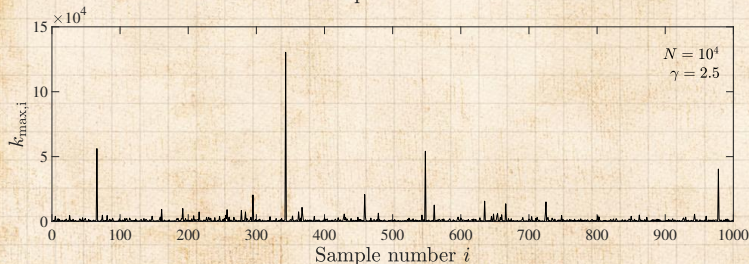
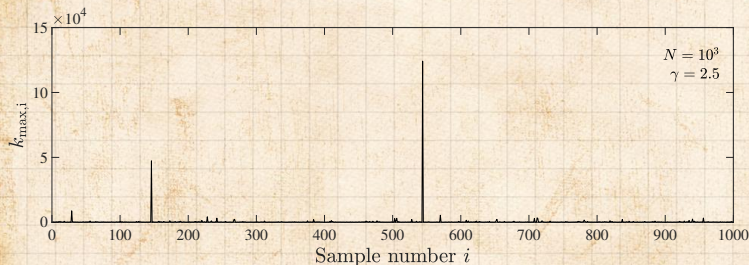
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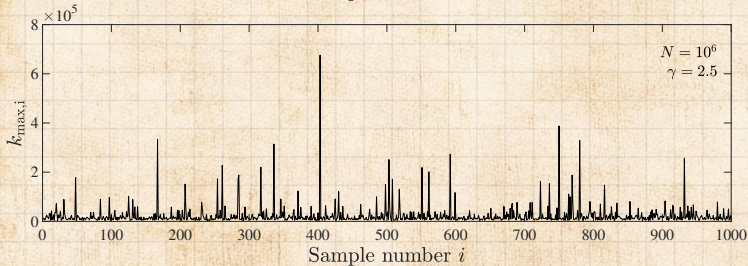
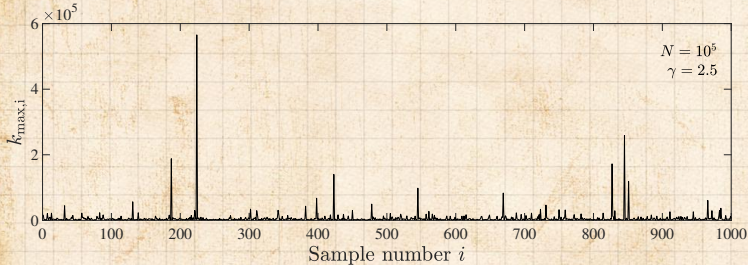
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 $\gamma = 5/2$, maxima of N samples, $n = 1000$ sets of samples:



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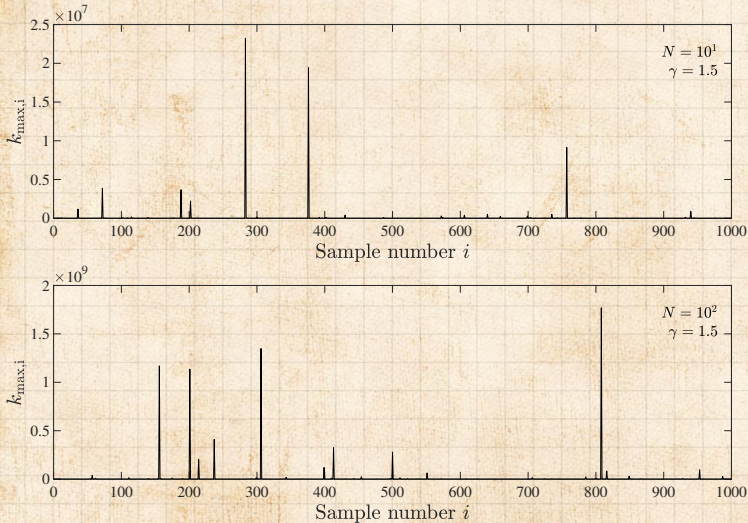
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 $\gamma = 3/2$, maxima of N samples, $n = 1000$ sets of samples:



