

## Random Variate Generation

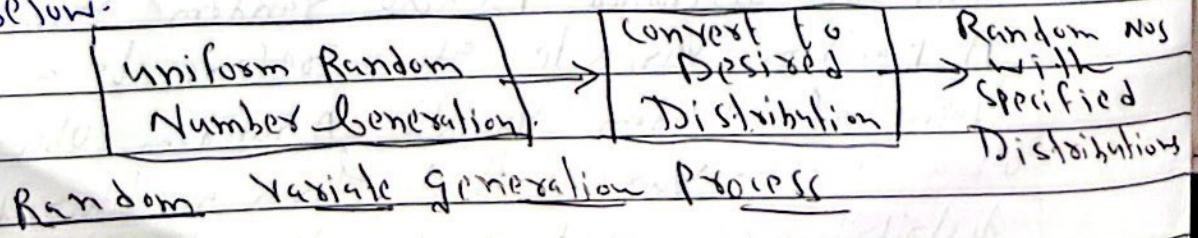
- In modeling and simulation, random numbers from a variety of probability distribution functions are generated to simulate the behavior of random events occurring in the future.
- RVE is used to simulate the uncertainty in the behavior of an entity in the system.
- If the form of randomness of the entity is known the entity is said to follow a particular probability distribution, else randomness is simulated by empirical distribution.
- In efficient generation of these nos can be a significant bottleneck for simulation applications generating these random numbers in precise can askew results.
- Once it has been established that a good uniform  $(0,1)$  random number generator is available, then the other statistics distributions may be generated from sum of uniform  $(0,1)$  Pseudo-random numbers.
- A Random Variable is a variable generated from uniformly distributed Pseudo random numbers.
- A Random Variable also represents a Probability value of Random Variable. A random observations of a Random Variable that form a desired probability distribution are called random variats. and one algorithms

that generates random variants for a particular probability distribution is called Random Variate Generator.

→ For example, a random variate generator for normal distribution generates random variants that satisfy normal probability distribution.

→ Random variable generators are of two.  
Types - univariate and multi variate  
A univariate RVE involves the generation of single variable at a time. Multi variate involves generation of vector of variables at a time, which do not demonstrate mutual independence.

→ Statistical and simulation applications require the inherent random phenomena to be characterized before running the model. A random phenomenon is characterized by collecting observations fitting an appropriate probability distribution to the observations and estimation of the parameters of fitted probability distributions. Once the random phenomenon has been characterized, the model calls the appropriate random variate generator with the estimated values of parameters. The generated random variates are then used to run the model. The random variate generation process is given in fig below.



→ There are various techniques available.

for random variate generation for common probability distribution. Some probability distribution have alternative algorithms also.

→ Some widely used techniques for generating random variables are

1) Inverse Transformation.

2) Convolution.

3) Acceptance - Rejection.

### Inverse Transformation Method

→ Let  $X$  be a continuously distributed random variable. Then its probability density function is given by

$$f(x) = \int_{-\infty}^x f(t) dt.$$

→ The distribution function can be obtained from density function which is

$$F(x) = \int_{-\infty}^x f(t) dt.$$

→ The distribution function being monotonically increasing and continuous the eqn  $F(x) = R$  (for any  $0 < R < 1$ ) can be solved to give a unique  $x$  or written alternatively,

$x = F^{-1}(R)$ . This essentially is the inverse transformation method for generating random variates.

→ It can be used to generate random variate from exponential, uniform, Weibull, triangular and empirical 'discrete' distributions.

→ The Probability integral transformation theorem states that if  $R_i$  ( $i = 1, 2, 3, \dots$ ) are independent, uniformly distributed random numbers over the period  $0 \leq 1$  and  $F^{-1}(x)$  is the inverse of cumulative distribution function for random variable  $X$ , then the random variables defined by  $X_i = F^{-1}(R_i)$  are a random sample of variable  $X$ .

→ In other words we can say that to produce random nos with a given distribution the inverse cumulative distribution function must be evaluated with a sequence of uniformly distributed nos. in the range  $0 \leq 1$ .

→ This technique is most useful when the CDF  $F(x)$  has simple form so that its inverse can be easily computed.

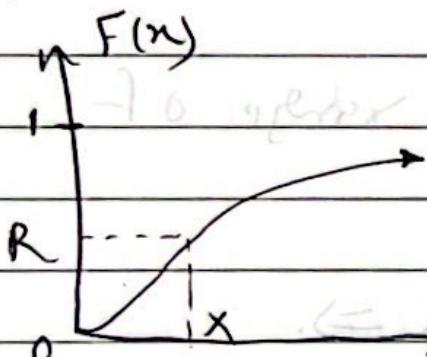
→ The generalized algorithm for inverse xform technique is given below and can be made specialized as per the distribution.

### Algorithm:-

- 1) Let one CDF of desired random variable  $X$ .
- 2) Generate  $R \sim U(0,1)$  and set  $F(X) = R$  on the range of  $X$ .
- 3) calculate  $F^{-1}$  by solving the equation  $F(X) = R$  in terms of  $R$  which returns  $X = F^{-1}(R)$ .
- 4) Generate uniform random nos  $R_1, R_2, \dots$  from  $(0,1)$  and use  $X_i = F^{-1}(R_i)$ , to generate variants.

### Graphical Method :-

- 1) Plot the CDF,  $F(x)$ .
- 2) For generating a random variable  $X$  with CDF,  $F(x)$ , first generate a random number  $R$  between 0 and 1.
- 3) Draw a horizontal line through  $R$  on the graph of CDF.
- 4) A vertical line is dropped from Point where the horizontal line bisects the CDF on the  $x$ -axis to get the random variable  $X$ .



