

I. Wigner 半圆.

$$(\Omega, \mathcal{F}, P) \quad X: \Omega \rightarrow \mathbb{R}(\mathbb{C})$$

$$\downarrow$$

$$\text{Mat}_{\infty}(\mathbb{R}) \subset \mathbb{C}$$

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样本
协方差矩阵

$$X_i = \begin{pmatrix} x_{i1} \\ \vdots \\ x_{pi} \end{pmatrix}$$

$$W = \frac{1}{n} \sum X_i X_i^T = \frac{1}{n} \sum_i (x_{ji} x_{ki})_{jk}.$$

$$= \frac{1}{n} X X^T \quad (X = (X_1 \dots X_p))$$

这里 $X_{ij} \sim N(0,1)$ iid X 联合密度为 $\prod_j \prod_i \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2} x_{ij}^2} = \frac{1}{(2\pi)^n} e^{-\frac{1}{2} \text{tr}(X X^T)}$

谱的渐近行为.

$\text{Tr}(H^k) \rightarrow$ 对称多项式 $\rightarrow$ 矩方法

定义 1.1 $A_n = (a_{ij})_n$ 对称

(1) a_{ij} 相互独立

$[a_{ii}] \sim Y, [a_{ij}] \sim Z.$

(2) 规格化 $E[Y] = E[Z] = 0, \text{Var}(Y) < \infty, \text{Var}(Z) = 1$

(3) $\forall k \geq 3, E[Y^k], E[Z^k] < \infty$

定理 1.2 $\forall k \in \mathbb{N}, \frac{1}{n} E[(\sum_{i=1}^n a_{ii})^k] \rightarrow \begin{cases} \frac{1}{m+1} \binom{2m}{m} & k=2m \\ 0 & k=2m+1 \end{cases}$ as $n \rightarrow \infty$

Remark 当 $k=2$ 时 $n E[a_{ij}^2] \sim n^2$

$$\int_{-2}^2 \frac{x^k}{\sqrt{4-x^2}} dx$$

Proof: 证明仍是组合配对

$$E[\text{tr} A_n^k] = \sum_{(i_1, \dots, i_k)} E[a_{i_1 i_2} \dots a_{i_k i_1}]$$

~~先假定 $i_2 = i_1, i_3 \neq i_1, i_4 \neq i_1, i_5 \neq i_1$~~

$$\Rightarrow a_{i_1 i_2} a_{i_2 i_3} \dots a_{i_k i_1}$$

一些组合的算法, 要自由度大的贡献大 $\Rightarrow i_1, \dots, i_k$ 成环, $(\frac{k}{2})$

这个对应到合法 (1) 表示. $\rightarrow$ Catalan 数 $\frac{1}{n+1} \binom{2n}{n}.$

非正规矩阵

2.

$$\text{GOE: } X_n(\omega) = (X_{ij}(\omega))_{ij} \quad A_n = \frac{1}{2}(X_n + X_n^T)$$

$$\Rightarrow a_{ij} = a_{ji} \sim N(0, \frac{1}{2}\sigma^2) \quad a_{ii} \sim N(0, \sigma^2)$$

$$dA_n = \pi da_{ii} \prod_{i < j} da_{ij} \quad f = 2^{-\frac{1}{2}} (\pi \sigma^2)^{-\frac{1}{4}n(n+1)} \exp(-\frac{1}{2\sigma^2} \text{tr} A_n^2) dA_n$$

GOE在正交变换下不变

$$\text{GUE} \quad X_{ij} = N(0, \sigma^2) + i N(0, \sigma^2)$$

$$A_n = \frac{1}{2}(X_n + X_n^H) \quad f = 2^{-\frac{n}{2}} (\pi \sigma^2)^{-\frac{n^2}{2}} \exp(-\frac{1}{2\sigma^2} \text{tr} A_n^2) dA_n$$

转换为特征值联合密度

$$\boxed{\text{Thm}} \quad A_n \sim \text{GOE}_n(\sigma) \quad \text{联合密度 } p(\lambda_1, \dots, \lambda_n) = \frac{1}{G_n} \exp(-\frac{1}{2\sigma^2} \sum_{j=1}^n \lambda_j^2) \prod_{j < k} |\lambda_j - \lambda_k|$$

其中 $\lambda_1, \dots, \lambda_n$ 为特征值

$$\text{这里 } G_n = (2\pi)^{\frac{n}{2}} \sigma^{\frac{1}{2}n(n+1)} \prod_{k=1}^n \frac{\Gamma(1+\frac{k}{2})}{\Gamma(1+\frac{1}{2})}$$

$$\text{proof. } X = R A R^T \quad R^T R = I \quad \Lambda = \text{diag}(\lambda_1, \dots, \lambda_n)$$

R 有 $p_1, \dots, p_l$ ($l = \frac{n(n-1)}{2}$ 个) 不同的变量

$$\frac{\partial X}{\partial \lambda_Y} = R \frac{\partial \Lambda}{\partial \lambda_Y} R^T \Rightarrow R^T \frac{\partial X}{\partial \lambda_Y} R = \frac{\partial \Lambda}{\partial \lambda_Y}$$

$$\Rightarrow \left[\sum_{j,k} r_{j\alpha} \frac{\partial x_{jk}}{\partial \lambda_Y} r_{k\beta} = \delta_{\alpha\beta} \delta_{\alpha Y} \right]$$

$$\left[\frac{\partial X}{\partial p_\mu} = \frac{\partial R}{\partial p_\mu} \Lambda R^T + R \Lambda \frac{\partial R^T}{\partial p_\mu} \right]$$

$$\Rightarrow R^T \frac{\partial X}{\partial p_\mu} R = S^{(\mu)} \Lambda - \Lambda S^{(\mu)}$$

$$\text{其中 } S^{(\mu)} = R^T \frac{\partial R}{\partial p_\mu} = -\frac{\partial R^T}{\partial p_\mu} R$$

$$\rightarrow \sum_{j,k} r_{j\alpha} \frac{\partial x_{jk}}{\partial \lambda_Y} r_{k\beta} = S_{\alpha\beta}^{(\mu)} (\lambda_\beta - \lambda_\alpha)$$

$$\text{接下来一步我不证. 反正 } |J| = \prod_{\alpha < \beta} |\lambda_\beta - \lambda_\alpha| f(p_1, \dots, p_l)$$

[Thm] 设 $A_n \sim \text{GUE}_n$ 记 $x_1, \dots, x_n$ 为 A_n 的特征值. 其联合密度为

$$p_n(x_1, \dots, x_n) = \frac{1}{C_n} \exp\left(-\frac{1}{2} \sum x_i^2\right) \prod (x_i - x_j)^2$$

$$C_n = (2\pi)^{\frac{n}{2}} \prod_{j=1}^n \frac{\Gamma(1+j)}{\Gamma(2)}$$

矩阵版 $p_n = \frac{1}{Z_n} \exp\left(-\frac{\beta}{4} \sum \lambda_i^2\right) |\Delta_n|^\beta$

GOE $\Rightarrow \beta=1$ $Z_n = (2\pi)^{\frac{n}{2}} \left(\frac{2}{\beta}\right)^{\frac{1}{2}n + \frac{\beta}{4}n(n-1)} \prod \frac{\Gamma(1+\frac{\beta}{2}j)}{\Gamma(1+\frac{\beta}{2})}$
 GUE $\Rightarrow \beta=2$

GUE 关系式

$$K_n(x, y) = \sum_{k=0}^n \frac{1}{k!} h_k(x) h_k(y) \sqrt{\phi(x)\phi(y)}$$

$\phi(x) = \frac{1}{\sqrt{\pi}} \exp(-\frac{1}{2}x^2)$ $h_k(x)$ 是 Hermite 多项式

$h_0(x)=1$, $h_k(x)\phi(x) = (-1)^k \frac{d^k}{dx^k} \phi$

Hermite 多项式有正交关系 $\int_{-\infty}^{\infty} h_i(x) h_j(x) \phi(x) dx = j! \delta_{ij}$

此时 $\int K_n(x, x) dx = n$, $\int K_n(x, y) K_n(y, z) dy = K_n(x, z)$

k 点关系函数 $p_n^{(k)} = \frac{n!}{(n-k)!} \int \dots \int p_n(\lambda) d\lambda_{k+1} \dots d\lambda_n$

[Thm] 1) $p_n(N) = \frac{1}{n!} \det [K_n(\lambda_i, \lambda_j)]_{i,j=1}^n$

2) $p_n^{(k)}(\lambda_1, \dots, \lambda_k) = \det [K_n(\lambda_i, \lambda_j)]_{i,j=1}^k$

3) 区间 $I \subseteq \mathbb{R}$ 内不含特征值的概率为

$$P(\lambda_j \in I^c, \forall j) = 1 + \sum \frac{(-1)^k}{k!} \int_I \dots \int_I \det [K_n(\lambda_i, \lambda_j)]_{i,j=1}^k d\lambda_1 \dots d\lambda_k$$

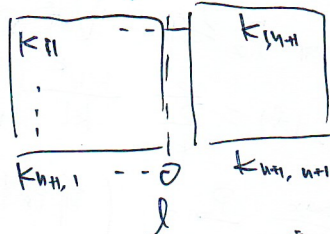
Dyson lemma

$$\int_{\mathbb{R}} \det [K_n(\lambda_i, \lambda_j)]_{i,j=1}^{k+1} d\lambda_{k+1} = (n-k) \det [K_n(\lambda_i, \lambda_j)]_{i,j=1}^k$$

$\det [K_n(\lambda_i, \lambda_j)]_{i,j=1}^{k+1} \xrightarrow{\text{Laplace}} \det [K_n(\lambda_i, \lambda_j)]_{i,j=1}^k K_n(\lambda_{k+1}, \lambda_{k+1})$

⑦

系数为 1?



