

Liouville's theorem
equation for $f(q, p, t)$
PDF for an ensemble
in phase space.

Density function for many phase points.

$$\frac{\partial f}{\partial t} + \sum_i \dot{q}_i \frac{\partial f}{\partial q_i} + \dot{p}_i \frac{\partial f}{\partial p_i} = 0$$

If we follow $(q(t), p(t))$, the phase trajectory, then $\frac{d}{dt} f = 0$

$$f(q(t+\Delta t), p(t+\Delta t), t+\Delta t) = f(q(t), p(t), t)$$

Equilibrium system \rightarrow equilibrium ensemble.
 $\frac{\partial f}{\partial t} = 0$,

Stationary distribution

$$\sum_i \dot{q}_i \frac{\partial f}{\partial q_i} + \dot{p}_i \frac{\partial f}{\partial p_i} = 0$$

$f(q, p)$ itself is a mechanical invariant.

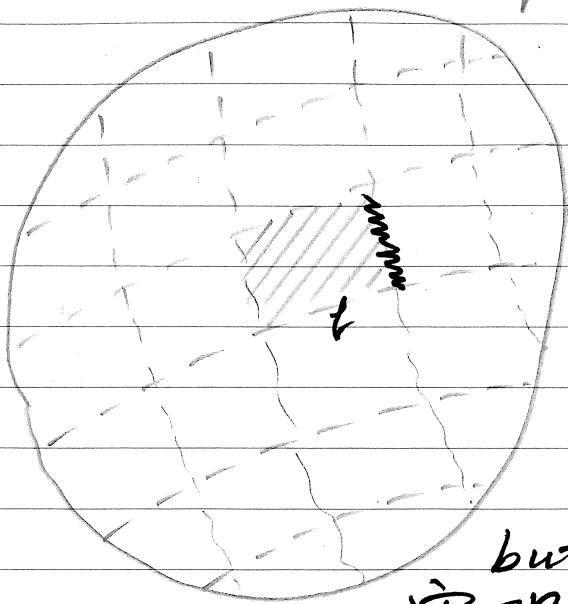
$f(q, p)$ is associated with $H(q, p)$
because

$$\sum_i \dot{q}_i \frac{\partial H}{\partial q_i} + \dot{p}_i \frac{\partial H}{\partial p_i} = 0, \quad H \text{ is a mech. invariant.}$$

$$f = f(H(q, p)) \rightarrow \sum_i \dot{q}_i \frac{\partial f}{\partial q_i} + \dot{p}_i \frac{\partial f}{\partial p_i} = 0$$

Statistical independence

Quasi-closed
subsystems



近独立子系,

Each subsystem is
still macroscopic.

Macroscopically small,
but microscopically large
宏观小
微观大。

Surface to volume ratio

$$\frac{t^2}{t^3} \sim \frac{1}{t} \rightarrow 0.$$

Interactions through the boundary.
Short range.

$t \gg$ short-range of
interaction

Very weak interaction between subsystems.

↓
Quasi-closed.

Statistical independence.

近独立

X, Y .

$$f_{xy}(x,y) = f_x(x)f_y(y)$$

Macroscopic system divided into many quasi-closed subsystems.

$$f = f_1 \cdot f_2 \cdot f_3 \cdots$$

↑
to label the subsystems.

$$\log_e f = \log f_1 + \log f_2 + \log f_3 + \cdots$$

$\log f$ is additive. ($\nabla f = f$)
is an extensive quantity.

① f is a mechanical invariant.
so that f is a stationary solution
to Liouville equation.

$$\frac{df}{dt} = 0, \quad \frac{\partial f}{\partial t} = 0 \Rightarrow \frac{d}{dt} f(q(t), p(t)) = 0$$

$$\sum_i f_i \frac{\partial f}{\partial q_i} + p_i \frac{\partial f}{\partial p_i} = 0.$$

② $\ln f$ is additive.

① & ② : $\log f$ is an additive
mechanical invariant.
→ Energy.

$$\bar{E} = E_1 + E_2 + \cdots$$

$$\log f_i = -\alpha_i - \beta E_i, \quad i: \text{ith subsystem.}$$

\downarrow same for
a normalization const.