Graphical view of inverse transform Method

### \* Inverse Transformation Method for Continuous Distribution

#### 1) Exponential

Given the CDF of desired R.V  $X$  -

$$F(x) = 1 - e^{-\lambda x}, x \geq 0$$

2) Set  $F(x) = R$  on the range of  $x$   
 $x \Rightarrow 1 - e^{-\lambda x} = R$ .

3) Solve one eqn  $F(x) = R$ .

$$1 - e^{-\lambda x} = R$$

$$e^{-\lambda x} = 1 - R$$

$$-\lambda x = \ln(1-R)$$

$$x = -\frac{1}{\lambda} \ln(1-R)$$

4) Generate uniform random nos  $R_1, R_2, \dots$

from  $(0,1)$  and calculate desired random variable.

↳

$$X_i = -\frac{1}{\lambda} \ln(1-R_i)$$

2) Uniform Distribution

SOP) Let. One CDF of desired  $R \sim U(0,1)$

$$F(x) = 0 \quad ; \quad x < a$$

$$F(x) = \frac{x-a}{b-a} \quad ; \quad a \leq x \leq b$$

$$F(x) = 1 \quad ; \quad x > b$$

2) Let.  $F(x) = R$  on one range of  $I$ .

$$x \Rightarrow \frac{x-a}{b-a} = R$$

3) Solve one eqn  $F(x) = R \Rightarrow$

$$\frac{x-a}{b-a} = R$$

$$x-a = (b-a)R$$

$$x = a + (b-a)R$$

4) Generate uniform random nos  $R_1, R_2, \dots$  from

$(0,1)$  and calculate desired random variable  $b$

$$X_i = a + (b-a)R_i$$

### 3) Weibull Distribution

Step 1) - Sel. One CDF of desired R.V  $X$  -

$$F(x) = 0, \quad x < 0.$$

$$= 1 - e^{-(\frac{x}{\lambda})^\beta}, \quad x \geq 0.$$

2) Sel.  $F(x) = R$  on one step of  $x$

$$X \Rightarrow 1 - e^{-(x/\lambda)^\beta} = R.$$

3) Solve one eq  $F(x) = R \Rightarrow$

$$1 - e^{-(x/\lambda)^\beta} = R \cdot (1 - e^{-1}) \Rightarrow e^{-(x/\lambda)^\beta} = 1 - R.$$

$$e^{-(x/\lambda)^\beta} = 1 - R \Rightarrow -\ln(1 - R) = \ln(e^{-(x/\lambda)^\beta})$$

$$-\left(\frac{x}{\lambda}\right)^\beta = \ln(1 - R).$$

$$\left(\frac{x}{\lambda}\right)^\beta = -\ln(1 - R).$$

$$x = \lambda \left[ -\ln(1 - R) \right]^{1/\beta}$$

4) Generate uniform random nos  $R, R_1, R_2, \dots$  from  $(0, 1)$  and calculate desired random variate by

$$X_i = \lambda \left[ -\ln(1 - R_i) \right]^{1/\beta}.$$

Example 1: A system has a component whose time to failure is exponentially distributed with failure rate  $1/6$ . Generate two random failure times from this distribution. Use  $R_1 = 0.38$  and  $R_2 = 0.45$

⇒ The exponential random variate is.

$$X_i = -\frac{1}{\lambda} \ln(1-R_i)$$

Given that failure rate,  $\lambda = 1/6$ .

$$\begin{aligned} X_i &= -1/16 \ln(1-R_i) \\ &= -6 \ln(1-R_i). \end{aligned}$$

$$\begin{aligned} \text{Now } X_1 &= -6 \ln(1-R_1) \\ &= -6 \ln(1-0.38) = 2.868 \end{aligned}$$

$$\begin{aligned} \text{and } X_2 &= -6 \ln(1-R_2) \\ &= -6 \ln(1-0.45) = 3.587 \end{aligned}$$

Example 2: The time required for Professor to travel from his house to college is uniformly distributed over the interval 30 to 35 minutes. Generate two random travel times from this distribution. Use  $R_1 = 0.5023$  and  $R_2 = 0.2916$ .

⇒ The uniform random variable is

$$X_i = a + (b-a)R_i$$

Given that  $a = 30$  and  $b = 35$

$$\begin{aligned} X_i &= 30 + (35-30)R_i \\ &= 30 + 5R_i \end{aligned}$$

$$\therefore X_1 = 30 + 5R_1 = 30 + 5(0.5023) = 32.515$$

$$\text{and } X_2 = 30 + 5R_2 = 30 + 5(0.2916) = 31.458.$$

**Example:-** The lifetime of a computer chip measure in hours (in Weibull) distributed with parameters  $\alpha = 0.2$ ,  $\beta = 0.5$  and  $\gamma = 0$ . Generate two random life time of computer chip from this distribution? Use  $R_1 = 0.6173$  and  $R_2 = 0.4829$ .

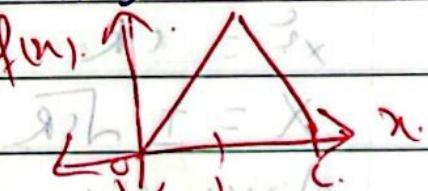
$\Rightarrow$  The Weibull Variate is -  
 $X_i = \alpha [-\ln(1-R_i)]^{1/\beta}$ .

Given that  $\alpha = 0.2$  and  $\beta = 0.5$ .

$$X_1 = 0.2 [-\ln(1-R_1)]^{1/0.5} \quad X > 0$$

$$X_1 = 0.2 [-\ln(1-0.6173)]^2 \\ = 0.1845$$

$$\text{and } X_2 = 0.2 [-\ln(1-0.4829)]^2 \\ = 0.08699$$



### Triangular Distribution

$\rightarrow$  If we have  $X \sim \text{triang}[0, 1, ((c-a)/(b-a))]$ ,

then  $x' = a + (b-a)x \sim \text{triang}(a, b, c)$

$\rightarrow$  Hence we restrict our discussion to  $\text{triang}(0, 1, c)$  random variables so that distribution function is easily inverted to get variate where  $0 < c < 1$ .