并不难. 熟悉就爱



4. 想考入 max 的根号 以下使用拿拿主义看得到

Hermite 多项式:
$$h_k = \frac{1}{\sqrt{k!}} \int_{\mathbb{R}} (it)^k \exp[-\frac{1}{2}(t-ix)^2] dt$$

$$x h_k = h_{k+1} + k h_{k-1} \quad x h_k = h_{k+1} + h_k'$$

$$h_k'' - x h_k' + k h_k = 0$$

C-D:
$$x \neq y: \sum_{k=0}^{\infty} \frac{1}{k!} h_k(x) h_k(y) = \frac{h_n(x) h_{n+1}(y) - h_{n+1}(x) h_n(y)}{(n-1)! (x-y)}$$

$$\sum_{k=0}^{\infty} \frac{1}{k!} h_k(x) h_k(x) = h_n(x)$$

$$x=y \text{ 的极限写的很奇怪, 应该是}$$

$$h_k(x+t) = \sum_{j=0}^k \binom{k}{j} h_j(x) t^{k-j}$$

简谐振子波函数

$$x \psi_k = \sqrt{k+1} \psi_{k+1} + \sqrt{k} \psi_{k-1}$$

$$\psi_k' = -\frac{x}{2} \psi_k + \sqrt{k} \psi_{k-1}$$

$$-\psi_k'' + \frac{x^2}{4} \psi_k = (k+\frac{1}{2}) \psi_k$$

$$x \neq y \quad \text{C-D: } K_n(x, y) = \frac{\psi_n(x) \psi_{n+1}'(y) - \psi_{n+1}(y) \psi_n'(x)}{x-y}$$

$$= \frac{1}{2} \psi_n(x) \psi_n(y)$$

定义
$$K_{Ai}(x, y) = \frac{Ai(x) Ai'(y) - Ai'(x) Ai(y)}{x-y}$$

$$Ai(z) = \frac{1}{2\pi i} \int_{\infty-i\infty}^{\infty} e^{z^3/3 + \frac{1}{2} \omega^2} d\omega$$

Airy 统计:
$$\lim_{n \rightarrow \infty} \frac{1}{n^{2/3}} \left(\frac{K_n \left(\sqrt{n} \left(2 + \frac{x}{n^{1/3}} \right), \sqrt{n} \left(2 + \frac{y}{n^{1/3}} \right) \right)}{n^{1/3}} \right) = \det (K_{Ai}(\hat{x}, \hat{y}))_{ij}$$

Idea 将 Ai 取化到有波函数的形式

$$\hat{K}_n(\hat{x}, \hat{y}) = \frac{1}{n^{2/3}} K_n \left(\sqrt{n} \left(2 + \frac{\hat{x}}{n^{1/3}} \right), \sqrt{n} \left(2 + \frac{\hat{y}}{n^{1/3}} \right) \right)$$

$$\hat{\psi}_n(\hat{x}) = n^{1/2} \psi_n \left(\sqrt{n} \left(2 + \frac{\hat{x}}{n^{1/3}} \right) \right)$$

要 $\lim_{n \rightarrow \infty} \hat{\psi}_n(\hat{x}) = Ai(\hat{x})$

用 laplace 鞍点方法(最合) $\Rightarrow$ 喂算 ψ ✓

Tracy-Widom F_2 分布: $\forall t \in \mathbb{R} \quad \lim_{n \rightarrow \infty} P(\lambda_{\max} \leq \sqrt{n} (2 + \frac{t}{n^{1/3}})) = F_2(t)$

$$F_2(t) = \sum_{k=0}^{\infty} \frac{(-1)^k}{k!} \int_t^{\infty} \dots \int_t^{\infty} \det [K_{Ai}(x_i, x_j)]_{i,j=1}^k dx_1 \dots dx_k$$

推论 $\frac{\lambda_{\max}}{\sqrt{n}} \xrightarrow{P} 2$. (前情提要 $P(\lambda_{\max} \leq a_n y + b_n) = 1 + \sum_{k=1}^{\infty} \frac{(-1)^k}{k!} \int_y^{\infty} \dots \int_y^{\infty} \dots$)

Friedholm 行列式

Ising 模型. 1 维周期序

Gibbs 测度 $\mu_{\Lambda; \beta; h}(\sigma) = \frac{1}{Z_{\Lambda; \beta; h}} e^{-\beta H(\sigma)}$

$H(\sigma) = \sum_{\langle i, j \rangle} \sigma_i \sigma_j - h \sum_i \sigma_i$
 相邻格点 $\uparrow$ 自旋

Λ 是有限格点集 $= [1, L]^d \subseteq \mathbb{Z}^d$
 σ_i 在构形空间 $\{-1, 1\}$ 中

磁化强度 $M_{\Lambda}(\sigma) = \sum_{i \in \Lambda} \sigma_i$

$Z_{\Lambda; \beta; h}$ 是配分函数 $= \sum_{\sigma_1, \dots, \sigma_N = \pm 1} \exp(\beta \sum_{\langle i, j \rangle} \sigma_i \sigma_j + h \sum_i \sigma_i)$

将 $\mu_{\Lambda; \beta; h}$ 矩阵化
 转移矩阵 $P = \begin{pmatrix} e^{\beta J + \beta h} & e^{-\beta J} \\ e^{-\beta J} & e^{\beta J - \beta h} \end{pmatrix}$

用 $\langle \sigma | P | \sigma' \rangle$ 表示 σ, σ' 之间的转移

$\Rightarrow \langle \sigma | P | \sigma' \rangle = \exp\left(\frac{1}{2}(\sigma + \sigma')\beta h + \beta J \sigma \sigma'\right)$

$\Rightarrow Z_{\Lambda; \beta; h} = \sum_{\sigma_1, \dots, \sigma_N = \pm 1} \prod_{i=1}^N \exp\left(\frac{1}{2}(\sigma_i + \sigma_{i+1})\beta h + \beta J \sigma_i \sigma_{i+1}\right)$

转移矩阵 $= \sum_{\sigma_1, \dots, \sigma_N = \pm 1} \prod_{i=1}^N \langle \sigma_i | P | \sigma_{i+1} \rangle$
 $\downarrow$
 $= \text{tr}(P^N)$

$\Lambda_+ := e^{\beta J} A_+(h)$

$\Lambda_- := e^{\beta J} A_-(h)$

$\Rightarrow Z_{\Lambda; \beta; h} = e^{\beta J N} (A_+^N + A_-^N)$

$E\left[\frac{M_N(\sigma)}{N}\right]$ 是什么 $= \sum_{\sigma \in \Omega} \frac{M_N(\sigma)}{N Z_{\Lambda; \beta; h}} \exp(-\beta H(\sigma))$

$\frac{\partial}{\partial h} \log Z_{\Lambda; \beta; h} = \frac{1}{Z_{\Lambda; \beta; h}} \sum_{\sigma} \frac{\partial}{\partial h} \exp(\beta M(\sigma)) \exp(-\beta H(\sigma))$

$\Rightarrow E\left[\frac{M_N(\sigma)}{N}\right] = \frac{1}{\beta N} \frac{\partial}{\partial h} \log Z_{\Lambda; \beta; h}$

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$$\begin{aligned}
 E\left[\frac{M_N(t)}{N}\right] &= \frac{1}{\beta N \delta h} \log \sum_{N_i} \beta_i h \quad \sum_{N_i} \beta_i h = e^{\beta J N} (A_+^N + A_-^N) \\
 &= \frac{1}{\beta h} \frac{\partial}{\partial h} \left[\beta J N + \log(A_+^N + A_-^N) \right] \\
 &= \frac{1}{\beta(A_+^N + A_-^N)} \left(A_+^N \frac{\partial}{\partial h} A_+ + A_-^N \frac{\partial}{\partial h} A_- \right) \quad \text{IR } N \text{ var.} \\
 &\sim \frac{1}{\beta \left(1 + \left(\frac{A_-}{A_+} \right)^N \right)} \frac{1}{A_+} \frac{\partial}{\partial h} A_+ \quad \beta \left(h + \frac{t}{\beta N \delta} \right) \\
 &= \frac{1}{\beta A_+} \frac{\partial}{\partial h} A_+
 \end{aligned}$$

用矩母函数 $E\left[\exp\left(\frac{t}{N\delta} M_N\right)\right]$ $\beta = 1, \frac{1}{2}$

可以导出 WLLN & CLT.

