

part II. PROVE THAT THE BOX-MULLER ALGORITHM BELOW GENERATES A NORMALLY DISTRIBUTED RANDOM NUMBER, FOLLOWING THE LECTURE SLIDES ON "MONTE CARLO BASICS".

$$p(\xi) = \sqrt{\frac{1}{2\pi}} \exp\left(-\frac{\xi^2}{2}\right)$$

(a) Generate uniform random numbers r_1, r_2 in the range $(0, 1)$

(b) Calculate $\xi_1 = (-2\ln(r_1))^{1/2} \cos(2\pi r_2)$

$\xi_2 = (-2\ln(r_1))^{1/2} \sin(2\pi r_2)$

Let r_1 and r_2 be uniform random numbers in the range between $[0,1]$ then it follows that there are a total Number of samples:

$$\underbrace{NP(r_1, r_2)}_1 \underbrace{dr_1 dr_2}_{\text{rectangle}} = N \times \underbrace{P'(z_1, z_2)}_{\text{density}} \underbrace{S(r_1, r_2, dr_1, dr_2)}_{\text{area}} \quad (1)$$

in a small rectangle of size $dr_1 dr_2$ around the point r_1 and r_2 there are a total number of samples

$$S = \left| \frac{\partial(z_1, z_2)}{\partial(r_1, r_2)} \right| dr_1 dr_2 \quad (\text{proven in lecture notes}) \quad (2)$$

Now, let us transform each point at each of these end point from r_1 and r_2 coordinate to this z_1 and z_2 coordinate

Now, let's substitute eqn (2) into (1). N and $dr_1 dr_2$ cancels, so we end up with:

$$P(r_1, r_2) = P'(z_1, z_2) \left| \frac{\partial(z_1, z_2)}{\partial(r_1, r_2)} \right| \quad \text{then solving for } P'(z_1, z_2) \text{ we get:}$$

$$\therefore P'(z_1, z_2) = \left| \frac{\partial(z_1, z_2)}{\partial(r_1, r_2)} \right|^{-1} P(r_1, r_2) = \left| \frac{\partial(r_1, r_2)}{\partial(z_1, z_2)} \right| \quad (\text{see lecture notes for proof}) \quad (3)$$

$$\left| \frac{\partial(r_1, r_2)}{\partial(z_1, z_2)} \right| = \det \begin{vmatrix} \frac{\partial r_1}{\partial z_1} & \frac{\partial r_2}{\partial z_1} \\ \frac{\partial r_1}{\partial z_2} & \frac{\partial r_2}{\partial z_2} \end{vmatrix} \quad \text{Total the derivatives we need to express } r_1 \text{ and } r_2 \text{ in terms of } z_1 \text{ and } z_2:$$

by squaring z_1 and z_2 we find that:

$$\begin{aligned} z_1^2 + z_2^2 &= \left(\sqrt{-2 \ln(r_1)} \cos(2\pi r_2) \right)^2 + \left(\sqrt{-2 \ln(r_1)} \sin(2\pi r_2) \right)^2 = \sqrt{-2 \ln(r_1)}^2 \left(\cos^2(2\pi r_2) + \sin^2(2\pi r_2) \right) \\ &= -2 \ln(r_1) \Rightarrow r_1 = e^{-\frac{1}{2}(z_1^2 + z_2^2)} \end{aligned} \quad (4)$$

so that $\frac{\partial r_1}{\partial z_1}$

And to find r_2 in terms of ξ_1 and ξ_2 , notice that the ratio:

$$\frac{\xi_2}{\xi_1} = \frac{-2 \ln(r_1) \sin(2\pi r_2)}{-2 \ln(r_1) \cos(2\pi r_2)} = \tan(2\pi r_2) \quad \text{From which we can we get } \frac{1}{\cos^2(2\pi r_2)} = 1 + \tan^2(2\pi r_2) = 1 + \left(\frac{\xi_2}{\xi_1}\right)^2$$

then we can get $d\xi_1$ and $d\xi_2$ by:

$$\boxed{-\frac{\xi_2}{\xi_1} d\xi_1 = \frac{2\pi dr_2}{\cos^2(2\pi r_2)}} \quad \text{and} \quad \boxed{\frac{d\xi_2}{\xi_1} = \frac{2\pi dr_2}{\cos^2(2\pi r_2)}} \quad (5)$$