$\rightarrow$  The P.d.f. of  $\text{triang}(0, 1, c)$  is given by

$$f(x) = \begin{cases} \frac{2(x-a)}{(1-a)(c-a)} = \frac{2x}{c}; & 0 \leq x \leq 1 \\ \frac{2(c-x)}{(c-1)(c-a)} = \frac{2(1-x)}{c(c-1)}; & 1 \leq x \leq c \end{cases}$$

→ Algorithm

1) Let the CDF of desired R.V.  $X$  using its PDF,

$$F(x) = \begin{cases} \frac{(x-a)^2}{(1-a)(c-a)} = \frac{x^2}{c}; & 0 \leq x \leq 1 \\ 1 - \frac{(c-x)^2}{(c-1)(c-a)} = 1 - \frac{(c-x)^2}{c(c-1)}; & 1 \leq x \leq c \end{cases}$$

2) Set  $F(x) = R$  on the range of  $x \Rightarrow \frac{x^2}{c} = R$  for  $0 \leq x \leq 1$

$$0 \leq x \leq 1 \text{ and } 1 - \frac{(c-x)^2}{c(c-1)} = R \text{ for } 1 \leq x \leq c$$

3) Solve the eqn  $F(x) = R \Rightarrow$

For  $0 \leq x \leq 1$ :

$$x^2 = R \quad (R \in [0, 1]) \Rightarrow x = \sqrt{R}$$

$$x^2 = cR \quad \text{and} \quad \cdot \text{ppd} \cdot 0 \cdot 0 =$$

$$x = \pm \sqrt{cR}$$

choose plus as  $F^{-1}$  should not be  $-18$

For  $1 \leq x \leq c$ :

$$1 - \frac{(c-x)^2}{c(c-1)} = R \quad x(c-1) + R = x \text{ and}$$

$$\frac{(c-x)^2}{c(c-1)} = 1-R \quad \text{from relation (2), (3)}$$

$$(c-x)^2 = c(c-1)(1-R)$$

$$-x = \pm \sqrt{c(c-1)(1-R)}$$

$$x = c \pm \sqrt{c(c-1)(1-R)}, \text{ choose minus as } F(0-R) = 1$$

4) Generate uniform random nos  $R_1, R_2 \dots$  from  $[0, 1]$  and calculate desired random variate b)

$$X_i = \begin{cases} CR_i & \text{if } 0 \leq R_i \leq 1/c \\ C - \sqrt{(c-1)(1-R_i)} & \text{if } \frac{1}{c} \leq R_i \leq 1 \end{cases}$$

$$\text{Else } X_i = C - \sqrt{(c-1)(1-R_i)} \text{ if } \frac{1}{c} \leq R_i \leq 1.$$

Example 2. A digital sensor is used to determine the quality of computer chips. The quality control department rejects chips whose fails which is triangularly distributed with  $a=0$ ,  $b=1$  and  $c=3$ . Generate two random rejected samples from this distribution. Use  $R_1 = 0.9536$  and  $R_2 = 0.2941$ .

$\Rightarrow$  Solution :-

The generating variable is

$$X_i = \begin{cases} CR_i & \text{for } 0 \leq R_i \leq \frac{1}{c} \\ C - \sqrt{(c-1)(1-R_i)} & \text{for } \frac{1}{c} \leq R_i \leq 1 \end{cases}$$

$$\text{and } X_i = 3 - \sqrt{3(3-1)(1-R_i)} \text{ for } \frac{1}{3} \leq R_i \leq 1$$

$$\text{Given that } c = 3. \quad \text{for } 0 \leq R_i \leq \frac{1}{3}$$

$$X_i = \sqrt{3R_i} \quad \text{for } 0 \leq R_i \leq \frac{1}{3}$$

$$\text{and } X_i = 3 - \sqrt{3(3-1)(1-R_i)} \text{ if } \frac{1}{3} \leq R_i \leq 1$$

$$= 3 - \sqrt{6(1-R_i)}$$

$$\text{Now } R_1 = 0.9536 \text{ but } \frac{1}{3} \leq R_1 = 0.9536 \leq 1.$$

$$X_1 = 3 - \sqrt{6(1-R_1)}$$

$$= 3 - \sqrt{6(1-0.9536)} = 2.472$$

$$\text{and } R_2 = 0.2941, \text{ but } 0 \leq R_2 = 0.2941 \leq \frac{1}{3}.$$

$$X_2 = \sqrt{3R_2} = \sqrt{3(0.2941)} = 0.939$$

## \* Empirical Continuous Distributions \*

- 1) It is used when no known theoretical distributions can be found to be a good ~~model~~ model for the input data.
- 2) We resample the original individual observation itself when input process is known to take on a finite no values.
- 3) If the data are drawn from continuous distribution then interpolate between the observed data points to fill in the gaps.
- 4) In case of original data as well as grouped data we used table - look up method for generating random variable from empirical continuous distribution.
- 5) A step distribution table is generated showing the interval and its corresponding Probability, Cumulative Probability and Slope.
- 6) In case of continuous data, since all values between tabulated values are possible, such an interpolation b/w tabulated values is required.
- 7) If generated random no falls in an interval b/w two tabulated observations the desired random variable is taken to be the top value of lower tabulated observation plus an increment that divides the top interval in same proportion that one input divides the input interval.
- 8) This is consistent with the assumption that the cumulative distib is approximated by straight line segments b/w the tabulated points.
- 9) The slopes of these line segments are required to carry out interpolation process numerically these slopes can be calculated and stored in table for generation of random nos in future.
- 10) Since we are using inverse of distib function the slope being calculated is the slope of  $y = F(x)$ .