Curie-Weiss 模型

$$\Lambda = [1, L]^d$$

平均场近似: $\sum_{j \in \Lambda} \sigma_j \sigma_i = 2d \sigma_i \frac{1}{2d} \sum_{j \in \Lambda} \sigma_j \approx \underbrace{(2d)}_{\text{相邻数}} \sigma_i \frac{1}{|\Lambda|} \sum \sigma_j$

$$\begin{aligned} \bar{\beta} H(\sigma) &= -J \sum_{i \sim j} \sigma_i \sigma_j - h \sum_{i \in \Lambda} \sigma_i \\ &\approx -\frac{Jd}{N} \left(\sum_{i=1}^N \sigma_i \right)^2 - h \sum_{i=1}^N \sigma_i \end{aligned}$$

C-W模型的 Gibbs 测度

$$\mu_{\Lambda, \beta, h}(\sigma) = \frac{1}{Z_{\Lambda, \beta, h}} \exp(-\beta H(\sigma))$$

$$Z_{\Lambda, \beta, h} = \sum_{\sigma} \exp(-\beta H(\sigma)) \quad \text{临界逆温度}$$

定理 LLN 意义下: $\beta_c = \frac{1}{2d} h=0$. $M_N = \frac{1}{N} \sum \sigma_i$

1) 当 $\beta \in (0, \beta_c]$, $\forall \varepsilon > 0 \exists C_1 = C_1(\beta, N)$ s.t.

高温

$$\mu_{N, \beta, 0}(|\frac{M_N}{N}| \geq \varepsilon) \leq 2e^{-C_1 N}$$

2) 当 $\beta \in (\beta_c, \infty)$, 存在自发磁化强度 $m^* = m^*(\beta) > 0$, s.t. $\forall \varepsilon > 0, \exists C_2 = C_2(\beta, \varepsilon) > 0$ 对充分大的 N 有

$$\mu_{N, \beta, 0}(|\frac{M_N}{N} - m^*| \geq \varepsilon) \leq 2e^{-C_2 N}$$

lim: $\frac{M_N}{N} \rightarrow \begin{cases} \delta_0 & \beta \leq \beta_c \\ \frac{1}{2}(\delta_{m^*} + \delta_{-m^*}) & \beta > \beta_c \end{cases}$

引理 1. 自由能函数 $f_{\beta}(m) = -\beta d m^2 - S(m)$ $m \in [-1, 1]$

$$S(m) = -\frac{1+m}{2} \log \frac{1+m}{2} - \frac{1-m}{2} \log \frac{1-m}{2}$$

β 是逆温
 $dm^2 - \frac{1}{\beta} S$ 物理中的
 $E(m) - TS(m)$ 自由能
 m^* 就是自由能极小
 $\Rightarrow$ 最可能的宏观态

$$\text{则有 } \lim_{N \rightarrow \infty} \frac{1}{N} \log Z_{N, \beta, 0} = -\min_{m \in [-1, 1]} f_{\beta}(m)$$

$$\text{更一般地 } k \in [-1, 1] \log \frac{1}{N} \log \mu_{N, \beta, 0}(\frac{M_N}{N} \in k) = -\min_{m \in k} f_{\beta}(m) + \min_{m \in [-1, 1]} f_{\beta}(m)$$

$$\text{证. } A_N = \left\{ -1 + \frac{2k}{N} \mid k=0, \dots, N \right\}$$

$$\mu_{N, \beta, 0}(\frac{M_N}{N} \in k) = \frac{1}{Z_{N, \beta, 0}} \sum_{m \in k} \binom{N}{\frac{(1+m)N}{2}} e^{\beta d m^2 + \beta h m N} \quad \mathbb{I} = mN$$

反解 k

证明 $\lim_{N \rightarrow \infty} \frac{1}{N} \log Z_{N,\beta;0} = -\min_{m \in [1,1]} f_{\beta}(m)$

有 $\Delta \leq Z_{N,\beta;0} \leq (N+1) \Delta$ ①, $\Delta := \max_{m \in A_N} \binom{N}{(1+m)N/2} \exp(\beta d m^2 N)$

$\frac{C_1}{\sqrt{N}} \exp(N \overline{f_{S(m)}}) \leq \binom{N}{(1+m)N/2} \leq \frac{C_2 \sqrt{N}}{\sqrt{N}} \exp(N \overline{f_{S(m)}})$ ②

$\forall \lambda \Rightarrow \downarrow \beta$:

$$\begin{aligned} Z_{N,\beta;0} &\leq (N+1) \sqrt{N} \frac{C_2}{\sqrt{N}} \exp \left(N \overline{f_{S(m)}} + \beta d m^2 N \right) \\ &\leq C_2 (N+1) \sqrt{N} \exp \left(-N \min f_{\beta} \right) \end{aligned}$$

$\Rightarrow \limsup \frac{1}{N} \log Z_{N,\beta;0} \leq -\min f_{\beta}$

$\exists m^* = \min f_{\beta}$

$N \Rightarrow \forall \delta. |f_{\beta}(m) - f_{\beta}(m^*)| < \delta \quad \exists m \in A_N$

$Z_{\beta;N;0} \geq \frac{C_1}{\sqrt{N}} \exp N \left(-\min f_{\beta} + \delta \right)$

$\frac{1}{N} \log Z_{\beta;N;0} > -\min f_{\beta}(m^*) - \delta \quad \delta \rightarrow 0. \quad \square$

$\bar{f}_{\beta}: f'_{\beta}(m) = -2\beta d m + \frac{1}{2} \log \frac{1+m}{1-m} \quad I_{\beta} = f_{\beta}(m) - \min_{m \in [1,1]} f'_{\beta}(m)$
 $f''_{\beta}(m) = -2\beta d + \frac{1}{1-m^2}$

$\boxed{2\beta d \leq 1} \quad f'' \geq 0 \quad f'_{\beta}(m) = 0 \quad \text{解为 } m=0$



$K = [1-\varepsilon] \cup [\varepsilon, 1]$. 最大值为 $C_1(\beta, \varepsilon) > 0$

$\frac{1}{N} \log \mu_{N,\beta;0} \left(\frac{M_N}{N} \in K \right) \leq -C_1$

$\Rightarrow \mu_{N,\beta;0} \left(\left| \frac{M_N}{N} \right| \geq \varepsilon \right) \leq 2e^{-C_1 N}$

$2\beta d > 1 \quad m = \pm \sqrt{1 - \frac{1}{2\beta d}} = \pm m^* \quad K = [-1, 1] \setminus (B(m^*, \varepsilon) \cup B(-m^*, \varepsilon))$

□

CLT: of G-W model

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$$\beta_c = \frac{1}{2d} \quad \mu=0 \quad M_N = \sum_{i=1}^N \sigma_i$$

$$(1) \beta < \beta_c \quad \sqrt{\frac{1-2\beta d}{N}} M_N \xrightarrow{D} N(0,1)$$

$$(2) \beta \geq \beta_c \quad \frac{M_N}{N^{\frac{1}{2d}}} \xrightarrow{D} Y \quad f_Y(y) = \frac{1}{C} e^{-\frac{1}{2} y^2}$$

$$\text{证: } M(t) = E\left[\exp\left(t \frac{M_N}{N^{\frac{1}{2d}}}\right)\right] = \frac{Z_{N;\beta,h}}{Z_{N;\beta,0}} \quad h = \frac{t}{\beta N^{\frac{1}{2d}}} \quad (\text{L-节投材})$$

$$Z_{N;\beta,h} = \sum_{\sigma_i} \exp\left(\frac{\beta d}{N} \left(\sum_{i=1}^N \sigma_i\right)^2 + \beta h \sum_{i=1}^N \sigma_i\right)$$

