

1. Examples and Applications of Log Normal Distribution

Welcome to the series of E-learning modules on Log Normal Distribution and its properties.

By the end of this session, you will be able to:

- Explain the examples of Log Normal Distribution and its applications
- Explain the probability distribution function and cumulative distribution function
- Explain median and mode
- Explain r^{th} raw moment, mean, variance, skewness and kurtosis
- Explain the relation between Pareto and Log Normal Distributions

Log normal is also written as log-normal or lognormal. The distribution is occasionally referred as Galton distribution or Galton's distribution, after Francis Galton, and other names such as McAlister, Gibrat and Cobb–Douglas have also been associated.

A variable might be modeled as log-normal if it is the multiplicative product of many independent random variables, each of which is positive.

For example, in finance, the variable could represent the compound return from a sequence of many trades (each expressed as its return + 1); or a long-term discount factor can be derived from the product of short-term discount factors. In wireless communication, the attenuation caused by shadowing or slow fading from random objects is often assumed to be log-normally distributed.

Examples of variates, which have approximately log normal distributions are:

- The size of silver particles in a photographic emulsion
- The survival time of bacteria in disinfectants
- The weight and blood pressure of humans
- Number of words written in sentences by George Bernard Shaw, etc.

Following are the different fields, where log normal distribution can be used:

- In Biology, variables whose logarithms tends to have a normal distribution include:
 - Measures of size of living tissue (length, skin area, weight)
 - The *length of inert* appendages (hair, claws, nails, teeth) of biological specimens, *in the direction of growth*
- Certain Physiological Measurements, such as blood pressure of adult humans (after separation on male/female subpopulations)
- In Hydrology, the log-normal distribution is used to analyze extreme values of such variables as monthly and annual maximum values of daily rainfall and river discharge volumes
- In Economics, there is evidence that the income of 97%–99% of the population is distributed log-normally
- In Finance, in particular the Black–Scholes model, changes in the *logarithm* of

exchange rates, price indices, and stock market indices are assumed normal (these variables behave like compound interest, not like simple interest, and so are multiplicative)

- In Reliability Analysis, the lognormal distribution is often used to model times to repair a maintainable system
- In Wireless Communication, the local-mean power expressed in logarithmic values has a normal (i.e. Gaussian) distribution
- It has been proposed that coefficients of friction and wear may be treated as having a lognormal distribution

2. PDF and CDF

Now, let us define log normal distribution.

A positive random variable X is said to have a log normal distribution if $\log X$ to the base e is normally distributed.

Let Y is equal to $\log X$ to the base e follows normal distribution with parameters μ and σ^2 . For x greater than zero,

$F_X(x)$ is equal to probability that X is less than or equal to x

Taking \log on both the sides, we get probability that $\log X$ to the base e is less than or equal to $\log x$ to the base e

Is equal to probability of Y is less than or equal to $\log x$ to the base e , since $\log X$ is monotonic increasing function.

Is equal to $\frac{1}{\sigma \sqrt{2\pi}} \int_{-\infty}^{\log x} e^{-\frac{y^2}{2\sigma^2}} dy$

Substituting y is equal to $\log u$, above integral can be written as, $\frac{1}{\sigma \sqrt{2\pi}} \int_{-\infty}^{\log x} e^{-\frac{(\log u)^2}{2\sigma^2}} du$

For x less than or equal to zero, $F_X(x)$ is equal to Probability of X less than or equal to x is equal to zero because X is a positive random variable.

Let us define

$f_X(u)$ is equal to $\frac{1}{u \sigma \sqrt{2\pi}} e^{-\frac{(\log u)^2}{2\sigma^2}}$, if u is greater than zero and is equal to zero if u is less than or equal to zero.

Then, $F_X(x)$ is equal to $\int_{-\infty}^x f_X(u) du$ for x and hence f of x is a probability density function of X .

Now, let us consider some remarks.

- If X follows Normal distribution with parameters μ and σ^2 , then Y is equal to e^X is called a log normal random variable since $\log Y$ is equal to X is a normal random variable.
- Log normal distribution arises in problems of economics, biology, geology, and reliability theory. In particular, it arises in the study of dimensions of a particle under pulverization.
- Moment generating function of log normal distribution does not exist on the domain \mathbb{R} but it exists on the half interval $[-\infty, 0]$.
- If X_1, X_2, \dots, X_n is a set of independently identically distributed random variables such that mean of each $\log X_i$ is μ and variance is σ^2 , then the product $X_1 \times X_2 \times \dots \times X_n$ is asymptotically distributed according to logarithmic normal distribution and with mean μ and variance $n \sigma^2$.