Question No.	1	2	3	4	5	6	7	8	9	10	11	12	Total
Marks Obtained	-	X	+	i									

11) Formally, in table look-up method, the input random number,  $R$  is compared with cumulative frequency. If it is equal to one of the values of cumulative freq then, the corresponding opp. value is taken.

12) The algorithm for computation of empirical continuous random variate from original and group data is given below.

Algorithm (original data) :-

- 1) Sort the data points in increasing order.
- 2) Generate a freq distribution table and assign a probability to each interval as  $1/n$ , where  $n$  is the no. of observations.

i	Interval $(x_{i-1} < x_i \leq x_i)$	Probability $1/n$	Cumulative Probability $i/n$	Slope $a_i$
1				
2				
n				

3) Draw observed empirical CDF,  $\hat{F}(x)$  and follow the graphical method.

4) Compute the slope ' $a_i$ ' of  $i$ th line segment.

$$a_i = \frac{x_i - x_{i-1}}{\frac{i}{n} - \frac{(i-1)}{n}} = \frac{x_i - x_{i-1}}{\frac{1}{n}} = n(x_i - x_{i-1})$$

5) Let me CDF of desired R.V.  $x$  -

$$F(x) = \begin{cases} 0 & \text{if } x < x_{(1)} \\ \frac{i-1}{n} + \frac{x - x_{(i-1)}}{n(x_{(i)} - x_{(i-1)})} & x_{(i-1)} \leq x \leq x_{(i)} \\ 1 & \text{if } x_n \leq x \end{cases}$$

6) Set  $F(x) = R$  on the range of  $x =$   
 $\frac{i-1}{n} + \frac{x - x_{(i-1)}}{n(x_{(i)} - x_{(i-1)})} = R$

7) Compute the inverse of empirical CDF by  
 Solving the eq  $\hat{F}(x) = R \Rightarrow$

$$\frac{i-1}{n} + \frac{x - x_{(i-1)}}{n(x_{(i)} - x_{(i-1)})} = R$$

$$\frac{x - x_{(i-1)}}{n(x_{(i)} - x_{(i-1)})} = R - \frac{i-1}{n}$$

$$x - x_{(i-1)} = n(x_{(i)} - x_{(i-1)})(R - \frac{i-1}{n})$$

$$x = x_{(i-1)} + n(x_{(i)} - x_{(i-1)})(R - \frac{i-1}{n})$$

$$x = x_{(i-1)} + a_i(R - \frac{i-1}{n})$$

8) Generate uniform random numbers  $R, R_2, \dots$   
 and compute desired random variable  $\{x\}$

$$x_i = \hat{F}^{-1}(R_i) = x_{(i-1)} + a_i(R_i - \frac{i-1}{n})$$

## Example 1 - Five observations of Fire Brigade.

Station response times to incoming alarms have been collected and are used in a simulation to investigate alternate staffing and fire brigade team scheduling policies. The response times are  $-1.60, 0.55, 1.12, 2.20, 1.94$ . Set up a table for generating response time by using lookup method and generate two value of response times using uniform random nos  $0.5426$  and  $0.1247$ .

→ Solution 1) Sort the data points in increasing order and let  $x_{(1)}, x_{(2)}, \dots, x_{(n)}$   
 $\therefore 0.55, 1.12, 1.60, 1.94, 2.20$ .

Since smallest value is  $0.55$ , so we define  
 here  $x_{(0)} = 0$ .

2) Given  $n=5$  observations.  
 Given that  $n=5$  observations.

$\therefore 1/5$  is one probability of each interval.

i	interval	Probability	Cumulative Probability	Slope
	$(x_{(i-1)}, x_i]$	$1/n$	$1/n$	$a_i = n(x_i) - x_{(i-1)}$
1	$0.0 < x \leq 0.55$	0.2	0.2	2.75
2	$0.55 < x \leq 1.12$	0.2	0.4	2.85
3	$1.12 < x \leq 1.60$	0.2	0.6	2.4
4	$1.60 < x \leq 1.94$	0.2	0.8	1.7
5	$1.94 < x \leq 2.20$	0.2	1.0	1.3

→ Summary of response time data complete the  $a_i$  steps.

$$a_1 = 5(x_1 - x_0) = 5(0.55 - 0) = 2.75$$

$$a_2 = 5(x_2 - x_1) = 5(1.12 - 0.55) = 2.85$$

$$a_3 = 5(x_3 - x_2) = 5(1.60 - 1.12) = 2.4$$

$$a_4 = 5(x_4 - x_3) = 5(1.94 - 1.60) = 1.7$$

$$a_5 = 5(x_5 - x_4) = 5(2.20 - 1.94) = 1.3$$

The empirical random variable of original data.  
(individual observation) is

$$X_j = F^{-1}(R_j) = x_{i-1} + a_i(R_j - \frac{i-1}{n})$$

Given that  $R_1 = 0.5426$  and  $R_2 = 0.1524$ .

