

Shifting interpolation formula.

Integre.

Polynomial of order $m = 2n$

↑
even, in other words.

$$F_{2n}(x) = f_k + \mu \mu \delta f_k + \frac{\mu^2}{2!} \delta^2 f_k + \dots$$

$$= f_k + \sum_{l=1}^m \binom{m+l-1}{2l-1}$$

$$\{ \mu \delta^{2l-1} f_k + \frac{\mu}{2l} \delta^{2l} f_k \}$$

$$+ O(\Delta x^{2n+1})$$

$$M = \frac{x - x_k}{\Delta x}$$

Example :

$$M=1 \quad (m=2)$$

$$\begin{aligned}
 F_2(x) &= f_k + \frac{\Delta f_k}{\Delta x} (x - x_k) \\
 &\quad + \frac{1}{2} \frac{\partial^2 f_k}{\Delta x^2} (x - x_k)^2 \\
 &\quad + O(\Delta x^3)
 \end{aligned}$$

This is the parabolic shifting formula.

Difference quotients:

$$\frac{d}{du} \binom{u}{l} = \binom{u}{l} \sum_{i=0}^{l-1} \frac{1}{u-i}$$

$$\frac{d^2}{du^2} \binom{u}{l} = \begin{cases} 0 & l=1 \\ \binom{u}{l} \sum_{i=0}^{l-1} \sum_{j=0}^{l-1} \frac{1}{(u-i)(u-j)}, & l \geq 2. \end{cases}$$

DNGF - Formulas

Difference - Newton- Gregory - formulas

$$F_m'(x) = \frac{1}{\Delta x} \sum_{l=1}^m \Delta^l f_k \binom{u}{l} \sum_{i=0}^{l-1} \frac{1}{u-i} + O(\Delta x^m)$$

$$F_m''(x) = \frac{1}{\Delta x^2} \sum_{l=2}^m \sum_{i=0}^{l-1} \sum_{j=0}^{l-1} \frac{1}{(u-i)(u-j)} + O(\Delta x^{m-1})$$

Now, we set $x = x_u$:

$$F_m'(x_u) = \frac{1}{\Delta x} \sum_{l=1}^m (-1)^{l-1} \frac{\Delta^l f_k}{l} + O(\Delta x^m)$$

$$\tilde{F}_m''(x_u) = \frac{1}{\Delta x^2} \sum_{l=2}^m \sum_{i=1}^{l-1} (-1)^{l+i} \frac{\Delta^l f_k}{l} \sum_{j=1}^{l-1} \frac{1}{j} + O(\Delta x^{m-1})$$

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Example:Solving $m = 2$:

$$F_2'(x_k) = \frac{1}{\Delta x} (\Delta f_k - \frac{\Delta^2 f_k}{2}) + O(\Delta x^2)$$

$$= \frac{1}{\Delta x} (-\frac{1}{2} f_{k+2} + 2f_{k+1} - \frac{3}{2} f_k) + O(\Delta x^2)$$

DNGBExample:

$$F_2'(x_k) = \frac{1}{\Delta x} (\nabla f_k - \frac{\nabla^2 f_k}{2}) + O(\Delta x^2)$$

$$= \frac{1}{\Delta x} (\frac{3}{2} f_k - 2f_{k-1} + \frac{1}{2} f_{k-2})$$

$$+ O(\Delta x^2).$$

DST - Differential Shifting formula

$$\begin{aligned}
 F_{2m}'(x_k) &= \frac{1}{\Delta x} (\mu \delta f_k - \frac{1}{6} \mu \delta^3 f_k \\
 &\quad + \frac{1}{30} \mu \delta^5 f_k - \frac{1}{140} \mu \delta^7 f_k + \dots) \\
 &\quad + O(\Delta x^{2m})
 \end{aligned}$$

$$\begin{aligned}
 F_{2m}''(x_k) &= \frac{1}{(\Delta x)^2} (\delta^2 f_k - \frac{1}{12} \delta^4 f_k + \frac{1}{90} \delta^6 f_k \\
 &\quad - \frac{1}{560} \delta^8 f_k + \dots) + O(\Delta x^{2m}) \\
 &\quad !
 \end{aligned}$$

In the DNGF and DNGB schemes, the error increases for each new order of derivation. This does not happen in the DST - scheme!