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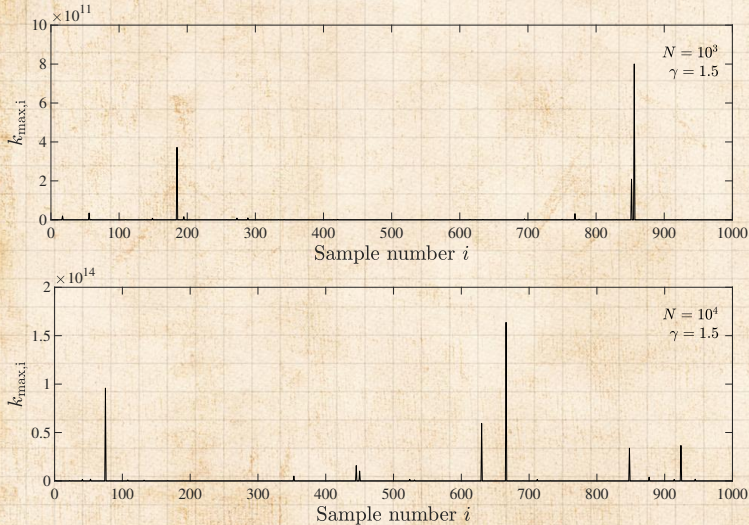
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 $\gamma = 3/2$, maxima of N samples, $n = 1000$ sets of samples:



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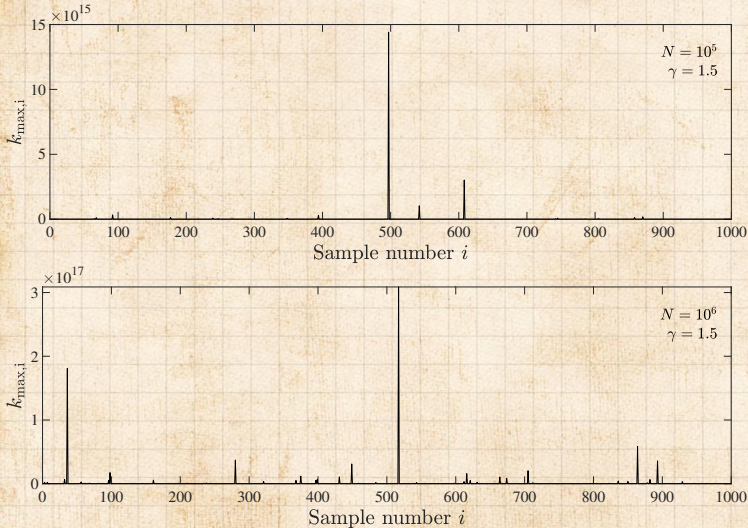
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 $\gamma = 3/2$, maxima of N samples, $n = 1000$ sets of samples:



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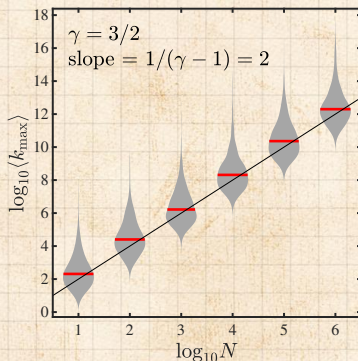
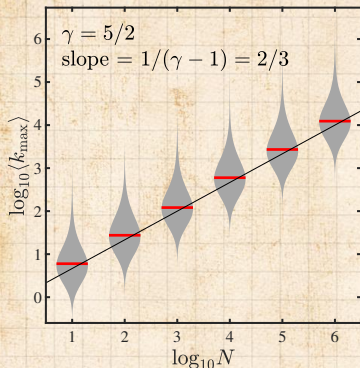
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Scaling of expected largest value as a function of sample size N :



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Fit for $\gamma = 5/2$: $k_{\max} \sim N^{0.660 \pm 0.066}$ (sublinear)

