# Power-Law Size Distributions

## Principles of Complex Systems | @pocsvox
## CSYS/MATH 300, Fall, 2016 | #FallPoCS2016


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Vermont Advanced Computing Core | University of Vermont



PoCS
Principles of Complex Systems
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What's the Story?






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

# These slides are brought to you by:




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# Outline

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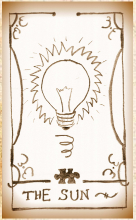


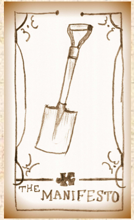


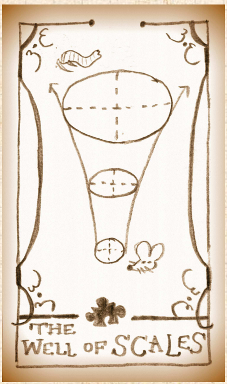


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## Two of the many things we struggle with cognitively:

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

## On counting and logarithms:

- Listen to Radiolab's 2009 piece: "Numbers.".
- Later: Benford's Law.

Also to be enjoyed: the magnificence of the Dunning-Kruger effect

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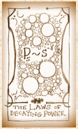

# Homo probabilisticus?

## The set up:

- A parent has two children.

## Simple probability question:

- What is the probability that both children are girls?
- 1/4...

## The next set up:

- A parent has two children.
- We know one of them is a girl.

## The next probabilistic poser:

- What is the probability that both children are girls?
- 1/3...



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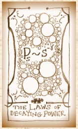


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## Try this one:

- 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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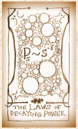

# Let's test our collective intuition:


Money

≡

Belief

## 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

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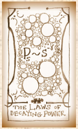

# Wealth distribution in the United States: [12]

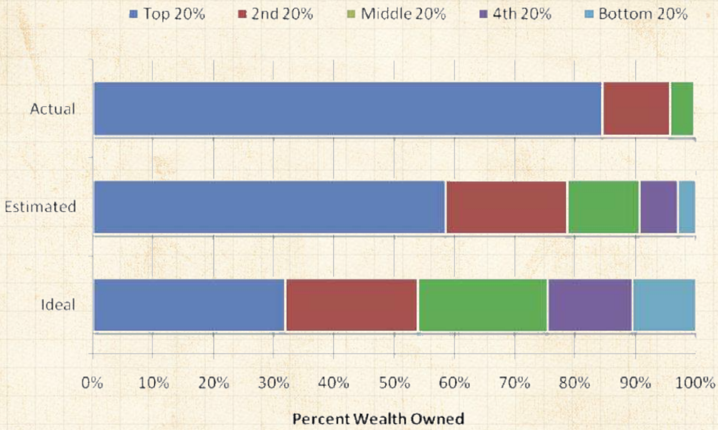


**Fig. 2.** The actual United States wealth distribution plotted against the estimated and ideal distributions across all respondents. Because of their small percentage share of total wealth, both the "4th 20%" value (0.2%) and the "Bottom 20%" value (0.1%) are not visible in the "Actual" distribution.

"Building a better America—One wealth quintile at a time"
Norton and Ariely, 2011. [12]



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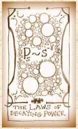

# Wealth distribution in the United States: [12]

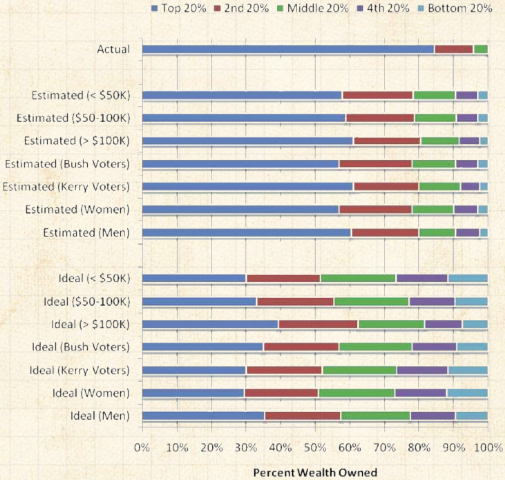


**Fig. 3.** The actual United States wealth distribution plotted against the estimated and ideal distributions of respondents of different income levels, political affiliations, and genders. Because of their small percentage share of total wealth, both the "4th 20%" value (0.2%) and the "Bottom 20%"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

A highly watched video based on this research is here.




