Power-Law Size Distributions

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Principles of Complex Systems, Vols. 1, 2, & 3D
CSYS/MATH 300, 303, & 394, 2022–2023 | @pocsvox

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Santa Fe Institute | University of Vermont

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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

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Definition

Examples

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Zipf's law

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References

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Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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Outline

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Definition

Examples

Wild vs. Mild

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References

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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.

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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     (see next two slides; Wikipedia entry here.)
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On counting and logarithms:

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

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Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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     (see next two slides; Wikipedia entry here.)
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On counting and logarithms:

- Listen to Radiolab's 2009 piece: "Numbers.".
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Also to be enjoyed: the magnificence of the Dunning-Kruger effect

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Homo probabilisticus?

The set up:

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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

Homo probabilisticus?

The set up:

- A parent has two children.

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Simple probability question:

- What is the probability that both children are girls?

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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

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Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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

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Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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

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The set up:

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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.

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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

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The next probabilistic poser:

- What is the probability that both children are girls?

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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

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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.
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The next probabilistic poser:

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Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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

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Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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Simple probability question:

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- 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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Try this one:

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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Try this one:

- A parent has two children.
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Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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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?

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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.

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

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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.

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

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?

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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Simple question #3:

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And ...

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Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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And ...

- What is the probability that both children are girls?
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$P(x) \sim x^{-\gamma}$

Let’s test our collective intuition:

Money

$\equiv$

Belief

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf’s law
Zipf ⇔ CCDF
References

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

Let’s test our collective intuition:

Money

$\equiv$

Belief

Two questions about wealth distribution in the United States:

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf’s law
Zipf ⇔ CCDF
References

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Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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.

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

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

Let's test our collective intuition:

Money
$\equiv$
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.

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Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

Let's test our collective intuition:

Money
$\equiv$
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.

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

Wealth distribution in the United States: [12]

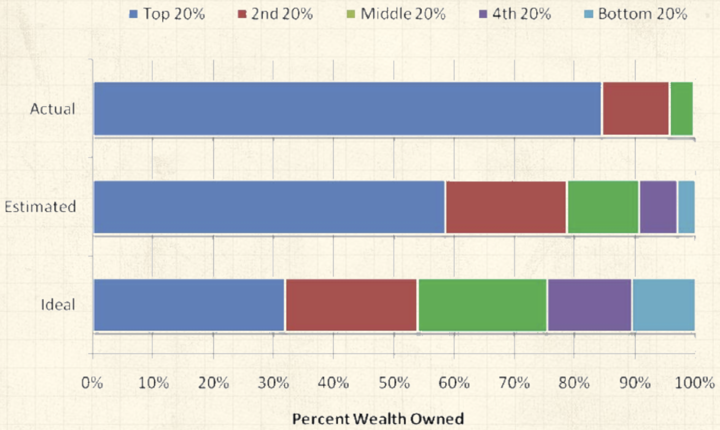


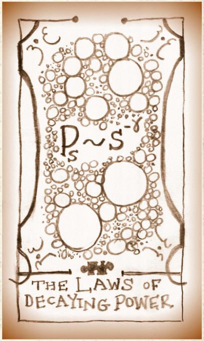
Fig. 2. The actual United States wealth distribution plotted against the estimated and ideal distributions across all respondents. Because of their small percentage share of total wealth, both the "4th 20%" value (0.2%) and the "Bottom 20%" value (0.1%) are not visible in the "Actual" distribution.

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

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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


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


$P_s \sim s^{-\gamma}$
THE LAWS OF DECAYING POWER

Wealth distribution in the United States: [12]

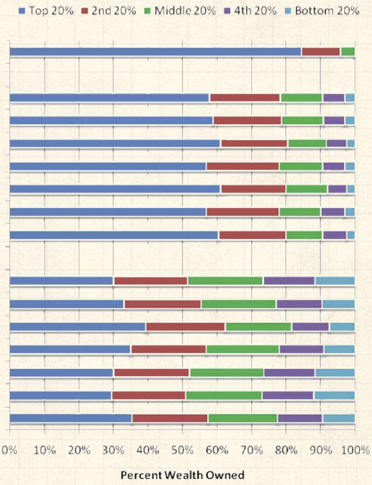
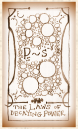


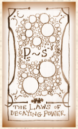
Fig. 3. The actual United States wealth distribution plotted against the estimated and ideal distributions of respondents of different income levels, political affiliations, and genders. Because of their small percentage share of total wealth, both the "4th 20%" value (0.2%) and the "Bottom 20%" value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



A highly watched video based on this research is

The Boggoracle Speaks:

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



Our Intuition

Definition

Examples

Wild vs. Mild

CCDFs

Zipf's law

Zipf ⇔ CCDF

References

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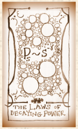


Our Intuition

Definition

Examples

Wild vs. Mild

CCDFs

Zipf's law

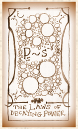
Zipf ⇔ CCDF

References

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

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

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



Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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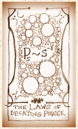
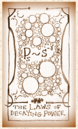
$$\text{where} \quad 0 < x_{\text{min}} < x < x_{\text{max}} \quad \text{and} \quad \gamma > 1.$$

- x_{min} = lower cutoff, x_{max} = upper cutoff



Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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- x_{min} = lower cutoff, x_{max} = upper cutoff
- Negative linear relationship in log-log space:

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

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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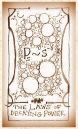
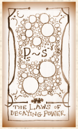
- We use base 10 because we are good people.



Size distributions:

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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

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

Size distributions:

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

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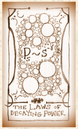
- Still use term 'power-law size distribution.'

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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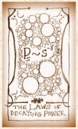
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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

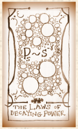
$$P(x) \sim c\,x^{-\gamma} \text{ for } x \text{ large.}$$

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



Size distributions:

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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:

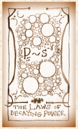
- Inverse power laws aren't the only ones: lognormals, Weibull distributions, ...