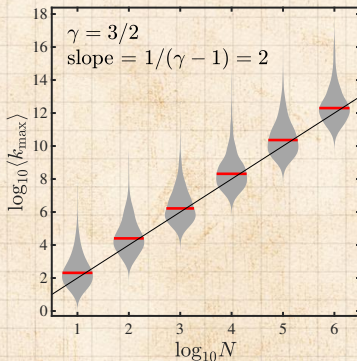
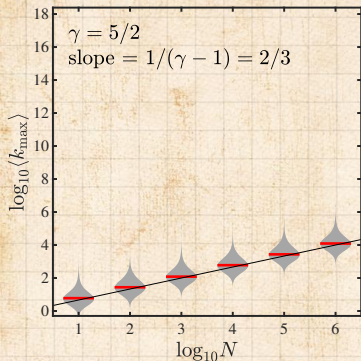


Fit for $\gamma = 3/2$: $k_{\max} \sim N^{2.063 \pm 0.215}$ (superlinear)





Scaling of expected largest value as a function of sample size N :



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Fit for $\gamma = 5/2$: $k_{\max} \sim N^{0.660 \pm 0.066}$ (sublinear)



Fit for $\gamma = 3/2$: $k_{\max} \sim N^{2.063 \pm 0.215}$ (superlinear)



Complementary Cumulative Distribution Function:

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Complementary Cumulative Distribution Function:

CCDF:



$$P_{\geq}(x) = P(x' \geq x) = 1 - P(x' < x)$$

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Complementary Cumulative Distribution Function:

CCDF:



$$P_{\geq}(x) = P(x' \geq x) = 1 - P(x' < x)$$



$$= \int_{x'=x}^{\infty} P(x') dx'$$

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Complementary Cumulative Distribution Function:

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$$P_{\geq}(x) = P(x' \geq x) = 1 - P(x' < x)$$



$$= \int_{x'=x}^{\infty} P(x') dx'$$



$$\propto \int_{x'=x}^{\infty} (x')^{-\gamma} dx'$$

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Complementary Cumulative Distribution Function:

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$$\propto \int_{x'=x}^{\infty} (x')^{-\gamma} dx'$$



$$= \frac{1}{-\gamma + 1} (x')^{-\gamma+1} \Big|_{x'=x}^{\infty}$$

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Complementary Cumulative Distribution Function:

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Complementary Cumulative Distribution Function:

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$$P_{\geq}(x) \propto x^{-\gamma+1}$$



Use when tail of P follows a power law.

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CCDF:



$$P_{>}(x) \propto x^{-\gamma+1}$$



- Use when tail of P follows a power law.



 Increases exponent by one.

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Complementary Cumulative Distribution Function:

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$$P_{\geq}(x) \propto x^{-\gamma+1}$$



Use when tail of P follows a power law.



Increases exponent by one.



Useful in cleaning up data.

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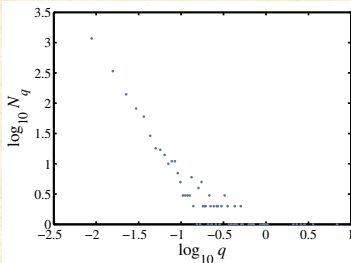
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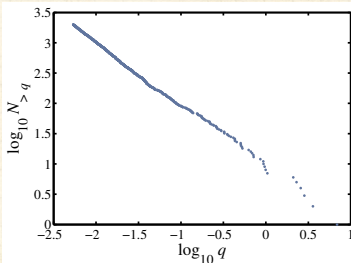
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Same story for a discrete variable: $P(k) \sim ck^{-\gamma}$.



$$P_{\geq}(k) = P(k' \geq k)$$

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Same story for a discrete variable: $P(k) \sim ck^{-\gamma}$.



$$P_{\geq}(k) = P(k' \geq k)$$

$$= \sum_{k'=k}^{\infty} P(k')$$

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Use integrals to approximate sums.

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Zipfian rank-frequency plots

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Power-Law Size
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George Kingsley Zipf:

- Noted various rank distributions have power-law tails, often with exponent -1 (word frequency, city sizes, ...)

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Power-Law Size
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 Zipf's 1949 Magnum Opus 



"Human Behaviour and the Principle of Least-Effort"  
by G. K. Zipf (1949). ^[19]

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 We'll study Zipf's law in depth ...

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Zipf's way:

 Given a collection of entities, rank them by size, largest to smallest.

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Zipf's way:

 Given a collection of entities, rank them by size, largest to smallest.

 x_r = the size of the r th ranked entity.

