

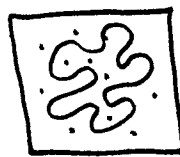
Random Numbers & their Generation[TeX95]  
[Press, Recipes]

Uses: Simulation - randomness in biology  
 large numbers of individuals  
 randomness in physics  
 large numbers of particles  
 quantum mechanics  
 randomness in systems  
 human behavior  
 large numbers of transactions  
 ... etc.

Testing - too many cases to test exhaustively; e.g. chip testing, hypothesis testing

Monte Carlo evaluation

- to estimate area, volume

prob{inside}  $\approx$  area

A good place to start learning about random number generators, read "man random"

on your unix system. May tell you method, hint at possible problems.

Anyone who considers arithmetical methods of producing random digits is, of course, in a state of sin.  
 – John von Neumann (1951)

What did von Neumann mean?

We can distinguish between "random"  
 "pseudorandom"

Pseudorandom numbers have the big advantage of repeatability, for debugging, comparisons, etc.

And they are all-digital, of course.

But they come at a price.

Most popular algorithm is

Linear Congruential Generator (LCG)

$$X_n = a X_{n-1} + c \pmod{M}$$

$U_n = \frac{X_n}{M}$  is  $\approx$  uniformly distributed in  $[0, 1)$

or  $U_n = \frac{X_n}{(M-1)}$  is  $\approx$  uniformly distributed in  $[0, 1]$

LCG's are simple, fast, pretty good most  
of the time.

### choosing good $a, c, M$

Notice that  $X_n$  are in the range  $0 \leq X_n < M$ .

Therefore the sequence  $X_1, X_2, \dots$  must repeat  
by  $X_M$ , and will periodic thereafter.

Conditions are known that ensure this maximum period:

**Theorem [Tez95]** An LCG with parameters  $a, c, M$   
has period length  $M$  if and only if

- (i)  $\gcd(c, M) = 1$ ;
- (ii)  $a \equiv 1 \pmod{p}$  for every prime  $p$  dividing  $M$ ;
- (iii)  $a \equiv 1 \pmod{4}$  if  $M$  is a multiple of 4.

this means we get all integers in  $\{0, \dots, M-1\}$   
in some order before repetition, then periodic.

But there are dangers lurking!

... More later

## Simple Ways to use RNG's

on my SUN workstation, some nonlinear RNG is used (evidently not LCG).

max entry states range is  $0, \dots, 2^{31} - 1 = \text{MAXINT}$   
 period  $\approx 16 * \text{MAXINT}$

Typically, I use:

```
#include <math.h>
```

```
#define MAXINT 2147483647
```

```
#define SEED 122061
```

```
long random();
```

```
double u_random()
```

```
{ double t;
```

```
  t = (double)random() / (double)MAXINT;
```

```
  return;
```

```
}
```

```
void init_random()
```

```
{
```

```
  srandom(SEED);
```

```
}
```

or, ... / (double)(MAXINT+1);  
 for [0,1)

→ Some of this may be system dependent!

→ portability of RNG's is a ~~perennial~~ perennial problem.

- Choosing an integer  $i$  between 1 and  $N$  randomly:

$$i = 1 + (\text{int})(N * u\_random());$$

use  $[0, 1)$  version,  
divide by  $(\text{MAXINT} + 1)$   
in  $u\_random$

$N * u\_random()$  is double in range  $[0, N)$

$(\text{int})$  truncates to  $0 \dots N-1$   
+1 gets to  $1 \dots N$

→ If we use  $[0, 1]$  version of  $u\_random$  — one out of  $2^{32}$  cases will yield  $N+1$

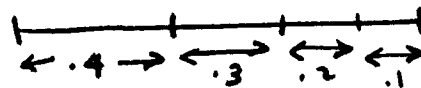
this will happen!

If you use `arrayofsomething[i]` you will dump core!