Size distributions:

Many systems have discrete sizes k:

- Word frequency

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

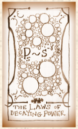


Size distributions:

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

Many systems have discrete sizes k:

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



Size distributions:

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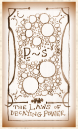
- Word frequency
- Node degree in networks: # friends, # hyperlinks, etc.
- # citations for articles, court decisions, etc.



Size distributions:

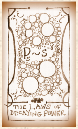
Many systems have discrete sizes k:

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

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

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

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

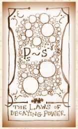


Word frequency:

Brown Corpus ($\sim 10^6$ words):

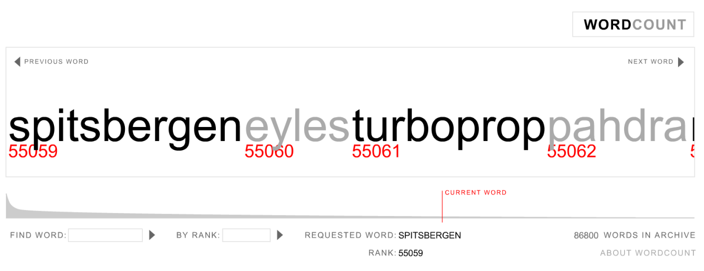
rank	word	% q
1.	the	6.8872
2.	of	3.5839
3.	and	2.8401
4.	to	2.5744
5.	a	2.2996
6.	in	2.1010
7.	that	1.0428
8.	is	0.9943
9.	was	0.9661
10.	he	0.9392
11.	for	0.9340
12.	it	0.8623
13.	with	0.7176
14.	as	0.7137
15.	his	0.6886

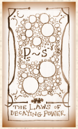
rank	word	% q
1945.	apply	0.0055
1946.	vital	0.0055
1947.	September	0.0055
1948.	review	0.0055
1949.	wage	0.0055
1950.	motor	0.0055
1951.	fifteen	0.0055
1952.	regarded	0.0055
1953.	draw	0.0055
1954.	wheel	0.0055
1955.	organized	0.0055
1956.	vision	0.0055
1957.	wild	0.0055
1958.	Palmer	0.0055
1959.	intensity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



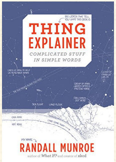
Jonathan Harris's Wordcount:

A word frequency distribution explorer:

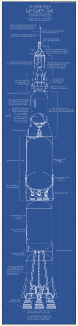


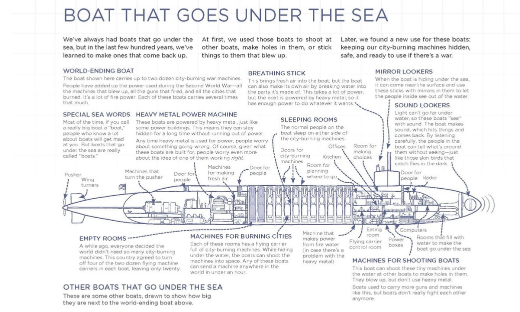


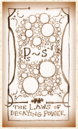
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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





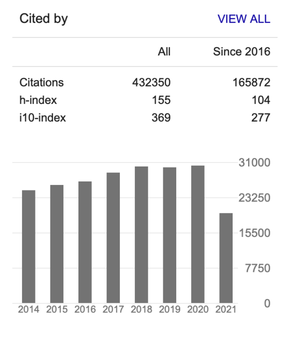


Up goer five

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

The long tail of knowledge:

Take a scrolling voyage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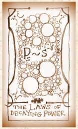

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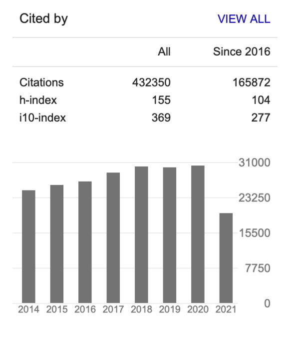
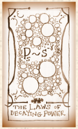


Take a scrolling voyage
to the citational abyss,

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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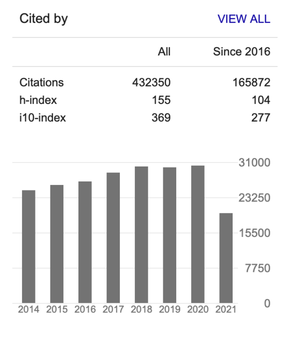
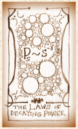


Take a scrolling voyage
to the citational abyss,
starting at the surface with



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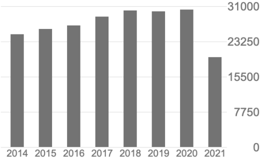
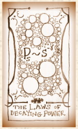


Take a scrolling voyage
to the citational abyss,
starting at the surface with
the lonely, giant citaceans,



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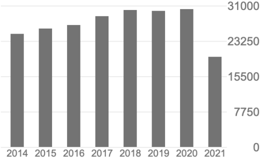
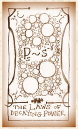


Take a scrolling voyage to the citational abyss, starting at the surface with the lonely, giant citaceans, moving down

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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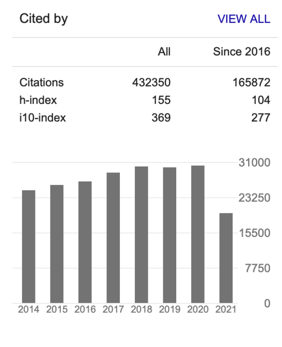

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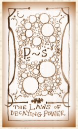
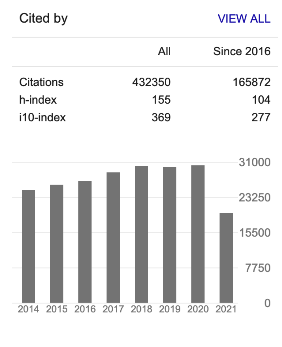
to the citational abyss,
starting at the surface with
the lonely, giant citaceans,
moving down
to the legion of strange,

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

The long tail of knowledge:



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Citations	432350	165872
h-index	155	104
i10-index	369	277

