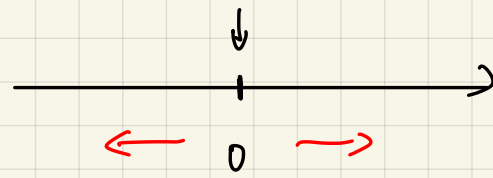


# Gaussian Everywhere

## ① Diffusion. (Micro & Macroscopic View)

ink pour on the axis at  $t=0$



Spatial distribution of ink?

Suppose Distribution  $f(x,t)$   $t \rightarrow$  variance (spread over time)

Introduce  $p(y,\tau)$ : describe the velocity of ink diffusing

random  $\swarrow$  Percentage of ink diffusing distance  $y$  in duration  $\tau$  also a distribution.

i)  $f(x, t+\tau) = \int_{\mathbb{R}} p(y, \tau) \cdot f(x-y, t) dy$  **key equation**

ii)  $\int_{\mathbb{R}} p(y, \tau) dy = 1$

iii)  $\int_{\mathbb{R}} y p(y, \tau) dy = 0$

iv)  $\int_{\mathbb{R}} y^2 p(y, \tau) dy = D(\tau)$

have to eliminate  $p(y, \tau)$  in the process of derivation to arrive at  $f(x, t)$ :

Taylor Expansion of  $f(x-y, t)$ :

$$f(x-y, t) = f(x, t) + (-y) \frac{\partial}{\partial x} f(x, t) + \frac{y^2}{2} \frac{\partial^2}{\partial x^2} f(x, t) + \dots$$

Taylor      Integration range  
Small enough  $\neq y \in \mathbb{R}$   
just ignore this imperfection

$$\therefore \int_{\mathbb{R}} \left[ f(x, t) + (-y) \frac{\partial}{\partial x} f(x, t) + \frac{y^2}{2} \frac{\partial^2}{\partial x^2} f(x, t) \right] \cdot p(y, \tau) dy = f(x, t+\tau)$$

$$\Rightarrow f(x, t) + \frac{D}{2} \frac{\partial^2}{\partial x^2} f(x, t) = f(x, t+\tau), \quad f(x, t+\tau) - f(x, t) = \frac{D}{2} \frac{\partial^2}{\partial x^2} f(x, t) \quad \frac{f(x, t+\tau) - f(x, t)}{\tau} = \frac{D}{2\tau} \frac{\partial^2}{\partial x^2} f(x, t)$$

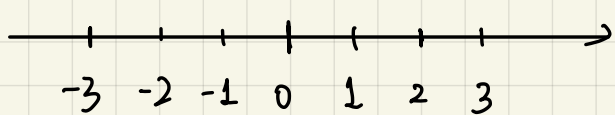
iv)  $\int_{\mathbb{R}} y^2 p(y, \tau) dy = D(\tau)$  when  $\tau \rightarrow 0$ ,  $D(\tau) \rightarrow 0$  (no time for diffusing, hence no spreading)

Suppose  $\lim_{\tau \rightarrow 0} \frac{D(\tau)}{\tau} = D \Rightarrow \frac{\partial f}{\partial t} = \frac{D}{2} \frac{\partial^2 f}{\partial x^2}$  **Diffusion Equation**

$$f(x, 0) = \delta(x) \Rightarrow f(x, t) = \frac{1}{\sqrt{2\pi Dt}} \exp\left(-\frac{x^2}{2Dt}\right)$$

Discrete Interpretation of this work:

$P(m, n)$ : position  $m$ , time  $n$ , Particle Number.



Random Walk.

$$P_{\text{left}} = P_{\text{right}} = \frac{1}{2}, \quad P(m, n+1) = ?$$

does not linger (always moving)

$$P(m, n+1) = \frac{1}{2} P(m+1, n) + \frac{1}{2} P(m-1, n)$$

**2<sup>nd</sup>-order difference on space**

$$P(m, n+1) - P(m, n) = \frac{1}{2} [P(m+1, n) - P(m, n)] - \frac{1}{2} [P(m, n) - P(m-1, n)]$$

**1<sup>st</sup> order difference on time.**

$$\frac{\partial P}{\partial t} = C \cdot \frac{\partial^2 P}{\partial x^2} \rightarrow \text{Diffusion Equation}$$

$\Downarrow$   
Gaussian Distribution

## ② Maximum Entropy:

distribution  $f(x)$ .  $f(x) \geq 0$ .  $\int_{\mathbb{R}} f(x) dx = 1$

Define Entropy for  $f(x)$ :

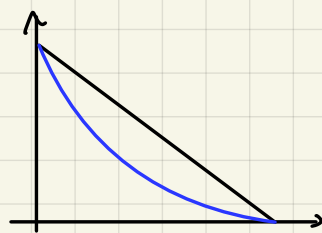
$$H(f) = - \int_{\mathbb{R}} f(x) \log f(x) dx \leftarrow \text{Measure of Randomness}$$

$\max_{f \cdot} H(f) = ?$ ,  $f(x) = ?$

Uniform Distribution only works in bounded case ( $|x| \leq B$ )

$\leftarrow$  functional analysis

eg. of functional analysis: Brachistochrone Curve



Methodology: Variational Method.

