Lognormals and friends

Principles of Complex Systems | @pocsvox
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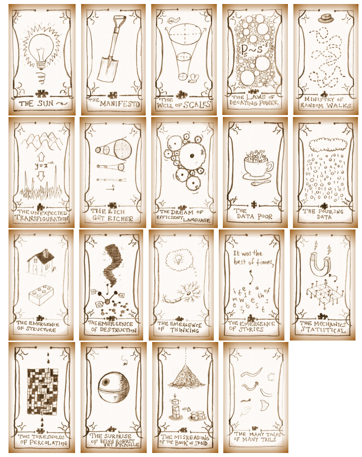
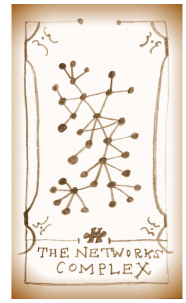
These slides are brought to you by:

Outline

Lognormals
- Empirical Confusability
- Random Multiplicative Growth Model
- Random Growth with Variable Lifespan

References





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.

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 μ and variance σ.
- Appears in economics and biology where growth increments are distributed normally.

lognormals

- Standard form reveals the mean μ and variance σ^2 of the underlying normal distribution:

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

- 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.

Derivation from a normal distribution

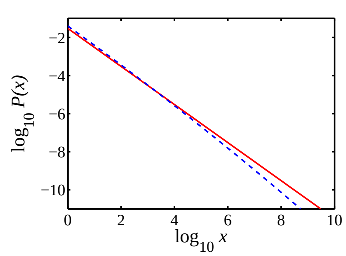
Take Y as distributed normally:

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

Set $Y = \text{ln}X$:

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

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:

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

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

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

If the first term is relatively small,

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

Confusion

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

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

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

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

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

- $\Rightarrow$ If you find a -1 exponent, you may have a lognormal distribution...

Generating lognormals:

Random multiplicative growth:

-
$$x_{n+1} = r x_n$$

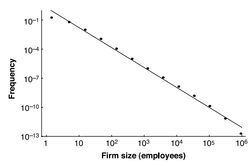
  where $r > 0$ is a random growth variable
- (Shrinkage is allowed)
- In log space, growth is by addition:

$$\text{ln}x_{n+1} = \text{ln}r + \text{ln}x_n$$

- $\Rightarrow \text{ln}x_n$ is normally distributed
- $\Rightarrow x_n$ is lognormally distributed

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).



Freq $\propto$ (size)$^{-\gamma}$
$\gamma \simeq 2$

- One piece in Gibrat's model seems okay empirically: Growth rate r appears to be independent of firm size. [1].

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:

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

Some math later...

Insert question from assignment 7

- Find $P(x) \sim x^{-\gamma}$
- where γ is implicitly given by

$$N = \frac{(\gamma-2)}{(\gamma-1)}\left[\frac{(c/N)^{\gamma-1}-1}{(c/N)^{\gamma-1}-(c/N)}\right]$$

  N = total number of firms.
- Now, if $c/N \ll 1$ and $\gamma > 2$ $\quad N = \frac{(\gamma-2)}{(\gamma-1)}\left[\frac{-1}{-(c/N)}\right]$
- Which gives $\gamma \sim 1 + \frac{1}{1-c}$
- Groovy... c small $\Rightarrow \gamma \simeq 2$

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: $P(t)\mathrm{d}t = a e^{-at}\mathrm{d}t$ where t = age.
- Back to no bottom limit: each x_i follows a lognormal
- Sizes are distributed as [6]

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

  (Assume for this example that $\sigma \sim t$ and $\mu = \ln m$)
- Now averaging different lognormal distributions.

Averaging lognormals

- $$P(x) = \int_{t=0}^{\infty} a e^{-at} \frac{1}{x\sqrt{2\pi t}} \exp\left(-\frac{(\ln \frac{x}{m})^2}{2t}\right) \mathrm{d}t$$
- Insert fabulous calculation (team is spared).
- Some enjoyable suffering leads to:

$$P(x) \propto x^{-1} e^{-\sqrt{2\lambda(\ln \frac{x}{m})^2}}$$

The second tweak

- $$P(x) \propto x^{-1} e^{-\sqrt{2\lambda(\ln \frac{x}{m})^2}}$$
- Depends on sign of $\ln \frac{x}{m}$, i.e., whether $\frac{x}{m} > 1$ or $\frac{x}{m} < 1$.
- $$P(x) \propto \begin{cases} x^{-1+\sqrt{2\lambda}} & \text{if } \frac{x}{m} < 1 \\ x^{-1-\sqrt{2\lambda}} & \text{if } \frac{x}{m} > 1 \end{cases}$$
- 'Break' in scaling (not uncommon)
- Double-Pareto distribution
- First noticed by Montroll and Shlesinger [7, 8]
- Later: Huberman and Adamic [3, 4]: Number of pages per website

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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