

# Simulation

## Random numbers

# Random numbers

- “Anyone who considers arithmetic methods of producing random digits is, of course, in a state of sin”, John v. Neumann
- Only seemingly random (pseudo random numbers) are used in simulation
- Random numbers should be
  - Reproducible and efficiently generated
  - Reflect the desired properties of the intended truly random sequence (apparent independency, statistics)
- Intended use dictates which features are important

# History

- Need to generate random numbers boomed after invention of computers
  - Simulation of nuclear reactions, Los Alamos
- Simplicity and computational efficiency were emphasized in the beginning
  - Simple arithmetics, simple parameters
- Later portability and quality issues
  - Efficient implementation with high level languages
  - Statistical properties

# Generation of random numbers

- Divided in two stages
  - Generation of Uniform  $(0,1)$  random numbers
    - Generate uniformly  $(0,m-1)$  distributed integers and divide with  $m$
    - Requires deep analysis for statistical properties
  - Generation of random numbers with given probability density function
    - Is done using  $\text{Unif}(0,1)$  random streams
    - Mainly a technical exercise

# Modelling of randomness

- Consider generation of pseudo random numbers as a case of simulation.
  - We go through the steps of simulation modelling process

# Modelling randomness

- Recognition of the system/problem
  - Which statistical properties of a truly random sequence we have to reproduce?
  - Right probability density function (easy part)
  - Sufficient (!) statistical independence between sampled values
  - Long enough sequences
  - Case: Sequences of millions of independent  $\text{Unif}(0,1)$  random numbers

# Modelling randomness

- Model design
  - System components and their interactions
  - Deterministic model with fixed parameters, (large but finite) state that is updated and fixed transform for output
  - $X_n = F(X_{n-1}), R_n = f(X_n)$
- Data collection and parameter estimation
  - Not relevant for  $U(0,1)$

# Lehmer generator

- Developed in 40s (D Lehmer) for first computers (Eniac)
- Basic operations: addition, multiplication and taking remainder
  - $X = (aX + c) \bmod m, R = X/m$
  - Parameters  $a$ ,  $c$  and  $m$  influence the properties of the sequence
  - Original generator was implemented as a separate physical unit. Random stream was read when needed (-> additional randomness)



# Lehmer generator

- Original Eniac generator
  - $m = 10^8 + 1$
  - $A = 23$
  - $C = 0$
- Simple and efficient to implement

# Lehmer generator

- Next  $X$  is uniquely defined from the previous value.
  - Sequence starts to repeat at first reoccurrence of  $X$
  - Domain of  $X:n$  defines the theoretical maximum for the length of sequence ( $=m$ )
- Conditions for reaching the maximum cycle are known
  - If  $q$  divides  $m$  (being prime or 4),  $a-1 \neq 0 \pmod q$
  - $C$  and  $m$  have no common divisors (and  $c$  is nonzero)

# Modelling randomness

- Software design
  - Description model structures and interaction patterns
    - Set up phase and iterator delivering the next instance
- Software implementation
  - Actual programming of the simulator
    - Portability + handling the intermediate large integers
- Software testing
  - Debugging

# Lehmer generator

```
real(dp), parameter :: m=2._dp**31-1._dp
```

```
m_1=1._dp/m
```

```
a=16807._dp
```

```
real(wp) function random()
```

```
seed=modulo(seed*a,m)
```

```
random=seed*m_1
```

```
return
```

```
end function random
```

# Modelling randomness

- Model validation
  - Qualitative/quantitative analysis of the model (comparisons to observation, intuitive expectations, simplified test cases, dependency of uncertain parameters)
  - Counter example (mid square)
- Model experimentation
  - Does the sequence appear as random?
  - In what sense we can prove that the sequence is valid (for our purposes)?
  - What kind of experiments are needed?