Let us find the distribution function.

Cumulative distribution function of log normal distribution is given by

$F_X(x)$ is equal to $\int_{-\infty}^x f_X(x) dx$

Is equal to $\frac{1}{2} \left[1 + \operatorname{erfc} \left(\frac{\log x - \mu}{\sigma \sqrt{2}} \right) \right]$

Is equal to $\frac{1}{2} \left[1 + \operatorname{erfc} \left(\frac{\log x - \mu}{\sigma} \right) \right]$, where erfc is the

complementary error function and is given by

$\text{Erfc of } x \text{ is equal to } \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} dt$ and Φ is the cumulative distribution function of the standard normal distribution.

3. Median and Mode

If M is the median of the distribution, then it divides the whole distribution into two equal parts. Or if we consider the cumulative distribution function, F_X of (x) is equal to half.

That is,

$\Phi\left(\frac{\log x - \mu}{\sigma}\right) = \frac{1}{2}$

Since Φ is standard normal variate, we know that $\Phi(0) = \frac{1}{2}$.

That is, $\frac{\log x - \mu}{\sigma} = 0$

Implies, $\log x = \mu$

$x = e^\mu$

Therefore, median of log normal distribution is given by

$M = e^\mu$

Mode is the value of x for which the probability density function attains its maximum. Hence, it is a solution of $f'(x) = 0$ and $f''(x) < 0$.

Probability density function of log normal distribution is given by,

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

Instead of differentiating the probability density function $f(x)$, we can work with the logarithm. Hence,

$\log f(x) = \log c - \log x - \frac{(\log x - \mu)^2}{2\sigma^2}$, where $c = \frac{1}{\sigma\sqrt{2\pi}}$

By differentiating with respect to x , we get,

$f'(x) = f(x) \left[-\frac{1}{x} - \frac{\log x - \mu}{\sigma^2} \right]$

Taking $f(x)$ on the other side, and taking common term outside, we get,

$f'(x) = f(x) \left[-\frac{1}{x} - \frac{\log x - \mu}{\sigma^2} \right] = 0$

$f'(x) = 0$ implies,

$-\frac{1}{x} - \frac{\log x - \mu}{\sigma^2} = 0$

Implies $\log x = \mu + \sigma^2$

Implies $\log x = \mu + \sigma^2$

Implies $x = e^{\mu + \sigma^2}$

Now, let us obtain the 2nd derivative $f''(x)$.

$f''(x) = \frac{d}{dx} \left[f(x) \left(-\frac{1}{x} - \frac{\log x - \mu}{\sigma^2} \right) \right]$

$f''(x) = f(x) \left[\frac{1}{x^2} - \frac{1}{\sigma^2} \right] + f'(x) \left(-\frac{1}{x} - \frac{\log x - \mu}{\sigma^2} \right)$

Observe that the above function is less than zero at $x = e^{\mu + \sigma^2}$

Hence, mode of the log normal distribution is given by $x = e^{\mu + \sigma^2}$

4. r^{th} Raw Moment, Mean, Variance, Skewness and Kurtosis

Now, let us obtain r th raw moment about origin of log normal distribution.

If Y follows normal μ σ^2 , then X is equal to e^Y is called a log normal random variable. r th raw moment about origin is given by,

μ_r is equal to expectation of X^r

Is equal to expectation of e^{rY}

Is equal to expectation of e^{rY} , which is same as $M_Y(r)$, that is moment generating function of Y , the normal distribution with parameters μ and σ^2 . We know that the moment generating function of normal distribution is given by

$M_Y(r)$ is equal to $e^{r\mu + \frac{r^2\sigma^2}{2}}$

Hence, r th raw moment is given by

μ_r is equal to $e^{r\mu + \frac{r^2\sigma^2}{2}}$

By putting r is equal to 1, we get mean of the log normal distribution as

μ_1 is equal to $e^{\mu + \frac{\sigma^2}{2}}$

By putting r is equal to 2, we get,

μ_2 is equal to $e^{2\mu + 2\sigma^2}$

Variance of the distribution is given by,

μ_2 is equal to μ_2 minus μ_1 the whole square.