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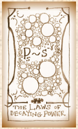

The sizes of many systems' elements appear to obey an inverse power-law size distribution:

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

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

- $x_{\text{min}}$ = lower cutoff, $x_{\text{max}}$ = 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.

- power-law decays in probability:
  The Statistics of Surprise.

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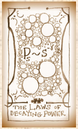


# Size distributions:



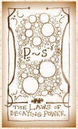
## Usually, only the tail of the distribution obeys a power law:

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

- Still use term 'power-law size distribution.'
- Other terms:
  - Fat-tailed distributions.
  - Heavy-tailed distributions.

## Beware:

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



# Size distributions:



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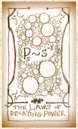
Many systems have discrete sizes $k$:

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

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

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

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



# The statistics of surprise—words:

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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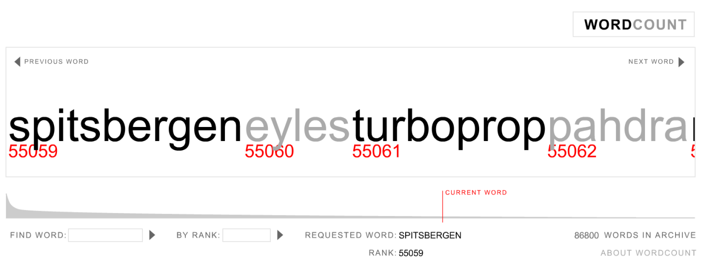
# Jonathan Harris's Wordcount:

## A word frequency distribution explorer: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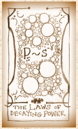

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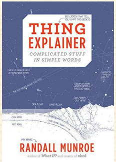
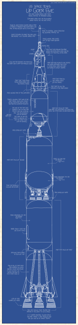
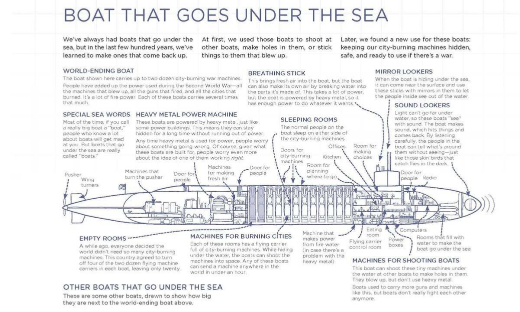
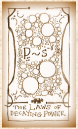



"Thing Explainer: Complicated Stuff in Simple Words" by Randall Munroe (2015). [10]






Up goer five

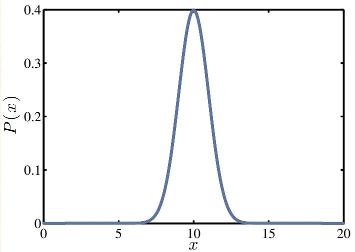


# The statistics of surprise—words:

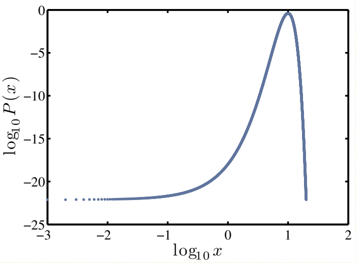
## First—a Gaussian example:

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

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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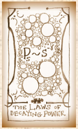
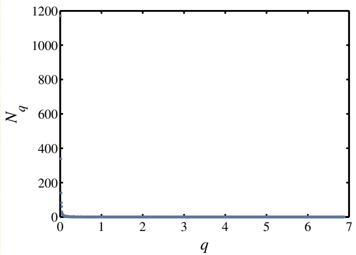


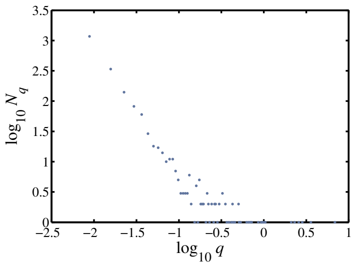
# The statistics of surprise—words:

## Raw ‘probability’ (binned) for Brown Corpus:

linear:




log-log




$q_w$ = frequency of occurrence of word $q$ expressed as a percentage.
$N_q$ = number of distinct words that have a frequency of occurrence $q$.