- Choosing a discrete distribution:

Suppose we want

$p(1) = 0.4$
$p(2) = 0.3$
$p(3) = 0.2$
$p(4) = 0.1$

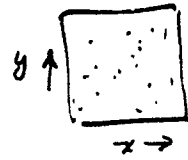


$t = u\_random();$

```
if (t < 0.4) { }
else if (t < 0.7) { }
else if (t < 0.9) { }
else { }
```

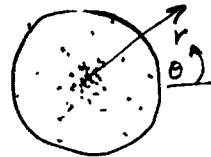
• Pick a random point in 2D:

1. Choose  $x, y$  <sup>with</sup>  $U\text{-random}()$



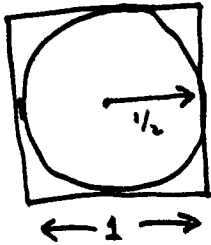
uniform in  
unit square

2. choose  $r$  uniform 0 to 1,  $\theta$  uniform 0 to  $2\pi$



clustered close  
to origin

3. How to pick points uniform in "unit" circle? ( $r = 1/2$ )  
rejection method. points discarded if outside



$$\frac{\text{Area unit circle}}{\text{Area unit square}} = \frac{\pi (1/2)^2}{1} = 78.5\%$$

... 3D?  
etc.

• Shuffle a deck of cards:

to shuffle cards  $C_1, \dots, C_m$ :

for  $j = m$  down to 2

{ choose random integer from 1 to  $j$ , say  $i$   
interchange  $C_i$  and  $C_j$  }

why does this work?



Random number generation is too important  
to be left to chance.  
– Robert R. Coveyou (1969)

1. Can be disastrous if  $\text{MAXINT}$  too small

For example, if  $\text{MAXINT} = 2^{15} - 1 = 32,767$

with  $10^6$  calls, sequence is repeated  $\approx 30$  times!  
awful for Monte Carlo

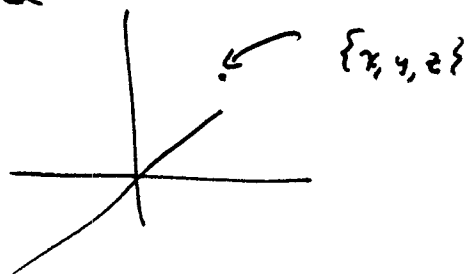
Moral: use at least 4 bytes,  $\text{MAXINT} = 2^{31} - 1$