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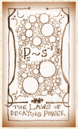
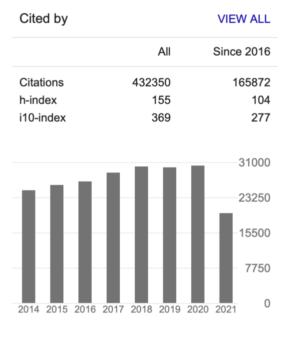
starting at the surface with
the lonely, giant citaceans,
moving down
to the legion of strange,
sometimes misplaced,



The long tail of knowledge:

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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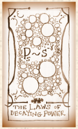

The long tail of knowledge:

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

Cited by VIEW ALL

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Citations	432350	165872
h-index	155	104
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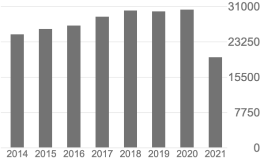

Take a scrolling voyage
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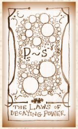
starting at the surface with
the lonely, giant citaceans,
moving down
to the legion of strange,
sometimes misplaced,
unloved creatures,
that dwell in



The long tail of knowledge:

Cited by — VIEW ALL

	All	Since 2016
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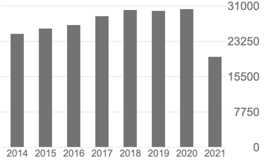
h-index	155	104
i10-index	369	277



Take a scrolling voyage
to the citational abyss,
starting at the surface with
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moving down
to the legion of strange,
sometimes misplaced,
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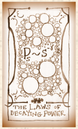
that dwell in
Kahneman's Google Scholar page

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

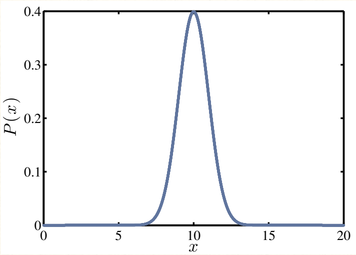


The statistics of surprise—words:

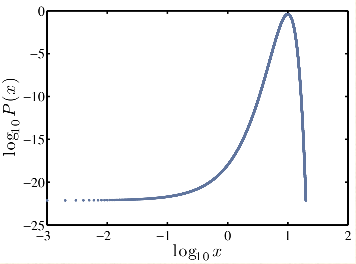
First—a Gaussian example:

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

linear:



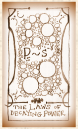
log-log



mean $\mu = 10$, variance σ^2 = 1.

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

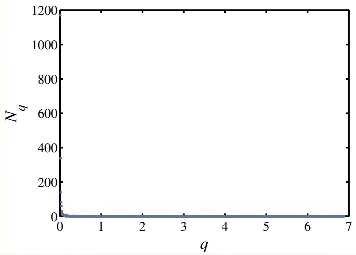
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



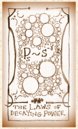
The statistics of surprise—words:

Raw ‘probability’ (binned) for Brown Corpus:

linear:



- 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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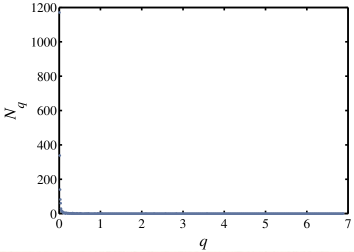
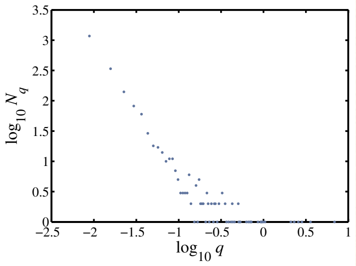


log-log



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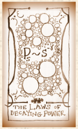
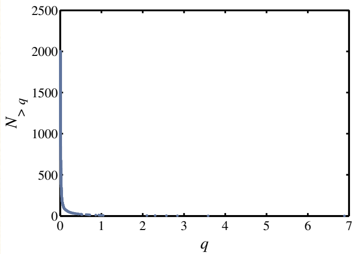


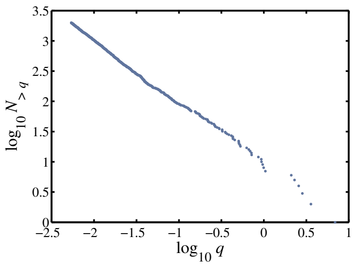
The statistics of surprise—words:

Complementary Cumulative Probability Distribution $N_{\geq q}$:

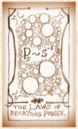
linear:



log-log



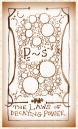
- Also known as the 'Exceedance Probability.'



My, what big words you have ...

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

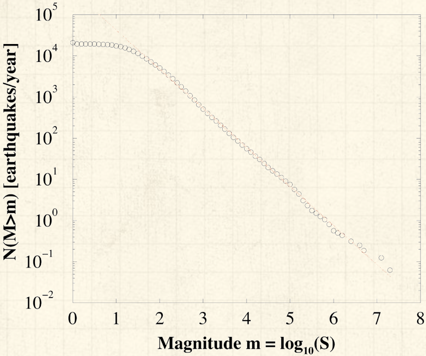
- This Man Can Pronounce Every Word in the Dictionary (story here)
- Best of Dr. Bailly



Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

The statistics of surprise:

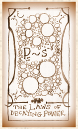
Gutenberg-Richter law



- Log-log plot
- Base 10
- Slope = -1

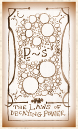
$N(M > m) \propto m^{-1}$

- From both the very awkwardly similar Christensen et al. and Bak et al.:
  "Unified scaling law for earthquakes" [4, 1]



The statistics of surprise:

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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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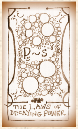
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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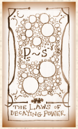

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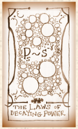
"'It did them a giant disservice," said Dr. Stein of the geological survey.



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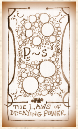
"'It did them a giant disservice," said Dr. Stein of the geological survey. That is not the first time that the earthquake potential of a fault has been underestimated.