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Zipf's way:

 Given a collection of entities, rank them by size, largest to smallest.

 x_r = the size of the r th ranked entity.

 $r = 1$ corresponds to the largest size.

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Zipf's way:

-  Given a collection of entities, rank them by size, largest to smallest.
-  x_r = the size of the r th ranked entity.
-  $r = 1$ corresponds to the largest size.
-  Example: x_1 could be the frequency of occurrence of the most common word in a text.

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Zipfian rank-frequency plots

Zipf's way:

- Given a collection of entities, rank them by size, largest to smallest.
- x_r = the size of the r th ranked entity.
- $r = 1$ corresponds to the largest size.
- Example: x_1 could be the frequency of occurrence of the most common word in a text.
- Zipf's observation:

$$x_r \propto r^{-\alpha}$$

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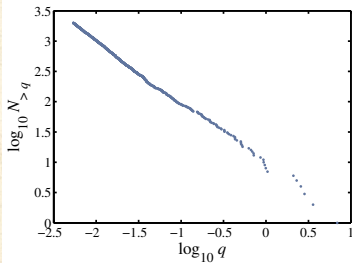
Size distributions:

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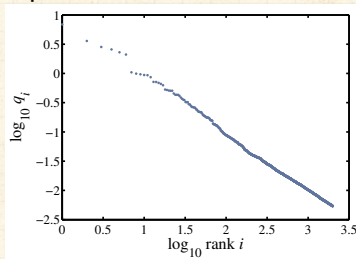
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Brown Corpus (1,015,945 words):

CCDF:



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🧱 The, of, and, to, a, ...= 'objects'

🧱 'Size' = word frequency



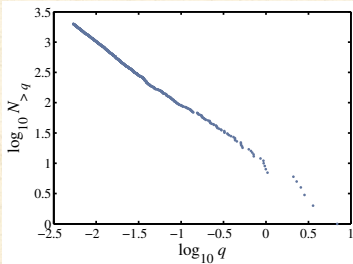
Size distributions:

PoCS
@pocsvox

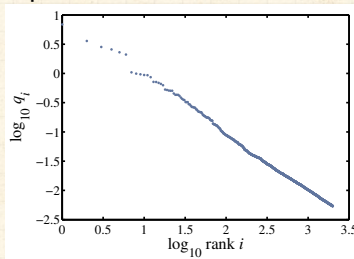
Power-Law Size
Distributions

Brown Corpus (1,015,945 words):

CCDF:



Zipf:



- 🧱 The, of, and, to, a, ...= 'objects'
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- 🧱 **Beep:** (Important) CCDF and Zipf plots are related

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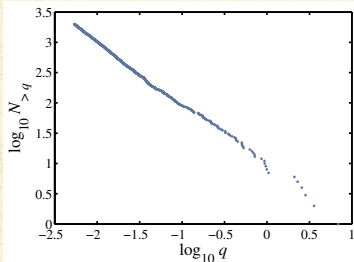
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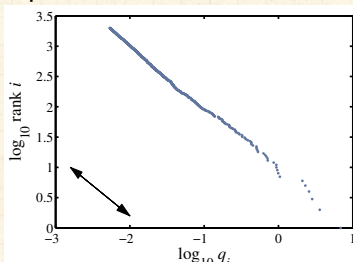
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Observe:

 $NP_{\geq}(x)$ = the number of objects with size at least x
where N = total number of objects.

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Observe:

 $NP_{\geq}(x)$ = the number of objects with size at least x
where N = total number of objects.

 If an object has size x_r , then $NP_{\geq}(x_r)$ is its rank r .

 So

$$x_r \propto r^{-\alpha} = (NP_{\geq}(x_r))^{-\alpha}$$

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 A rank distribution exponent of $\alpha = 1$ corresponds to a size distribution exponent $\gamma = 2$.

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"Zipf's Law in the Popularity Distribution of Chess Openings" ↗

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Phys. Rev. Lett., **103**, 218701, 2009. [3]

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Show "the frequencies of opening moves are distributed according to a power law with an exponent that increases linearly with the game depth, whereas the pooled distribution of all opening weights follows Zipf's law with universal exponent."

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Propose hierarchical fragmentation model that produces self-similar game trees.