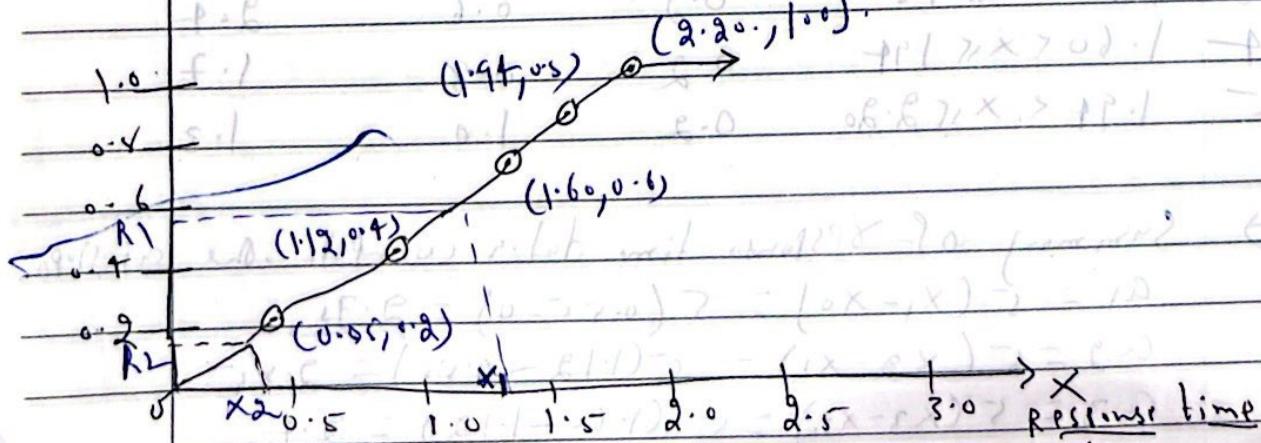
Now,  $R_1 = 0.5426$  which is lying between  $\frac{2}{5} = 0.4$  and  $\frac{3}{5} = 0.6$  i.e. third interval, hence.

$$\begin{aligned} \Rightarrow X_1 &= x_{3-1} + a_3(R_1 - \frac{3-1}{5}) \\ &= 1.12 + 2.4(0.5426 - \frac{2}{5}) \\ &= 1.46224 \end{aligned}$$

Similarly,  $R_2 = 0.1524$  which is lying between  $0$  and  $\frac{1}{5} = 0.2$  i.e. first interval. Hence  $i=1$ .

$$\begin{aligned} \Rightarrow X_2 &= x_{1-1} + a_1(R_2 - \frac{1-1}{5}) \\ &= 0 + 2.75(0.1524 - 0) \\ &= 0.419 \end{aligned}$$

Graphically, the process of generating the random variable is shown.



ubject : [Probability &amp; Statistics] X : [CR-F]

Question No.	1	2	3	4	5	6	7	8	9	10	11	12	Total
Marks Obtained	10	10	10	10	20	10	10	10	10	10	10	10	100

## Discrete Distributions

All discrete distributions can be generated via the inverse xform technique either numerically through a table look-up procedure or, in some cases, algebraically the final genot scheme being in terms of a formula.

### A discrete uniform Distribution

Consider discrete uniform distribution on  $\{1, 2, \dots, k\}$  with pmf and cdf given by:

$$P(x) = 1/k, \quad x=1, 2, \dots, k.$$

$$F(x) = \begin{cases} 0, & x < 1 \\ 1/k, & 1 \leq x < 2 \\ 2/k, & 2 \leq x < 3 \\ \vdots & \vdots \\ \frac{k-1}{k}, & k-1 \leq x < k \\ 1, & k \leq x. \end{cases}$$

Let  $x_i = i$  and  $\gamma_i = P(1) + \dots + P(n_i) = F(n_i) = i/k$  for  $i=1, 2, \dots, k$ , if generated random number  $R$  satisfies.

$$\gamma_{i-1} = \frac{i-1}{k} < R \leq \gamma_i = \frac{i}{k}$$

then  $x$  is generated by setting  $x = i$ . Now above inequality can be solved for  $i$ ,

$$s-1 < R_k \leq s \\ R_k \leq s < R_{k+1}$$

Let  $\lceil y \rceil$  denote smallest integer  $\geq y$ ,  
for e.g.  $\lceil 7.82 \rceil = 8$ ,  $\lceil 1.13 \rceil = 6$  and  $\lceil -1.32 \rceil = -1$

for  $y \geq 0$ ,  $\lceil y \rceil$  is a function that  
rounds up. This notation and inequality  
yields a formula for generating "x",

$$x = \lceil R_k \rceil$$

→ For p.g. consider the generating of a  
random variable  $x$  that is uniformly distributed  
on  $\{1, 2, \dots, 10\}$ . The variable  $x$  might  
represent the no. of pallets to be loaded  
onto a truck. Using Table A-1 as a  
source of random no. R and using  
above eqn with  $k=10$  yields

$$R_1 = 0.747 \quad x_1 = \lceil 7.47 \rceil = 8$$

$$R_2 = 0.03 \quad x_2 = \lceil 0.3 \rceil = 1$$

$$R_3 = 0.23 \quad x_3 = \lceil 2.3 \rceil = 3$$

$$R_4 = 0.97 \quad x_4 = \lceil 9.7 \rceil = 10.$$

## \* The Geometric Distribution \*

Consider geometric distribution with Pmf.

$$P(x) = p(1-p)^x, \quad x=0, 1, 2, \dots$$

Where  $0 < p < 1$ , its cdf is given by

$$F(x) = \sum_{j=0}^x p(1-p)^j$$

$$= p \{ 1 - (1-p)^{x+1} \}$$

$$= 1 - (1-p)^{x+1}$$

For  $x=0, 1, 2, \dots$  using the inverse x form technique i.e. inequality, that a geometric random variable  $X$  will assume the value.

$$F(x-1) \Rightarrow 1 - (1-p)^x < R \leq 1 - (1-p)^{x+1} = F(x)$$

Where  $R$  is a generated random number

assumed  $0 < R < 1$ , solving the above eqn.

