

The Log-Normal Distribution

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

The Gaussian Probability Distribution

In the continuous Gaussian probability function the random variable is x . In the law of proportionate effect, the random variable is $\ln x$. \therefore Substitute $x \rightarrow \ln x$.

$$P_{LN}(x) dx = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{(\ln x - \mu)^2}{2\sigma^2}\right] d(\ln x)$$

$\frac{d(\ln x)}{dx} = \frac{1}{x}$

$$\Rightarrow P_{LN}(x) dx = \frac{1}{\sqrt{2\pi}\sigma} \cdot \frac{1}{x} \cdot \exp\left[-\frac{(\ln x - \mu)^2}{2\sigma^2}\right] dx$$

- The log-normal probability distribution.

The Mode of the log-normal ^{probability density} distribution:

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

$$\frac{dP}{dx} = \frac{1}{\sqrt{2\pi}\sigma} \cdot \frac{-1}{x^2} \exp\left[-\frac{(\ln x - \mu)^2}{2\sigma^2}\right] + \frac{1}{\sqrt{2\pi}\sigma} \cdot \frac{1}{x} \exp\left[-\frac{(\ln x - \mu)^2}{2\sigma^2}\right] \cdot \frac{-2(\ln x - \mu)}{2\sigma^2} \cdot \frac{1}{x}$$

$$\Rightarrow \frac{dP}{dx} = -\frac{P}{x} - \frac{P}{x} \frac{(\ln x - \mu)}{\sigma^2}$$

At the mode $\frac{dP}{dx} = 0$

[P.T.O.]

$$\Rightarrow \frac{\ln x - \mu}{\sigma^2} = -1 \Rightarrow \boxed{\ln x = \mu - \sigma^2}$$

$$\Rightarrow \boxed{x_{\text{mode}} = e^{\mu - \sigma^2}} \rightarrow \text{Here } P_{LN}(x) \text{ is maximum.}$$

$$P_{\text{max}} = \frac{1}{\sqrt{2\pi}\sigma} \cdot \frac{e^{\sigma^2}}{e^{\mu}} \cdot \exp\left[-\frac{(-\sigma^2)^2}{2\sigma^2}\right]$$

$$\Rightarrow P_{\text{max}} = \frac{1}{\sqrt{2\pi}\sigma} \cdot \frac{e^{\sigma^2}}{e^{\mu}} \cdot e^{-\sigma^2/2} = \frac{e^{\sigma^2/2 - \mu}}{\sqrt{2\pi}\sigma}$$

$$\therefore \boxed{P_{\text{max}} = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(\frac{\sigma^2}{2} - \mu\right)} \rightarrow \text{The Peak value.}$$

i) When $x \rightarrow 0$, $\frac{1}{x} \rightarrow \infty$, $\ln x \rightarrow -\infty$.

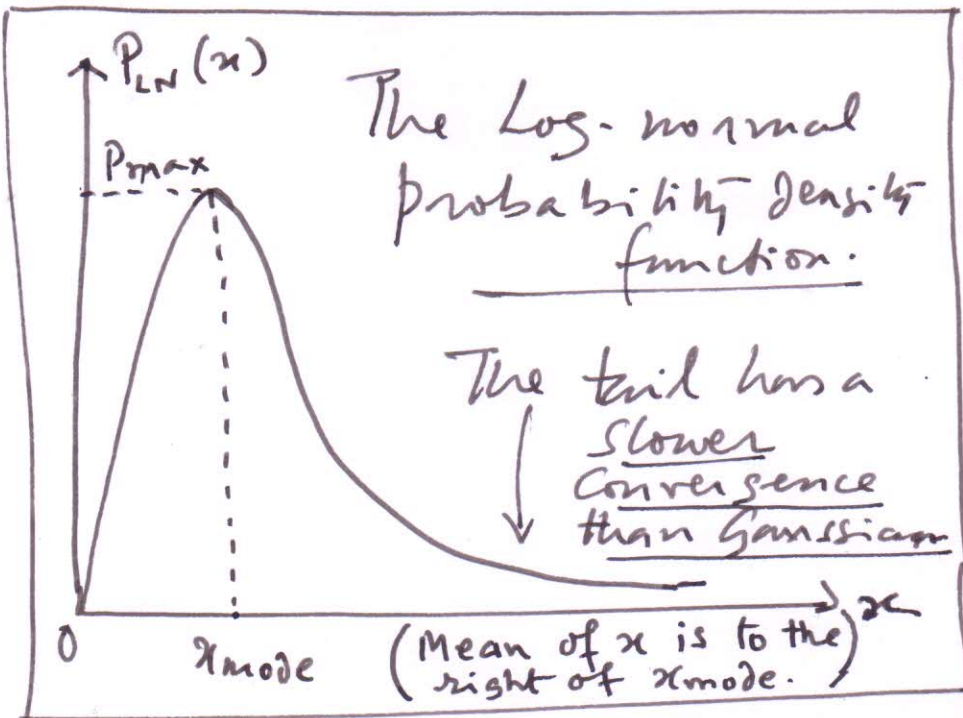
$$\therefore P \sim \frac{1}{x} e^{-(\ln x)^2} \rightarrow 0$$

$\therefore e^{-\infty^2}$ has a faster convergence than x^{-1} .

ii) Also when $x \rightarrow \infty$,

both $e^{-(\ln x)^2}$ and $x^{-1} \rightarrow 0 \Rightarrow P \rightarrow 0$

$$P_G(x) \sim e^{-x^2}$$



1. The Gaussian tail is like $\sim e^{-x^2}$. The log-normal tail has much Slower Convergence.

2. For $x \rightarrow \infty$, $P_{LN}(x) \gg P_G(x)$. Hence large x fluctuations are more probable.

The log-log Representation

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

$$\Rightarrow \ln P = -\ln(\sqrt{2\pi}\sigma) - \ln x - \left[\frac{(\ln x)^2}{2\sigma^2} - \frac{2\mu \ln x}{2\sigma^2} + \frac{\mu^2}{2\sigma^2} \right]$$

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

In a log-log plot $\ln P$ is a parabolic $\ln x$ function of $\ln x$. For a small part of the function will appear like

$$\ln P \sim \left(\frac{\mu}{\sigma^2} - 1\right) \ln x \quad \text{giving the impression of a power law.}$$

Moments of a Log-Normal Variable x .

1. $E[x^n] = e^{n\mu + \frac{1}{2}n^2\sigma^2}$ \rightarrow n -th moment of the variable x .
($E \rightarrow$ expectation)

2. $E[x] = e^{\mu + \frac{\sigma^2}{2}}$ \rightarrow The first moment (Mean)

3. $E[x^2] = e^{2\mu + 2\sigma^2}$ \rightarrow The second moment.

4. $\text{Var}[x] = E[x^2] - E[x]^2 = e^{2\mu + 2\sigma^2} - e^{2\mu + \sigma^2} = e^{2\mu + \sigma^2}(e^{\sigma^2} - 1)$

5. $\sqrt{\text{Var}[x]} = e^{\mu + \frac{\sigma^2}{2}} \sqrt{e^{\sigma^2} - 1}$ \rightarrow The standard deviation.