

26.11.2012

①

5.12.2012

DICHOTOM-PR.

GENETIC  
- evolution.STOCHASTIC DIFFUSION FROM  
SCALING OF DISCRETE TIME  
PROCESSESNoise - evol.  
frontiers  
in genetic  
modelsChandler  
- the  
concept  
of friction

Brownian motion is a regular diffusion process on the interval  $(-\infty, \infty)$  with a drift term  $A(x) = 0$  and a diffusion term  $B(x) = \sigma^2$

$$\Delta_h X = X(h) - X(0) \text{ normally distributed}$$

$$\text{with } E[\Delta_h X] = 0$$

$$\text{Var}[\Delta_h X] = \sigma^2 h$$

$$E[\Delta_h X | X(0) = x] = 0$$

$$E[(\Delta_h X)^2 | X(0) = x] = \sigma^2 h$$

$$E[(\Delta_h X)^4 | X(0) = x] =$$

$$= \frac{1}{\sqrt{2\pi h} \sigma} \int_{-\infty}^{+\infty} y^4 \exp\left(-\frac{1}{2} \frac{y^2}{\sigma^2 h}\right) dy$$

$$= \left(\frac{y^2}{\sigma^2 h} = 2z, \quad \frac{2y dy}{\sigma^2 h} = 2 dz \rightarrow dy = \frac{\sigma^2 h dz}{y}\right)$$

$$y = (2\sigma^2 h z)^{1/2}$$

$$= \frac{1}{(\sqrt{2\pi h})^{1/2} \sigma} 2 \int_0^{+\infty} (2\sigma^2 h z)^2 \frac{\sigma^2 h dz}{(2\sigma^2 h z)^{1/2}} e^{-z}$$

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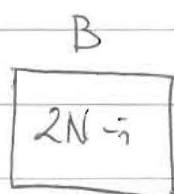
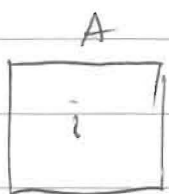
$$= \frac{1}{(2\pi h)^{1/2} \sigma} 2 \int_{-\infty}^{+\infty} \frac{4\sigma^4 h^2 \cdot \sigma^2 \cdot h}{\sigma (2h)^{1/2}} z^{3/2} e^{-z} dz$$

$$= \frac{1}{\sqrt{\pi}} 2 \int_{-\infty}^{+\infty} 2\sigma^4 h^2 z^{3/2} e^{-z} dz$$

$$= \frac{4\sigma^4 h^2}{\sqrt{\pi}} \int_0^{\infty} z^{3/2} e^{-z} dz = \frac{3\sqrt{\pi}}{4} \cdot \frac{4\sigma^4 h^2}{\sqrt{\pi}}$$

0-U process from the Ehrenfest urn model

$i \rightarrow$  urn A } 2N balls  
 $2N-i \rightarrow$  B



Any of boxes chosen with prob  $1/2$ , then

$$P_{ij} = \begin{cases} \frac{2N-i}{N} \cdot \frac{1}{2} & j = i+1 \\ \frac{1}{2N} & j = i-1 \\ 0 & \text{otherwise} \end{cases}$$

$$\frac{1}{2} \frac{2N-i}{N} = \frac{2N-i}{2N} = 1 - \frac{i}{2N} \quad i \rightarrow i+1$$

$$\frac{1}{2} \frac{i}{N} \quad i \rightarrow i-1$$

Let us define

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$$\text{Prob} \left\{ \Delta X = \pm 1 \mid X_N(t) = x \right\} = \frac{1}{2} + \frac{N-x}{2N} =$$

$X_N(t)$  = number of particles in box A  
at time  $t$

$$\Delta X = X_N(t + \Delta t) - X_N(t)$$

$x \equiv i$

$$\left. \begin{aligned} \frac{1}{2} + \frac{N-x}{2N} \\ \frac{1}{2} - \frac{N-x}{2N} \end{aligned} \right\} \begin{aligned} &= \frac{1}{2} + \frac{1}{2} - \frac{x}{2N} = 1 - \frac{x}{2N} \quad (\Delta X = +1) \\ &= \frac{1}{2} - \frac{1}{2} + \frac{x}{2N} = \frac{x}{2N} \quad (\Delta X = -1) \end{aligned}$$