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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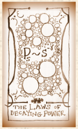
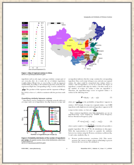
“‘It did them a giant disservice,” said Dr. Stein of the geological survey. That is not the first time that the earthquake potential of a fault has been underestimated. Most geophysicists did not think the Sumatra fault could generate a magnitude 9.1 earthquake, …’

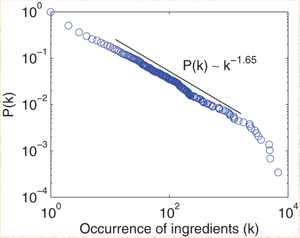
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf’s law
Zipf ⇔ CCDF
References



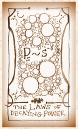
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



"Geography and similarity of regional cuisines in China"
Zhu et al.,
PLoS ONE, **8**, e79161, 2013. [18]

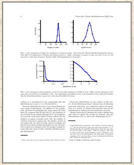


- Fraction of ingredients that appear in at least k recipes.
- Oops in notation: $P(k)$ is the Complementary Cumulative Distribution $P_{\geq}(k)$



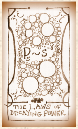
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

"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. [11]

"Power-law distributions in empirical data"
Clauset, Shalizi, and Newman,
SIAM Review, **51**, 661–703, 2009. [5]



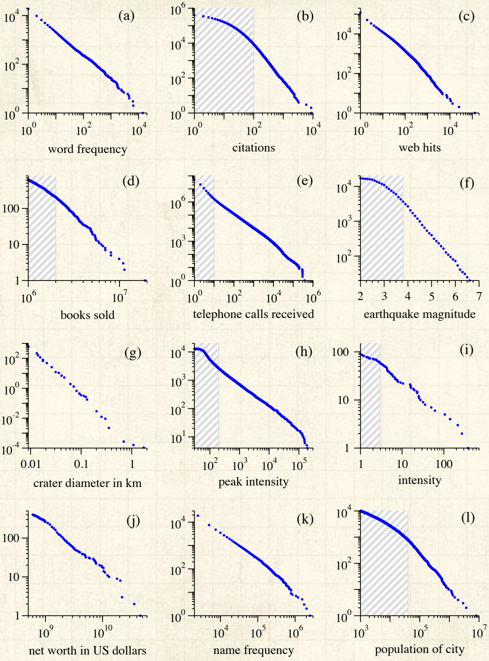
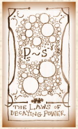


FIG. 4 Cumulative distributions or "rank/frequency plots" of twelve quantities reputed to follow power laws. The distributions were computed as described in Appendix A. Data in the shaded regions were excluded from the calculations of the exponents in Table I. Source references for the data are given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

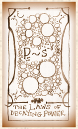
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



Size distributions:

Some examples:

- Earthquake magnitude (Gutenberg-Richter law): [8, 1] $P(M) \propto M^{-2}$



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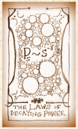
- # war deaths: [14] $P(d) \propto d^{-1.8}$



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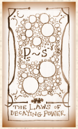
- Sizes of forest fires [7]

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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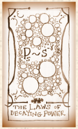
- Sizes of cities: [15] $P(n) \propto n^{-2.1}$



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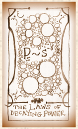

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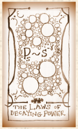
- Note: Exponents range in error

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



Size distributions:

More examples:

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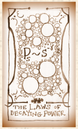
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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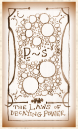
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



Size distributions:

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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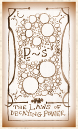

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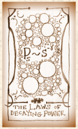

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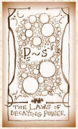
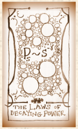
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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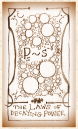
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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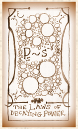

Size distributions:

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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- # species per genus: [17, 15, 5] $P(k) \propto k^{-2.4 \pm 0.2}$.

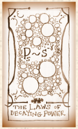


Table 3 from Clauset, Shalizi, and Newman [5]:

*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	4 167.35	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

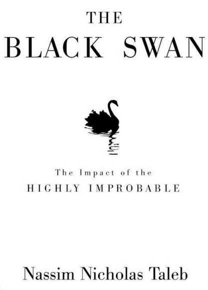
- We'll explore various exponent measurement techniques in assignments.

power-law size distributions

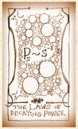
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

Gaussians versus power-law size distributions:

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

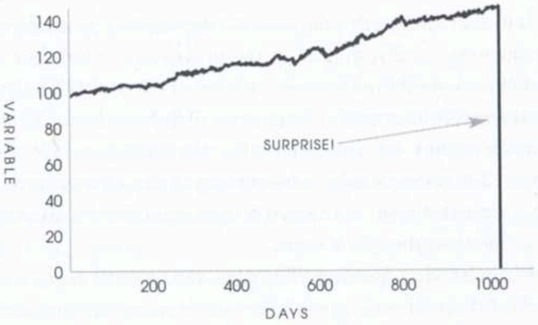


- See "The Black Swan" by Nassim Taleb. [16]
- Terrible if successful framing: Black swans are not that surprising ...



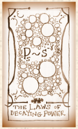
Turkeys ...

FIGURE 1: ONE THOUSAND AND ONE DAYS OF HISTORY



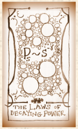
A turkey before and after Thanksgiving. The history of a process over a thousand days tells you nothing about what is to happen next. This naïve projection of the future from the past can be applied to anything.

From "The Black Swan" [16]



Taleb's table [16]

Mediocristan/Extremistan



Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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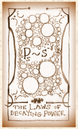
Mediocristan/Extremistan

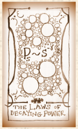
- Most typical member is mediocre/Most typical is either giant or tiny



Taleb's table [16]

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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Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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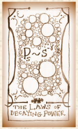
- When you observe for a while, you know what's going on/It takes a very long time to figure out what's going on



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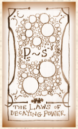
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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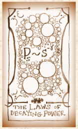
Taleb's table [16]

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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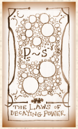
- Tyranny of the collective/Tyranny of the rare and accidental



Size distributions:

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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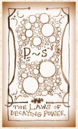

Size distributions:

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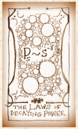
- Pareto noted wealth in Italy was distributed unevenly (80–20 rule; misleading).