2. Don't use low-order bits!

to get random bit, don't use even/odd test

3. Points tend to be serially correlated.

if  $R$  successive random numbers are used to plot  
points in  $R$ -space

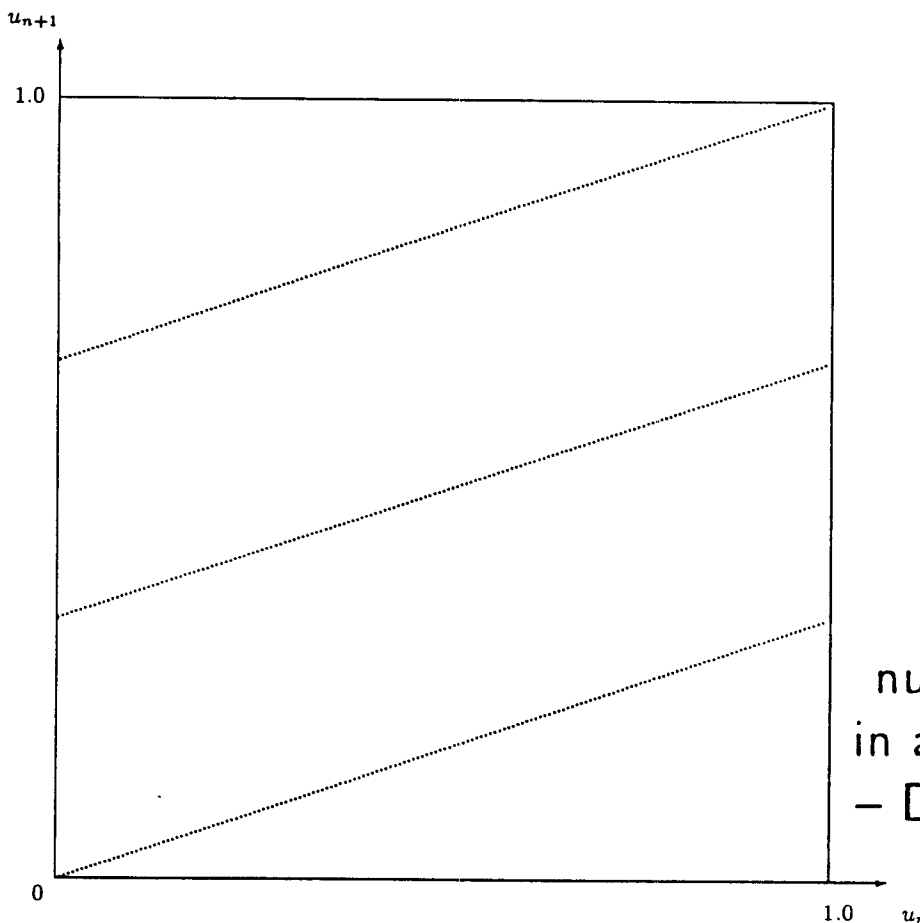


Random numbers fall mainly in the planes.  
 – George Marsaglia (1968)

points of LCG's tend to lie on at most  
 $m^{1/k}$   $(k-1)$ -D planes.

if  $m = 2^{15}$ ,  $m^{1/3} = 32$  UGH!  
 even  $m = 2^{32}$ ,  $m^{1/3} = 1600$  UGH!

old RANDU on IBM mainframes in 60's was badly botched,  
 points on only 11 planes!



small  
 example  
 from  
 Tezuda [Tez95]

...

Every random  
 number generator will fail  
 in at least one application.  
 – Donald E. Knuth (1969)

Figure 3.1 A set of two-dimensional points,  $(u_n, u_{n+1})$ ,  $n = 1, \dots, 508$ , produced by  $u_n = X_n/509$ , where the LCG is given as  $X_n = 170X_{n-1} \pmod{509}$ .



How about other distributions?

12.9

... exponential?

... Gaussian?

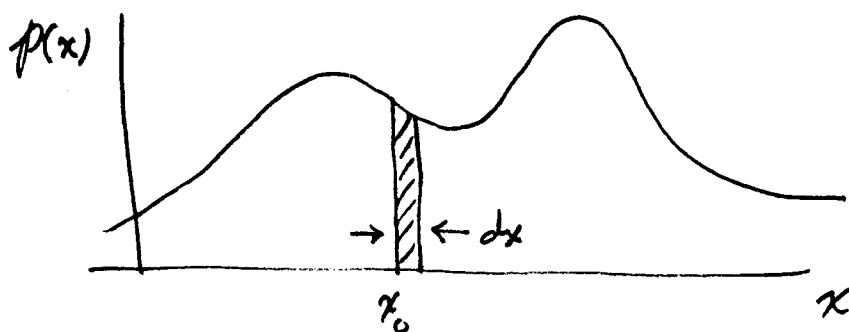
We need some probability theory - quick review

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We consider for now continuous random variables

that is, real values, like  $u\_random()$  

$p(x)$  = probability density fn (pdf)



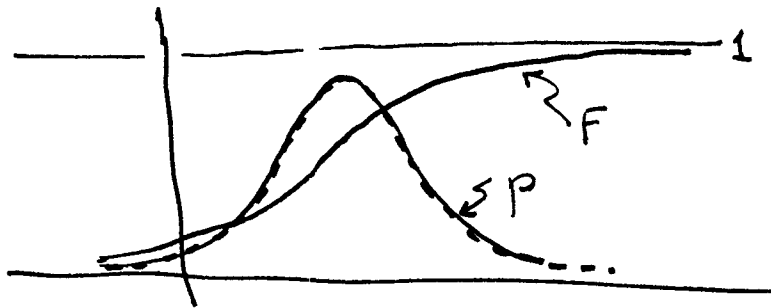
$$\text{prob}(x_0 \leq x \leq x_0 + dx) = p(x_0) \cdot dx$$

$$\text{always } \begin{cases} p(x) \geq 0 \\ \int_{-\infty}^{\infty} p(x) dx = 1 \end{cases}$$