Is equal to $e^{2\mu + 2\sigma^2} - e^{2\mu + \sigma^2}$ divided by 2 the whole square.

By taking the common terms outside, and simplifying we get,

$e^{2\mu + 2\sigma^2} - e^{2\mu + \sigma^2}$

Putting r is equal to 3 in μ_r , we get,

μ_3 is equal to $e^{3\mu + \frac{9\sigma^2}{2}}$

Is equal to $e^{3\mu + 9\sigma^2}$ divided by 2.

Third central moment μ_3 is equal to μ_3 minus 3 into μ_2 into μ_1 plus 2 into μ_1 cube

Is equal to $e^{3\mu + 9\sigma^2}$ divided by 2 minus 3 into $e^{2\mu + 2\sigma^2}$ into $e^{\mu + \frac{\sigma^2}{2}}$ plus 2 into $e^{3\mu + \frac{3\sigma^2}{2}}$

By taking common terms outside we get, $e^{3\mu + 9\sigma^2}$ divided by 2 into $e^{3\mu + 9\sigma^2}$ minus 3 into $e^{3\mu + 9\sigma^2}$ plus 2.

Putting r is equal to 4 into μ_r , we get

μ_4 is equal to $e^{4\mu + 8\sigma^2}$ divided by 2

Is equal to $e^{4\mu + 8\sigma^2}$

μ_4 is equal to μ_4 minus 4 into μ_3 into μ_1 plus 6 into μ_2 into μ_1 square minus 3 into μ_1 whole power 4

Is equal to $e^{4\mu + 8\sigma^2}$ minus 4 into $e^{3\mu + 9\sigma^2}$ plus 6 into $e^{2\mu + 2\sigma^2}$ into $e^{2\mu + \sigma^2}$

power 2 into mu plus 2 into sigma square into e power mu plus sigma square divided by 2 whole square minus 3 into e power mu plus sigma square divided by 2 the whole power 4.

By taking common terms outside we get,

$$E^{\mu+2\sigma^2} - 3E^{3\mu+2\sigma^2} + 3E^{6\mu+2\sigma^2} - E^{9\mu+2\sigma^2} > 0$$

Coefficient of skewness is given by,

Beta 1 is equal to μ^3 divided by μ^2 cube

Is equal to
$$\frac{E^{3\mu+3\sigma^2} - 3E^{3\mu+\sigma^2} + 3E^{6\mu+\sigma^2} - E^{9\mu+\sigma^2}}{E^{2\mu+\sigma^2} - 3E^{3\mu+\sigma^2} + 3E^{6\mu+\sigma^2} - E^{9\mu+\sigma^2}}$$

Is equal to
$$\frac{E^{3\mu+3\sigma^2} - 3E^{3\mu+\sigma^2} + 3E^{6\mu+\sigma^2} - E^{9\mu+\sigma^2}}{E^{2\mu+\sigma^2} - 3E^{3\mu+\sigma^2} + 3E^{6\mu+\sigma^2} - E^{9\mu+\sigma^2}}$$
, which is greater than zero.

Therefore, log normal distribution is positively skewed.

Coefficient of kurtosis is given by,

Beta 2 is equal to μ^4 divided by μ^2 square

Is equal to
$$\frac{E^{4\mu+2\sigma^2} - 4E^{3\mu+2\sigma^2} + 6E^{6\mu+2\sigma^2} - 4E^{9\mu+2\sigma^2} + E^{12\mu+2\sigma^2}}{E^{2\mu+\sigma^2} - 3E^{3\mu+\sigma^2} + 3E^{6\mu+\sigma^2} - E^{9\mu+\sigma^2}}$$

Is equal to
$$\frac{E^{4\mu+2\sigma^2} - 4E^{3\mu+2\sigma^2} + 6E^{6\mu+2\sigma^2} - 4E^{9\mu+2\sigma^2} + E^{12\mu+2\sigma^2}}{E^{2\mu+\sigma^2} - 3E^{3\mu+\sigma^2} + 3E^{6\mu+\sigma^2} - E^{9\mu+\sigma^2}}$$

On simplification, we get,
$$E^{4\mu+2\sigma^2} - 4E^{3\mu+2\sigma^2} + 6E^{6\mu+2\sigma^2} - 4E^{9\mu+2\sigma^2} + E^{12\mu+2\sigma^2} > 3(E^{2\mu+\sigma^2} - 3E^{3\mu+\sigma^2} + 3E^{6\mu+\sigma^2} - E^{9\mu+\sigma^2})$$

Hence, log normal distribution has leptokurtic curve.