处理=次项! H-S变换 $e^{ax^2} = \frac{1}{\sqrt{\pi a}} \int dy \exp\left(-\frac{y^2}{2a} + 2xy\right)$

$$\begin{aligned} \Rightarrow Z_{N;\beta,h} &= \sqrt{\frac{N}{\pi \beta d}} \int \sum_{\sigma_i} \exp\left(-\frac{N}{\beta d} y^2 + (2y + \beta h) \sum_{i=1}^N \sigma_i\right) dy \\ &= \sqrt{\frac{N}{\pi \beta d}} \int dy \left(\exp(2y + \beta h) + \exp(-2y - \beta h)\right)^N \exp\left(\frac{N}{\beta d} y\right) dy \\ &= \sqrt{\frac{N}{\pi \beta d}} \int dy \exp\left(-\frac{\beta h^2 N}{4d} + \frac{hN}{2d} y - N g(y)\right) \end{aligned}$$

$$y \mapsto \frac{y - \beta h}{2} \quad g(y) = \frac{1}{4\beta d} y^2 - \log(e^y + e^{-y})$$

$$\text{证: } \frac{1}{N} \ln M(t) = \int_{\mathbb{R}} \exp\left(\frac{N^{-\frac{1}{2d}} t y}{2\beta d} - N g(y)\right) dy$$

$$M(t) = \exp\left(-\frac{N^{-\frac{1}{2d}} t^2}{4\beta d}\right) \frac{I_N(t)}{I_N(0)}$$

$$g'(y) = \frac{y}{2\beta d} - \frac{e^y - e^{-y}}{e^y + e^{-y}} \quad \left. \begin{array}{l} 2\beta d \leq 1 \quad y_0=0 \text{ 为 } g \text{ 之零} \\ \beta < \beta_c \quad \beta = \frac{1}{2} \end{array} \right\}$$

$$g''(y) = \frac{1}{2\beta d} - \frac{4e^{2y}}{(e^y + 1)^2} \quad I_N(t) \sim e^{-N g(0)} \int_{-\infty}^{\infty} \exp\left(\frac{1}{\beta d} N^{\frac{1}{2}} t y - \frac{N}{2} \left(\frac{1}{\beta d} - 1\right) y^2\right) dy$$

$$\sim e^{-N g(0)} \frac{1}{\sqrt{N}} \cdot 2 \sqrt{\frac{\pi \beta d}{1-2\beta d}} \exp\left(\frac{t^2}{4\beta d(1-2\beta d)}\right) \quad y_0 < c1$$

$$\Rightarrow M(t) \rightarrow e^{\frac{1}{2} (bt)^2} \quad b = \frac{1}{\sqrt{1-2\beta d}}$$

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$$\beta = \beta_c. \quad S = \frac{3}{\phi}$$

$$g(y) - g(y_0) = \frac{1}{12} y^4 \quad \text{比较难算}$$

李杨单位圆

铁磁模型 $H(\sigma) = -\sum_{i,j} J_{ij} \sigma_i \sigma_j - h \sum_{i=1}^N \sigma_i$

逆温度 $\beta \geq 0$ 铁磁耦合 J_{ij} 令 $J = J_{ij} \Rightarrow$ Ising 模型

指标 $[N] = \{1, \dots, N\}$; $\sigma = (\sigma_1, \dots, \sigma_N)$

$X(\sigma) = \{i \in [N] : \sigma_i = -1\}$

$Z_{N,\beta,h} = \sum_{\sigma} \exp \left(\beta \sum_{i,j} J_{ij} \sigma_i \sigma_j + \beta h \sum_{i=1}^N \sigma_i \right)$

$= \exp \left(\beta h N + \beta \sum_{i,j} J_{ij} \right) \cdot \sum_{\sigma} \exp \left(\beta h \sum_{i=1}^N (\sigma_i - 1) + \beta \sum_{i,j} J_{ij} (\sigma_i - 1)(\sigma_j - 1) \right)$

$= \exp \left(\beta h N + \beta \sum_{i,j} J_{ij} \right) \cdot \sum_{X \subseteq [N]} z^{|X|} \prod_{i \in X} \prod_{j \notin X} a_{ij}$

$z = e^{-2\beta h}$
 $a_{ij} = a_{ji} = e^{-2\beta J_{ij}}$

杨引入多项式 $P_A(z_1, \dots, z_N) = \sum_{S \subseteq [N]} z^{|S|} \prod_{i \in S} \prod_{j \notin S} a_{ij}$

$\left[z^{|S|} \prod_{i \in S} z_i \right]$

李杨单位圆定理 $A = (a_{ij})_{i,j}^N$ Hermita $|a_{ij}| \leq 1 \Rightarrow \forall |z_i| \leq 1 \quad i=1, \dots, N$

$P_A(z_1, \dots, z_N) \neq 0$

Proof 1: $\forall N$ 归纳, 没看懂.

$P_A(z_1, \dots, z_N) = \sum_{S \subseteq [N]} z^{|S|} \prod_{i \in S} \prod_{j \notin S} a_{ij} + \sum_{S \subseteq [N]} z^{|S|} \prod_{i \in S} \prod_{j \notin S} a_{ij}$

Proof 2: ~~form 1: $a \in [-1, 1]$~~ $\checkmark$ 类: (1) $P_1(z_1) \neq 0$ ($J \leq 1$) 的等次多项式非零
(2) $|z_i| < 1, P_1(z_1) \neq 0$ (李杨性)

(2.1) $a \in [-1, 1] \Rightarrow P(z_1, z_2) = z_1 z_2 + a(z_1 + z_2) + 1 \in \mathcal{A}$

$\Rightarrow P_i(z_i) \in \mathcal{A}, P_j(z_j) \in \mathcal{A} \Rightarrow P_{I \cup J}(z_{I \cup J}) := P(z_i)P(z_j) \in \mathcal{A}$
 $I \cap J = \emptyset$

(3) Asano 缩并: $I \cap J \neq \emptyset$

$P_{I \cup J}(z_{I \cup J}) = A z_i z_j + B z_i + C z_j + D$

A, B, C, D 是 z_i 多项式

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对 $r \neq 1$ 定义 $\Phi_{I \cup \{r\}}(z_{I \cup \{r\}}) = Az_r + D$

则 $P_{I \cup \{r\}}(z_{I \cup \{r\}}) \in \mathcal{A} \Rightarrow P_{I \cup \{r\}}(z_{I \cup \{r\}}) \in \mathcal{A}$

因为 $|\frac{D}{A}| \geq 1$

不知道啥情况, 反证 $\prod_{i < j} A_{ij} \xrightarrow{A_{\text{same}}} P(z_1, \dots, z_N)$

讨论结论得3.

清偏其本: $M_X(h) = E[\exp hX] = z^{-\frac{N}{2}} \frac{P(z, \dots, z)}{P(1, \dots, 1)} \Leftrightarrow$
 $z = e^{-2\beta h}$

$\Rightarrow M_X(h)$ 只有纯虚数点.

复习与补缺

1. Wigner 矩阵与半圆律

$$\begin{cases} A_n = (a_{ij})_{i,j=1}^n & a_{ij} = a_{ji} \\ a_{ii} \sim Y, a_{ij} \sim Z & E[Y]=0=E[Z] \quad \text{Var}(Y) < \infty \quad \text{Var}(Z)=1 \\ Y, Z \text{ 高阶矩存在} \end{cases}$$

$$\lim_{n \rightarrow \infty} E \left[\frac{1}{n} \text{tr} \left(\frac{A_n}{\sqrt{n}} \right)^k \right] \longrightarrow \gamma_k \quad \gamma_k = \begin{cases} \frac{1}{m+1} \binom{2m}{m} & k=2m \\ 0 & k=2m+1 \end{cases}$$

$$\int_{-2}^2 \frac{x^k}{2\pi} \sqrt{4-x^2} dx$$

$$\text{LHS} = \lim_{n \rightarrow \infty} \frac{1}{n^{\frac{k}{2}+1}} \sum_{i_1, \dots, i_k} a_{i_1 i_2} \dots a_{i_{k-1} i_k} a_{i_k i_1}$$

自由度大 $\rightarrow$ 贡献大
主项

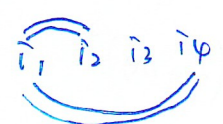
项数计算: 计算可见 顶点有 $\frac{k}{2}+1$ 个 $(k \text{ 偶})$
 $\parallel$
 $2m$

