Colm Connaughton Notes

CDF method for distribution of products and powers of normal random variables

1 Notation

For a random variable, X, we denote the Probability Density Function (PDF) of X by $f_X(x)$ and the corresponding Cumulative Density Function (CDF) by $F_X(x)$. By definition we have

 $\frac{dF_X(x)}{dx} = f_X(X). \tag{1}$

Given a pair of random variables, X and Y, we will denote their joint PDF by $f_{X,Y}(x,y)$.

Let X be distributed normally with mean μ and standard deviation σ :

$$f_X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}},$$
 (2)

$$F_X(x) = \frac{1}{2} \left[1 + erf\left(\frac{x-\mu}{\sqrt{2}\sigma}\right) \right].$$
 (3)

2 PDF of square of a normal random variable

Now consider $Z=X^2.$ To find an explicit formula for the PDF of Z, we first construct the CDF and then differentiate it to get the PDF.

$$F_{Z}(z) = \mathbb{P}(Z \le z)$$

$$= \mathbb{P}(X^{2} \le z)$$

$$= \mathbb{P}(-\sqrt{z} \le X \le \sqrt{z})$$

$$= \mathbb{P}(X \le \sqrt{z}) - \mathbb{P}(X \le -\sqrt{z})$$

$$= F_{X}(\sqrt{z}) - F_{X}(-\sqrt{z}).$$

We can now differentiate with respect to \boldsymbol{z} with the chain rule to get the PDF:

$$f_Z(z) = \frac{dF_Z(z)}{dz}$$

$$= F'_X(\sqrt{z}) \frac{d}{dz} \sqrt{z} - F'_X(-\sqrt{z}) \frac{d}{dz} (-\sqrt{z})$$

$$= \frac{1}{2\sqrt{z}} \left(f_X(\sqrt{z}) + f_X(-\sqrt{z}) \right)$$

The calculation so far works for any distribution, $f_X(x)$, for the random variable X. For the specific case of a normal distribution we have:

$$f_Z(z) = \frac{1}{2\sqrt{2\pi\sigma^2}z} \left(e^{-\frac{(\sqrt{z}-\mu)^2}{2\sigma^2}} + e^{-\frac{(\sqrt{z}+\mu)^2}{2\sigma^2}} \right).$$
(4)

This formula is checked against some empirical data in Fig. 1.

3 PDF of cube of a normal random variable

A similar calculation works for the cube. Let $Z=X^3$. Then

$$F_{Z}(z) = \mathbb{P}(Z \leq z)$$

$$= \mathbb{P}(X^{3} \leq z)$$

$$= \mathbb{P}(X \leq \operatorname{sgn}(z) |z|^{\frac{1}{3}})$$

$$= F_{X}(\operatorname{sgn}(z) |z|^{\frac{1}{3}}).$$

We can again differentiate with respect to z with the chain rule to get the PDF:

$$f_{Z}(z) = \frac{dF_{Z}(z)}{dz}$$

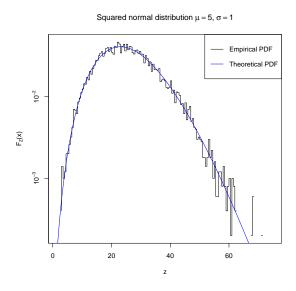
$$= F'_{X}(\operatorname{sgn}(z)|z|^{\frac{1}{3}}) \frac{d}{dz} \left(\operatorname{sgn}(z)|z|^{\frac{1}{3}}\right)$$

$$= \frac{1}{3|z|^{\frac{2}{3}}} f_{X}(\operatorname{sgn}(z)|z|^{\frac{1}{3}})$$

Specialising to the case of a normal distribution we get

(2)
$$f_Z(z) = \frac{1}{3\sqrt{2\pi\sigma^2}} \frac{1}{|z|^{\frac{2}{3}}} e^{-\frac{1}{2\sigma^2} \left[\operatorname{sgn}(z)|z|^{\frac{1}{3}} - \mu\right]^2}.$$
 (5)

This formula is checked against some empirical data in Fig. 2.



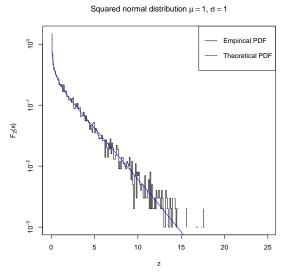
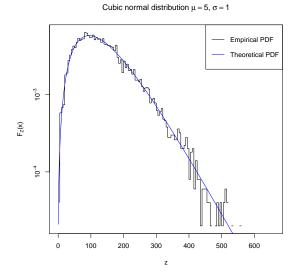


Figure 1: Comparison of Eq. (4) against empirical distribution obtained by sampling and squaring 10000 independent normal random variables.

Colm Connaughton Notes



Cubic normal distribution $\mu = 1$, $\sigma = 1$

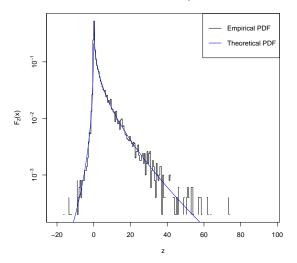


Figure 2: Comparison of Eq. (5) against empirical distribution obtained by sampling and cubing 10000 independent normal random variables.