Example :

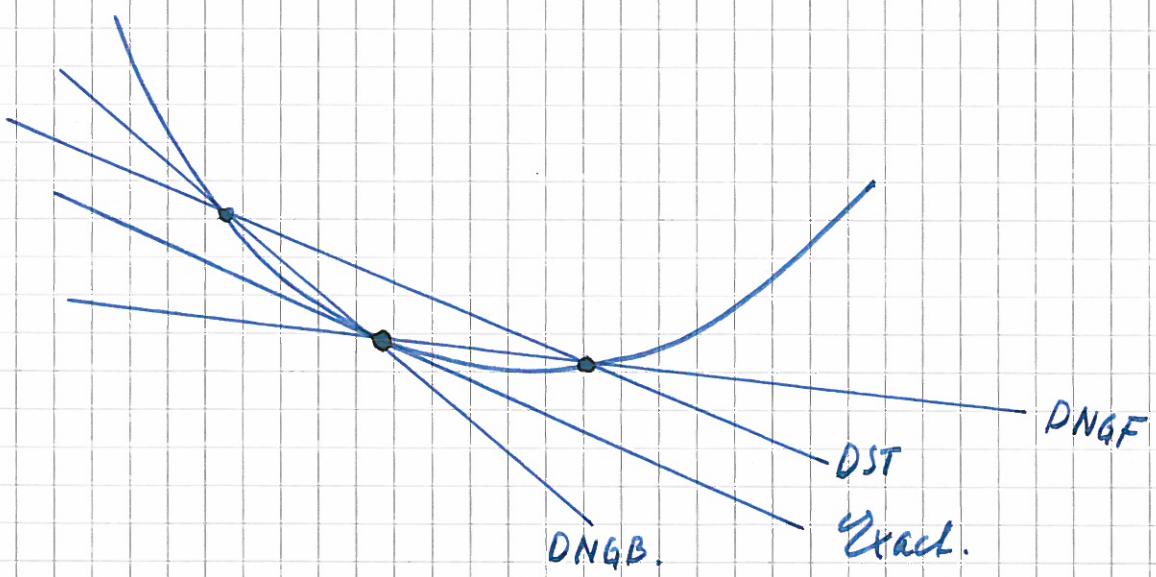
$$F_2'(x_k) = \frac{1}{\Delta x} (\mu f_{k+1} - f_{k-1}) + O(\Delta x^2)$$

$$= \frac{1}{2\Delta x} (f_{k+1} - f_{k-1}) + O(\Delta x^2)$$

$$F_2''(x_k) = \frac{\delta^2 f_k}{\Delta x^2} + O(\Delta x^2)$$

$$= \frac{1}{\Delta x^2} (f_{k+1} - 2f_k + f_{k-1}) + O(\Delta x^2).$$

Why don't these work so well? Consider
the following graphical representation.



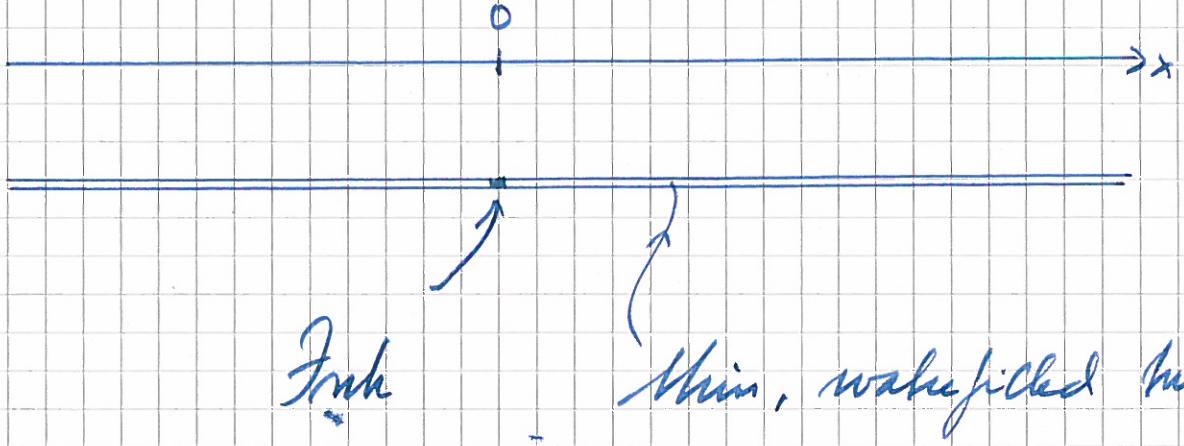
3. Stochastic Processes.