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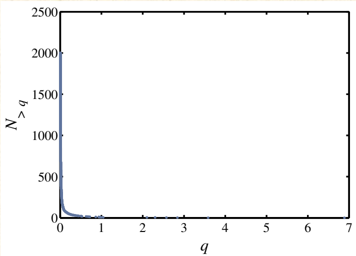
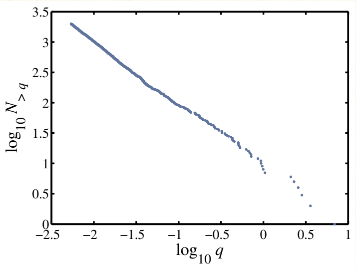
# The statistics of surprise—words:

## Complementary Cumulative Probability Distribution $N_{>q}$:

linear:




log-log




- Also known as the 'Exceedance Probability.'

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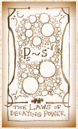

# My, what big words you have...



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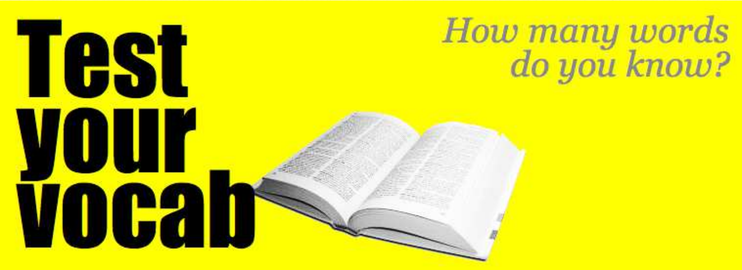
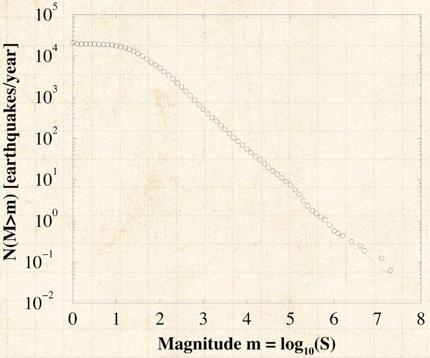



- Test capitalizes on word frequency following a heavily skewed frequency distribution with a decaying power-law tail.

# The statistics of surprise:

## 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" [3, 1]

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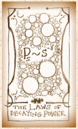

# The statistics of surprise:

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. 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. 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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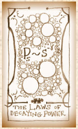
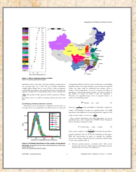
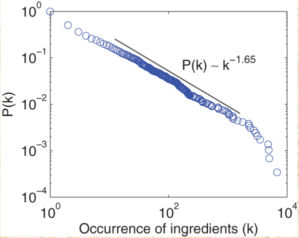




"Geography and Similarity of Regional Cuisines in China"
Zhu et al.,
PLoS ONE, **8**, e79161, 2013. [17]




- 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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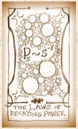

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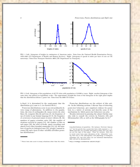
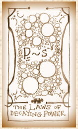
"On a class of skew distribution functions"
Herbert A. Simon,
Biometrika, **42**, 425–440, 1955. [14]



"Power laws, Pareto distributions and Zipf's law"
M. E. J. Newman,
Contemporary Physics, **46**, 323–351, 2005. [11]

"Power-law distributions in empirical data"
Clauset, Shalizi, and Newman,
SIAM Review, **51**, 661–703, 2009. [4]