$\max_{f \cdot} H(f) \Rightarrow f_0(x)$ : optimal solution,  $g(t) = H(f_0 + t \cdot h)$   $h(x)$ : arbitrary function  
 $t \in \mathbb{R}$

Since  $f_0(x)$  is optimal,  $g(0) \geq g(t) \Rightarrow \frac{dg(t)}{dt} \Big|_{t=0} = 0$

$$g(t) = H(f_0 + t h) = - \int_{\mathbb{R}} (f_0 + t h) \log(f_0 + t h) dx \Rightarrow \text{function of } t$$

has to optimize the variance and scaling factor as well  $\Rightarrow \max_{f \cdot} H(f)$ , s.t.  $E[X] = m$ ,  $E[X^2] = 6^2$   
characterize randomness 1st, 2nd order moment

$$\therefore \max_{f \cdot} H(f), E[X] = m, E[X^2] = 6^2$$

$$L(t, \lambda_1, \lambda_2, \lambda_3) = \int_{\mathbb{R}} (f_0 + t h) \log(f_0 + t h) dx + \lambda_1 \left[ \int_{\mathbb{R}} x (f_0 + t h) dx - m \right] + \lambda_2 \left[ \int_{\mathbb{R}} x^2 (f_0 + t h) dx - 6^2 \right] + \lambda_3 \left[ \int_{\mathbb{R}} (f_0 + t h) dx - 1 \right]$$

$$\frac{\partial}{\partial t} L(t, \lambda_1, \lambda_2, \lambda_3) = 0$$

$$\frac{\partial}{\partial t} L = \int_{\mathbb{R}} (h \log(f_0 + t h) + h) dx + \lambda_1 \int_{\mathbb{R}} x \cdot h dx + \lambda_2 \int_{\mathbb{R}} x^2 \cdot h dx + \lambda_3 \int_{\mathbb{R}} h dx = 0$$

$$= \int_{\mathbb{R}} h(x) \left[ \log(f_0 + t h) + \lambda_1 x + \lambda_2 x^2 + \lambda_3 \right] dx$$

$$\frac{dg(t)}{dt} \Big|_{t=0} = 0 \Rightarrow \frac{\partial L}{\partial t} \Big|_{t=0} = 0, \therefore \forall h, \int_{\mathbb{R}} h(x) \left[ \log f_0 + \lambda_1 x + \lambda_2 x^2 + \lambda_3 \right] dx = 0$$

Gaussian

$$f_0 = \exp(-\lambda_2 x^2 - \lambda_1 x + \lambda_3) \cdot C$$

Central Limit Theorem:  $E[X_k] = 0$ ,  $E[X_k^2] = 1$ ,  $\{X_n\}$  i.i.d., Then  $\frac{1}{\sqrt{n}} \sum X_k \rightarrow N(0,1)$

Characteristic Function:  $X \sim f_X(x)$ ,  $\phi_X(\omega) = E[\exp(j\omega X)] = \int_{\mathbb{R}} \exp(j\omega x) f_X(x) dx$

$X_1, X_2$  indep.  $Y = X_1 + X_2$ ,  $Y \sim f_{X_1} * f_{X_2}$

Proof:  $f_Y = f_{X_1} * f_{X_2}$

$$\phi_Y(\omega) = E[\exp(j\omega(X_1 + X_2))] = E[\exp(j\omega X_1) \exp(j\omega X_2)] = E[\exp(j\omega X_1)] E[\exp(j\omega X_2)] = \phi_{X_1} \cdot \phi_{X_2}$$

$$\phi_Y(\omega) = \phi_{X_1} \phi_{X_2} \xleftrightarrow{\text{F.T.}} f_Y = f_{X_1} * f_{X_2}$$

CLT

$$\lim_{n \rightarrow \infty} \frac{X_1 + \dots + X_n}{\sqrt{n}}, \quad E[X_k] = 0, \quad \text{var}(X_k) = 1, \quad k = 1, \dots, n$$

$$\phi_{\frac{\sum X_k}{\sqrt{n}}} = E[\exp(j\omega \frac{\sum X_k}{\sqrt{n}})] = E[\prod_k \exp(j\frac{\omega}{\sqrt{n}} X_k)] = \prod_k E[\exp(j\frac{\omega}{\sqrt{n}} X_k)] = \prod_k \phi_{X_k}(\frac{\omega}{\sqrt{n}}) \xrightarrow{\text{i.i.d.}} [\phi_{X_1}(\frac{\omega}{\sqrt{n}})]^n$$