$(i_1, i_2, \dots, i_{2m})$ 中 ~~至少~~ 2 人, $m+1$ 个顶点

$k=4$ 时

$$a_{i_1 i_2} a_{i_2 i_3} a_{i_3 i_4} a_{i_4 i_1}$$

$i_3 = i_1$



$$i_1 i_2 i_1 i_4$$

$k=6$ 时



总之, 对应到非交叉图

$$\overline{i_1 i_2 i_3 i_4} \quad (i_1 i_2 i_3 i_4 i_3 i_2)$$

对应 路径 $(i_1, \dots, i_{2m}) \longrightarrow (a_1, \dots, a_{2m})$

$$a_j = \begin{cases} 1 & j \text{ 首次出现} \\ -1 & \text{otherwise} \end{cases}$$

$\Rightarrow$ 随机游荡 $S_i \geq 0$

$$\frac{1}{m+1} \binom{2m}{m}$$

主项贡献系数



2. GOE & GUE 随机矩阵

$$X = (X_{ij})_{i,j=1}^n \quad X_{ij} \sim N(0,1)$$

$$H = \frac{1}{\sqrt{2}} (X + X^T) \quad H_{ij} \sim N(0,1) \quad H_{ij} \quad 1 \leq i < j \leq n$$

$$H_{ii} \sim N(0,2)$$

$$\text{复} : H = \frac{1}{2} (X + iY) + (X^T - iY^T) \quad X_{ij}, Y_{ij} \sim N(0,1)$$

Wigner — 想研究对易矩阵的谱 — GOE & GUE

$$\text{结论 } \rho_{n\beta}(\lambda_1, \dots, \lambda_n) = \frac{1}{Z_{n\beta}} e^{-\frac{\beta}{2} \sum_{i=1}^n \lambda_i^2} \prod_{j < k} |\lambda_j - \lambda_k|^\beta$$

$$\beta = 1 \quad \text{GOE}$$

$$\beta = 2 \quad \text{GUE}$$

$$Z_{n\beta} = (2\pi)^{\frac{n}{2}} \left(\frac{2}{\beta}\right)^{\frac{1}{2} + \frac{\beta}{2}n(n-1)} \frac{\prod_{j=1}^n \Gamma(1 + \frac{\beta}{2}j)}{\Gamma(1 + \frac{\beta}{2})}$$

($\beta=1$) 矩阵元素的微分 + 矩阵计算后

$$\Rightarrow J = \frac{\prod_{i=1}^n \rho(\lambda_i)}{\text{Selberg 积分}} \prod_{\alpha < \beta} |\lambda_\alpha - \lambda_\beta|$$

□

$$\text{定义 } k\text{-点关联 } \rho_n^{(k)}(\lambda_1, \dots, \lambda_n) = \frac{n!}{(n-k)!} \int \dots \int_{\mathbb{R}^{n-k}} \rho_n(\lambda) d\lambda_{k+1} \dots d\lambda_n$$

$$\text{GUE: } \rho_n(\lambda) = \frac{1}{Z_{n2}} e^{-\frac{1}{2} \sum \lambda_i^2} (A_n(\lambda))^2$$

$$A_n = \begin{pmatrix} 1 & & & 1 \\ & \ddots & & \\ & & 1 & \\ \lambda_1^{n-1} & & & \lambda_n^{n-1} \end{pmatrix}$$

$$\Rightarrow \det A_n = \det[h_{ij}(\lambda_j)]_1^n = \prod_{i=0}^{n-1} c_i \det(\frac{1}{c_{i+1}} h_{i+1}(\lambda_j))$$

范德蒙

$$\text{范德蒙} : P(\lambda_{n-k+1} < a + b) = 1 + \sum_{k=1}^n \frac{(-1)^k}{k!} \int_a^\infty \dots \int_a^\infty \det U_n$$

Laplace方法

例 $I_n = \int e^{nf(x)} e^{\frac{i x^2}{2}} dx$ $f(x) = -\frac{1}{2}x^2 + \log(1+x) + iux$

$f'(x) =$ ~~形 $\int e^{nf(x)} dx$~~

这个例子太困难. Concept: 利用 n 将小区间大权重拉平至 $\mathbb{R}$.
凑凑高斯积分.

作业题回顾:

随机矩阵: 主项贡献来自二次型项.

1. $X = (X_{ij})_{i,j}^n$ $X_{ij} \stackrel{iid}{\sim} N(0,1)$ $\alpha = n-p$ fixed.

$\frac{1}{p} \mathbb{E} \left[\text{tr} \left(\left(\frac{XX^T}{p} \right)^m \right) \right] = \frac{1}{p^{m+1}} \mathbb{E} \sum_{i_1, i_2, \dots, i_m} \dots$

$Y = (XX^T) = \left(\sum_{k=1}^n X_{ik} X_{jk} \right)_{i,j}$
 $= \frac{1}{p^{m+1}} \mathbb{E} \left[\sum_{\substack{i_1, \dots, i_m \\ k_1, \dots, k_m}} X_{i_1 k_1} X_{i_2 k_1} X_{i_2 k_2} X_{i_3 k_2} \dots X_{i_m k_m} X_{i_1 k_m} \right]$

$i_1, \dots, i_m$ 取值于 $1, \dots, p$
 $k_1, \dots, k_m$ 取值于 $1, \dots, n$.

$m=2$ 时 $X_{i_1 k_1} X_{i_2 k_1} X_{i_2 k_2} X_{i_1 k_2}$
 $k_1 = k_2$ 3个项

3 $X_{i_1 k_1} X_{i_2 k_1} X_{i_2 k_2} X_{i_3 k_2} X_{i_3 k_3} X_{i_1 k_3}$

$k=k_3$ $k_2=k_1$

自由指标为 $m+1$ 个. 有 $2m$ 个指标 每指标两次

$\frac{1}{m+1} \binom{2m}{m} \binom{m+1}{\phi}$ 近似误差
非对称

$\Rightarrow \frac{1}{p} \mathbb{E} \text{tr} \left(\frac{XX^T}{p} \right)^m \rightarrow \frac{1}{m+1} \binom{2m}{m}$ $\square$

Idea: 找到非对称项 $\Rightarrow \frac{1}{m+1} \binom{2m}{m}$

2. 矩方法: $A_n = (a_{ij})_{i,j}^n$ $\{a_{ij} : i=j\}$ 独立, $E[a_{ij}] = 0$ $\forall i \neq j$ $Var(a_{ij}) = 1$
 Wigner
 高斯矩阵一致分布. 证 $\lim_{n \rightarrow \infty} P(\|A_n\|_2 \geq n^{\frac{1}{2}+\delta}) = 0 \quad \forall \delta > 0$

Note: 由于实对称, 所以不用区别奇异值和特征值了.

$$\|A_n\|_2 = \max |\lambda_i| \leq \left(\sum \lambda_i^2 \right)^{\frac{1}{2}}$$

$$P(\|A_n\|_2 \geq n^{\frac{1}{2}+\delta}) \leq \frac{E(\sum \lambda_i^2)}{n^{m+2m\delta}} \leq \frac{E(\sum \lambda_i^{2m})}{n^{m+2m\delta}}$$

$$\leq \frac{E(\text{tr}(A_n^{2m}))}{n^{m+2m\delta}} \approx \frac{\frac{1}{m+1} \binom{2m}{m} n^{m+1}}{n^{m+2m\delta}} \rightarrow 0$$

$\frac{1}{2} + 2m\delta > 1 \quad \checkmark \quad \square$

3. 复版本. $A_n = A_n^H$ a_{ij} , $\text{Re } a_{ij}$, $\text{Im } a_{ij}$ 独立
 $\begin{matrix} \{ \\ \gamma \end{matrix}$ $\begin{matrix} \{ \\ z \end{matrix}$ $\begin{matrix} \{ \\ z \end{matrix}$

$E[\gamma] = 0$, $E[z] = 0$ $Var(\gamma) < \infty$ $Var(z) = 1$ 高斯矩阵

证半圆律 $\frac{1}{n} E[\text{tr}(\frac{A_n}{\sqrt{n}})^k] \rightarrow \gamma_k$
 这里的主项是 $i \bar{j} - \gamma_k$ $j \bar{i} - \gamma_k \rightarrow \frac{1}{m+1} \binom{2m}{m}$
 $E[|a_{ij}|^2] = 1. \quad \square$