$$(1-p)^{x+1} \leq 1 - R < (1-p)^x$$

$$(x+1) \ln(1-p) \leq \ln(1-R) < x \ln(1-p).$$

B/c.  $1-p < 1$  implies then  $\ln(1-p) < 0$   
So that,

$$\frac{\ln(1-R)}{\ln(1-p)} - 1 \leq x \leq \frac{\ln(1-R)}{\ln(1-p)}$$

Thus  $X=x$  for that integer value of  $x$  satisfying inequality above, in brief applying round up function  $[.]$ , we have.

$$X = \left[ -\frac{\ln(1-R)}{\ln(1-P)} - 1 \right] \text{ and } *$$

Since \$P\$ is a fixed parameter

Since \$P\$ is a fixed parameter, let

$$\beta = -1/\ln(1-P) \text{, then } \beta > 0 \text{ and}$$

so  $\beta \ln(1-R)$  is an exponentially distributed random variable.

$$X = \left[ -\beta \ln(1-R) - 1 \right]$$

$\Rightarrow -\beta \ln(1-R)$  is an exponentially distributed random variable (with mean  $\beta$ ), so one way of generating geometric variate with parameter  $P$  is to generate an exponential variate with parameter  $\beta^{-1} = -\ln(1-P)$ , subtract one and round up.

$\Rightarrow$  Occasionally, there is need for a geometric variate  $X$  that can assume values  $\{q, q+1, q+2, \dots\}$  with pmf  $P(x) = P(1-P)^{x-q}$  ( $x = q, q+1, \dots$ )

Such variates can be generated from  $\beta$ .

$$X = q + \left[ \frac{-\ln(1-R)}{\ln(1-P)} - 1 \right]$$

One of most common cases is  $q=1$ .

$$(1-P)^{x-1} > (1-P)^q \Rightarrow (1-P)^{x-1} > (1-P)^1$$

$$0 < (1-P)^{x-1} < 1 \Rightarrow 0 < (1-P)^{x-1} < 1$$

Question No.	1	2	3	4	5	6	7	8	9	10	11	12	Total
Marks Obtained													

Example The CDF of a discrete random variable  $X$  is given by -

$$F(x) = \frac{n(n+1)(2n+1)}{n(n+1)(2n+1)}, n = 1, 2, \dots, n.$$

Generate two values of  $x$  using random no. 0.38 and 0.75 and when  $n=5$ .

$\Rightarrow$  For a given random number,  $X$  will take one value in  $R_x = \{1, 2, 3, 4, 5\}$  provided that -

$$F(x_{i-1}) < R < F(x_i), i.e. 0 = 19 \text{ works}$$

$$F(x) = \frac{n(n+1)(2n+1)}{n(n+1)(2n+1)}$$

Put  $n=5$  we have -

$$F(x) = \frac{n(n+1)(2n+1)}{330}$$

$\rightarrow$  we know that

$$F(x_{i-1}) < R < F(x_i).$$

$$= \frac{(n-1)n(2n-1)}{330} < R < \frac{n(n+1)(2n+1)}{330}$$

As  $n=1, 2, \dots, 5$

$$F(1) = (1)(2)(3)/330 = 0.019$$

$$F(2) = (2)(3)(5)/330 = 0.091.$$

$$F(3) = (3)(4)(7)/330 = 0.255.$$

$$F(4) = \frac{4(5)(9)}{330} = 0.546.$$

$$F(5) = \frac{5(6)(11)}{330} = 1.$$

Now  $x$  can be generated by table look-up method using table.

$x_i$	$F(x_i)$
1	0.018
2	(0.09) $\approx 0.09$
3	(0.25) $\approx 0.25$

+ finds  $x + 0.546$  v next decimal  
 $5 - 0.546$  ended b/w  $0.75$  &  $0.9$ .

The discrete random variable is  $x$ .

$x = i$  if  $F(x_{i-1}) < r \leq F(x_i)$ .

Now  $R_1 = 0.38$  and  $R_2 = 0.75$ .

Now  $[F(x_3) = 0.25] \leq [R_1 = 0.38] \leq [F(x_4) = 0.546]$ .

$\Rightarrow i = 4$  and  $x_1 = x_4 = 4$ .

Similarly,  $[F(x_4) = 0.546] \leq [R_2 = 0.75] \leq [F(x_5) = 1]$ .

$\Rightarrow i = 5$  and  $x_2 = x_5 = 5$ .

Example In a company, group of particular items is accepted by performing certain quality control tests which will be approximated by geometric distribution on the range  $\{x \geq 1\}$  with mean of 3 items, generate two values of  $x$  using random nos.  $0.238$  and  $0.502$

$\Rightarrow$  Given that geometric distibution is defined on the range  $\{x \geq 1\}$ .

$\therefore$  Pmf is  $P(x) = p(1-p)^{x-1}$  for  $x=1, 2, \dots$  with mean  $1/p$ .

$\rightarrow$  The geometric random variable is.

$$X_i = q + \left\lceil \frac{\ln(1-R_i)}{\ln(1-p)} - 1 \right\rceil$$

Given that mean =  $3 = 1/p$ .