Let  $N$  increase and  $\Delta t$  decrease while  
 $N\Delta t = 1 = \text{const}$

Define  $\Rightarrow Y_N(\tau) \equiv \frac{X_N([N\tau]) - N}{\sqrt{N}}$

approximating process

Hence:  $X_N([N\tau]) = \sqrt{N} \cdot Y_N(\tau) + N$

Now

$$\text{Pr} \left\{ \Delta Y = \pm \frac{1}{\sqrt{N}} \mid Y_N(\tau) = y \right\} = \text{Pr} \left\{ \Delta X = \pm 1 \mid X_N([N\tau]) = \right.$$

$$x = N + y\sqrt{N} \left. \right\} = \frac{1}{2} \pm \frac{N - (N + y\sqrt{N})}{2N} \quad (\text{same as above})$$

$$= \frac{1}{2} \pm \frac{(N-x)}{2N} = \frac{1}{2} \mp \frac{y}{2\sqrt{N}}$$

We would like to estimate

?

$$\lim_{h \rightarrow 0} \frac{1}{h} E[\Delta Y(h) | Y(t) = y] \rightarrow A(y)$$

$$\lim_{h \rightarrow 0} \frac{1}{h} E[\Delta Y^2(h) | Y(t) = y] \rightarrow B(y)$$

$$h = \frac{1}{N}$$

Pr {  $\Delta Y = \pm \frac{1}{\sqrt{N}}$  (when  $\Delta X$  changes by 1,  $\Delta Y$  as a rescaled variable changes by  $\frac{1}{\sqrt{N}}$  ) }

$$\begin{aligned}
 Y(t) = y \quad \& \Pr \{ \Delta X = \pm 1 \mid X[N\tau] = x = N + y\sqrt{N} \} \\
 &= \frac{1}{2} \pm \frac{N - x}{2N} = \frac{1}{2} \pm \frac{N - (N + y\sqrt{N})}{2N} \\
 &= \frac{1}{2} \mp \frac{y}{2\sqrt{N}}
 \end{aligned}$$

$$\begin{aligned}
 E[\Delta Y(h) | Y(t) = y] &= \frac{1}{\sqrt{N}} \left( \frac{1}{2} - \frac{y}{2\sqrt{N}} \right) + \\
 &+ (-) \frac{1}{\sqrt{N}} \cdot \left( \frac{1}{2} + \frac{y}{2\sqrt{N}} \right) = -\frac{y}{N} = -y \cdot h
 \end{aligned}$$

hence  $\lim_{h \rightarrow 0} \frac{1}{h} E[\Delta Y(h) | Y(t) = y] = -y$  !

$$\Delta Y^2(h) = \frac{1}{N} \rightarrow$$

$$E[\Delta Y^2(h) | Y(t)=y] = \frac{1}{N} \cdot \left( \frac{1}{2} - \frac{y}{2\sqrt{N}} \right) + \frac{1}{N} \left( \frac{1}{2} + \frac{y}{2\sqrt{N}} \right) = \frac{1}{N}$$

$$\lim_{h \rightarrow 0} \frac{1}{h} E[\Delta Y^2(h) | Y(t)=y] = N \cdot \frac{1}{N} = 1$$

similar computation leads to

$$\frac{1}{h} E[\Delta Y^4(h) | Y(t)=y] = \frac{1}{N} \rightarrow 0$$

hence the process scales to a diffusion process

$$\dot{y} = -y + (\sigma) \xi(t) \quad L\mathbb{E}_y$$

KBE  $\frac{\partial p(y,t)}{\partial t} = -y \partial_y p(y,t) + \frac{1}{2} \partial_{yy} p(y,t)$