4 PDF of an arbitrary power of the absolute value of a random variable

The CDF method also gives a general formula for any power, α , of the absolute value of a random variable. The absolute value is required since X^{α} is generally not defined for X<0. In practice, this is likely to be most useful when we already know that X is a positive random variable. Let $Z=|X|^{\alpha}$. Then

$$F_{Z}(z) = \mathbb{P}(Z \le z)$$

$$= \mathbb{P}(|X|^{\alpha} \le z)$$

$$= \mathbb{P}(|X| \le |z|^{\frac{1}{\alpha}})$$

$$= \int_{-\frac{1}{z}}^{0} dx f_{X}(x) + \int_{0}^{\frac{1}{z}} dx f_{X}(x)$$

$$= F_{X}(a(z)) - F_{X}(-a(z)),$$

where $a(z)=\frac{1}{z}.$ We can now get the PDF of z by differentiating:

$$f_{Z}(z) = \frac{dF_{Z}((a(z)))}{dz} - \frac{dF_{Z}((-a(z)))}{dz}$$

$$= (F'_{X}(a(z)) - F'_{X}(-a(z))) \frac{da(z)}{dz}$$

$$= \frac{1}{\alpha} \left[f_{X}\left(z^{\frac{1}{\alpha}}\right) - f_{X}\left(-z^{\frac{1}{\alpha}}\right) \right] z^{\frac{1-\alpha}{\alpha}}. (6)$$

5 PDF of the product of two random variables

Let the random variables X and Y have joint PDF $F_{X,Y}(x,y)$ and let Z=XY. We need not assume that X and Y are independent. The CDF of Z is

$$F_{Z}(z) = \mathbb{P}(Z \leq z)$$

$$= \mathbb{P}(XY \leq z)$$

$$= \mathbb{P}(XY \leq z \mid X < 0) + \mathbb{P}(XY \leq z \mid X > 0)$$

$$= \mathbb{P}\left(Y \geq \frac{z}{X} \mid X < 0\right) + \mathbb{P}\left(Y \leq \frac{z}{X} \mid X > 0\right)$$

$$= \int_{-\infty}^{0} \int_{\frac{z}{u}}^{\infty} dy f_{X,Y}(x, y) + \int_{0}^{\infty} dx \int_{0}^{\frac{z}{u}} dy f_{X,Y}(x, y).$$

To get the PDF, we differentiate with respect to z. This is straightforward because the only z-dependence is via the combination $a(z)=\frac{z}{x}$ appearing in the respective lower and upper limits of the inner integrals. An almost trivial application of the chain rule then gives

$$f_Z(z) = \frac{dF_Z((a(z)))}{dz} = \frac{dF_Z(a)}{da} \frac{da}{dz}$$

The derivatives with respect to a come immediately from the Fundamental Theorem of Calculus. We end up with

$$f_Z(z) = -\int_{-\infty}^0 \frac{dx}{x} f_{X,Y}(x, \frac{z}{x}) + \int_0^\infty \frac{dx}{x} f_{X,Y}(x, \frac{z}{x})$$
$$= \int_{-\infty}^\infty \frac{dx}{|x|} f_{X,Y}(x, \frac{z}{x}). \tag{7}$$

This is the formula attributed to Rohatqi [?] in [?]

6 PDF of error in the cube of a quantity with normally distributed error

This is motivated by understanding the distribution of the uncertainty in power, p, given noisy measurements of the streamwise velocity, v, assuming a cubic relationship between the two:

$$p = v^3. (8)$$

Suppose that $v=u+\delta u$ where u is the true streamwise velocity and $\delta u\sim N(0,\sigma^2)$ is a normally distributed measurement error. Then the power is

$$p = u^3 + \delta p, (9)$$

where

$$\delta p = 3u^2(\delta u) + 2u(\delta u)^2 + (\delta u)^3.$$
 (10)

Colm Connaughton Notes

To find the distribution of δp we need to find the distribution of

$$Z = X^3 + 3aX^2 + 3a^2X \tag{11}$$

where a is a constant. Proceeding as before:

$$F_Z(z) = \mathbb{P}(Z \le z)$$

$$= \mathbb{P}(X^3 + 3aX^2 + 3a^2X \le z)$$

$$= \mathbb{P}(X \le r_z),$$

where r_z is the root of the equation

$$x^3 + 3ax^2 + 3a^2x = z. (12)$$

There is a single real root:

$$r_z = -a + (a^3 + z)^{\frac{1}{3}}. (13)$$

Thus we have

$$F_Z(z) = F_X(-a + (a^3 + z)^{\frac{1}{3}})$$
 (14)

Now differentiate to get the PDF, $f_Z(z)$:

$$f_Z(z) = \frac{dF_Z(z)}{dz}$$

= $F'_X(r_z) \frac{dr_z}{dz}$.