4. GOE 的谱分布 $n=2$

$$\begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \quad (\lambda - a_{11})(\lambda - a_{22}) - a_{12}^2 = 0$$

$$0 = \left(\lambda - \frac{a_{11} + a_{22}}{2} \right)^2 + a_{11}a_{22} - a_{12}^2 - \frac{(a_{11} - a_{22})^2}{4}$$

$$= \left(\lambda - \frac{a_{11} + a_{22}}{2} \right)^2 - \frac{4a_{12}^2 + (a_{11} - a_{22})^2}{4}$$

$$\begin{cases} \lambda_+ = \frac{(a_{11} + a_{22}) + \sqrt{4a_{12}^2 + (a_{11} - a_{22})^2}}{2} \\ \lambda_- = \frac{(a_{11} + a_{22}) - \sqrt{4a_{12}^2 + (a_{11} - a_{22})^2}}{2} \end{cases}$$

$$f(\lambda_+, \lambda_-, a_{12}) = \frac{1}{2\sqrt{2\pi}} \exp \left(-\frac{1}{4}(\lambda_+^2 + \lambda_-^2) \right) \cdot \left| \frac{\partial(\lambda_+, \lambda_-, a_{12})}{\partial(a_{11}, a_{22}, a_{12})} \right|^{-1}$$

$$|J| = \begin{vmatrix} \frac{1 + \frac{a_{11} - a_{22}}{\sqrt{\Delta}}}{2} & \frac{1 - \frac{a_{11} - a_{22}}{\sqrt{\Delta}}}{2} & \frac{a_{12}}{2\sqrt{\Delta}} \\ \frac{1 - \frac{a_{11} - a_{22}}{\sqrt{\Delta}}}{2} & \frac{1 + \frac{a_{11} - a_{22}}{\sqrt{\Delta}}}{2} & -\frac{a_{12}}{\sqrt{\Delta}} \\ 0 & 0 & 1 \end{vmatrix}$$

$$= \frac{\left(1 + \frac{a_{11} - a_{22}}{\sqrt{\Delta}}\right)^2 - \left(1 - \frac{a_{11} - a_{22}}{\sqrt{\Delta}}\right)^2}{4} = \frac{a_{11} - a_{22}}{\sqrt{\Delta}}$$

$$\lambda_+ + \lambda_- = \frac{a_{11} + a_{22}}{2}$$

$$\lambda_+ - \lambda_- = \sqrt{\Delta}$$

$$\lambda_+ \lambda_- = \frac{a_{11}a_{22} - a_{12}^2}{2}$$

$$(a_{11} - a_{22})^2 = \frac{(\lambda_+ + \lambda_-)^2 - 4(\lambda_+ + \lambda_- + a_{12})}{2} = \frac{(\lambda_+ - \lambda_-)^2 - 4a_{12}^2}{2}$$

$$\Rightarrow |J| = \frac{\sqrt{(\lambda_+ + \lambda_-)^2 - 4(\lambda_+ + \lambda_- + a_{12})}}{\lambda_+ - \lambda_-} = \frac{\sqrt{(\lambda_+ - \lambda_-)^2 - 4a_{12}^2}}{\lambda_+ - \lambda_-}$$

$$f(\lambda_+, \lambda_-, a_{12}) = \frac{1}{2\sqrt{2\pi}} \exp \left(-\frac{1}{4}(\lambda_+^2 + \lambda_-^2) \right) \frac{\lambda_+ - \lambda_-}{\sqrt{(\lambda_+ - \lambda_-)^2 - 4a_{12}^2}}$$

$$\frac{1}{2} \int_{-\frac{\lambda_+ - \lambda_-}{2}}^{\frac{\lambda_+ - \lambda_-}{2}} \frac{da_{12}}{\sqrt{\left(\frac{\lambda_+ - \lambda_-}{2}\right)^2 - a_{12}^2}} = \frac{1}{2} \int_{-1}^1 \frac{dx}{\sqrt{1-x^2}} = \frac{\pi}{2}$$

$$\Rightarrow f(\lambda_+, \lambda_-) = \frac{1}{4\sqrt{2\pi}} \exp \left(-\frac{1}{4}(\lambda_+^2 + \lambda_-^2) \right) (\lambda_+ - \lambda_-) \quad \square$$

5. GUE. 密度矩阵

$$H = \frac{1}{2} \left((X+iY) + (X+iY)^H \right)$$

$$\text{二维. } f(z) = \frac{1}{\pi} e^{-|z|^2}$$

$$\text{二维. } f(x) = \frac{1}{2\pi} \exp \left(-\frac{1}{2}x^2 \right)$$

$$f(H) = \frac{1}{(2\pi)^{\frac{N}{2}} \cdot \pi^{\frac{N(N-1)}{2}}} \prod_{i=1}^N \exp \left(-\frac{1}{2}x_i^2 \right) \prod_{i < j} \exp \left(-|z_{ij}|^2 \right) = \frac{1}{2^{\frac{N}{2}} \pi^{\frac{N}{2}}} \exp \left(-\frac{1}{2} \text{tr} H^2 \right)$$

酉不变性.

$$f(H) \propto \exp -\frac{1}{2} \text{tr} H^2 = \exp -\frac{1}{2} \text{tr} H H^T$$

$$Y = U H U^T \quad U \text{ 酉}$$

$$f(Y) \propto \exp -\frac{1}{2} \text{tr} U H U^T U H U^T = \exp -\frac{1}{2} \text{tr} Y^2$$

谱必相同 (同分布).

GUE 和 GOE 取矩. Wick 公式.

$$1. a_p(n) = \mathbb{E}[\text{tr}(H^{2p})]$$

$$= \sum_{i_1, \dots, i_{2p}} \mathbb{E}[H_{i_1 i_2} \dots H_{i_{2p-1} i_{2p}}]$$

$$= \sum_{i_1, \dots, i_{2p}} \sum_{\text{pair}} \prod \mathbb{E}[H_{i_1 i_2} \dots H_{i_{2p-1} i_{2p}}]$$

$$\text{GOE} \quad H_{ii} \sim N(0, 2)$$

$$H_{ij} \sim N(0, 1)$$

$$\text{GUE} \quad H_{ii} \sim N(0, 1)$$

$$H_{ij} \sim N_c(0, 1)$$

$$p=1. \quad a_1(n) = \mathbb{E}[\text{tr}(H^2)] = 2N + 2 \cdot \frac{n(n-1)}{2} = N^2$$

$$p=2. \quad \sum_{i_1, \dots, i_4} \mathbb{E}[H_{i_1 i_2} H_{i_2 i_3} H_{i_3 i_4} H_{i_4 i_1}]$$

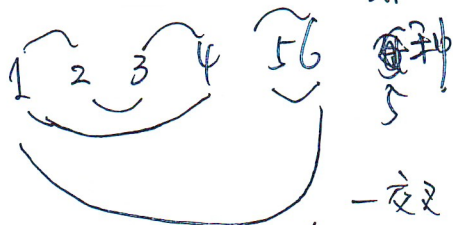
$$= \sum_{i_1, \dots, i_4} \langle i_1 i_2 | i_2 i_3 | i_3 i_4 | i_4 i_1 \rangle + \langle i_1 i_2 | i_3 i_2 | i_4 i_3 | i_1 i_4 \rangle + \langle i_1 i_2 | i_3 i_4 | i_4 i_1 | i_2 i_3 \rangle + \langle i_1 i_2 | i_4 i_3 | i_3 i_2 | i_1 i_4 \rangle$$

$$= \sum_{i_1, \dots, i_4} \sum_{i_2=i_1} N \downarrow \quad \sum N \downarrow \quad \sum N \downarrow$$

$$2(N^3 - 3N^2 + 2N) + N = 2N^3 + N$$

$$p=3.$$

$$\frac{6 \ 54}{6 \cdot 4}$$



$$\frac{1}{6} \cdot \frac{6}{4} \cdot \frac{6}{3} = 1$$



$$(123456)(13)(24)(56) = (14)(25)(36)$$



$$\text{利用代数} (1234)(12)(34) = (13)(24)(4)$$

$$(1234)(14)(23) = (14)(3)(2)$$

$$(1234)(13)(24) = (1432)$$

$$(123456)(12)(34)(56) =$$

$$(135)(24)(16)$$

$$(123456)(13)(24)(56) = (1432516)$$

$p=4$. 非交 $\frac{1}{4} \binom{8}{4} = \frac{8 \cdot 7 \cdot 6 \cdot 5}{4 \cdot 3 \cdot 2 \cdot 1} = 14$

5.



$(1\ 2\ 3\ 4\ 5\ 6\ 7\ 8)(12)(34)(57)(68) = (1\ 3\ 5\ 8\ 7\ 6)(2)(4)$ 3

= 交 $(1\ 2\ 3\ 4\ 5\ 6\ 7\ 8)(13)(24)(57)(68) = (1\ 4\ 3\ 2\ 5\ 8\ 7\ 6)$ 1

= 交 $(1\ 2\ 3\ 4\ 5\ 6\ 7\ 8)(15)(26)(37)(48) = (1\ 6\ 3\ 8\ 5\ 2\ 7\ 4)$ 1.

7 5 3 = 105

~~相对~~ ~~8~~ ~~2~~ +

要了. 没有去轮椅 搜 Zaqien.

GOE 低维可轮椅-T

$p=1$. n^2+n

$(1\ 2\ 3\ 4)(1\ 3)(2\ 4) = (1\ 4\ 3\ 2)$

$p=2$.



$2(n^2+n) + 4n + (n^2+n)$

轮椅部人砸了. $\pi_1 \pi$.

