# Lognormals and friends

## Principles of Complex Systems | @pocsvox
## CSYS/MATH 300, Fall, 2015 | #FallPoCS2015

Prof. Peter Dodds | @peterdodds

Dept. of Mathematics & Statistics | Vermont Complex Systems Center
Vermont Advanced Computing Core | University of Vermont


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# Outline

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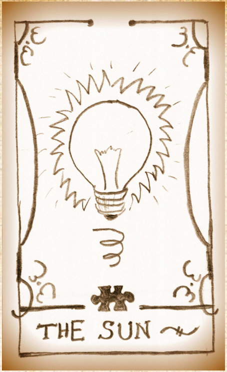


# Outline

# Alternative distributions

There are other 'heavy-tailed' distributions:

1. The Log-normal distribution

$$P(x) = \frac{1}{x\sqrt{2\pi}\sigma} \exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right)$$

2. Weibull distributions

$$P(x)\mathrm{d}x = \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{\mu-1} e^{-(x/\lambda)^{\mu}}\mathrm{d}x$$

CCDF = stretched exponential.

3. Gamma distributions, and more.



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# lognormals





## The lognormal distribution:

$$P(x) = \frac{1}{x\sqrt{2\pi}\sigma} \exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right)$$

- $\ln x$ is distributed according to a normal distribution with mean $\mu$ and variance $\sigma$.
- Appears in economics and biology where growth increments are distributed normally.

# lognormals





- Standard form reveals the mean $\mu$ and variance $\sigma^2$ of the underlying normal distribution:

$$P(x) = \frac{1}{x\sqrt{2\pi}\sigma} \exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right)$$

- For lognormals:

$$\mu_{\text{lognormal}} = e^{\mu + \frac{1}{2}\sigma^2}, \qquad \text{median}_{\text{lognormal}} = e^{\mu},$$

$$\sigma_{\text{lognormal}} = (e^{\sigma^2} - 1)e^{2\mu + \sigma^2}, \qquad \text{mode}_{\text{lognormal}} = e^{\mu - \sigma^2}.$$

- All moments of lognormals are finite.

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# Derivation from a normal distribution

Take $Y$ as distributed normally:

- $$P(y)\mathrm{d}y = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{(y-\mu)^2}{2\sigma^2}\right)\mathrm{d}y$$

Set $Y = \ln X$:

- Transform according to $P(x)\mathrm{d}x = P(y)\mathrm{d}y$:
- $$\frac{\mathrm{d}y}{\mathrm{d}x} = 1/x \Rightarrow \mathrm{d}y = \mathrm{d}x/x$$
- $$\Rightarrow P(x)\mathrm{d}x = \frac{1}{x\sqrt{2\pi}\sigma}\exp\left(-\frac{(\ln x-\mu)^2}{2\sigma^2}\right)\mathrm{d}x$$





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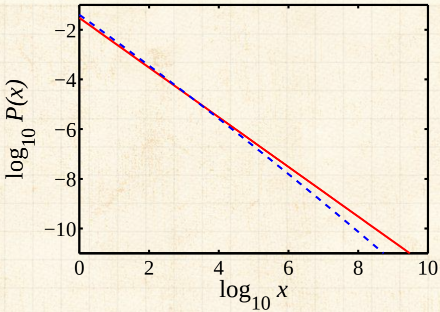
# Confusion between lognormals and pure power laws








Near agreement over four orders of magnitude!

- For lognormal (blue), $\mu = 0$ and $\sigma = 10$.
- For power law (red), $\gamma = 1$ and $c = 0.03$.