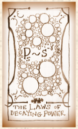


Size distributions:

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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.



Devilish power-law size distribution details:

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

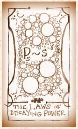


Exhibit A:

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

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

Insert question from assignment 2

Devilish power-law size distribution details:

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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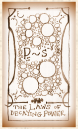
Insert question from assignment 2



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Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
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- Mean 'blows up' with upper cutoff if $\gamma < 2$.
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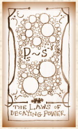
Insert question from assignment 2



Devilish power-law size distribution details:

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
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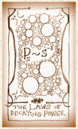
- $\gamma < 2$: Typical sample is large.

Insert question from assignment 2



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Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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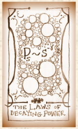
- $\gamma < 2$: Typical sample is large.
- $\gamma > 2$: Typical sample is small.

Insert question from assignment 2

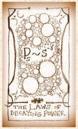


And in general ...

Moments:

- All moments depend only on cutoffs.

Insert question from assignment 3



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Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

Moments:

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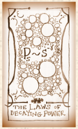

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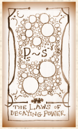
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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Insert question from assignment 3

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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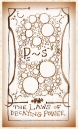
For many real size distributions: $2 < \gamma < 3$

Insert question from assignment 3



Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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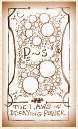

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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

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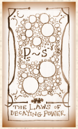

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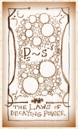
Insert question from assignment 3

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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

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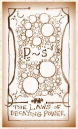
- σ^2 = variance is 'infinite' (depends on upper cutoff)
- Width of distribution is 'infinite'
- If $\gamma > 3$, distribution is less terrifying and may be easily confused with other kinds of distributions.

Insert question from assignment 3

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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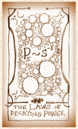
Standard deviation is a mathematical convenience:

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



Moments

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

Standard deviation is a mathematical convenience:

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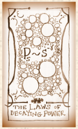


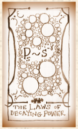
Moments

Standard deviation is a mathematical convenience:

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

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

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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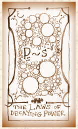

Moments

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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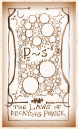
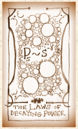


Moments

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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

How sample sizes grow ...

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

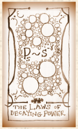
- We can show that after n samples, we expect the largest sample to be[1]

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

Insert question from assignment 4
Insert question from assignment 6

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

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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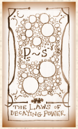

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- e.g., for $P(x) = \lambda e^{-\lambda x}$, we find

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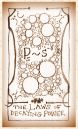
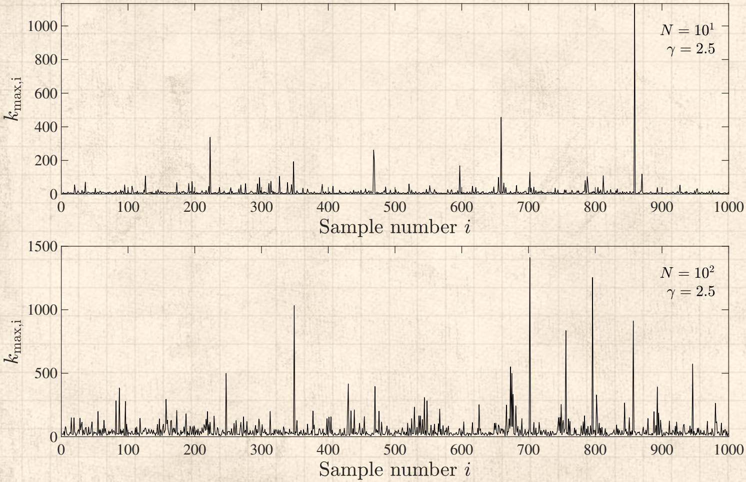
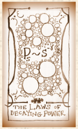
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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





Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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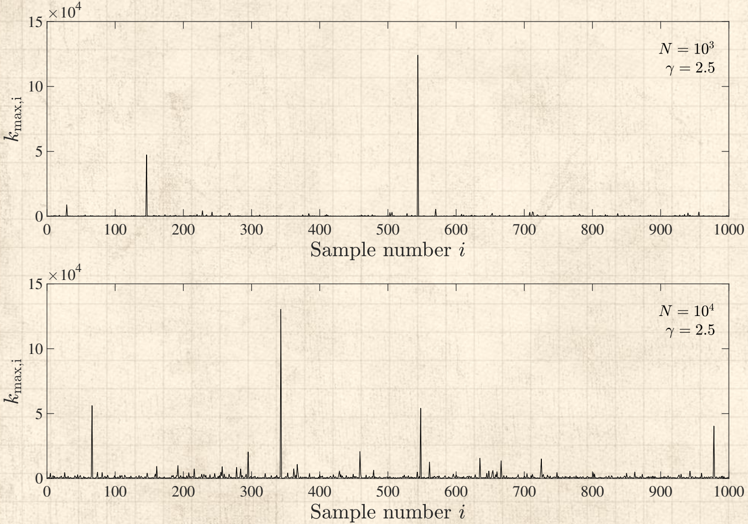

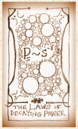

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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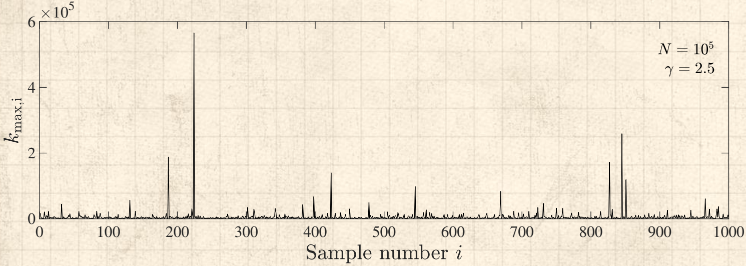