$p=3$

熵 $H(X) = -\int \ln f(x) \cdot f(x) dx$

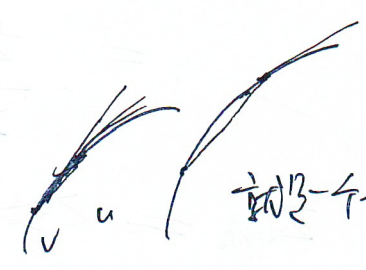
条件熵 $\Rightarrow$ 相对熵 $H_Y(X) = -\sum p(x_i|y) \ln p(x_i|y)$

$$\begin{cases} H_Y(X) \leq H(X) \\ H(X,Y) = H_Y(X) + H(X|Y) \end{cases}$$

Gibbs $u - u \log u \leq v - v \log v$
 $\Leftrightarrow u - v \leq u(\log u - \log v)$
 $\Leftrightarrow \frac{1}{u} \leq \frac{\log u - \log v}{u - v}$

$u, v > 0$

$u > v$



就是一个切线不等式.

$\Rightarrow -\int f \log f \leq \int g \log g$

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如何用 Gibbs: 1. $E[X] = 0$ $Var(X) = 1$ 何时熵最大 ϕ
 f 在 $(-\infty, \infty) \subseteq \mathbb{R}$.

$$\begin{aligned} -\int f \log f &\leq -\int f \log \frac{1}{\sqrt{2\pi}} \exp(-\frac{1}{2}x^2) \\ &= -\int f \log \frac{1}{\sqrt{2\pi}} + \frac{1}{2} \int x^2 f \\ &= -\log \frac{1}{\sqrt{2\pi}} + \frac{1}{2} = \log \sqrt{2\pi e}. \end{aligned}$$

2. $D = (0, \infty)$ $E[X] = \frac{1}{\lambda}$

$$\begin{aligned} -\int f \log f &\leq -\int f \log \lambda e^{-\lambda x} \\ &= -\int f \log \lambda + \int \lambda x f \\ &= -\log \lambda + 1 = \log \frac{e}{\lambda}. \end{aligned}$$

3. $D = (0, a)$

$$-\int f \log f \leq -\int f \log \frac{1}{a} = \log a.$$

~~$\sum_{i=1}^n$~~

1. Jensen 不等式.

Ising 模型

$$1. \langle e^{\frac{t}{\beta} H_0} \rangle = \frac{1}{Z_{N, \beta, h}} \sum_{\{\sigma\}} e^{t \sum \sigma_i} \cdot e^{-\beta H(\sigma)}$$

$$= \frac{1}{Z_{N, \beta, h}} \sum_{\{\sigma\}} \exp\left(\beta J \sum_{i,j} \sigma_i \sigma_j + \beta \left(h + \frac{t}{\beta}\right) \sum \sigma_i\right)$$

$$= \frac{Z_{N, \beta, h + \frac{t}{\beta}}}{Z_{N, \beta, h}}$$

$$Z_{N, \beta, h} = \text{tr}(P^N)$$

$$P = \begin{pmatrix} e^{\beta J + \beta h} & e^{-\beta J} \\ e^{-\beta J} & e^{\beta J - \beta h} \end{pmatrix}$$

$$\frac{(\lambda_{h+\frac{t}{\beta}}^+)^N + (\lambda_{h+\frac{t}{\beta}}^-)^N}{(\lambda_h^+)^N + (\lambda_h^-)^N}$$

$$\approx \left(\frac{\lambda_{h+\frac{t}{\beta}}^+}{\lambda_h^+} \right)^N = \exp N \log \left(1 + \frac{\lambda_{h+\frac{t}{\beta}}^+ - \lambda_h^+}{\lambda_h^+} \right)$$

尺度变换.

$$\langle \exp \left(t \frac{MN}{N} \right) \rangle \xrightarrow{\text{Scale}} \exp \left(N \frac{t}{\beta \lambda_h^+} \frac{d \lambda_h^+}{d h} \right) = \exp \left(t \frac{d \log \lambda_h^+}{d h} \right)$$

$$\Rightarrow \langle \exp \left(t \frac{MN}{N} \right) \rangle \longleftrightarrow \exp \left(\frac{t \lambda_h^+}{\beta \lambda_h^+} \right)$$

$$\frac{MN}{N} \xrightarrow{\mathcal{P}} \frac{\lambda_h^+}{\beta \lambda_h^+} \quad \text{参数 } D, \text{ 但 } h \text{ fixed.}$$

$$\begin{aligned} \langle \exp \left(t \frac{MN}{N} \right) \rangle &= \mathbb{A} \exp N \left(\frac{\lambda_{h+\frac{t}{\beta}}^+ - \lambda_h^+}{\lambda_h^+} - \frac{1}{2} \left(\frac{\lambda_{h+\frac{t}{\beta}}^+ - \lambda_h^+}{\lambda_h^+} \right)^2 \right) \\ &= \exp \left(N \left(\frac{t}{\beta} \frac{d \lambda_h^+}{d h} - \left(\frac{t}{\beta} \right)^2 \frac{d^2 \lambda_h^+}{d h^2} \right) - \frac{1}{2} \left(\frac{t}{\beta} \right)^2 \frac{d \lambda_h^+}{d h} \right) \\ &= \exp \left(N \left(\lambda_h^{+ \prime} \frac{t}{\beta} - \frac{1}{2} \left(\frac{t}{\beta} \right)^2 \left(\frac{d^2 \lambda_h^+}{d h^2} - \frac{1}{2} \frac{d \lambda_h^+}{d h} \right) \right) \right) \end{aligned}$$

OK ✓.

$$\begin{aligned} \log' &= \left(\frac{1}{\lambda_h^+} \frac{d \lambda_h^+}{d h} \right)' \\ &= - \frac{1}{\lambda_h^+{}^2} \frac{d \lambda_h^+}{d h} + \frac{1}{\lambda_h^+} \frac{d^2 \lambda_h^+}{d h^2} \end{aligned}$$

6.3.

$$\begin{aligned} \mu=0 \quad \phi(|MN| \geq N\epsilon) &= 2\phi(MN \geq N\epsilon) \\ &= 2\phi\left(\frac{MN}{\sqrt{N}} \geq \sqrt{N}\epsilon\right) \quad \text{标准化与解算.} \\ &\leq 2 \frac{\exp\left(\frac{MN}{N}\right)}{e^{N\epsilon}} \leq \exp(-N\epsilon) \end{aligned}$$

BC ✓.

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C-W 模型

$$\mu_{\beta, h}(\sigma) = \frac{1}{Z_{\beta, h}} \exp(\beta H(\sigma))$$

$$H(\sigma) = -\frac{d}{N} \left(\sum \sigma_i \right)^2 - h \sum \sigma_i$$

$$M_N = \sum_{i=1}^N \sigma_i \quad \text{对 } \frac{M_N}{N} \text{ 进行极限估计和涨落估计}$$

$$p(M_N = m) = \frac{1}{Z_{\beta, h}} \binom{N}{\frac{1+m}{2}N} \exp\left(\frac{\beta d}{N} m^2 N + \beta h m N\right) \quad d=1$$

$$= \frac{1}{Z_{\beta, h}} \binom{N}{\frac{1+m}{2}N} \exp\left(\beta d m^2 N + \beta h m N\right)$$

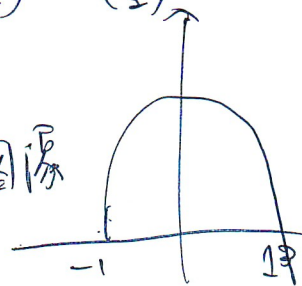
6.1.2:

$$p(M_N = m) = \frac{1}{Z_{\beta, h}} \binom{N}{\frac{1+m}{2}N} \exp\left(\frac{\beta d m^2 N^2}{N}\right)$$

$$\binom{N}{\frac{1+m}{2}N} = \frac{N!}{\left(\frac{1+m}{2}N\right)! \left(\frac{1-m}{2}N\right)!} \approx \frac{\left(\frac{N}{e}\right)^N}{\left(\frac{1+m}{2}N\right)^{\frac{1+m}{2}N} \left(\frac{1-m}{2}N\right)^{\frac{1-m}{2}N}} \approx \frac{1}{\left(\frac{1+m}{2}\right)^{\frac{1+m}{2}N} \left(\frac{1-m}{2}\right)^{\frac{1-m}{2}N}}$$

$$= \exp\left(N\left(-\frac{1+m}{2} \log \frac{1+m}{2} - \frac{1-m}{2} \log \frac{1-m}{2}\right)\right)$$

$$= \exp N(S(m))$$



$$\approx \frac{1}{Z_{\beta, h}} \exp\left(N S(m) + \beta d m^2 N + o(N)\right) \quad S(m)$$

