

回顾基本的 Brown Motion

$$dx = \mu dt + \sigma dw \Leftrightarrow P(x, t) \Leftrightarrow \frac{\partial P}{\partial t} = D \frac{\partial^2 P}{\partial x^2}$$

↓
宏观过程
宏观分布
Brown motion

$$\begin{cases} \frac{\partial P}{\partial t} + \vec{v} \cdot \vec{\nabla} P = 0 \\ \vec{v} = \mu \vec{p} - \frac{1}{2} \partial_x \vec{\sigma}^2 P \end{cases} \Rightarrow \int dx p(x) = 1$$

$P(x, t) \geq 0$

如果我们已知 $p(x, t)$ ，问其对应的随机过程（逆向）更困难。
 $dx = (\) dt + (\) dw$?

上节课 ① Random Matrix \Rightarrow 随机概率分布(本征值).

$$P(\lambda_1, \lambda_2, \dots, \lambda_N) \propto \prod_{i,j} |\lambda_i - \lambda_j|^{\beta} e^{-\sum_i \lambda_i^2}$$

② Disordered many-body model

$$H = H_{\text{mean}} + H_{\text{disorder}}$$

$$\frac{\partial}{\partial t} u = A \nabla^2 u + B u^3 + \eta$$

今天 $P(\lambda_1, \lambda_2, \dots, \lambda_N) \propto \prod_{i,j} |\lambda_i - \lambda_j|^{\beta} e^{-\sum_i \lambda_i^2}$

问入步是什么样的随机过程.

① $d\lambda$ 本征值 \Rightarrow 理解为第 i 个点的位置

② 目前 P 是散射理论还是有不一样的物理意义?

$$\left\{ \begin{array}{l} d\lambda_i = \mu_i dt + \sigma_i dW_i \\ \text{找出 } \mu_i \text{ 和 } \sigma_i \end{array} \right.$$

$$\mu_i \Rightarrow \text{drift term} \quad \frac{d\lambda_i}{dt} = \vec{f} \Leftrightarrow d\vec{v} = \vec{f} dt$$

Ref: ① Mehta 随机矩阵 第九章

② Dyson 原始论文, 1962, "A Brownian Motion Model" for the eigenvalues of a Random matrix"

$$\vec{f} = C e^{-\beta W} = C \prod_{i,j} |x_i - x_j|^\beta e^{-\frac{\beta}{2k_B T} \sum_i x_i^2}$$

$$W = - \sum_{i,j} \ln(|x_i - x_j|) + \underbrace{\sum_i \frac{1}{2k_B T} x_i^2}_{\text{Potential}} \quad \text{Potential}$$

$$\text{Coulomb gas model.} \quad \bar{E}(x_i) = -\frac{\partial W}{\partial x_i}$$

$$\frac{d^2 x_i^2}{dt^2} = -\frac{d\lambda_i}{dt} + \bar{E}(x_i) + A(x_i)$$

↑ ↑
外力 随机力

$$\beta = \frac{1}{k_B T}$$

$$\langle \lambda_i(t) \lambda_j(t') \rangle = \frac{2k_B T}{\pi} \delta_{ij} \delta(z - z')$$

代入 Boltzmann-Planck equation

$$f \frac{\partial P}{\partial t} = \sum_i k_B T \frac{\partial^2 P}{\partial x_i^2} - \frac{\partial}{\partial x_i} (\bar{E}(x_i) P)$$

稳定解 $\frac{\partial P}{\partial t} = 0$

$$\Rightarrow \sum_i \frac{\partial}{\partial x_i} [k_B T \frac{\partial^2 P}{\partial x_i^2} - \bar{E}(x_i) P] = 0$$

$$k_B T \frac{\partial^2 P}{\partial x_i^2} = \bar{E}(x_i) P$$

$$\Rightarrow \bar{E}(x_i) = - \frac{\partial \ln P}{\partial x_i}$$

$$d\lambda_{\nu} = \sqrt{\frac{2}{\beta N}} d\omega_{\nu} + \frac{1}{N} \sum_{j=0}^{N-1} \frac{dx_j}{(x_j - k_j)}$$

$$\text{Dyson} \Rightarrow \begin{cases} f(\delta x_i) = \bar{E}(x_i) \delta x_i \\ f(\delta x_i^2) = 2k_B T \delta x_i \end{cases}$$

下面讨论一个有趣的图像

$$\left\{ \begin{array}{l} \text{矩阵} \\ M = (M_{ij})_{\mu \times \alpha} \Rightarrow \text{元素 } M_{ij}, \mu = 1, \dots, \alpha \\ P(M_1, \dots, M_\alpha) dM_1 dM_2 \dots dM_\alpha \text{ 为 } [M_1, M_1 + dM_1] \text{ 之测度} \end{array} \right.$$

$$\left\{ \begin{array}{l} f(\delta \mu_{\mu}) = -\mu_{\mu}/a^2 \delta t \\ f(\delta \mu_{\mu}^2) = g_{\mu} k_B T \delta t \end{array} \right. \quad \mu_{\mu} = \text{const}$$

$$f \frac{\partial P}{\partial t} = \tilde{\mu} \left[\frac{1}{2} k_B T \mu_{\mu} \frac{\partial^2 P}{\partial \mu_{\mu}^2} + \frac{1}{a^2} \frac{\partial}{\partial \mu_{\mu}} (\lambda_{\text{exp}}) \right]$$

假设 μ 变化 $\Rightarrow t + \delta t$, $\mu \rightarrow \mu + \delta \mu$

$\lambda_{\text{eff}} = \lambda_i$ 是在 t 时的本征值.

$$t \rightarrow t + \delta t \quad \lambda_i' = \lambda_i + \delta \lambda_i$$

不用 = PT Perturbation

$$\delta \lambda_i = \delta \mu_{\mu} + \tilde{\mu} \left(\frac{|\delta \mu_{\mu}|^2}{\lambda_i - \lambda_j} \right)$$

$$\delta \lambda_i = \left(\dots \delta \mu_{\mu} + \tilde{\mu} \left(\frac{13 \delta t}{\lambda_i - \lambda_j} \right) \right)$$

$\lambda_i = \text{所求的解}$

$|\lambda_i - \lambda_j|^{\beta}$ 因子.