$$\Rightarrow p = 1/3 \text{ and } q = 1.$$

$$\text{and } R_1 = 0.238 \text{ and } R_2 = 0.502.$$

$$X_1 = 1 + \left\lceil \frac{\ln(1-R_1)}{\ln(1-\frac{1}{3})} - 1 \right\rceil$$

$$= 1 + \left\lceil -2.466 \ln(1-0.238) - 1 \right\rceil$$

$$= 1 + 0 = 1.$$

$$X_2 = 1 + \left\lceil -2.466 \ln(1-0.502) - 1 \right\rceil$$

$$= 1 + 1 = \underline{2}$$

## Convolution Method

- The probability distribution of a sum of two or more independent random variables is convolution of the distributions of Variables.
- This method is used when random variable  $X$  can be expressed as a sum of other random variables i.e.  $(X = X_1 + X_2 + \dots + X_n)$  that are independent and identically distributed and easier to generate than  $X$ .
- The assumption here is that  $X_1 + X_2 + \dots + X_n$  has same distribution as  $X$ .
- Hence we say that this method adds two or more random variables to get a new random variable with desired distribution.
- This method is used to generate exponential and binomial variables.
- As  $X = X_1 + X_2 + \dots + X_n$  and let  $X$  have distribution function  $F$  and  $X_i$  has distribution function  $f_i$ .
  - 1) Generate  $n$  number of  $X_i$ 's which are independent and identically distributed each with distribution function  $f_i$ .
  - 2) Return  $X = X_1 + X_2 + \dots + X_n$ .
- This method is unambiguous provided that generation of each  $X_i$  is easy. However it is not the most efficient algorithm.
- Convolution method can be considered as a special case of the more general method of transforming

Some intermediate random variables info.  
One desired variate.

→ \* Erlang Distribution \*

→ we know that an Erlang Variable  $X$  with parameters  $k$  and  $\theta$  is sum of  $k$  independent exponential random variables  $x_i (i=1, 2, \dots, k)$ , each with mean  $1/k\theta$ .

$$\text{i.e } X = \sum_{i=1}^k x_i$$

→ As each  $x_i$  is exponentially distributed with mean  $1/\lambda$ , so it can be generated by inverse transform technique.

$$x_i = -\frac{1}{\lambda} \ln R_i$$

$$X = \sum_{i=1}^k -\frac{1}{\lambda} \ln R_i$$

$$\rightarrow 1/\lambda = 1/k\theta$$

$$\therefore X = \sum_{i=1}^k -\frac{1}{k\theta} \ln R_i = -\frac{1}{k\theta} \ln \left\{ \prod_{i=1}^k R_i \right\}$$

→ From above eqn we say that  $k$  uniform random nos are required to generate a single Erlang Variate.

Algorithm

- 1) Generate  $x_1, x_2, \dots, x_k$  as independent and identically distributed exponential random variables.
- 2) Compute desired random variable  $b$   
$$X = -\frac{1}{k\theta} \ln \left\{ \prod_{i=1}^k R_i \right\}$$

3) if  $k$  is large then Erlang variates are generated efficiently using acceptance-rejection technique for Gamma distribution.

$\Rightarrow$  Example The daily consumption of bread in a hostel is approximated by Erlang distribution with parameters  $k=3$  and  $\theta=10$ . Generate two values of consumption from this distribution. Use  $R_1 = 0.381, R_2 = 0.142, R_3 = 0.659$ .

$\Rightarrow$  The Erlang random variate is.

$$X = -\frac{1}{k\theta} \ln \left\{ \prod_{i=1}^k R_i \right\}$$

$$k=3, \theta=10$$

$$X = -\frac{1}{3(10)} \ln [(0.381)(0.142)(0.659)]$$

$$= 0.11$$

## Acceptance-Rejection Technique

→ Suppose that analyst needed to devise a method for generating random variates,  $X$ , uniformly distributed between  $1/4$  and  $1$ . One way to proceed would be to follow these steps.

Step 1: Generate random number  $R$ .

Step 2(a):- If  $R \geq 1/4$  accept  $x = R$  go to step 3.

Step 2(b):- If  $R < 1/4$  reject  $R$  return to step 1.

Step 3:- If another uniform random variate on  $[1/4, 1]$  is needed repeat the procedure beginning at Step 1, if not, stop.

→ Each time Step 1 is executed a new random number  $R$  must be generated. Step 2(a) is an "acceptance" and Step 2(b) is "rejection".

→ To summarize the technique, random variates,  $(R)$  with some distribution (here uniform on  $[0, 1]$ ) are generated until some condition ( $R \geq 1/4$ ) is satisfied. When the condition is finally satisfied, the desired random variate,  $x$ . (here uniform on  $[1/4, 1]$ ) can be computed ( $x = R$ ). This procedure can be shown to be correct by recognizing that accepted values of  $R$  are conditioned values;  $R$  itself does not have the desired distribution but  $R$  conditioned on the event  $\{R \geq 1/4\}$  does have the desired distribution.

To show this, take  $1/4 \leq a < b \leq 1$ , then

$$P(a < R \leq b | 1/4 \leq R \leq 1) = \frac{P(a < R \leq b)}{P(1/4 \leq R \leq 1)} = \frac{b-a}{3/4}.$$

which is correct. Probability for uniform distribution on  $[1/4, 1]$ , the above eqn says that. Probability dist'n of  $R$ , given that  $R$  is between  $1/4$  and  $1$  (all other values of  $R$  thrown out) is the desired dist'n: if  $1/4 \leq R \leq 1$  then  $x = R$ .

- The efficiency of acceptance-rejection technique depends heavily on being able to minimize the no. of rejections.
- In this example, the probability of rejection is  $P(R < 1/4) = 1/4$ , so that the no. of rejections is a geometrically distributed random variable with probability of "success" being  $p = 3/4$  and mean no. of rejections  $(1/p - 1) = 4/3 - 1 = 1/3$ .
- The mean no. of random numbers  $R$  required to generate one variate  $X$  is one more than the number of rejections, hence it is  $4/3 = 1.33$ .
- In other words, to generate 1000 values of  $X$  would require approximately 1333 random nos.  $R$ .
- In the present situation, an alternate procedure exists for generating a uniform variate on  $[1/4, 1]$  (uniform distribution), i.e., in inverse transformation which operates  $x = a + (b-a)R$  or  $R = \frac{x-1}{4} + (1-\frac{1}{4})$ . The latter is more efficient. An alternate procedure is to generate random nos.  $R$  and use  $x = \frac{1}{4} + (\frac{3}{4})R$ .
- However, for some important distributions, such as normal, gamma and beta, the inverse CDF does not exist in closed form and therefore inverse transform technique is difficult.

