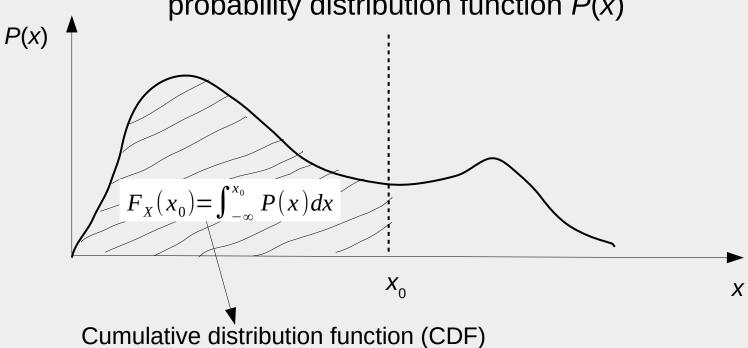


Stochastic methods in Mathematical Modelling

Lecture 3. Distribution sampling 1

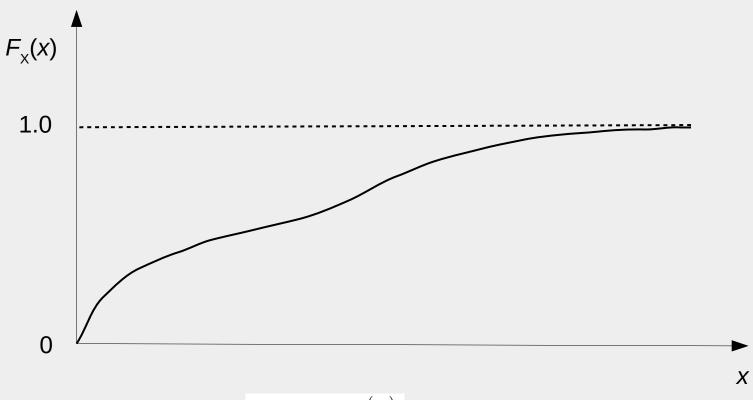
Cumulative distribution function for probability distribution function P(x)



N.B. CDF can also be defined for discrete and mixed distributions



Cumulative distribution function $F_x(x)$



$$P(x) = \frac{dF_X(x)}{dx}$$

if the derivative exists



How does one sample random variables from a distribution by using CDF $F_{x}(X)$?

Let's define
$$Y = F_X(X)$$

Notice that $F_x(x)$ transforms a function defined on R to the function defined on [0,1]. $F_x^{-1}(x)$ is unique and exists since CDF is monotonous. Then

$$F_Y(y) = \Pr(Y \le y) = \Pr(X \le F_X^{-1}(y)) = F_X(F_X^{-1}(y)) = y, y \in [0, 1]$$

$$f_Y(y) = \begin{cases} 1 & y \in [0,1] \\ 0 & \text{otherwise.} \end{cases}$$

Y is uniform distribution on [0,1]

$$Y \sim U([0,1])$$



How does one sample random variables from a distribution by using CDF?

Inverse transform sampling. The algorithm

- 1. Find the inverse function of the CDF, $F_x^{-1}(x)$
- 2. Generate a random number u from U[0,1]
- 3. Compute $X = F_{x}^{-1}(u)$. The computed random variable X has the sought distribution



How does one sample random variables from a distribution by using CDF?

The example. The exponential PDF $P(x)=\lambda e^{-\lambda x}$

The CDF for exponential PDF reads $F_x(x)=1-e^{-\lambda x}$

$$x = F_X^{-1}(y) = \frac{-1}{\lambda} \ln(1 - y)$$

Since y belongs to [0,1] one can simply generate the exponential with

$$x = F_X^{-1}(y) = \frac{-1}{\lambda} \ln(y)$$
 y is drawn from U[0,1]

Q: Do this for $P(x)\sim 1/(1+x^2)$, $-\infty \le x < \infty$



Q. Find a way to sample the values from a distribution with the PDF $P(x)\sim 1/(1+x^2)$, $-\infty \le x < \infty$

CDF:
$$X dX$$

$$F_{X}(X) = \frac{1}{\pi(1+X^{2})} = \frac{1}{\pi} \arctan X + \frac{1}{2} = y$$

$$X = \tan \left(\pi(y - 1/2) \right)$$



Box-Muller transform for generation of Gaussian distributions

For the Gaussian case it would be difficult to use the method above due to the lack of analytic form for $F_x^{-1}(x)$