# Confusion

## What's happening:

$$\ln P(x) = \ln \left\{ \frac{1}{x\sqrt{2\pi}\sigma} \exp\left( -\frac{(\ln x - \mu)^2}{2\sigma^2} \right) \right\}$$

$$= -\ln x - \ln \sqrt{2\pi}\sigma - \frac{(\ln x - \mu)^2}{2\sigma^2}$$

$$= -\frac{1}{2\sigma^2}(\ln x)^2 + \left(\frac{\mu}{\sigma^2} - 1\right)\ln x - \ln \sqrt{2\pi}\sigma - \frac{\mu^2}{2\sigma^2}.$$

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$$\boxed{\ln P(x) \sim -\left(1-\frac{\mu}{\sigma^2}\right)\ln x + \text{const.}} \Rightarrow \boxed{\gamma = 1-\frac{\mu}{\sigma^2}}$$





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# Confusion

- If $\mu < 0$, $\gamma > 1$ which is totally cool.
- If $\mu > 0$, $\gamma < 1$, not so much.
- If $\sigma^2 \gg 1$ and $\mu$,

$$\boxed{\ln P(x) \sim -\ln x + \text{const.}}$$

- Expect -1 scaling to hold until $(\ln x)^2$ term becomes significant compared to $(\ln x)$:

$$-\frac{1}{2\sigma^2}(\ln x)^2 \simeq 0.05\left(\frac{\mu}{\sigma^2} - 1\right)\ln x$$

$$\Rightarrow \log_{10} x \lesssim 0.05 \times 2(\sigma^2 - \mu)\log_{10} e \simeq 0.05(\sigma^2 - \mu)$$

- $\Rightarrow$ If you find a -1 exponent,
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# Outline

# Generating lognormals:





## Random multiplicative growth:

- $$x_{n+1} = r x_n$$
  where $r > 0$ is a random growth variable
- (Shrinkage is allowed)
- In log space, growth is by addition:
  $$\ln x_{n+1} = \ln r + \ln x_n$$
- $\Rightarrow \ln x_n$ is normally distributed
- $\Rightarrow x_n$ is lognormally distributed

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# Lognormals or power laws?

- Gibrat [2] (1931) uses preceding argument to explain lognormal distribution of firm sizes ($\gamma \simeq 1$).
- But Robert Axtell [1] (2001) shows a power law fits the data very well with $\gamma = 2$, not $\gamma = 1$ (!)
- Problem of data censusing (missing small firms).
- One piece in Gibrat's model seems okay empirically: Growth rate $r$ appears to be independent of firm size. [1].

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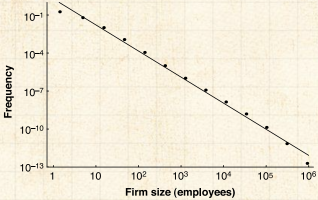


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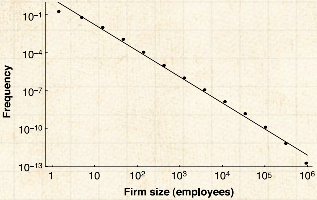


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# An explanation

- Axtel cites Malcai et al.'s (1999) argument [5] for why power laws appear with exponent $\gamma \simeq 2$
- The set up: $N$ entities with size $x_i(t)$
- Generally:

$$x_i(t+1) = r x_i(t)$$

where $r$ is drawn from some happy distribution
- Same as for lognormal but one extra piece.
- Each $x_i$ cannot drop too low with respect to the other sizes:

$$x_i(t+1) = \max(r x_i(t), c \langle x_i \rangle)$$

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# Outline

# The second tweak





## Ages of firms/people/... may not be the same

- Allow the number of updates for each size $x_i$ to vary
- Example: $P(t)\mathrm{d}t = ae^{-at}\mathrm{d}t$ where $t$ = age.
- Back to no bottom limit: each $x_i$ follows a lognormal
- Sizes are distributed as [6]

$$P(x) = \int_{t=0}^{\infty} ae^{-at} \frac{1}{x\sqrt{2\pi t}} \exp\left(-\frac{(\ln x - \mu)^2}{2t}\right) \mathrm{d}t$$

(Assume for this example that $\sigma \sim t$ and $\mu = \ln m$)

- Now averaging different lognormal distributions.

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- 'Break' in scaling (not uncommon)
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# Summary of these exciting developments:

- Lognormals and power laws can be awfully similar
- Random Multiplicative Growth leads to lognormal distributions
- Enforcing a minimum size leads to a power law tail
- With no minimum size but a distribution of lifetimes, the double Pareto distribution appears
- Take-home message: Be careful out there...

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