$$\phi_{X_1}(\frac{\omega}{\sqrt{n}}) = E[\exp(j\frac{\omega}{\sqrt{n}} X_1)] = E[1 + j\frac{\omega}{\sqrt{n}} X_1 + \frac{1}{2!} (j\frac{\omega}{\sqrt{n}} X_1)^2 + o(\frac{1}{n})]$$

$$\lim_{n \rightarrow \infty} (1 + \frac{a}{n})^n = \exp(a)$$

$$\lim_{n \rightarrow \infty} (1 + \frac{a}{n} + o(\frac{1}{n}))^n = \exp(a)$$

$$\lim_{n \rightarrow \infty} (1 + \frac{a}{\sqrt{n}} + o(\frac{1}{\sqrt{n}}))^n \text{ unknown}$$

$$= E[1 + j\frac{\omega}{\sqrt{n}} X_1 + (\frac{1}{2} - \frac{\omega^2}{n} X_1^2) + o(\frac{1}{n})]$$

$$= E[1 - \frac{\omega^2}{2} X_1^2 \cdot \frac{1}{n} + o(\frac{1}{n})]$$

$$= 1 - \frac{\omega^2}{2} \cdot \frac{1}{n} + o(\frac{1}{n})$$

$$\therefore \phi_{\frac{\sum X_k}{\sqrt{n}}} = [1 - \frac{\omega^2}{2} \cdot \frac{1}{n} + o(\frac{1}{n})]^n \xrightarrow{n \rightarrow \infty} \exp(-\frac{\omega^2}{2}) \quad \text{Gaussian}$$

Gaussian FT Pair:

$$\exp(-\frac{t^2}{2\sigma^2}) \leftrightarrow \exp(-\frac{\sigma^2}{2} \omega^2)$$

$$\phi_{\frac{X_1 + \dots + X_n}{n}}(\omega) = (\dots)^n, \quad E[X_k] = m, \quad \text{i.i.d.}$$

$$= E[1 + j\frac{\omega}{n} X + o(\frac{1}{n})]^n = [1 + j\frac{\omega}{n} m + o(\frac{1}{n})]^n \xrightarrow{n \rightarrow \infty} \exp(j\omega m)$$

Constant. m's  
characteristic func.

$$\therefore \frac{X_1 + \dots + X_n}{n} \xrightarrow{D.} m \Leftrightarrow \frac{X_1 + \dots + X_n}{n} \xrightarrow{P.} m \quad (\text{convergence to a constant})$$

$$P(X=m) = 1$$

Random Walk:

$$\xrightarrow{\frac{1}{2} \quad \frac{1}{2}} S_n = X_1 + \dots + X_n \quad X_k \sim \begin{pmatrix} \Delta x & 0 \\ \frac{1}{2} & \frac{1}{2} \end{pmatrix}$$

discrete  $\rightarrow$  continuous ( $\Delta t \rightarrow 0, \Delta x \rightarrow 0$ )

$$E[X_k] = \frac{\Delta x}{2}, \quad \text{var}(X_k) = \frac{\Delta x^2}{4}$$

$$\text{in } [0, t], \quad n = \frac{t}{\Delta t} \quad \tilde{X}_k = \frac{X_k - \frac{\Delta x}{2}}{\sqrt{\frac{(\Delta x)^2}{4}}}, \quad X_k = \frac{\Delta x}{2} \tilde{X}_k + \frac{\Delta x}{2} \Rightarrow S_n = \sum_k X_k = \frac{\Delta x}{2} \sum_k \tilde{X}_k + \frac{n \Delta x}{2} \quad \text{deterministic}$$

$$\frac{S_n - \frac{n \Delta x}{2}}{\frac{\Delta x}{2}} = \sum_1^n X_k \Rightarrow \frac{S_n - \frac{n \Delta x}{2}}{\frac{\Delta x}{2} \sqrt{n}} = \frac{\sum_1^n \tilde{X}_k}{\sqrt{n}} \xrightarrow{n \rightarrow \infty} \mathcal{N}(0, 1)$$

$$n = t/\Delta t \Rightarrow \frac{\Delta x}{2} \sqrt{n} = \frac{\Delta x}{2} \sqrt{\frac{t}{\Delta t}} = \frac{\sqrt{t}}{2} \frac{\Delta x}{\sqrt{\Delta t}} \xrightarrow{\Delta t \rightarrow 0} \sqrt{D} \quad (\text{when time slot approaches 0, } \Delta x \rightarrow 0)$$

in Diffusion (1<sup>st</sup> example),  $\frac{D(t)}{t} \xrightarrow{t \rightarrow 0} D$   $\frac{\frac{\Delta x}{2}}{\sqrt{\Delta t}} \xrightarrow[n \rightarrow \infty]{\Delta t \rightarrow 0} \sqrt{D}$ , then  $\frac{S_n - \frac{n \Delta x}{2}}{\sqrt{t} \sqrt{D}} \sim \mathcal{N}(0, 1), \quad \text{var}(S_n) = Dt$