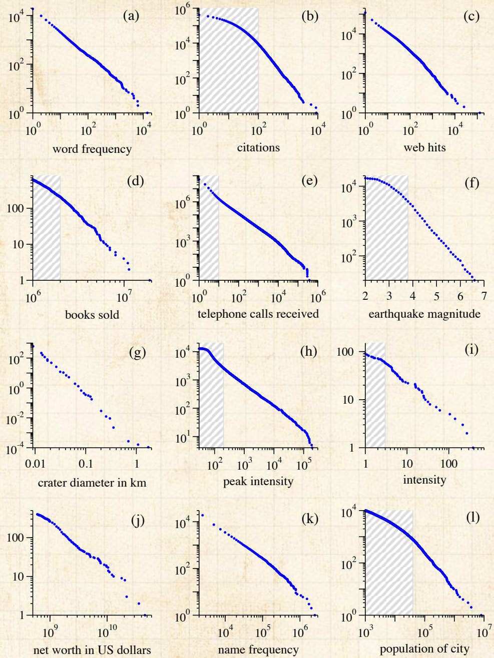
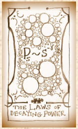



FIG. 4 Cumulative distributions or "rank/frequency plots" of twelve quantities reputed to follow power laws. The distributions were computed as described in Appendix A. Data in the shaded regions were excluded from the calculations of the exponents in Table I. Source references for the data are given in the text. (a) Numbers of occurrences of words in the novel *Moby Dick* by Hermann 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 1910 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:

## Some examples:

- Earthquake magnitude (Gutenberg-Richter law): [8, 1] $P(M) \propto M^{-2}$
- # war deaths: [13] $P(d) \propto d^{-1.8}$
- Sizes of forest fires [7]
- Sizes of cities: [14] $P(n) \propto n^{-2.1}$
- # links to and from websites [2]

- Note: Exponents range in error

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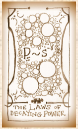

# Size distributions:

## More examples:

- # citations to papers:[5, 6] $P(k) \propto k^{-3}$.
- 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:[9] $P(F) \propto F^{-5/2}$. (See the Holtsmark distribution and stable distributions.)
- Diameter of moon craters:[11] $P(d) \propto d^{-3}$.
- Word frequency:[14] e.g., $P(k) \propto k^{-2.2}$ (variable).
- # religious adherents in cults:[4] $P(k) \propto k^{-1.8\pm0.1}$.
- # sightings of birds per species (North American Breeding Bird Survey for 2003):[4] $P(k) \propto k^{-2.1\pm0.1}$.
- # species per genus:[16, 14, 4] $P(k) \propto k^{-2.4\pm0.2}$.

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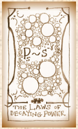