$$\frac{N}{N} = 0 \quad \approx \frac{1}{Z_{\beta, h}} \exp N(S(m))$$

$$p(M_N \notin (-\varepsilon, \varepsilon)) = \frac{\sum_{m \notin (-\varepsilon, \varepsilon)} \exp(N S(m))}{Z_{\beta, h}} \leq \frac{N \exp N S(\varepsilon)}{e^{N S(0)}} \rightarrow 0$$

$$\frac{N}{N} = 0 \quad p(M_N \in (1-\varepsilon, 1-\varepsilon)) \leq \frac{N \exp C(\varepsilon) \left(\frac{N^2}{N}\right) (1-\varepsilon)^2}{\exp \left(\beta d \frac{N^2}{N}\right)} \rightarrow 0$$

$$\psi_p(h) = \lim_{N \rightarrow \infty} \frac{1}{N} \log Z_{N,p,h} \quad \text{关于 } h \text{ 凸}$$

$$Z_{N,p,h} = \sum_i \binom{N}{i} \exp \left(\beta \left(\frac{N-i}{N} \right)^2 N + h \frac{N-i}{N} \cdot N \right)$$

$$\frac{1}{N} \log Z_{N,p,h} \leq \left(\frac{N}{\frac{N-i}{N}} \right) \exp \left(S(m) + (h m + \beta m^2) \right)$$

$$\max \frac{1}{N} \log Z_{N,p,h} = \max_{N \rightarrow \infty} \left(S(m) + h m + \beta m^2 \right)$$

$$\max \left(h m - f(m) \right)$$

$$f = -f - S m$$

✓

$$\psi(h+a) + \psi(h-a) = \max \left(S(m) + h+a + \beta m^2 \right) + \max \left(S(m) + h-a + \beta m^2 \right)$$

取一次 max 和两次 max.

知识回顾:

1. Wigner 半圆 $k=2m$ $2m \leq \Rightarrow \frac{1}{m+1} \binom{2m}{m}$

$$\frac{1}{n} \mathbb{E} \left[\text{tr} \left(\frac{A^k}{n} \right) \right] \approx \frac{1}{n^{1+m}} \cdot \frac{1}{m+1} \binom{2m}{m} \cdot n^{1+m}$$

$m+1$ 个自由度

非对称作用 $\leq$ cycle 自由度

GUE 每个元素都相等

GOE 对称 - 2

2. GOE 密度 $f(\lambda) =$

对称 Var 2
非对称 Var 1

$$\frac{1}{(4\pi)^{\frac{n}{2}}} \cdot \frac{1}{(2\pi)^{\frac{n(n-1)}{4}}} \exp \left(-\frac{1}{4} \sum H_{ii}^2 + \frac{1}{2} \sum H_{ij}^2 \right)$$

$$= \frac{1}{2^{\frac{n(n+1)}{2}}} \frac{1}{\pi^{\frac{n(n-1)}{2}}} \exp \left(-\frac{1}{4} \text{tr} H^2 \right)$$

$$\frac{1}{(4\pi)^{\frac{n}{2}}} \frac{1}{(2\pi)^{\frac{n(n-1)}{4}}}$$

GUE

$$\left(\frac{1}{\pi} \exp -\lambda^2 \right)$$

非对称

$$\frac{1}{\pi} \exp \left(-\frac{1}{2} \lambda^2 \right)$$

π

24. Gibbs 不等式 $u \log u \leq v - u \log v$
 $\Rightarrow -\int u \log u \leq -\int u \log v$

Boole's theorem $P(X=E_i) = p_i$

$q_i = f(p_i) = \frac{\exp(-\frac{E_i}{\beta})}{Z}$

由 Gibbs $\Rightarrow$

Ising $H(\sigma) = -J \sum_{\langle i,j \rangle} \sigma_i \sigma_j - \beta \sum \sigma_i$

转移 $P = \begin{pmatrix} \exp(\beta J + \beta h) & \exp(-\beta J) \\ \exp(-\beta J) & \exp(\beta J - \beta h) \end{pmatrix}$

$Z_{N;\beta;h} = \text{tr}(P^N) = \exp(\beta J N) \cdot (\lambda_+^N + \lambda_-^N)$

$\mathbb{E} \left[\exp \left(\frac{1}{N} \sum \sigma_i \right) \right] = \frac{Z_{N;\beta;h+\frac{1}{N}}}{Z_{N;\beta;h}} \approx \left(\frac{\lambda_{+,h+\frac{1}{N}}}{\lambda_{+,h}} \right)^N$

$\frac{\sum \exp \left(\frac{1}{N} \sum \sigma_i \right) \cdot \exp \left(\beta J \sum \sigma_i \sigma_{i+1} + \beta \sum \sigma_i \right)}{Z_{N;\beta;h}}$

a.s. 收敛可以用 命 + $\exp$ - Markov. 极路 $|M| = \beta \eta \log \eta$.
 $\phi(|M_N| > N\epsilon) \leq 2P(|M_N| > N\epsilon) = 2P \left(e^{\frac{N\epsilon}{\beta \eta}} \geq e^{\epsilon \eta} \right)$
 $\leq \frac{2 \mathbb{E} \left[e^{\frac{|M_N|}{\beta \eta}} \right]}{e^{\epsilon \eta}}$

Ising v.s. Curie-Weiss

1

2.

$$1: H(\sigma) = -J \sum_{i=1}^N \sigma_i \sigma_{i+1} - h \sum_{i=1}^N \sigma_i \quad \mu_{N;\beta,h}(\sigma) = \exp \left(\beta J \sum_{i=1}^N \sigma_i \sigma_{i+1} + \beta h \sum_{i=1}^N \sigma_i \right)$$

$$2: H(\sigma) = -\frac{J}{N} \left(\sum_{i=1}^N \sigma_i \right)^2 - h \sum_{i=1}^N \sigma_i \quad \mu_{N;\beta,h}(\sigma) = \frac{\exp \left(\frac{J\beta}{N} \left(\sum_{i=1}^N \sigma_i \right)^2 + \beta h \sum_{i=1}^N \sigma_i \right)}{Z_{N;\beta,h}}$$

1: 配分函数局部展开

$$\text{期望: } E\left[\frac{M_N}{N}\right] = \frac{\sum_i \left(\frac{N}{N} \sigma_i\right) \cdot \exp \left(J\beta \sum_{i=1}^N \sigma_i \sigma_{i+1} + \beta h \sum_{i=1}^N \sigma_i \right)}{Z_{N;\beta,h}}$$

$$= \frac{1}{\beta N} \frac{\partial \log Z_{N;\beta,h}}{\partial h} = \frac{1}{\beta N} \frac{\partial}{\partial h} \log \left(e^{\beta J N} (\lambda_+^N + \lambda_-^N) \right) \Rightarrow \frac{1}{\beta} \frac{\partial \log \lambda_+}{\partial h} \cdot \frac{1}{\lambda_+}$$

$$Z_{N;\beta,h} = \text{tr}(P^N)$$

$$P = \begin{pmatrix} e^{\beta J + \beta h} & e^{-\beta J} \\ e^{-\beta J} & e^{\beta J - \beta h} \end{pmatrix}$$

$$\lambda^2 - e^{\beta J} (e^{\beta h} + e^{-\beta h}) \lambda + (e^{2\beta J} - e^{-2\beta J}) = 0$$

$$e^{\beta J} (e^{\beta h} + e^{-\beta h}) \pm \sqrt{e^{2\beta J} (e^{2\beta h} + 2e^{-2\beta h} + 1) - 4(e^{2\beta J} - e^{-2\beta J})}$$

$$= e^{\beta J} \left[\cosh(\beta h) \pm \sqrt{\sinh^2(\beta h) + 4e^{-\beta J}} \right]$$

LLN 用 矩阵函数展开计算

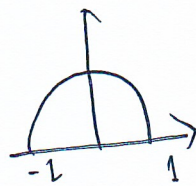
CLT 用 矩阵函数二阶展开计算

$$2: \text{组合估计} \quad \left(\frac{H_M}{\frac{N}{2}} \right) \approx \frac{S(M)}{\exp(S(M) + o(1))} = -\frac{1-M}{2} \log \frac{1-M}{2} - \frac{1+M}{2} \log \frac{1+M}{2}$$

扰动项在 $\frac{1}{N} \log$ 阶下消失。

对 m_N 进行相变估计

$$P(m_N \in \dots) = \frac{\dots}{Z_N} \quad \begin{matrix} \text{N 边界项} \\ \text{和项} \end{matrix} \rightarrow \text{Vanish} \dots$$



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考粉

$$H(\sigma) = - \sum J_{ij} \sigma_i \sigma_j \quad \text{for } \sigma_i$$

unspio:

$$X = \beta \sum_{i=1}^N \sigma_i \quad (\text{Mach}) \quad \text{只加修正项}$$