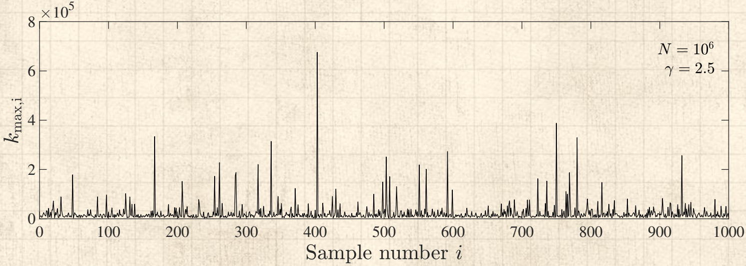

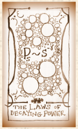

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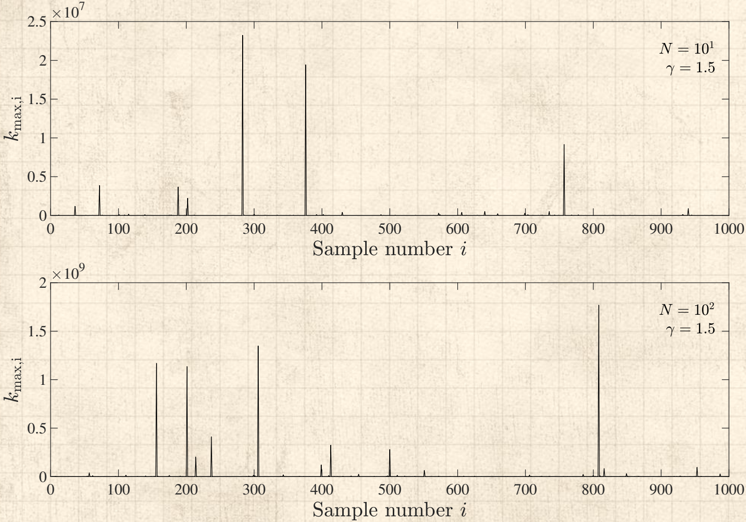

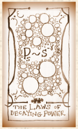

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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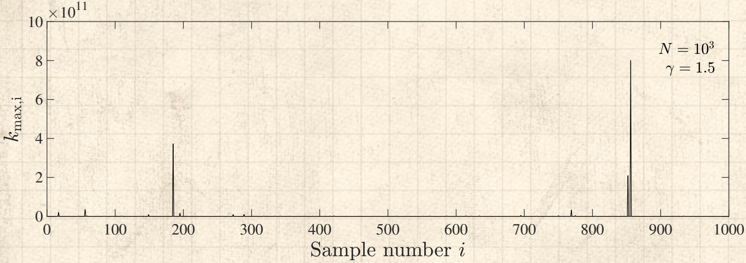

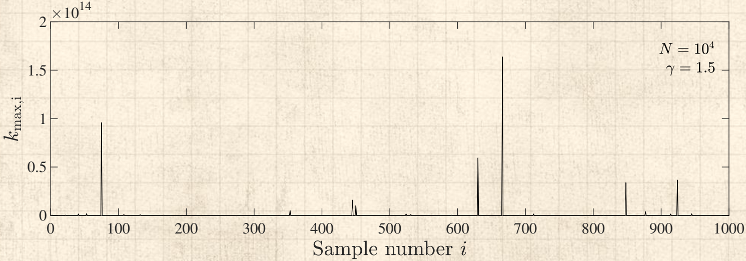

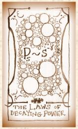

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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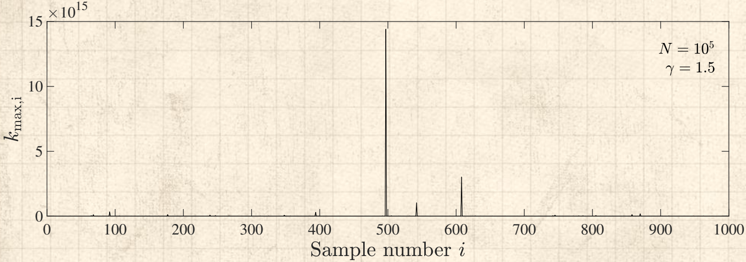
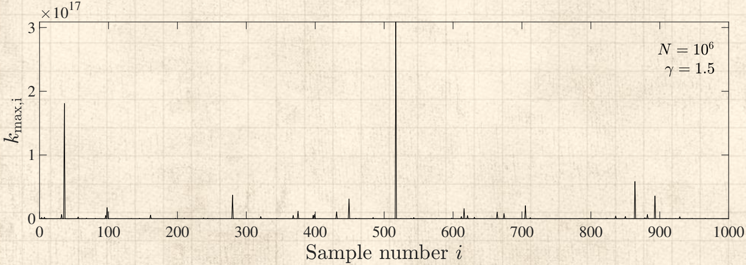
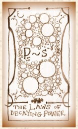
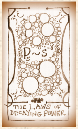
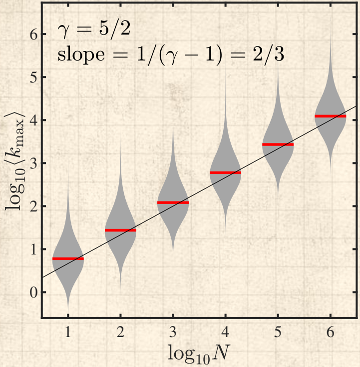


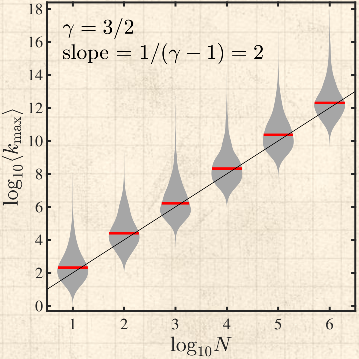






- Scaling of expected largest value as a function of sample size N:





- Fit for $\gamma = 5/2$:[2] $k_{\max} \sim N^{0.660\pm0.066}$ (sublinear)
- Fit for $\gamma = 3/2$: $k_{\max} \sim N^{2.063\pm0.215}$ (superlinear)