# Table 3 from Clauset, Shalizi, and Newman [4]:

*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****).*

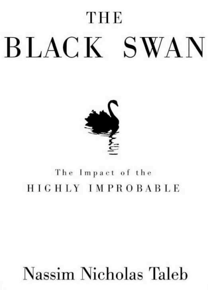
| Quantity | $n$ | $\langle x \rangle$ | $\sigma$ | $x_{\max}$ | $\hat{x}_{\min}$ | $\hat{\alpha}$ | $n_{\text{tail}}$ | $p$ |
|---|---|---|---|---|---|---|---|---|
| count of word use | 18 855 | 11.14 | 148.33 | 14 086 | $7 \pm 2$ | 1.95(2) | $2958 \pm 987$ | **0.49** |
| protein interaction degree | 1846 | 2.34 | 3.05 | 56 | $5 \pm 2$ | 3.1(3) | $204 \pm 263$ | **0.31** |
| metabolic degree | 1641 | 5.68 | 17.81 | 468 | $4 \pm 1$ | 2.8(1) | $748 \pm 136$ | 0.00 |
| Internet degree | 22 688 | 5.63 | 37.83 | 2583 | $21 \pm 9$ | 2.12(9) | $770 \pm 1124$ | **0.29** |
| telephone calls received | 51 360 423 | 3.88 | 179.09 | 375 746 | $120 \pm 49$ | 2.09(1) | $102\,592 \pm 210\,147$ | **0.63** |
| intensity of wars | 115 | 15.70 | 49.97 | 382 | $2.1 \pm 3.5$ | 1.7(2) | $70 \pm 14$ | **0.20** |
| terrorist attack severity | 9101 | 4.35 | 31.58 | 2749 | $12 \pm 4$ | 2.4(2) | $547 \pm 1663$ | **0.68** |
| HTTP size (kilobytes) | 226 386 | 7.36 | 57.94 | 10 971 | $36.25 \pm 22.74$ | 2.48(5) | $6794 \pm 2232$ | 0.00 |
| species per genus | 509 | 5.59 | 6.94 | 56 | $4 \pm 2$ | 2.4(2) | $233 \pm 138$ | **0.10** |
| bird species sightings | 591 | 3384.36 | 10 952.34 | 138 705 | $6679 \pm 2463$ | 2.1(2) | $66 \pm 41$ | **0.55** |
| blackouts ($\times 10^3$) | 211 | 253.87 | 610.31 | 7500 | $230 \pm 90$ | 2.3(3) | $59 \pm 35$ | **0.62** |
| sales of books ($\times 10^3$) | 633 | 1986.67 | 1396.60 | 19 077 | $2400 \pm 430$ | 3.7(3) | $139 \pm 115$ | **0.66** |
| population of cities ($\times 10^3$) | 19 447 | 9.00 | 77.83 | 8 009 | $52.46 \pm 11.88$ | 2.37(8) | $580 \pm 177$ | **0.76** |
| email address books size | 4581 | 12.45 | 21.49 | 333 | $57 \pm 21$ | 3.5(6) | $196 \pm 449$ | **0.16** |
| forest fire size (acres) | 203 785 | 0.90 | 20.99 | 4121 | $6324 \pm 3487$ | 2.2(3) | $521 \pm 6801$ | 0.05 |
| solar flare intensity | 12 773 | 689.41 | 6520.59 | 231 300 | $323 \pm 89$ | 1.79(2) | $1711 \pm 384$ | **1.00** |
| quake intensity ($\times 10^3$) | 19 302 | 24.54 | 563.83 | 63 096 | $0.794 \pm 80.198$ | 1.64(4) | $11\,697 \pm 2159$ | 0.00 |
| religious followers ($\times 10^6$) | 103 | 27.36 | 136.64 | 1050 | $3.85 \pm 1.60$ | 1.8(1) | $39 \pm 26$ | **0.42** |
| freq. of surnames ($\times 10^3$) | 2753 | 50.59 | 113.99 | 2502 | $111.92 \pm 40.67$ | 2.5(2) | $239 \pm 215$ | **0.20** |
| net worth (mil. USD) | 400 | 2388.69 | 4 167.35 | 46 000 | $900 \pm 364$ | 2.3(1) | $302 \pm 77$ | 0.00 |
| citations to papers | 415 229 | 16.17 | 44.02 | 8904 | $160 \pm 35$ | 3.16(6) | $3455 \pm 1859$ | **0.20** |
| papers authored | 401 445 | 7.21 | 16.52 | 1416 | $133 \pm 13$ | 4.3(1) | $988 \pm 377$ | **0.90** |
| hits to web sites | 119 724 | 9.83 | 392.52 | 129 641 | $2 \pm 13$ | 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 | $3684 \pm 151$ | 2.336(9) | $28\,986 \pm 1560$ | 0.00 |

- We'll explore various exponent measurement techniques in assignments.

# power-law size distributions

## Gaussians versus power-law size distributions:

- Mediocristan versus Extremistan
- Mild versus Wild (Mandelbrot)
- Example: Height versus wealth.




- See “The Black Swan” by Nassim Taleb. [15]
- Terrible if successful framing: Black swans are not that surprising ...

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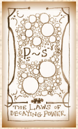
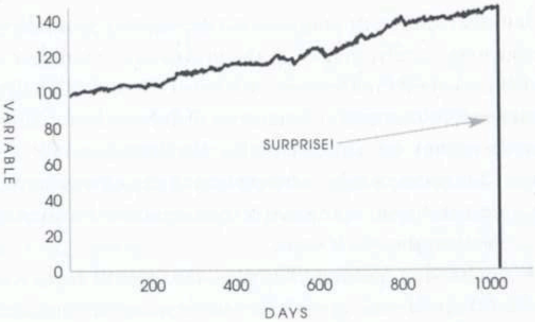


# Turkeys...

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.