So, from (4) we have $\frac{\partial \Gamma_1}{\partial \xi_1} = -\xi_1 e^{-\frac{1}{2}(\xi_1^2 + \xi_2^2)}$ and $\frac{\partial \Gamma_1}{\partial \xi_2} = -\xi_2 e^{-\frac{1}{2}(\xi_1^2 + \xi_2^2)}$ (6)

From (5) we get $\frac{\partial \Gamma_2}{\partial \xi_1} = -\frac{\xi_2}{\xi_1} \cos^2(2\pi r_2) = -\frac{\xi_2}{\xi_1} (1 + \tan^2(2\pi r_2))^{-1} = -\frac{\xi_2}{\xi_1} \frac{1}{1 + \left(\frac{\xi_2}{\xi_1}\right)^2}$ (7)

Finally, $\frac{\partial \Gamma_2}{\partial \xi_2} = \frac{1}{2\pi \xi_1} \cos^2(2\pi r_2) = \frac{1}{2\pi \xi_1} \frac{1}{1 + \left(\frac{\xi_2}{\xi_1}\right)^2}$ (8)

Now we can compute the jacobian in equation (3) using (6), (7) and (8):

$$\begin{aligned} P'(\xi_1, \xi_2) &= \left| \frac{\partial \Gamma_1}{\partial \xi_1} \frac{\partial \Gamma_2}{\partial \xi_2} - \frac{\partial \Gamma_1}{\partial \xi_2} \frac{\partial \Gamma_2}{\partial \xi_1} \right| = \left| \left(-\xi_1 e^{-\frac{1}{2}(\xi_1^2 + \xi_2^2)} \right) \left(\frac{1}{2\pi \xi_1} \frac{1}{1 + \left(\frac{\xi_2}{\xi_1}\right)^2} \right) - \left(-\xi_2 e^{-\frac{1}{2}(\xi_1^2 + \xi_2^2)} \right) \left(-\frac{\xi_2}{\xi_1} \frac{1}{1 + \left(\frac{\xi_2}{\xi_1}\right)^2} \right) \right| \\ &= \left| -e^{-\frac{1}{2}(\xi_1^2 + \xi_2^2)} \left(\frac{1}{2\pi \left(1 + \left(\frac{\xi_2}{\xi_1}\right)^2\right)} + \frac{\xi_2}{\xi_1 \left(1 + \left(\frac{\xi_2}{\xi_1}\right)^2\right)} \right) \frac{\xi_1^2}{\xi_1^2} \right| = \frac{e^{-\frac{1}{2}(\xi_1^2 + \xi_2^2)}}{2\pi} \left(\frac{\xi_1^2}{\xi_1^2 + \xi_2^2} + \frac{\xi_2 \xi_1}{\xi_1^2 + \xi_2^2} \right) \end{aligned}$$

$$\boxed{= \frac{e^{-\frac{1}{2}(\xi_1^2 + \xi_2^2)}}{2\pi}}$$

Which is a normal distribution

which can be further expanded into a product of factors, each depending only on one variable:

$$P(\xi_1, \xi_2) = \frac{1}{2\pi} e^{-\frac{1}{2}(\xi_1^2 + \xi_2^2)} = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\xi_1^2} \cdot \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\xi_2^2} = P(\xi_1)P(\xi_2) \quad \text{which means (10)}$$

Which means that the expectation value of the two variable function is the same as product of the two independently computed expectation values for the two single variable functions i.e.:

$$\begin{aligned} \langle AB \rangle &= \int d\xi_1 \int d\xi_2 P(\xi_1, \xi_2) A(\xi_1) B(\xi_2) = \int d\xi_1 P(\xi_1) A(\xi_1) \int d\xi_2 P(\xi_2) B(\xi_2) \\ &= \langle A \rangle \langle B \rangle \quad \text{hence, they are uncorrelated where each} \end{aligned}$$

of them follow a normal distribution, independently:

$$P(\xi) = \frac{1}{\sqrt{2\pi}} e^{-\xi^2/2}$$