# Mid square method

```
integer,parameter :: m0=100,m1=10000  
integer :: seed
```

```
real function random()  
seed=seed*seed  
seed=seed/m0  
seed=modulo(seed,m1)  
random=real(seed)/real(m1)  
return  
end function random  
3456
```

```
0.9439 9.47000E-02 0.8968 0.425 6.25000E-02 0.3906 0.2568 0.5946  
0.3549 0.5954 0.4501 0.259 0.7081 0.1405 0.974 0.8676 0.2729  
0.4474 1.66000E-02 2.75000E-02 7.56000E-02 0.5715 0.6612 0.7185  
0.6242 0.9625 0.6406 3.68000E-02 0.1354 0.8333 0.4388 0.2545  
0.477 0.7529 0.6858 3.21000E-02 0.103 6.09000E-02 0.3708 0.7492  
0.13 0.69 0.61 0.21 0.41 0.81 0.61 0.21 0.41 0.81 0.61 0.21
```

# Model validation

- "All models are wrong but some may still be useful"
  - We can not prove models to be "right"
  - Goal is to find models that resist our attempts to prove them wrong (in given regime at least)
  - For stochastic models the basic technique is hypothesis testing

# Testing of randomness

## – Easy tests

- Test distribution of  $x_i$  under condition  $x_{(i-1)}$  from  $[a,b]$
- Test distribution of  $k$  successive values within the unit cube of  $R^k$  or distribution of  $\max(x_i, \dots, x_{(i+k-1)})$  in  $R$ .
- Try these to original Lehmer generator



# Testing of randomness

## – More elaborated tests

- See Knuth vol II for history
- DIEHARD (classical test pattern from 1995, see [http://www.phy.duke.edu/~rgb/General/rand\\_rate.php](http://www.phy.duke.edu/~rgb/General/rand_rate.php))
- Big Crush (collection of 100+ tests, see <http://www.iro.umontreal.ca/~simardr/testu01/tu01.html> for tutorial + software downloads)

# Lehmer generator

- Popular basic generators in practice
- Conceptually simple arithmetics
- $2^{31}-1$  (maxint) is prime
- Portable implementation simple (using double precision arithmetics and small **a** if 64 bit integers are not supported)
- Well studied and known
  - Too short cycle for modern needs

