Random Numbers and Monte Carlo Integration

Vignesh M Pai (20211132)

1 Transforming One Dimensional Probability Distributions

We start with a random number generator X that uniformly gives a random number in the range $[0, 1]$. The problem is to transform this number by a bijective function $f : [0, 1] \to [a, b]$ such that the resulting random function $Y = f(X)$ has probability distribution function ρ. In other words, we need to satisfy the equation

$$p(Y \in [y, y + dy]) = \rho(y)dy \tag{1}$$

We know that

$$p(Y \in [f(x), f(x) + f'(x)dx]) = p(X \in [x, x + dx]) = dx \tag{2}$$

substituting $y = f(x)$ and $dy = f'(x)dx$, we get

$$p(Y \in [y, y + dy]) = \frac{dy}{f'(x)} = \frac{dy}{f'(f^{-1}(y))} \tag{3}$$

Let the inverse of f be g, then

$$f'(f^{-1}(y)) = f'(g(y)) = \frac{1}{g'(y)} \tag{4}$$

Substituting back to (1), we get that

$$\begin{aligned} g'(y) &= \rho(y) \\ f^{-1}(y) &= \int_a^y \rho(y)dy \end{aligned}$$

Hence, to find f, ρ needs to be integrable and the integral needs to be invertible. Let's calculate f for some common values of ρ.

1.

$$\begin{aligned} \rho(x) &= e^{-\lambda x}, \quad x \geq -\frac{\ln \lambda}{\lambda} \\ g(y) &= 1 - \frac{e^{-\lambda y}}{\lambda} \\ f(x) &= -\frac{\ln(\lambda(1 - x))}{\lambda} \end{aligned}$$

2.

$$\begin{aligned} \rho(x) &= \lambda e^{-\lambda x}, \quad x \geq 0 \\ g(y) &= 1 - e^{-\lambda y} \\ f(x) &= -\frac{\ln(1 - x)}{\lambda} \end{aligned}$$

2 Transforming the Gaussian Distribution

Suppose we wish to calculate f for ρ given by

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

Clearly, this is not integrable, hence calculating f is not so simple. However, we know that $\rho'(x,y) = \rho(x)\rho(y)$ is integrable once transformed to polar coordinates.

$$\begin{aligned}
\rho'(x,y)dxdy &= \rho'(r\cos(\theta), r\sin(\theta))rdrd\theta \\
&= \frac{1}{2\pi}\exp\left(-\frac{r^2}{2}\right)rdrd\theta \\
&= -d\left(\exp\left(-\frac{r^2}{2}\right)\right)d\left(\frac{\theta}{2\pi}\right)
\end{aligned}$$

If we choose the change of variables

$$\begin{aligned}
U &= \exp\left(-\frac{r^2}{2}\right) \\
V &= \frac{\theta}{2\pi}
\end{aligned}$$

then note that U, V lie in the range $[0,1]$. If U, V set to be random variables, and we write x, y as

$$\begin{aligned}
x &= r\cos(\theta) = \sqrt{-2\ln U}\cos(2\pi V) \\
y &= r\sin(\theta) = \sqrt{-2\ln U}\sin(2\pi V)
\end{aligned}$$

then x, y will each be random variables with the distribution ρ. The proof of this fact essentially lies in the change of variables we performed to derive U, V.

It turns out trigonometric functions are expensive to compute. Therefore, in practice, we can use the Marsaglia polar method. Let u, v be random variables in $[-1,1]$ (they represent $\sqrt{U}\cos\theta$ and $\sqrt{U}\sin\theta$), let $s = u^2 + v^2$ and continue until $s \leq 1$. We now write x, y as

$$\begin{aligned}
x &= \sqrt{-2\ln s}\frac{u}{\sqrt{s}} = \sqrt{\frac{-2\ln s}{s}}u \\
y &= \sqrt{-2\ln s}\frac{v}{\sqrt{s}} = \sqrt{\frac{-2\ln s}{s}}v
\end{aligned}$$

It can be verified that x, y have distribution ρ.

Note that if a random variable X has distribution ρ, then $\sigma X + \mu$ has Gaussian distribution with mean μ and variance σ^2.

3 Monte Carlo Integration

Suppose we wish to calculate the following integral

$$I = \int_0^1 J(x)dx$$

Let X be the uniform random variable in $[0,1]$ as before, then we can approximate I as

$$I \approx \langle J \rangle = \frac{1}{N}\sum_{i=1}^{N} J(x_i)$$

where $x_1, ..., x_N$ are N samples of X. By CLT, it is obvious that the distribution of I will be a Gaussian with standard deviation

$$\sigma = \frac{\sigma_J}{\sqrt{N}} = \sqrt{\frac{\langle J^2 \rangle - \langle J \rangle^2}{N}}$$

the averages of J, J^2 could be computed using $J(x_i)$.

For integrals with different limits, we would need to transform our random variables. Suppose our limits are a, b and ρ is a probability distribution function on $[a, b]$. Then we can write

$$I = \int_a^b J(y)dy = \int_a^b \frac{J(y)}{\rho(y)} \rho(y)dy$$

Define $\tilde{J}(y) = J(y)/\rho(y)$ and suppose Y is a random variable with distribution ρ, then we can approximate I as

$$I \approx \frac{1}{N} \sum_{i=1}^{N} \tilde{J}(y_i)$$

where $y_1, ..., y_N$ are N samples of Y. Usually, Y is obtained by a transformation f of X.

$$I \approx \frac{1}{N} \sum_{i=1}^{N} \tilde{J}(f(x_i))$$

where $x_1, ..., x_N$ are N samples of X. When the distribution ρ is chosen to be of a similar shape to J, it is known as importance sampling.