Let's take U₁ and U₂ are uniformly distributed RVs on [0,1]

Then Z_0 and Z_1 are two independently distributed Gaussian RVs from N[0,1]

$$Z_0 = \sqrt{-2 \ln U_1} \sin \left(2 \pi U_2\right)$$

$$Z_1 = \sqrt{-2 \ln U_1} \cos(2 \pi U_2)$$



Joint probability distribution of functions of random variables

- 1. X_1 and X_2 are continuous RVs with joint PDF $f_{x_1,x_2}(x_1,x_2)$
- 2. $Y_1 = g_1(X_1, X_2)$, $Y_2 = g_2(X_1, X_2)$ and there is a *unique* solution $x_1 = h_1(y_1, y_2)$, $x_2 = h_2(y_1, y_2)$
- 3. Also g_1 and g_2 have continuous PDFs at all points x_1, x_2 i.e.

$$J(X_{1}, X_{2}) = \begin{vmatrix} \frac{\partial g_{1}}{\partial x_{1}} \frac{\partial g_{1}}{\partial x_{2}} \\ \frac{\partial g_{2}}{\partial x_{1}} \frac{\partial g_{2}}{\partial x_{2}} \end{vmatrix} \neq 0$$

then

$$f_{Y_1,Y_2}(y_1,y_2)=f_{X_1,X_2}(x_1,x_2)|J(x_1,x_2)|^{-1}$$



Joint probability distribution of functions of random variables

RVs:
$$X_1, X_2 \rightarrow Y_1, Y_2 \qquad Y_1 = g_1(X_1, X_2)$$

assumptions:

1) $y_1 = g_1(x_1, x_2)$ unique solution

 $y_2 = g_2(x_1, x_2) \qquad x_1 = h_1(y_1, y_1)$
 $x_2 = h_2(y_1, y_2)$

2) g_1, g_2 have continuous partial derivatives for all x_1, x_2

and

$$\int_{X_1 X_2} \begin{cases} g_1 \\ g_2 \end{cases} \qquad g_2 \end{cases}$$
then
$$\int_{X_1 X_2} (y_1, y_2) = \int_{X_1 X_2} (x_1, x_2) \left| \int_{X_1 X_2} (x_1, x_2) \right| \int_{X_1 X_2} (x_1, x_2) \left| \int_{X_1 X_2} (x_1, x_2) \right| \int_{X_1 X_2} (x_1, x_2) \left| \int_{X_1 X_2} (x_1, x_2) \right| \int_{X_1 X_2} (x_1, x_2) \left| \int_{X_1 X_2} (x_1, x_2) \right| \int_{X_1 X_2} (x_1, x_2) \left| \int_{X_1 X_2} (x_1, x_2) \right| \int_{X_1 X_2} (x_1, x_2) \left| \int_{X_1 X_2} (x_1, x_2) \right| \int_{X_1 X_2} (x_1, x_2) \left| \int_{X_1 X_2} (x_1, x_2) \right| \int_{X_1 X_2} (x_1, x_2) \left| \int_{X_1 X_2} (x_1, x_2) \right| \int_{X_1 X_2} (x_1, x_2) \left| \int_{X_1 X_2} (x_1, x_2) \right| \int_{X_1 X_2} (x_1, x_2) \left| \int_{X_1 X_2} (x_1, x_2) \right| \int_{X_1 X_2} (x_1, x_2) \left| \int_{X_1 X_2} (x_1, x_2) \right| \int_{X_1 X_2} (x_1, x_2) \left| \int_{X_1 X_2} (x_1, x_2) \right| \int_{X_1 X_2} (x_1, x_2) \left| \int_{X_1 X_2} (x_1, x_2) \right| \int_{X_1 X_2} (x_1, x_2) \left| \int_{X_1 X_2} (x_1, x_2) \right| \int_{X_1 X_2} (x_1, x_2) \left| \int_{X_1 X_2} (x_1, x_2) \right| \int_{X_1 X_2} (x_1, x_2) \left| \int_{X_1 X_2} (x_1, x_2) \left| \int_{X_1 X_2} (x_1, x_2) \right| \int_{X_1 X_2} (x_1, x_2) \left| \int_{X_1 X_2$$



Box-Muller transform derivation

Box-Muller transforming
$$f(x,y) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2\sqrt{2\pi}}} e$$