FPE  $\frac{\partial p(y,t)}{\partial t} = \partial_{yy} p(y,t) + \frac{1}{2} \partial_{yyy} p(y,t)$

## Itô transformation rules

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How to determine the form of infinitesimal parameters of new processes built from certain transformations applied to original processes?

$$Y(t) = g(X(t)) \quad g - \text{continuous and monotone}$$

$$\left\{ X(t), t > 0 \right\} \rightarrow \begin{array}{cc} \mu(x), & \sigma^2(x) \\ \text{drift} & \text{diffusion} \end{array}$$

Assumption:

Two uniformly continuous  $g'(x)$  and  $g''(x)$  exist.

$$\left\{ Y(X(t)), t > 0 \right\} \\ y \in [g(t), g(\tau)]$$

$$\mu_Y(y) = \frac{1}{2} \sigma^2(x) g''(x) + \mu(x) g'(x)$$

$$\sigma_Y^2(y) = \sigma^2(x) [g'(x)]^2$$

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PROOF:

$$\underline{f(x+\Delta x)} = f(x) + \Delta x f'(x) + \frac{1}{2} (\Delta x)^2 f''(x) +$$

$$+ \frac{1}{2} (\Delta x)^2 [f''(\xi) - f''(x)]$$

where  $\xi \in [x, x+\Delta x]$

↓

$$\underline{f(X(t+h))} = f(X(t)) + \Delta X f'(X) + \frac{1}{2} (\Delta X)^2 f''(X)$$

$$+ \frac{1}{2} (\Delta X)^2 [f''(\xi(X)) - f''(X(t))]$$

or otherwise

$$\underline{Y(t+h) - Y(t)} = \Delta X f'(X) + \frac{1}{2} (\Delta X)^2 f''(X)$$

$$+ \frac{1}{2} (\Delta X)^2 [f''(\xi(X)) - f''(X(t))]$$

$$\lim_{h \rightarrow 0} \frac{1}{h} E[Y(t+h) - Y(t) | Y(t) = y] =$$

$$\lim_{h \rightarrow 0} E \left[ \frac{\Delta X}{h} f'(X) + \frac{1}{2} \frac{1}{h} (\Delta X)^2 f''(X) + \right.$$

$$\left. + \frac{1}{2} \frac{(\Delta X)^2}{h} [f''(\xi(X)) - f''(X(t))] \right]$$

convergent

= 0 by continuity of  $f''$ !

≡

$$= \mu(x) f'(x) + \frac{1}{2} \sigma^2(x) f''(x)$$

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second moment:

$$[Y(t+h) - Y(t)]^2 = \Delta X^2 [g'(x)]^2 + R$$

where  $R$  contains  $(\Delta X)^3$  and higher order terms

Since  $\lim_{h \rightarrow 0} \frac{1}{h} E[|\Delta X|^n | X(t) = x] = 0$  for  $n \geq 3$

(by definition, for any stochastic diffusion process  $X(t)$ )

$$\begin{aligned} \Rightarrow \lim_{h \rightarrow 0} \frac{1}{h} E[\{Y(t+h) - Y(t)\}^2 | Y(t) = y] &= \\ &= \sigma^2(x) [g'(x)]^2 \end{aligned}$$

EXAMPLE:

The Euclidean distance from the origin of an  $n$ -dim Brownian motion  $\sqrt{Z}$ , where

$$Z(t) \equiv X_1^2(t) + \dots + X_n^2(t)$$

Let

$$\begin{aligned} X_1(t + \Delta t) = x_1 + \Delta X_1, \quad Z(t + \Delta t) &= z + \Delta Z \\ &= x_1^2 + \dots + x_n^2 + \Delta Z \end{aligned}$$

$$\begin{aligned} \Rightarrow \Delta Z &= [X_1(t + \Delta t)]^2 - x_1^2 + \dots + [X_n(t + \Delta t)]^2 - x_n^2 \\ &= 2(x_1 \Delta X_1 + \dots + x_n \Delta X_n) + [(\Delta X_1)^2 + \dots + (\Delta X_n)^2] \end{aligned}$$



