**Theorem** The exponentiation of a  $N(\mu, \sigma^2)$  random variable is a log normal $(\alpha, \beta)$  random variable.

**Proof** Let the random variable X have the normal distribution with probability density function

$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} - \infty < x < \infty.$$

The transformation  $Y = g(X) = e^X$  is a 1–1 transformation from  $\mathcal{X} = \{x \mid -\infty < x < \infty\}$  to  $\mathcal{Y} = \{y \mid y > 0\}$  with inverse  $X = g^{-1}(Y) = \ln(Y)$  and Jacobian

$$\frac{dX}{dY} = \frac{1}{Y}.$$

Therefore by the transformation technique, the probability density function of Y is

$$f_Y(y) = f_X\left(g^{-1}(y)\right) \left| \frac{dx}{dy} \right|$$
$$= \left(\frac{1}{\sqrt{2\pi}\sigma}\right) e^{-\frac{1}{2}\left(\frac{\ln(y)-\mu}{\sigma}\right)^2} \left| \frac{1}{y} \right| \qquad y > 0.$$

Let  $\mu = \ln(\alpha)$  and  $\sigma = \beta$ . Then

$$f_Y(y) = \left(\frac{1}{\sqrt{2\pi}y\beta}\right) e^{-\frac{1}{2}\left(\frac{\ln(y/\alpha)}{\beta}\right)^2} \qquad y > 0,$$

which is the probability density function of the log normal distribution.

**APPL Verification:** The APPL statements

X := NormalRV(mu, sigma);

 $g := [[x \rightarrow exp(x)], [-infinity, infinity]];$ 

Y := Transform(X, g);

Z := LogNormalRV(mu, sigma);

yield identical probability density functions for Y and Z.