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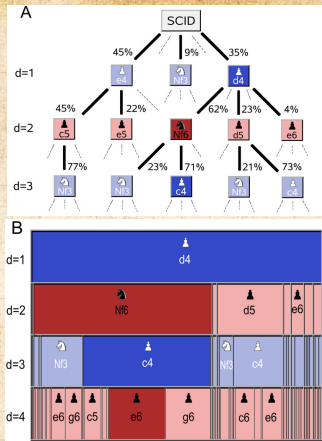


FIG. 1 (color online). (a) Schematic representation of the weighted game tree of chess based on the SCIDBASE [6] for the first three half moves. Each node indicates a state of the game. Possible game continuations are shown as solid lines together with the branching ratios r_d . Dotted lines symbolize other game continuations, which are not shown. (b) Alternative representation emphasizing the successive segmentation of the set of games, here indicated for games following a 1.d4 opening until the fourth half move $d = 4$. Each node σ is represented by a box of a size proportional to its frequency n_{σ} . In the subsequent half move these games split into subsets (indicated vertically below) according to the possible game continuations. Highlighted in (a) and (b) is a popular opening sequence 1.d4 Nf6 2.c4 e6 (Indian defense).

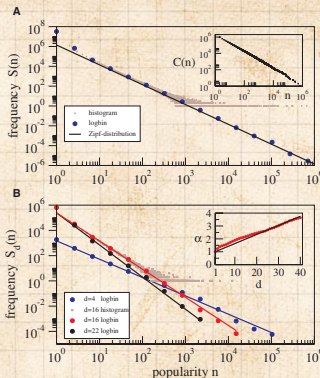


FIG. 2 (color online). (a) Histogram of weight frequencies $S(n)$ of openings up to $d = 40$ in the Scid database and with logarithmic binning. A straight line fit (not shown) yields an exponent of $\alpha = 2.05$ with a goodness of fit $R^2 > 0.9992$. For comparison, the Zipf distribution Eq. (8) with $\mu = 1$ is indicated as a solid line. Inset: number $C(n) = \sum_{m=n+1}^N S(m)$ of openings with a popularity $m > n$. $C(n)$ follows a power law with exponent $\alpha = 1.04$ ($R^2 = 0.994$). (b) Number $S_d(n)$ of openings of depth d with a given popularity n for $d = 16$ and histograms with logarithmic binning for $d = 4$, $d = 16$, and $d = 22$. Solid lines are regression lines to the logarithmically binned data ($R^2 > 0.99$ for $d < 35$). Inset: slope α_d of the regression line as a function of d and the analytical estimation Eq. (6) using $N = 1.4 \times 10^6$ and $\beta = 0$ (solid line).

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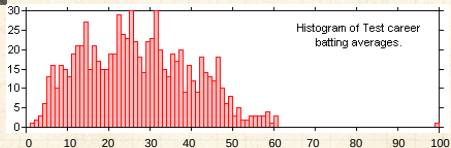
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Extreme deviations in test cricket:



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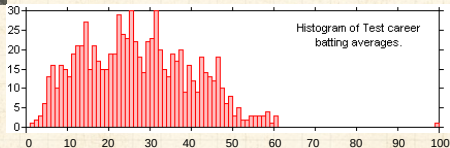
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Extreme deviations in test cricket:



Don Bradman's batting average ↗
= 166% next best.

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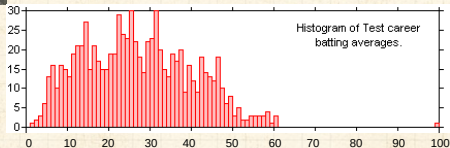
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Extreme deviations in test cricket:



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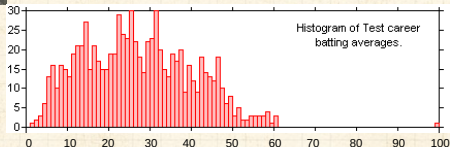
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Extreme deviations in test cricket:



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Later in the course: Understanding success—
is the Mona Lisa like Don Bradman?

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A good eye:

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<http://www.youtube.com/watch?v=9o6vTXgYdqA?rel=0>



The great Paul Kelly's tribute to the man who
was "Something like the tide"



Neural reboot (NR):

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