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## MAGIC CONSTANT IN *HOW TO MEASURE ANYTHING IN CYBERSECURITY RISK*

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This is an investigation into the properties of lognormal distributions, to illuminate a mystery found in Chapter 3 of *How To Measure Anything in Cybersecurity*.

There is a mysterious constant in the Chapter 3 Excel spreadsheet, in column J, "Expected Inherent Loss": 3.28971, that is never explained. A little searching uncovers [some clues](#) but it leaves open questions.

In this paper, we will work through some relevant math to uncover what this constant means, and why it is hard-coded.

The normal distribution has a [probability density function](#) defined as:

$$(1) \quad f_Z(x) = \frac{1}{\sigma\sqrt{2\pi}} \cdot e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

A random variable  $X$  with a log-normal distribution has the property that  $\log X$  has a normal distribution. Using a log-normal distribution tends to reflect many common domains in which negative values are impossible, since a log-normally distributed variable  $X$  will never be negative, and tends to have a low-probability *long tail*. This makes sense, for example, to used to model the number of break-in attempts or the financial loss due to a security issue. The only possible values are 0 or greater, there tends to be a relatively modest expectation value, but there is a finite (but small) probability the expected values will be large.

The [log-normal probability density function](#) is defined as:

$$(2) \quad f_X(x) = \frac{1}{x} \cdot \frac{1}{\sigma\sqrt{2\pi}} \cdot e^{-\frac{1}{2}\left(\frac{\ln x - \mu}{\sigma}\right)^2}$$

The [ProbOnto](#) website characterizes R's implementation of the normal and lognormal distributions as "lognormal1." These are represented in R using the `dnorm` and `dlnorm` funtions, respectively.

The book asks the estimator to choose a lower bound  $L$  and an upper bound  $U$  such that the estimator believes there is a 90% chance the observed value will be

within that range. This means that  $L$  describes the 5th percentile of distribution, and  $U$  describes the 95th percentile.

For a [log-normal distribution](#), the integral of the probability density function, called the cumulative distribution function (CDF) is described in terms of the CDF for a normal distribution: (in R, `plnorm`) as:

$$(3) \quad F_X(x) = \Phi\left(\frac{\log x - \mu}{\sigma}\right)$$

In R, this is represented as `plnorm`.

The challenge is to demonstrate that, given a particular value for  $L$  and  $U$ , the parameters  $\mu$  and  $\sigma$  are defined.

If this is true, then we can solve for  $\mu$  and  $\sigma$  in the following system of equations:

$$(4) \quad F_X(L, \mu, \sigma) = 0.05$$

$$(5) \quad F_X(U, \mu, \sigma) = 0.95$$

... which is the same as

$$(6) \quad \Phi\left(\frac{\log L - \mu}{\sigma}\right) = 0.05$$

$$(7) \quad \Phi\left(\frac{\log U - \mu}{\sigma}\right) = 0.95$$

which leads to

$$(8) \quad \frac{\log L - \mu}{\sigma} = \Phi_{0.05}^{-1}$$

$$(9) \quad \frac{\log U - \mu}{\sigma} = \Phi_{0.95}^{-1}$$

$$(10) \quad \log L - \mu = \sigma \cdot \Phi_{0.05}^{-1}$$

$$(11) \quad \log U - \mu = \sigma \cdot \Phi_{0.95}^{-1}$$

...where  $\Phi^{-1}$  is the inverse CDF, also called the *quantile function* (in R, `qnorm`).

Adding these together lets us solve for  $\mu$ :

$$\begin{aligned}
 (\log L + \log U) - 2\mu &= \sigma(\Phi_{0.05}^{-1} + \Phi_{0.95}^{-1}) \\
 (\log L + \log U) - 2\mu &= 0 \\
 \mu &= \frac{\log L + \log U}{2}
 \end{aligned}
 \tag{12}$$

In the last step, we are able to remove the  $\Phi$  term because the normal distribution is symmetric, so we know that  $\Phi(0.05) = -\Phi(0.95)$ . We can approximately confirm this in R:

```
qnorm(0.05) + qnorm(0.95)

## [1] -1.110223e-15
```

Subtracting them lets us solve for  $\sigma$ :

$$\begin{aligned}
 \frac{\log L - \mu}{\sigma} - \frac{\log U - \mu}{\sigma} &= \Phi_{0.05}^{-1} - \Phi_{0.95}^{-1} \\
 \log L - \mu - (\log U - \mu) &= \sigma(\Phi_{0.05}^{-1} - \Phi_{0.95}^{-1}) \\
 \sigma &= \frac{\log L - \log U}{\Phi_{0.05}^{-1} - \Phi_{0.95}^{-1}} \\
 \sigma &= \frac{\log U - \log L}{2\Phi_{0.95}^{-1}}
 \end{aligned}
 \tag{13}$$

...which is the result.

There is [no closed form expression](#) for  $\Phi^{-1}$ . Therefore, the author uses the hard-coded value, though we could use an excel function to compute it, which would increase clarity. In Excel, this is the `NORM.INV` function, [documented here](#).

In R,

```
2*qnorm(0.95)

## [1] 3.289707
```

The corresponding evaluation in Excel, `=2*NORM.INV(0.95,0,1)` yields 3.289707254.

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