→ Acceptance-rejection technique is illustrated below for generation of random variables for Poisson, nonstationary Poisson and gamma distributions.

### \* Poisson Distribution \*

→ A Poisson random variable  $N$ , with mean  $\lambda > 0$  has Pmf

$$P(n) = P(N=n) = \frac{e^{-\lambda} \lambda^n}{n!}, n=0,1,2,\dots$$

→  $N$  can be interpreted as no of arrivals from a Poisson arrival process in one unit of time.

→ For e.g. interarrival times  $A_1, A_2, \dots$  of successive customers are exponentially distributed with rate  $\lambda$  (i.e.  $\lambda$  is the mean no. of arrivals per unit time).

→ There is a relationship between the (discrete) Poisson and continuous exponential distribution.

If and only if

$$A_1 + A_2 + \dots + A_{n-1} \leq t < A_1 + \dots + A_n$$

→ The above eqn says that  $N=n$  says there were exactly  $n$  arrivals during one unit of time, but second relation says that  $n$ th arrival occurred before time  $t$  while  $(n+1)$ th arrival occurred after time  $t$ . Clearly these two statements are equivalent.

→ Proceed now by generating exponential inter arrival times until some arrival say  $n+1$  occurs after time  $t$ , then set  $N=n$ .

→ For efficient generation purposes, above relation is usually simplified by using exp exponential distribution exp.

$$A_i = (-1/\alpha) \ln R_i \text{ to obtain}$$

$$\sum_{i=1}^{n+1} -\frac{1}{\alpha} \ln R_i \leq 1 < \sum_{i=1}^{n+1} -\frac{1}{\alpha} \ln R_i$$

→ Multiplying by  $-\alpha$  which reverses the sign of inequality and use the fact that a sum of logarithms is the logarithm of a product to get:

$$\ln \prod_{i=1}^{n+1} R_i = \sum_{i=1}^{n+1} \ln R_i > -\alpha > \sum_{i=1}^{n+1} \ln R_i = \ln \prod_{i=1}^{n+1} R_i$$

From the relation  $e^{\ln x} = x$  for any no  $x$  to obtain:

$$\prod_{i=1}^{n+1} R_i > e^{-\alpha} > \prod_{i=1}^{n+1} R_i$$

⇒ The procedure for generating a Poisson random variate  $N$  is given by following steps.

Step 1: Set  $n=0$ ,  $P=1$

Step 2: Generate random no  $R_{n+1}$ , replace  $P$  by  $P \cdot R_{n+1}$ .

Step 3: if  $P < e^{-\lambda}$ , then accept  $N=n$  otherwise repeat.

The process continues until  $N$  is obtained.

Step 4: Stop.

→ Notice that upon completion of step 2,  $P$  is equal to one rightmost expression in above yet. The basic idea of rejection technique is again exhibited if  $P > e^{-\lambda}$  in step (3).

If  $n$  is rejected and generating process must proceed through  $n+1$ . (last one more trial).

→ How many random nos will be required, on average to generate one Poisson variable,  $N$ ? if  $n = n$ , then  $n+1$  random nos are required so the avg no is given by

$$E(N+1) = \alpha + 1$$

which is quite large if mean of Poisson distribution is large.

Example Generator thro. Poisson Variables with mean  $\alpha = 0.2$  first compute  $e^{-\alpha} = e^{-0.2} = 0.8187$ . Next get sequence of random nos  $R$  from table A.1 and follow steps

Step 1 Set  $n = 0$ ,  $P = 1$ .

Step 2 -  $R_1 = 0.4357$ ,  $P = 1 - R_1 = 0.4357$ .

Step 3 - Since  $P = 0.4357 < e^{-\alpha} = 0.8187$  accept  $N = 0$ .

Step 1-3. ( $R_1 = 0.4146$  leads to  $N = 1$ )

Step 1 Set  $n = 0$ ,  $P = 1$ .

Step 2  $R_1 = 0.8353$ ,  $P = 1 - R_1 = 0.8353$ .

Step 3 Since  $P > e^{-\alpha}$ , reject  $N = 0$  and go back to 1.

Step 2 with  $n = 1$ .

Step 2  $R_2 = 0.9952$ ,  $P = 1 - R_2, R_2 = 0.9952$ .

Step 3 Since  $P > e^{-\alpha}$ , reject  $N = 1$  and go back to 1.

Step 2 with  $n = 2$ .

Step 2  $R_3 = 0.8004$ ,  $P = R_1 R_2 R_3 = 0.6654$ .

Step 3 Since  $P < e^{-\alpha}$ , accept  $N = 2$ .

Marks Obtained	0	1	2	3	4	5	6	7	8	9	10	11	12	Total
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The calculations required for generation of these three Poisson variables are summarized below.

n	R <sub>n+1</sub>	P	Accept/Reject-	Result-
0	0.4357	0.4357	P < $\bar{e}^{\lambda}$ (accept)	N=0
0	0.4146	0.4146	P < $\bar{e}^{\lambda}$ (accept).	N=0
0	0.4353	0.8353	P > $\bar{e}^{\lambda}$ (reject).	
1	0.9952	0.8313	P > $\bar{e}^{\lambda}$ (reject).	
2	0.8004	0.6654	P < $\bar{e}^{\lambda}$ (accept), N=2.	

If took five random nos R to generate three Poisson variable here ( $N=0$ ,  $N=0$  and  $N=2$ ) but in long run, to generate say 1000 Poisson variable with mean  $\lambda = 0.9$ , it would require approximately 1000( $\lambda+1$ ) or 1900 random nos.