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$\Delta X_i$  are independent and normally distributed with zero mean ( $\mu=0$ ) and variance  $\Delta t$



$$E[\Delta Z | Z(t)=z] = n \cdot \Delta t$$

$$E[(\Delta Z)^2 | Z(t)=z] = 4(x_1^2 + \dots + x_n^2) \Delta t + o(\Delta t) \\ = 4z \Delta t$$

$$E[(\Delta Z)^4 | Z(t)=z] = O((\Delta t)^2)$$



$$\mu(z) = n \\ \sigma^2(z) = 4z$$

$Y(t) = g(Z) = \sqrt{Z}$  defines a Bessel process

$$g'(z) = \frac{1}{2} z^{-1/2}; \quad g'' = -\frac{1}{4} z^{-3/2}$$

$$\Rightarrow \mu(z) = n, \quad \sigma^2(z) = 4z \Rightarrow \sigma^2(y) = ?$$

$$\mu_Y(y) = \frac{1}{2} \sigma^2(z) \cdot g''(z) + \mu(z) g'(z) \Big|_{y^2=z}$$

$$= \frac{1}{2} \cdot 4z \cdot \left(-\frac{1}{4}\right) z^{-3/2} + n \frac{1}{2} z^{-1/2}$$

$$= -\frac{1}{2} z^{-1/2} + \frac{n}{2} z^{-1/2} = \frac{n-1}{2} z^{-1/2}$$

$$= \frac{n-1}{2} \frac{1}{y}$$

$$\sigma_y^2(y) = \sigma^2(z) [g'(z)]^2 \Big|_{y^2=z}$$

$$\sigma_y^2(y) = 1 \quad \left\{ \begin{array}{l} \sigma^2(z) = 4z = 4y^2 \\ g'(z) = \frac{1}{2} z^{-1/2} = \frac{1}{2} y^{-1} \\ [g'(z)]^2 = \frac{1}{4} y^{-2} \end{array} \right.$$

The Bessel process is governed by a Langevin equation:

$$dY_t = \frac{n-1}{2Y} dt + dW_t$$

$$\text{FPEq} \quad \frac{\partial}{\partial t} p(y, t) = - \frac{\partial}{\partial y} \left( \frac{n-1}{2y} p(y, t) \right) + \frac{1}{2} \frac{\partial^2}{\partial y^2} p(y, t)$$

$$P_n(y) = N \exp \left( 2 \int^y \frac{n-1}{2y'} dy' \right) \sim C |y|^{n-1}$$

## WRIGHT-FISHER GENETIC MODEL

$$P_{ij} = \binom{N}{j} p_i^j (1-p_i)^{N-j}$$

$$\text{where } p_i = \frac{(1+s) [i(1-\alpha) + (N-i)\beta]}{(1+s) [i(1-\alpha) + (N-i)\beta] + [i\alpha + (N-i)(1+\beta)]}$$

### PARENTAL POPULATION

$i$  A type       $N-i$  a type

is subject to mutation, selection + sampling forces

$N \rightarrow \infty$  ) diffusion approximation

(composition of the next generation is determined through  $N$  binomial trials)

$$\text{let } \alpha = \frac{r_1}{N} \quad r_1, r_2, s > 0$$

$$\beta = \frac{r_2}{N}$$

$$Y_N(x) \equiv \frac{X([Nx])}{N}, \quad h = \frac{1}{N}$$

1) We analyze changes in the population of genes with mutations, only.