[2] 95% confidence interval

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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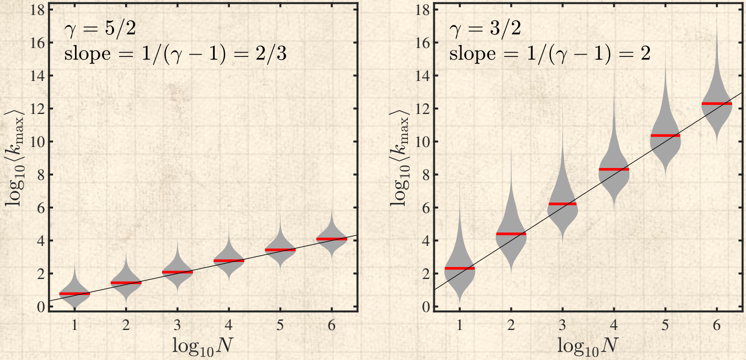

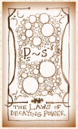

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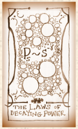
[2] 95% confidence interval

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

Complementary Cumulative Distribution Function:

CCDF:



Complementary Cumulative Distribution Function:

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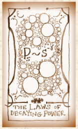
$$P_{\geq}(x) = P(x' \geq x) = 1 - P(x' < x)$$

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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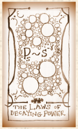

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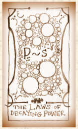
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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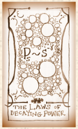
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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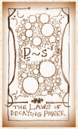
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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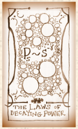
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



Complementary Cumulative Distribution Function:

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- $$P_{\geq}(x) \propto x^{-(\gamma-1)}$$
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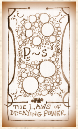
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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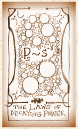

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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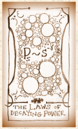

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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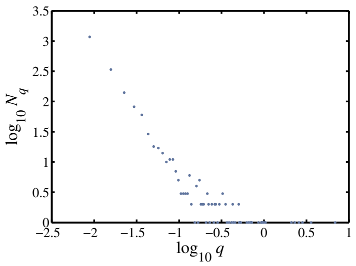
PDF:



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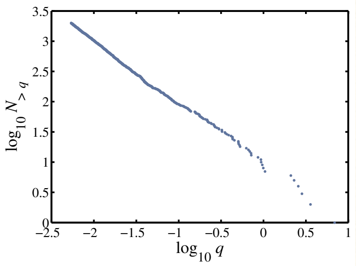
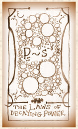




Complementary Cumulative Distribution Function:

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

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

Our Intuition

Definition

Examples

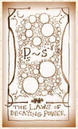
Wild vs. Mild

CCDFs

Zipf's law

Zipf ⇔ CCDF

References



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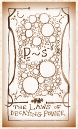

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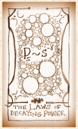

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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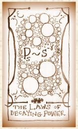
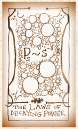
  $$\propto k^{-(\gamma-1)}$$
- Use integrals to approximate sums.



The Boggoracle Speaks:

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

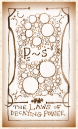


Zipfian rank-frequency plots

George Kingsley Zipf:

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

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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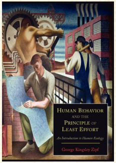
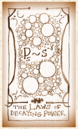


"Human Behaviour and the Principle of Least-Effort"
by G. K. Zipf (1949). [19]

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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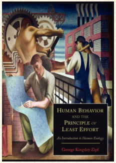

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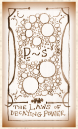
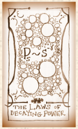
- We'll study Zipf's law in depth ...



Zipfian rank-frequency plots

Zipf's way:

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

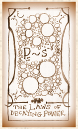


Zipfian rank-frequency plots

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

Zipf's way:

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



Zipfian rank-frequency plots

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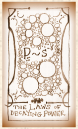

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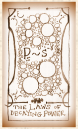

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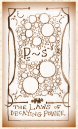

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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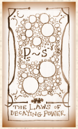
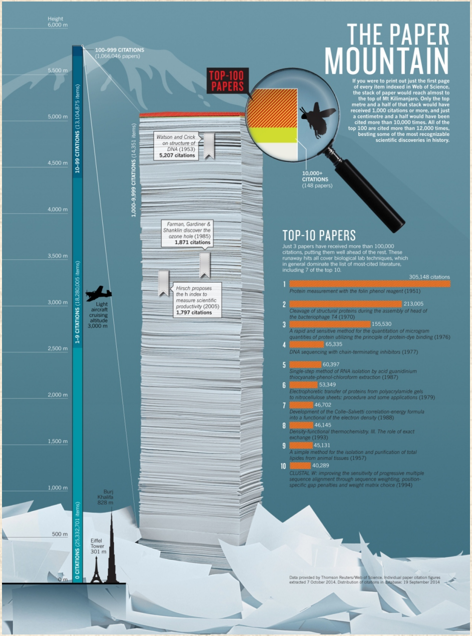
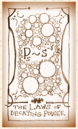
- Zipf's observation:

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





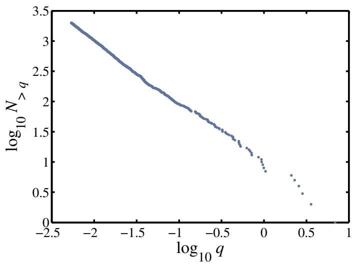
Nature (2014):
Most cited papers of all time



Size distributions:

Brown Corpus (1,015,945 words):

CCDF:



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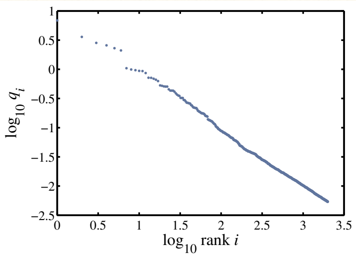
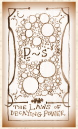


- The, of, and, to, a, ...= ‘objects’
- ‘Size’ = word frequency

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf’s law
Zipf ⇔ CCDF
References



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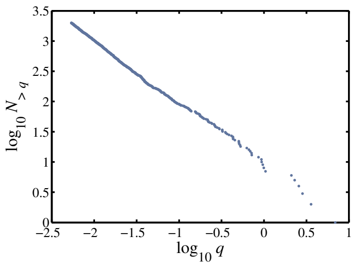

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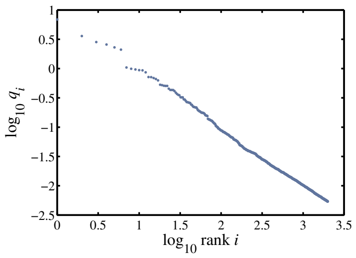

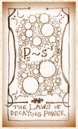

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- Beep: (Important) CCDF and Zipf plots are related ...