# Cumulative Distribution Fun. (cdf)

1.2.10

$$F(y) = \text{prob. } \{x \leq y\} = \int_{-\infty}^y p(x) dx$$

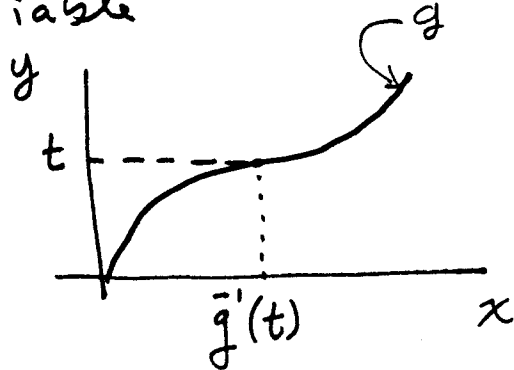


$$p(x) = \frac{dF(x)}{dx}$$

Suppose we generate random  $x$  and then compute

$$y = g(x)$$

where  $g(\cdot)$  is monotonic (increasing, say) and differentiable



So  $g^{-1}(\cdot)$  is well defined, unique.

$$\text{prob}\{y \leq t\} = \text{prob}\{x \leq g^{-1}(t)\}$$

Usually, we start with  $x = u \text{ random}()$ ,  
 so

$$\text{prob} \{ x \leq \bar{g}'(t) \} = \bar{g}'(t)$$

&  $\therefore$

$$\text{prob} \{ y \leq t \} = \bar{g}'(t)$$

Cumulative Distr. fun. for  $t$

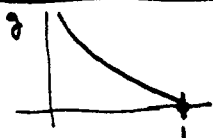
$$\therefore p(t) = \frac{d}{dt} \bar{g}'(t)$$

to take care of case when  $g(\cdot)$  is mono. decreasing

$$p(t) = \left| \frac{d \bar{g}'(t)}{dt} \right|$$

Example 1

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

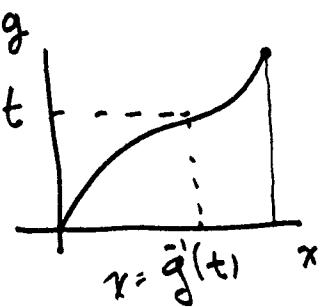


$$x = e^{-\lambda g(x)} = e^{-\lambda t} = \bar{g}'(t)$$

$$p(t) = \left| \frac{d \bar{g}'(t)}{dt} \right| = \left| -\lambda e^{-\lambda t} \right|$$

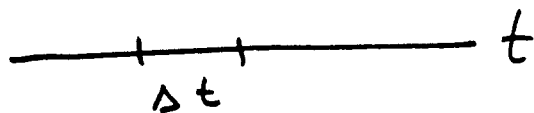
$$p(t) = \lambda e^{-\lambda t}$$

"exponential"  
distribution



this is an important distribution.

## Physical Interpretation



Suppose an event occurs in a small time interval with  $\text{prob}\{\text{event}\} = \lambda \Delta t$

$\lambda = \text{expected \# events / second}$

$$\text{prob}\left\{\begin{array}{l} \text{exactly } k \text{ events} \\ \text{in time } t \end{array}\right\} = \frac{(\lambda t)^k e^{-\lambda t}}{k!}$$

→ Poisson distribution

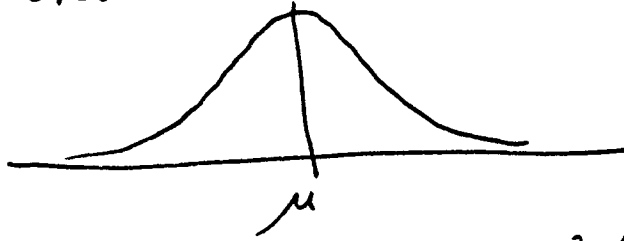
$$\text{prob}\left\{\begin{array}{l} 0 \text{ events} \\ \text{in time } t \end{array}\right\} = e^{-\lambda t}$$

$$\text{prob. density fctn. of time } t \text{ to first event} = \lambda e^{-\lambda t}$$

(expected value =  $1/\lambda$ )

Example 2 Another very important distribution

Gaussian = Normal = "Bell-shaped"



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

- arises everywhere  $\rightarrow$  sums of small errors that are independent tend to Gaussian
  - used to model experimental errors
- 

Generation Method 1

Pick  $N$  independent samples using  $U_{\text{random}}()$ ; average

$\rightarrow$  quick & dirty, tails no good.