$$\Delta Y_N(x, h) = Y_N\left(x + \frac{1}{N}\right) - Y_N(x) =$$

$$\left\{ X\left(\lfloor Nx \rfloor + 1\right) - X\left(\lfloor Nx \rfloor\right) \right\} N^{-1}$$

$$E\left[\Delta Y_N(x, h) \mid Y_N(x) = \xi = \frac{i}{N}\right] = E\left[\left\{ Y_N\left(x + \frac{1}{N}\right) - Y_N(x) \right\} \mid Y_N(x) = \frac{i}{N}\right] =$$

$$= \left( N Y_N\left(x + \frac{1}{N}\right) \text{ is distributed binomially!} \right) =$$

$$= P_i - \frac{i}{N} = \left[ \frac{i}{N}(1-\alpha) + \frac{N-i}{N}\beta \right] - \frac{i}{N}$$

$$= \frac{1}{N} \left[ -\alpha \frac{i}{N} + (1-\alpha)\beta \right]$$

$$\text{hence } \lim_{h \rightarrow 0} \frac{1}{h} E\left[\Delta Y_N(x, h) \mid Y_N(x) = \xi\right] =$$

$$= -\alpha \xi + (1-\alpha)\beta$$

$$\text{where } \xi = \lim_{N \rightarrow \infty} \frac{i}{N}$$

$$\lim_{h \rightarrow 0} \frac{1}{h^2} E\left[\Delta^2 Y_N(x, h) \mid Y_N(x) = \xi\right] =$$

$$= \lim_{N \rightarrow \infty} N E\left[\Delta^2 Y_N(x, h) \mid Y_N(x) = \xi\right] \quad \left(h = \frac{1}{N}\right)$$

$$\left( Y_N^2\left(x + \frac{1}{N}\right) - 2Y_N\left(x + \frac{1}{N}\right)Y_N(x) + Y_N^2(x) \right)$$

$$= \lim_{N \rightarrow \infty} N E\left[ \frac{N^2 Y_N^2\left(x + \frac{1}{N}\right)}{N^2} - \frac{2N Y_N\left(x + \frac{1}{N}\right)}{N} (\xi) + \xi^2 \right]$$

Recall, that for binomial PDF

$$\phi(s) = \langle s^m \rangle = \sum_{m=0}^N \binom{N}{m} p^m s^m q^{N-m} = (ps + q)^N$$

hence,

$$\phi''(s) \Big|_{s=1} = N(N-1)p^2 = \langle m^2 \rangle - \langle m \rangle^2 \text{ and}$$

$$\langle m \rangle = Np$$

↓

$$\text{and} \\ \langle m^2 \rangle = N(N-1)p^2 + Np$$

$$\mathbb{E} \left[ \frac{N^2 Y_N^2 (x + \frac{1}{N})}{N^2} \right] = \frac{1}{N^2} [Np_i(1-p_i) + N^2 p_i^2]$$

$$\lim_{N \rightarrow \infty} N \mathbb{E} \left[ \frac{1}{N^2} \{ Np_i(1-p_i) + N^2 p_i^2 \} - 2p_i \xi + \xi^2 \right] =$$

$$\text{where } \xi = \frac{i}{N}$$

$$\alpha = \frac{q_1}{N}, \quad \beta = \frac{q_2}{N} = \xi(1-\xi)$$

$$\text{and } p_i = \frac{i(1-\alpha) + (N-i)\beta}{i(1-\alpha) + (N-i)\beta + i\alpha + (N-i)(1-\beta)} =$$

$$= \frac{i - \alpha i + N\beta - i\beta}{N}$$

Resulting diffusion process is

described by

$$\begin{aligned} \mu(x) &= -\gamma_1 x + (1-x)\gamma_2 \\ &= -(\gamma_1 + \gamma_2)x + \gamma_2 \end{aligned}$$

$$\sigma^2(x) = x(1-x)$$

$$\begin{aligned} \frac{\partial p(x, t)}{\partial t} &= \frac{\partial}{\partial x} \left\{ [(\gamma_1 + \gamma_2)x - \gamma_2] p(x, t) \right. \\ &\quad \left. + \frac{\partial^2}{\partial x^2} x(1-x) p(x, t) \right\} \end{aligned}$$

$$\lim_{t \rightarrow \infty} p(x, t) = p_{\infty}(x) = \frac{\Gamma(2(\gamma_1 + \gamma_2))}{\Gamma(2\gamma_1)\Gamma(2\gamma_2)} x^{2\gamma_1 - 1} (1-x)^{2\gamma_2 - 1}$$