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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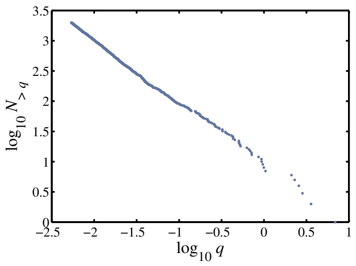

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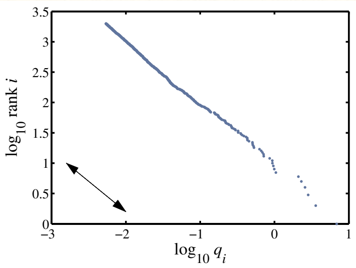

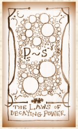

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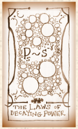
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

Observe:

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



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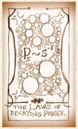
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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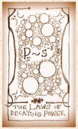
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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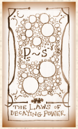
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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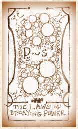
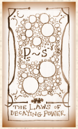
We therefore have $1 = -(\gamma - 1)(-\alpha)$ or:

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

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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

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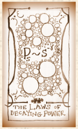
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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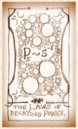
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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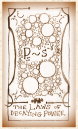
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf’s law
Zipf ⇔ CCDF
References



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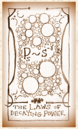
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf’s law
Zipf ⇔ CCDF
References



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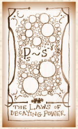
- Show "the frequencies of opening moves are distributed according to a power law with an exponent that increases linearly with the game depth, whereas the pooled distribution of all opening weights follows Zipf's law with universal exponent."
- Propose hierarchical fragmentation model that produces self-similar game trees.

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

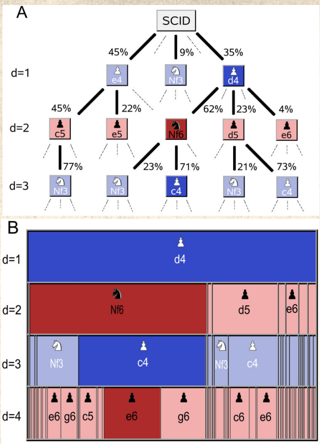


FIG. 1 (color online). (a) Schematic representation of the weighted game tree of chess based on the SCIDBASE [6] for the first three half moves. Each node indicates a state of the game. Possible game continuations are shown as solid lines together with the branching ratios r_d. Dotted lines symbolize 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).

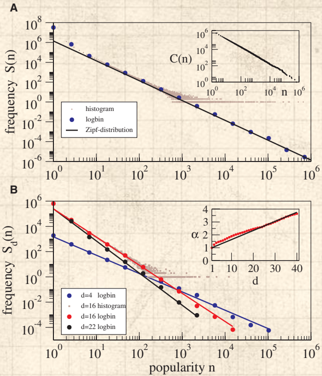
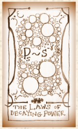
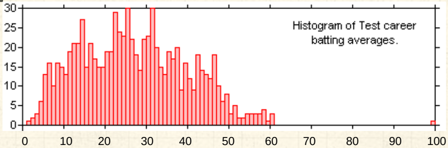


FIG. 2 (color online). (a) Histogram of weight frequencies $S(n)$ of openings up to $d = 40$ in the Scid database and with logarithmic binning. A straight line fit (not shown) yields an exponent of $\alpha = 2.05$ with a goodness of fit $R^2 > 0.9992$. For comparison, the Zipf distribution Eq. (8) with $\mu = 1$ 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).

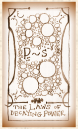


The Don.

Extreme deviations in test cricket:



Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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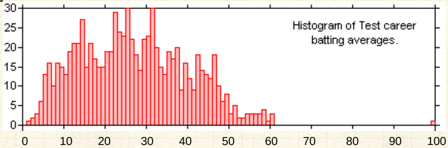

- Don Bradman's batting average = 166% next best.

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

The Don.

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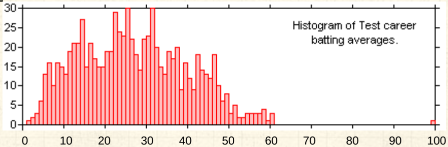

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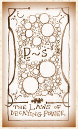
Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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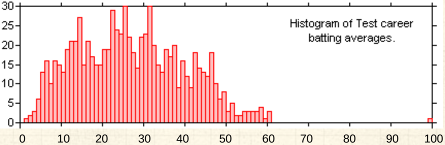

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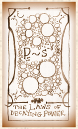
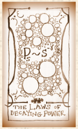
- Later in the course: Understanding success— is the Mona Lisa like Don Bradman?





A good eye:

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

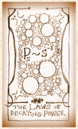
- The great Paul Kelly's tribute to the man who was "Something like the tide"

Neural reboot (NR):

Monotrematic Love

http://www.youtube.com/watch?v=a6QHzIJO5a8?rel=0

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References



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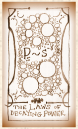

References II

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
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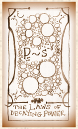

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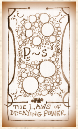

References IV

Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References

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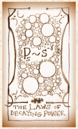

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Our Intuition
Definition
Examples
Wild vs. Mild
CCDFs
Zipf's law
Zipf ⇔ CCDF
References