Stochastics is the opposite of statistics.

Statistics: Generate distributions from data.

Stochastics: Generate data from distributions.

Example : Diffusion.



Show does the milk spread in time?

Ink concentration: $P(x,t)$

Diffusion equation:

$$\boxed{\frac{\partial P}{\partial t} = \frac{D}{2} \frac{\partial^2 P}{\partial x^2}}$$

Initial condition: $P(x,0) = \delta(x)$

Solution: $P(x,t) = \frac{e^{-x^2/2Dt}}{\sqrt{\pi Dt}}$

Incidentally, diffusion coefficient $\sim D = 0.1 \cdot \frac{m^2}{s}$
for water molecules in water.

The diffusion equation is an example
of a Fokker-Planck equation.

In every Fokker-Planck equation,
there is a corresponding Langevin equation.

$$\frac{\partial P}{\partial t} = \frac{D}{2} \frac{\partial^2 P}{\partial x^2} \iff$$

$$\dot{x} = \eta(t)$$

Noise term.

$$\langle \eta \rangle = 0$$

$$\left\{ \langle \eta(t) \eta(t') \rangle = D \delta(t-t') \right.$$

Un-correlated white noise.

Integrating the Langevin equation:

$$x(t) = x_0 + \int_0^t \eta(t') dt' = \int_0^t \eta(t') dt'$$

$x_0 = 0$

We set $x_0 = 0$

gb

$$\langle X(t) \rangle = \left\langle \int_0^t \eta(t') dt' \right\rangle$$

$$= \int_0^t \langle \eta(t') \rangle dt' = \underline{0}$$

$$\langle X^2(t) \rangle = \left\langle \int_0^t \eta(t') dt' \int_0^t \eta(t'') dt'' \right\rangle$$

$$= \int_0^t dt' \int_0^t dt'' \langle \eta(t') \eta(t'') \rangle$$

$$= D \int_0^t dt' \int_0^t dt'' \delta(t' - t'') = D \int_0^t dt' = \underline{Dt}$$

From the solution of the diffusion equation

$$P(x, t) = \frac{e^{-x^2/2Dt}}{\sqrt{2\pi Dt}}$$

$$\langle X \rangle = \int_{-\infty}^{+\infty} dx \times P(x, t) = \underline{0}$$

$$\langle X^2 \rangle = \int_{-\infty}^{+\infty} dx \times x^2 P(x, t) = \underline{Dt}$$

All moments of X calculated with
the Langvii equation and the
corresponding Fokker-Planck equation
give the same result.

\Rightarrow Langvii equation gives a
stochastic realization of the
corresponding Fokker-Planck
equation.

Random numbers.

Benford's law

The first digit of numbers
occurring naturally in lists
follows the law

$$\log_{10} \left(1 + \frac{1}{d} \right).$$

$d=1$	$\log_{10}(1 + \frac{1}{1}) = 30.1\%$
$d=2$	$\log_{10}(1 + \frac{1}{2}) = 17.6\%$
$d=3$	$\log_{10}(1 + \frac{1}{3}) = 12.5\%$
$d=4$	$\log_{10}(1 + \frac{1}{4}) = 9.7\%$
$d=5$	$\log_{10}(1 + \frac{1}{5}) = 7.9\%$
$d=6$	$\log_{10}(1 + \frac{1}{6}) = 6.7\%$
$d=7$	$\log_{10}(1 + \frac{1}{7}) = 5.8\%$
$d=8$	$\log_{10}(1 + \frac{1}{8}) = 5.1\%$
$d=9$	$\log_{10}(1 + \frac{1}{9}) = 4.6\%$

Why?

Probability density without interval
to calc: $\frac{dx}{x}$

$$\int_{d}^{d+1} \frac{dx}{x} = \ln(d+1) - \ln d = \ln(1 + \frac{1}{d})$$

Normalizing:

$$\int_1^{10} \frac{dx}{x} = \ln 10$$

Probability :

$$\frac{\ln(1+\frac{1}{\alpha})}{\ln 10} = \log_{10}(1+\frac{1}{\alpha})$$

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How to generate random numbers that can be trusted.

$$ran \rightarrow r ; 0 < r < 1.$$

Random number generators should be:

1 Random

2 Reproducible

3 Portable

4 Efficient.

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There is no universal random number generator. Always look your random number generator in the application you have in mind.