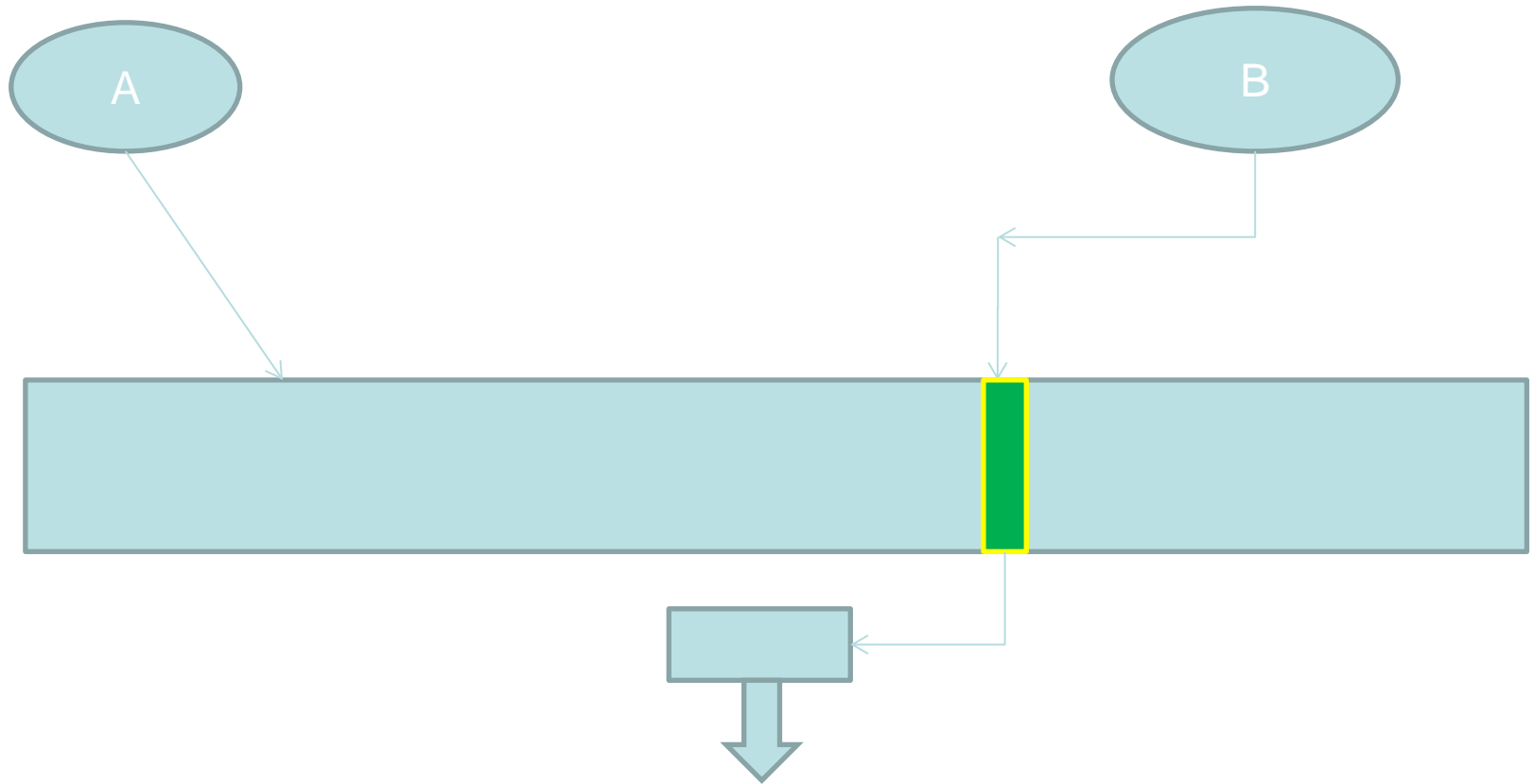
# Combined generators

- Developed in the era of 16-bit processors, (Wichman-Hill)
- Uses several generators with short cycles
  - Take cycles  $m_1, m_2$  ja  $m_3$
  - Produce streams  $X_i$  and  $U_i = X_i/m_i$
  - Set  $U = U_1 + U_2 + U_3 \bmod 1$
- With appropriate choices the cycle is  $m_1 * m_2 * m_3$ 
  - Fully standard (32-bit) arithmetics (if  $m_i < 2^{14}$ )

# Shuffled generators

- Used both for longer cycles and reduced serial correlation
  - Generate random numbers with method A to a table
  - Using generator B to select value from the table (for output) and replace it with new value from A
  - Requires an initialization, some memory and two random numbers for each output value
  - Cycle can be longer (but how much)

# Shuffled generator



# Modern RNGs

- Current de facto standard is Mersenne Twister
  - Developed at late 1990s
  - Very long cycle ( $2^{19937} - 1$ )
  - Needs a working memory (and initialization) of 624-words
  - Available for several languages
  - Some serial correlation problems
    - Slow escape of "zero state"

# Mersenne twister

- The main ideas
  - $X_{(N+1)} = F(X_N, \dots, X_{(N-623)})$ 
    - "State vector" has  $624 \times 32 = 19968$  bits
    - Theoretical maximal cycle would go through all states
    - Ruling out some bits of  $X_{(N-623)}$  and the zero state from possible states we get the wanted length of theoretical maximal cycle (Mersenne prime which gives the name)

# Mersenne twister

- We need an  $F$ , that
  - Is computationally light
  - Leads to reaching the maximal cycle
- Can be found in the family of
  - $X_{(N+1)} = X_N * A_0 + \dots X_{(N-k)} * A_k$
  - $A_i$ :s are coefficient matrices
  - The family has theory for maximum cycles
  - Found  $F$  with only three  $A$ :s with non zero values
    - I.e. only three distinct old  $X$  values are used on each round.



