

• MCMC 产生任意 $P(x)$ 及 MC 结合 (PPT)

产生一组 $P(x_i)$ 分布的随机数

马尔可夫链 $P(x^{i+1} | x^i, x^{i-1}, \dots, x^1) = P(x^{i+1} | x^i)$

Metropolis 算法

$$x^{i+1} = \begin{cases} x^{\text{new}} & p=r \\ x^i & p=1-r \end{cases} \quad r = \frac{P(x^{\text{new}})}{P(x^i)}$$

$r > 1$, 完全接受 $x^{i+1} = x^{\text{new}}$ $x^1 \rightarrow x^2 \rightarrow \dots \rightarrow x^K$ K 足够大, 满足平衡分布

考虑 $\frac{dP_n}{dt} = \sum_m P_m W_{m \rightarrow n} - P_n W_{n \rightarrow m}$
"0", 细致平衡

tips

$7/4 \times 0.25\pi \sim$ 循环里的常数 (π 几之类) 放在外面算

作业 2D Ising 的相变 (见下)

• 重要抽样

均匀分布 $\langle f \rangle = \frac{\int f(x) dx}{\int dx} = \int f(x) dx$

高维 $\frac{1}{V} \int f(x) dx = \int f(x) dx$

• 2D Ising

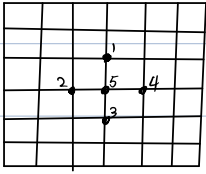
$$H = -J \sum_{ij} s_i s_j \quad (s_i = \pm 1)$$

100 x 100 $|K| = 2^{10^4}$

$$x^{i+1} = \begin{cases} x^{\text{new}} & \dots \\ x^k & \dots \end{cases} \quad x^k \rightarrow s_i$$

高维 X 如何产生?

$$r = \frac{P(x^{\text{new}})}{P(x^k)} = e^{-\beta(E(x^{\text{new}}) - E(x^k))}$$



$$E^{\text{new}} - E^{\text{K}} = -J(S_1 + S_2 + S_3 + S_4)S_5$$

相变点附近涨落大, 翻转多, MC可能不精确

翻转 $J(S_1 + S_2 + S_3 + S_4)S_5$

$$\langle m \rangle = \frac{\sum m(s_i) e^{-\beta H(s_i)}}{Z} = \frac{1}{N} \sum m(s_i)$$

$$\chi \propto \langle m^2 \rangle - \langle m \rangle^2$$

χ 怎么过渡到 $S_1, S_2 \dots S_n$

· 转移矩阵方法 (1d 为例)

$$H = -J \sum_i \sigma_i \sigma_{i+1} + \sum_i h \sigma_i$$

$$Z = \sum_{\{\sigma_i\}} e^{\beta J \sum \sigma_i \sigma_{i+1} + \beta h \sum \sigma_i}$$

$$= \sum_{\{\sigma_i\}} P_{\sigma_0 \sigma_1} P_{\sigma_1 \sigma_2} \dots P_{\sigma_{N-1} \sigma_N} = \text{Tr}(P^N) = \text{Tr}(U^+ \lambda^N U) = \text{Tr}(\lambda^N)$$

$$P_{\sigma_1 \sigma_2} = e^{\beta J \sigma_1 \sigma_2 + \frac{\beta h}{2} (\sigma_1 + \sigma_2)} \quad \sigma_i = \pm 1$$

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

$$Z = e^{-\beta F} = \lambda_{\text{max}}^N = e^{N \ln \lambda_{\text{max}}}$$

$$\beta F = -N \ln \lambda_{\text{max}} \quad \boxed{\beta f = -\ln \lambda_{\text{max}}}$$

作业1 讨论函数性质

Onsager $F = -k_B T \ln Z, \quad Z = \lambda^N$

$$\ln \lambda = \ln [2 \cosh(2\beta J)] + \frac{1}{\pi} \int_0^\pi \ln \left[\frac{1}{2} (1 + \sqrt{1 - k^2 \sin^2 \omega}) \right] d\omega$$

$$k = \frac{2 \sin(2\beta J)}{(\cosh(2\beta J))^2} \quad \text{相变点: } k_B T_c = \frac{2J}{\ln(1 + \sqrt{2})}$$

$$\begin{cases} E = -\frac{\partial \ln Z}{\partial \beta} & Z = e^{-\beta F} \\ C_V = \frac{\partial E}{\partial T} = \frac{\partial E}{\partial \beta} \frac{\partial \beta}{\partial T} = -\frac{1}{k_B T^2} \frac{\partial E}{\partial \beta} = \frac{1}{k_B T^2} \left[\frac{1}{Z} \left(\frac{\partial Z}{\partial \beta} \right) \right] \end{cases}$$

$$-\frac{1}{k_B T^2} \left[-\frac{1}{Z^2} \left(\frac{\partial Z}{\partial \beta} \right)^2 + \frac{1}{Z} \frac{\partial^2 Z}{\partial \beta^2} \right]$$

$$\downarrow$$

$$\left(\frac{\partial \ln Z}{\partial \beta} \right)^2 = -E^2 = -\langle E \rangle^2$$

证明 $C_V \propto \langle E^2 \rangle - \langle E \rangle^2$ 只要证明 $\frac{1}{Z} \frac{\partial^2 Z}{\partial \beta^2} = \langle E^2 \rangle$

类比 $h \leftrightarrow \beta$ $M = \frac{\partial \ln Z}{\partial h}$

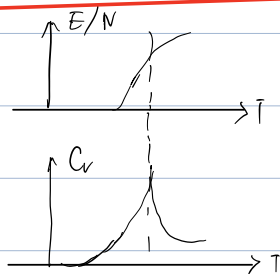
$m \leftrightarrow E$ $\chi = \frac{\partial M}{\partial h} \propto \langle M^2 \rangle - \langle M \rangle^2$

$$Z = \int e^{-\beta H} dx$$

$$\frac{1}{Z} \frac{\partial^2 Z}{\partial \beta^2} = \int H^2 e^{-\beta H} dx / Z = \langle E^2 \rangle$$

$$\ln \lambda^N$$

$$E = -N \frac{\partial \ln \lambda}{\partial \beta}$$



计算 $C_V \propto \frac{1}{|T-T_c|^\nu}$ 的 ν

$$\ln C_V \propto -\nu \ln |T-T_c| + \text{const}$$

Tips: 线性拟合

作业2