From "The Black Swan" [15]

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# Taleb's table [15]

## Mediocristan/Extremistan

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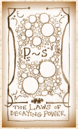

# Size distributions:

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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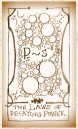

# Devilish power-law size distribution details:

## Exhibit A:

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

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

- 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.

Insert question from assignment 2

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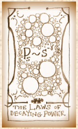

# And in general...

## Moments:

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

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

- mean is finite (depends on lower cutoff)
- $\sigma^2$ = 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.

Insert question from assignment 3

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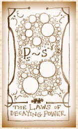


# Moments



## Standard deviation is a mathematical convenience:

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

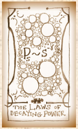
$$\text{Mean average deviation (MAD)} = \langle |x - \langle x \rangle | \rangle$$

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

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

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

Insert question from assignment 2



# How sample sizes grow...



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

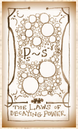
- We can show that after $n$ samples, we expect the largest sample to be

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

- 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 2



# Complementary Cumulative Distribution Function:

## CCDF:

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

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

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

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

$$\propto x^{-\gamma+1}$$

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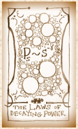
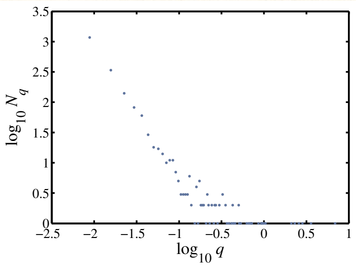


# Complementary Cumulative Distribution Function:

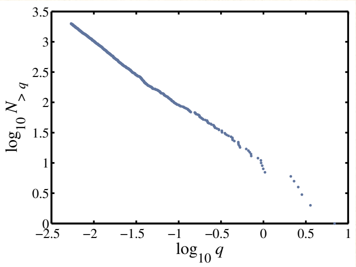
## CCDF:

- $$P_{\geq}(x) \propto x^{-\gamma+1}$$
- Use when tail of $P$ follows a power law.
- Increases exponent by one.
- Useful in cleaning up data.

PDF:




CCDF:

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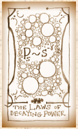

## Complementary Cumulative Distribution Function:

- Same story for a discrete variable: $P(k) \sim ck^{-\gamma}$.
- $$P_{\geq}(k) = P(k' \geq k)$$
  $$= \sum_{k'=k}^{\infty} P(k)$$
  $$\propto k^{-\gamma+1}$$
- Use integrals to approximate sums.

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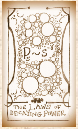

# Zipfian rank-frequency plots

## George Kingsley Zipf:

- Noted various rank distributions have power-law tails, often with exponent -1 (word frequency, city sizes...)
- Zipf's 1949 Magnum Opus:

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

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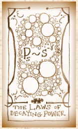

# Zipfian rank-frequency plots



## 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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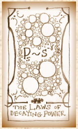
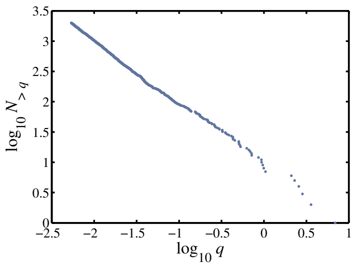


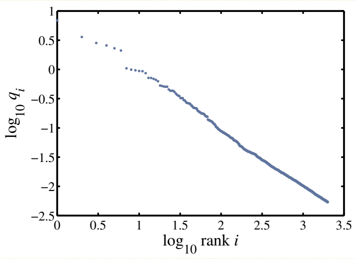
# Size distributions:

## Brown Corpus (1,015,945 words):

CCDF:




Zipf:




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

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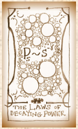