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Transformation method above doesn't work in closed form - in 1-D. (one at a time)

Generation Method 2Box - Muller

1.2.14

Generate  $x_1 = u\_random()$  $x_2 = u\_random()$ get  $y_1 = \sqrt{-2 \cdot \ln x_1} \cos(2\pi x_2)$  $y_2 = \sqrt{-2 \cdot \ln x_1} \sin(2\pi x_2)$ then  $y_1, y_2$  are independent and Gaussianwith  $\begin{cases} \mu=0 \\ \sigma=1 \end{cases}$ 

n.b. this works in 2-D & not 1-D because we need to integrate  $p(x, x_2)$  to get  $\bar{g}'$ . Can't in 1-D, but can use polar coordinates in 2-D

double n-random()

/\* throws second one away \*/

{ double u1, u2;

double x;

u1 = u-random();

u2 = u-random();

x = pow(-2.0 \* log(u1), 0.5) \*

cos(2.0 \* M\_PI \* u2);

return(x);

}

Note: avoid u-random  
= 0  
this time

# The Neave Effect:

1.2.15



TAILS MAY  
BAD:

H.R. Neave, "On using the box-muller transformation with multiplicative congruential pseudo random number generators," Applied Statistics, 22, 92-97, 1973

[Tez95]

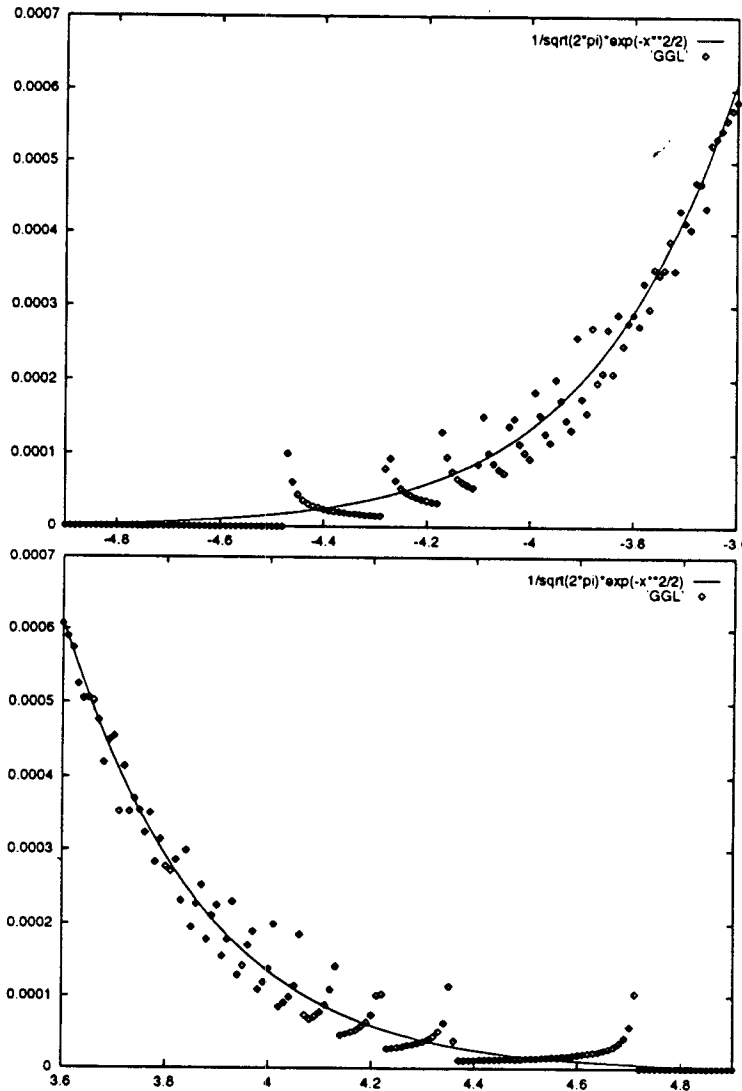


Figure 5.1 Tail distribution in the Box-Muller method with the linear congruential sequence,  $X_n = 16807X_{n-1} \pmod{2^{31} - 1}$ , over the entire period.

Note also truncation  $\sqrt{-2 \log_2 2^{-32}} \approx 6.66$  upper bound