Consider the following remarks.

We know that variance of the distribution is,

$$\mu^2 = \frac{E^{2\mu+\sigma^2} - 2E^{3\mu+\sigma^2} + E^{6\mu+\sigma^2}}{E^{2\mu+\sigma^2} - 3E^{3\mu+\sigma^2} + 3E^{6\mu+\sigma^2} - E^{9\mu+\sigma^2}}$$

Hence, the standard deviation, SD is equal to
$$\sqrt{\frac{E^{2\mu+\sigma^2} - 2E^{3\mu+\sigma^2} + E^{6\mu+\sigma^2}}{E^{2\mu+\sigma^2} - 3E^{3\mu+\sigma^2} + 3E^{6\mu+\sigma^2} - E^{9\mu+\sigma^2}}}$$

Also, mean is given by,
$$\mu = \frac{E^{\mu+\sigma^2} - E^{3\mu+\sigma^2} + E^{6\mu+\sigma^2} - E^{9\mu+\sigma^2}}{E^{2\mu+\sigma^2} - 3E^{3\mu+\sigma^2} + 3E^{6\mu+\sigma^2} - E^{9\mu+\sigma^2}}$$

Hence coefficient of variation is given by,

C.V. is equal to standard deviation divided by mean

Is equal to
$$\frac{\sqrt{E^{2\mu+\sigma^2} - 2E^{3\mu+\sigma^2} + E^{6\mu+\sigma^2}}}{E^{\mu+\sigma^2} - E^{3\mu+\sigma^2} + E^{6\mu+\sigma^2} - E^{9\mu+\sigma^2}}$$

Given mean μ and variance μ^2 of log normal distribution, we can find μ and σ^2 as follows.

$$\mu = \frac{E^{\mu+\sigma^2} - E^{3\mu+\sigma^2} + E^{6\mu+\sigma^2} - E^{9\mu+\sigma^2}}{E^{2\mu+\sigma^2} - 3E^{3\mu+\sigma^2} + 3E^{6\mu+\sigma^2} - E^{9\mu+\sigma^2}}$$

Taking logarithms and simplifying the above equations, we get,

$$\mu = \frac{\log(E^{\mu+\sigma^2}) - \log(E^{3\mu+\sigma^2}) + \log(E^{6\mu+\sigma^2}) - \log(E^{9\mu+\sigma^2})}{\log(E^{2\mu+\sigma^2}) - \log(E^{3\mu+\sigma^2}) + \log(E^{6\mu+\sigma^2}) - \log(E^{9\mu+\sigma^2})}$$

And σ^2 is equal to
$$\frac{\log(E^{2\mu+\sigma^2}) - \log(E^{3\mu+\sigma^2}) + \log(E^{6\mu+\sigma^2}) - \log(E^{9\mu+\sigma^2})}{\log(E^{2\mu+\sigma^2}) - \log(E^{3\mu+\sigma^2}) + \log(E^{6\mu+\sigma^2}) - \log(E^{9\mu+\sigma^2})}$$

5. Relation between Pareto and Log Normal Distributions

Now, let us observe the relation between Pareto distribution and log normal distribution.

Note that the Pareto distribution and log-normal distributions are alternative distributions for describing the same types of quantities. One of the connections between the two is that they are the distributions of the exponential of random variables distributed according to other common distributions, respectively the exponential distribution and normal distribution.

(Both of these latter two distributions are "basic" in the sense that the logarithms of their density functions are linear and quadratic, respectively, functions of the observed values.)

Here's a summary of our learning in this session, where we have understood:

- The examples of log normal distribution and its applications
- The pdf and cumulative distribution function
- The median and mode
- The r^{th} raw moment, mean, variance, skewness and kurtosis
- The relation between Pareto and log normal distributions