# Mersenne twister

- Method produces a very long cycle
- Is computationally relatively light
- Serial correlation has to be addressed
  - This can be affected shuffling bits in the output
  - Use  $Y=BX$  as output (B permutes the least correlated bits to be the most significant)
- More recent versions (WELL) with improved serial correlation available

# Xorshift generators

- Simple generators based on efficient bit-level shift and XOR operations
  - Marsaglia (2003)
  - Three successive right/left shifts and XORs
  - Full cycle for selected parameters, good properties
  - Standard int/long operations for 32/64 bits

```
y ^= (y<<13); y ^= (y>>17); return y ^= (y<<5);
```

- For longer cycles few ints needed

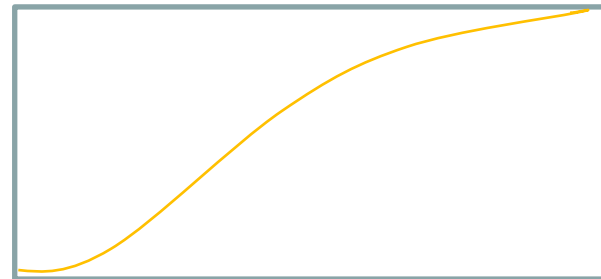
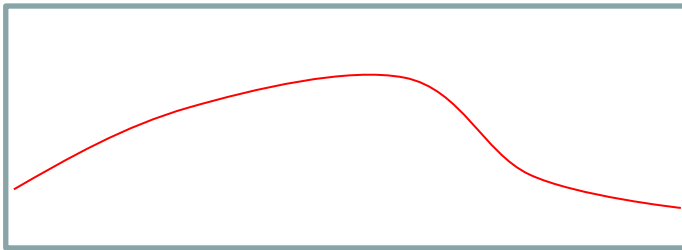
```
tmp=(x^(x<<15)); x=y; y=z; z=w;  
return w=(w^(w>>21))^(tmp^(tmp>>4));
```

# Summary

- Generation of random numbers has over 60-years of history
  - Tested and known generators are available
  - Don't try to do it yourself
  - Do not use unknown and undocumented generator (details, references missing) without testing (vs the "secret" generator of IBM PC:s Basic language)
  - You have to understand the generator to make controlled replications
    - Initialization, ensuring independent streams

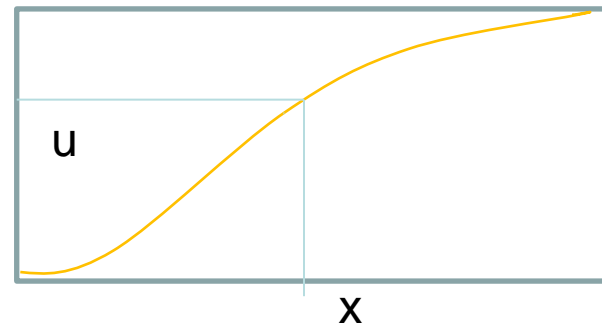
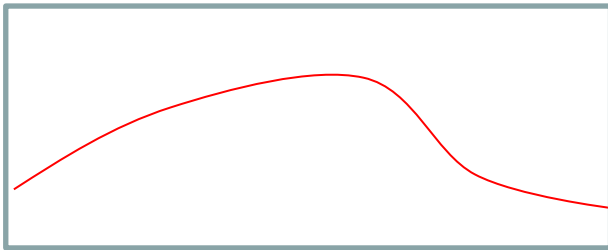
# Random numbers and probability distributions

- How to generate random numbers with given probability distribution function (pdf).
- Method of inverse probability
  - Let  $f$  be a given pdf. It has a cumulative probability function  $F: x \rightarrow (0,1)$ .



# Inverse probability method

- Pick  $u$  from  $\text{Unif}(0,1)$
- Set  $x = F^{-1}(u)$ .
- Pdf of  $x$  is  $f$ .
- We have to know  $F^{-1}$  in closed form