More complex random number generators \nrightarrow better generators.

Often, the opposite is the case.

Linear congruence random number generator

$$I_{j+1} = (a I_j + b) \text{ mod. } m$$

\uparrow
modulus.

$$(\text{Modular: } j \cdot \text{mod. } m = j - \underbrace{\left[\frac{j}{m} \right]}_{\text{Integer}} \cdot m)$$

Integer division

$$\text{Example: } 7 \cdot \text{mod. } 5 = 7 - \left[\frac{7}{5} \right] \cdot 5 = 7 - 1 \cdot 5 = 2$$

$\stackrel{''}{1}$

Period $\leq m$, hopefully $\approx m$.

m is usually large; $m = 2^{32} \approx 4.3 \cdot 10^9$.

Generators produce sequences of random numbers. Group them.

$$\vec{R}_i = (\underline{r_1, r_2, \dots, r_n})_i$$

↑
ith sequence

Sequence plotted as
a n -dimensional
vector

Plot $\vec{R}_1, \vec{R}_2, \dots, \vec{R}_N$.

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The points will fall on $(k-1)$ -dimensional planes.

The number of planes will be $m^{1/k}$ or less.

The better the generator, the more planes.

Lewis, Gordan and Miller

"Minimal Standard Generator"

$$I_{j+1} = \underbrace{(16807 \cdot I_j)}_{\uparrow} \text{ mod. } \underbrace{2147483647}_{= 2^{31}-1}$$

"

"Magic number"

Produces random numbers in the range

$$-(2^{31}-1) < I_{j+1} < (2^{31}-1)$$

on a 32-bit machine.

(Why can multiplication of two positive numbers give a negative number?)

Very well used and can usually be trusted.

Bits of higher order (more significant - further to the left) can be trusted

more than bits of low order.

To generate random numbers between 1 and 10, use the following method:

$$j = 1 + \text{int}(10 * r),$$

\uparrow

$0 < r < 1.$

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This would be significantly
worse:

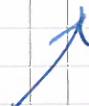
$$j = 1 + (\text{first}(1000 * n)) \cdot \text{mod.} 10.$$

Never do the following to
generate 10 random bits:

do $i = 1, 10$

$k = \text{and}(1, \text{ishtf}(I, i))$

enddo



random
ishtf.

Kirkpatrick - Stoll generator R250.

Initially:

250 integers containing random
bits.

$N(1), \dots, N(250)$.

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Based on the XOR logical operation.

XOR	1	0
1	0	1
0	1	0

$$N(251) = \text{XOR} (N(1), N(148))$$



A new random number.

Generally:

$$N(k) = \text{XOR} (N(k-250), N(k-103))$$

magic numbers.

To generate the first 250 random numbers $N(1), \dots, N(250)$:

```

do k = 1, 250
  ICI = 0
  do I = 1, 32
    ICI = ISHIFT (ICI, 1)
    IBM = IBM * 16807
    IF (IBM .LT. 0) ICI = ICI + 1
  enddo
  N(k) = ICI .
end do

```

Hence, use 16807 to generate each bit in $N(1), \dots, N(250)$.

Java implementation of R250.

$N(\text{and}(255, h))$

Reads the 8 last bits of h .

= $\text{XOR}(N(\text{and}(255, h-250)),$

$N(\text{and}(255, h-103)))$.

Now, h may proceed to ∞ , but
the dimension of N is still only 256:

$N(0), \dots, N(255)$.

Which generator is best of 16807 and R250?

Before, R250 was considered best, but
in 1992, Landau's group at the
University of Georgia found a 7%

error in the Ising model when
using the R252. 16807 worked
well.

However, Dietrich Stauffer at the
University of Cologne has had
problems with 16807 in
connection with the Ising model.

Some hints:

✓ Initialize 16807 with odd
numbers.

✓ Use odd lattice sizes ($L = 31$, rather
than $L = 32$).

✓ Generate an ultra random #
from time to time.

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Another "magic" number:

65539.

Use this to test 16807 (by substituting 16807 by 65539).

Never use 65539 for production runs.

Generating numbers x that follow a probability distribution $p(x)$.

Cumulative probability

$P(x)$

\uparrow

Probability to find a value

$x' \leq x$.

$$P(-\infty) = 0$$

$$P(\infty) = 1.$$