# Size distributions:



## Brown Corpus (1,015,945 words):

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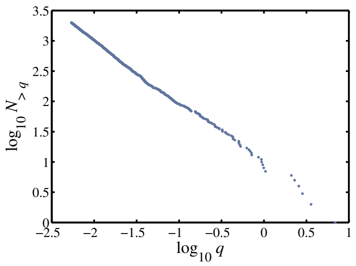
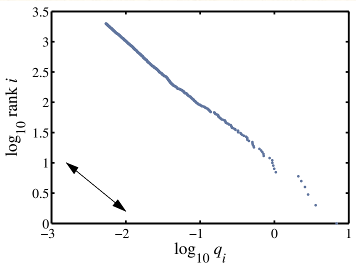



Zipf:




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

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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

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

$$\propto x_r^{(-\gamma+1)(-\alpha)} \text{ since } P_{\geq}(x) \sim x^{-\gamma+1}.$$

We therefore have $1 = (-\gamma + 1)(-\alpha)$ or:

$$\boxed{\alpha = \frac{1}{\gamma - 1}}$$

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

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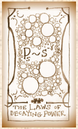
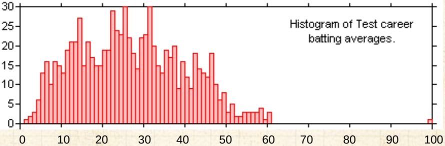


# The Don.

## Extreme deviations in test cricket:




- Don Bradman's batting average = 166% next best.
- That's pretty solid.
- Later in the course: Understanding success— is the Mona Lisa like Don Bradman?

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# A good eye:

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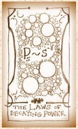
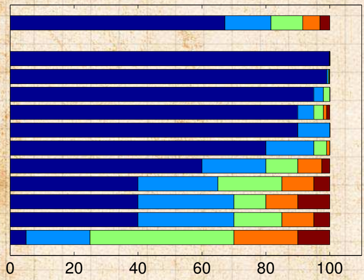


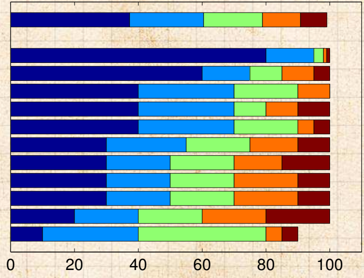
Actual:

Fall 2014:




Ideal:

Fall 2014:

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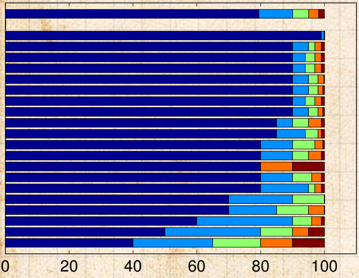
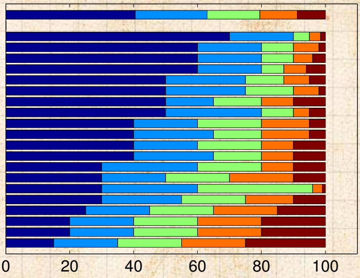
## Actual:

## Fall 2013:

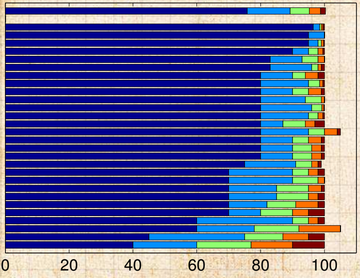



## Ideal:

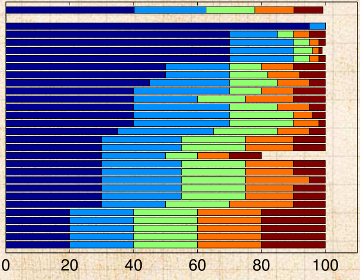
## Fall 2013:




## Spring 2013:




## Spring 2013:

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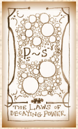

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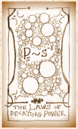

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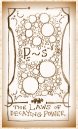

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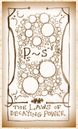

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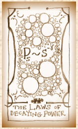

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