Substituting everything in and simplifying, we get

$$f_Z(z) = \frac{1}{3\sqrt{2\pi\sigma^2} |a^3 + z|^{\frac{2}{3}}} e^{-\frac{1}{2\sigma^2} \left[-a + |a^3 + z|^{\frac{1}{3}}\right]^2}.$$

We can get the same formula from Eq. (5) by defining a shifted variable $W=Z-\mu^3$ representing the difference between the cube of the random variable and the cube of its mean and then substituting $Z=W+\mu$.

7 A better model the wind speed and power distributions

The power is the cube of a the speed and the speed, by definition, cannot be negative. The normal fluctuations assumed in the previous section therefore cannot be generally correct. To fix this, let us assume a 2-dimensional velocity vector with mean direction $(\mu,0)$ and i.i.d. normal fluctuations in the parallel and transverse directions having mean 0 and standard deviation σ . The is, we model the x and y components of the wind velocity as random variables, y and y, with distributions

$$f_U(u) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[\frac{1}{2} \frac{(u-\mu)^2}{\sigma^2}\right]$$
$$f_V(v) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[\frac{1}{2} \frac{v^2}{\sigma^2}\right].$$

The joint distribution is

$$f_{U,V}(u,v) = \frac{1}{2\pi\sigma^2} \exp\left[-\frac{1}{2\sigma^2} ((u-\mu)^2 + v^2)\right].$$

The speed is

$$Z = \sqrt{U^2 + V^2}$$

Let us now use the CDF method to obtain the PDF of speed.

$$F_Z(z) = \mathbb{P}(Z \le z)$$

$$= \mathbb{P}\left(\sqrt{U^2 + V^2} \le z\right)$$

$$= \mathbb{P}\left(U^2 + V^2 \le z^2\right)$$

$$= \iint_{u^2 + v^2 \le z^2} \frac{du \, dv}{2\pi\sigma^2} \exp\left[-\frac{1}{2\sigma^2}\left((u - \mu)^2 + v^2\right)\right].$$

Writing this integral in polar coordinates,

$$u = r\cos\theta$$
$$v = r\sin\theta,$$

we get

$$F_Z(z) = \int_0^{2\pi} \frac{d\theta}{2\pi\sigma^2} \int_0^z r \, dr \exp\left[-\frac{1}{2\sigma^2} \left((r\cos\theta - \mu)^2 + r^2\sin^2\theta \right) \right].$$

Now differentiating with respect to z, noting that z only enters as the upper limit of the integral over the radial coordinate, we get:

$$f_Z(z) = \int_0^{2\pi} \frac{d\theta}{2\pi\sigma^2} z \exp\left[-\frac{1}{2\sigma^2} \left((z\cos\theta - \mu)^2 + z^2\sin^2\theta \right) \right]$$
$$= \frac{z}{2\pi\sigma^2} \exp\left[-\frac{z^2 + \mu^2}{2\sigma^2}\right] \int_0^{2\pi} d\theta \exp\left[\frac{z\mu}{\sigma^2}\cos\theta\right].$$

The integral representation of the modified Bessel function, $I_{\nu}(x)$, is

$$I_{\nu}(x) = \frac{1}{\pi} \int_{0}^{\pi} dt \exp\left[x \cos t\right] \cos t.$$

Using this, the integral over θ is seen to be $2\pi I_0\left(\frac{z\mu}{\sigma^2}\right)$. The speed distribution is therefore

$$f_Z(z) = \begin{cases} \frac{z}{\sigma^2} \exp\left[-\frac{z^2 + \mu^2}{2\sigma^2}\right] I_0\left(\frac{z\mu}{\sigma^2}\right) & z \ge 0\\ 0 & z < 0. \end{cases}$$
(16)

This PDF is nonzero only for positive values. It looks normal for μ much larger than σ and more like a Weibull for $\mu\sim\sigma$.

Colm Connaughton Notes

This allows it to capture some of the qualitative features of observed wind speed distributions.

We can now substitute Eq. (16) into Eq. (6) with $\alpha=3$ to get a better model of the PDF of the power:

$$f_Z(z) = \left\{ \begin{array}{l} \frac{1}{3\,\sigma^2 z^{\frac{1}{3}}} \exp\left[-\frac{z^{\frac{2}{3}} + \mu^2}{2\sigma^2}\right] I_0\left(\frac{z^{\frac{1}{3}} \mu}{\sigma^2}\right) & z \geq 0 \\ 0 & z < 0. \end{array} \right.$$
 [2] Guolong Cui, Xianxiang Yu, Salvatore lommelli, and Lingjiang Kong. Exact distribution for the product of two correlated Gaussian random variables. *IEEE Signal Production of the product of two correlated Gaussian random variables.*

In this model, the power is roughly a stretched exponential

distribution with an integrable singularity at 0.

References

- [1] VK Rohatgi. An Introduction to Probability Theory and Mathematical Statistics. John Wiley & Sons, New York,
- correlated Gaussian random variables. IEEE Signal Processing Letters, 23(11):1662-1666, 2016.