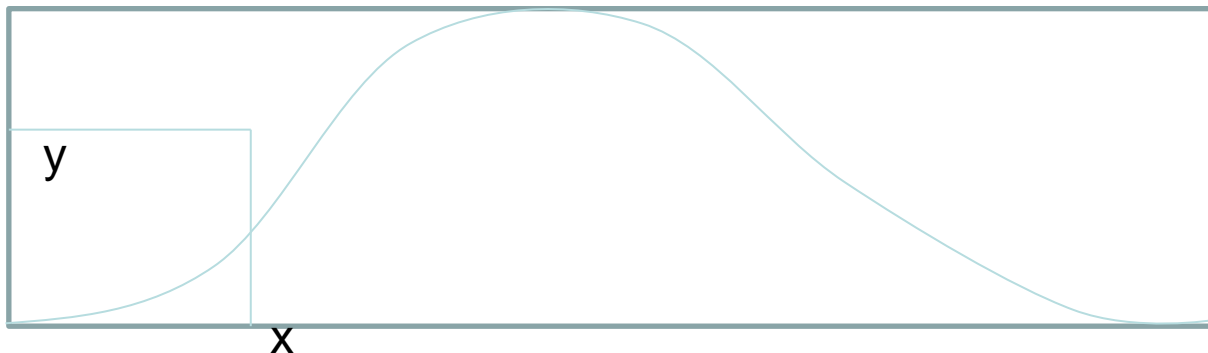


# Inverse probability method

- Consider the exponential distribution
  - Pdf  $f(x) = a e^{-ax}$
  - Cumulative pf is  $F(x) = 1 - e^{-ax}$
  - So  $F^{-1}(U) = -\ln(1-U)/a$
  - Numbers obeying exponential pdf are obtained generating  $U \sim \text{Unif}(0,1)$  and reporting
    - Either  $-\ln(1-U)/a$
    - Or  $-\ln(U)/a$  if  $U > 0$  always

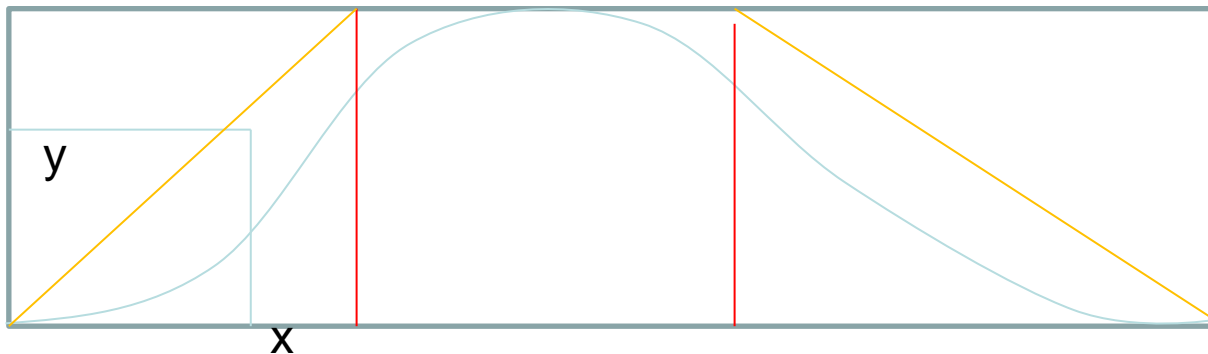
# Elimination method

- General method that requires only pdf values
  - Let  $f$  be a pdf supported on  $(a,b)$  with values  $0 < f < c$ .
  - Pick  $x$  in  $\text{Unif}(a,b)$ ,  $y$  in  $\text{Unif}(0,c)$ .
  - If  $y < f(x)$ , accept  $x$ .
  - Else reject  $x$  and pick new values for  $x,y$



# Elimination method

- Method is most efficient when there is least amount of rejections
  - One can divide  $(a,b)$  to subintervals and/or change the pdf of  $y$  to approximate  $f$  better.
  - If  $f < cg$  (on some subinterval),  $g$  is a known pdf, pick  $x$  from  $g$ -distribution and  $y$  from  $\text{Unif}(0, cg(x))$





# Elimination method

## – When using subintervals

- First one has to draw which subinterval to select for  $x$  (probabilities computed beforehand)
- Then draw  $x$  from  $g$  corresponding to subinterval and  $y \text{ Unif}(0, c_g(x))$  and test for  $y < f(x)$ .
- Subdivision of interval can be an art (Marsaglia, cf Knuth vol II)