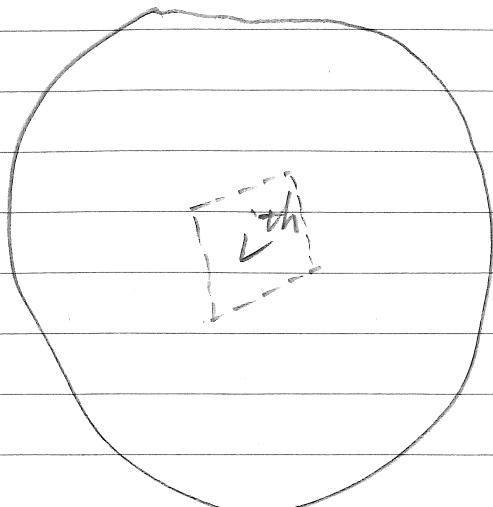
$$\log f = \sum_j (-\alpha_j - \beta E_j) = \sum_j \log f_j$$

different subsystems

$$= -\sum_j \alpha_j - \beta \sum_j E_j = -\alpha - \beta E.$$

temperature

\downarrow same for
different subsystems.



i^{th} subsystem

$$f_i = e^{-\alpha_i - \beta E_i}$$

$$\log f_i = -\alpha_i - \beta E_i$$

α_i for normalization.

β is related to temperature.

β is the same for all the subsystems in equilibrium.

$$\sum_j -\beta E_j = -\beta \sum_j E_j$$

$$\beta = \frac{1}{k_B T}, \quad T, \text{ absolute temperature}$$

$$f_i = e^{-\alpha_i - \beta E_i} \xrightarrow{H(q,p)} \\ f \propto e^{-\beta E} = e^{-\frac{E(q,p)}{k_B T}}$$

$T \rightarrow 0^+$, only low-energy states are occupied with significant probabilities.

$T \rightarrow \infty$, all the energy states are equally occupied.

$$f \propto e^{-\frac{E}{k_B T}} \quad \text{Gibbs distribution.}$$

for a macroscopic system in thermal contact with the environment.

$$E \uparrow, f \downarrow$$

The Gibbs ensemble, the canonical ensemble

$$f \propto e^{-\beta E}$$

$$\int f(q,p) dq dp = \int dq dp e^{-\alpha - \beta E(q,p)}$$

吉布斯 .

Entropy . S to be expressed

through a distribution

$f(q,p)$: q & p are continuous variables.

$$S = \int dq dp f \log f$$

For the sake of clarity in expression,
I switch to summation over discrete states .

Quantum physics .

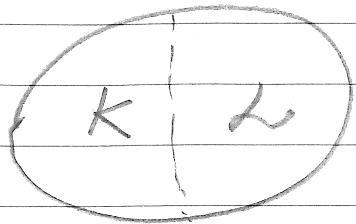
$$f(q,p) \rightarrow w_n$$

$$\int dq dp f = 1 \quad \sum_n w_n = 1$$

$$\int dq dp f \log f \rightarrow \sum_n w_n \log w_n \\ = S$$

w_n : probabilities of discrete states .

S : additive .



$$f = f_K \cdot f_L$$

$$w = w_K \cdot w_L$$

$S = S_K + S_L$ additive.

$$S = \sum_n w_n (\log w_n), \quad n = (n_K, n_L)$$

$$= \sum_{n_K, n_L} (w_{n_K} w_{n_L}) (\log w_{n_K} + \log w_{n_L})$$

$$w_n = w_{n_K} w_{n_L}$$

$$= \sum_{n_K, n_L} w_{n_K} w_{n_L} \underbrace{\log w_{n_K}}_{n_K, n_L} + \sum_{n_K, n_L} w_{n_K} w_{n_L} \underbrace{\log w_{n_L}}_{n_K, n_L}$$

$$= \sum_{n_K} w_{n_K} \log w_{n_K} + \sum_{n_L} w_{n_L} \log w_{n_L}$$

$$\left\{ \begin{array}{l} \sum_{n_L} w_{n_L} = 1 \\ \sum_{n_K} w_{n_K} = 1 \end{array} \right. \quad = S_K + S_L$$

$$\sum_{n_K} w_{n_K} = 1 \quad \text{Entropy additive} \quad \text{JJK量}$$

Meaning of S . for the Gibbs ensemble.

$$w_n = \frac{e^{-\beta E_n}}{\sum_m e^{-\beta E_m}}, \quad \sum_n w_n = 1$$

$$S = - \sum_n w_n \log w_n$$

"—" just added, additivity
not changed by adding "—".

TO FROM DATE NO

$$\begin{aligned}
 S &= - \sum_n w_n (\log w_n), \quad w_n = \frac{e^{-\beta E_n}}{\sum_m e^{-\beta E_m}} \\
 &= - \sum_n w_n (-\beta E_n - \log Z) \\
 &= -(-\beta \langle E \rangle) - (-\log Z) \\
 &= \beta \langle E \rangle + \log Z
 \end{aligned}$$

mean energy $\langle E \rangle$ $\sum_n w_n E_n$
 $= \langle E \rangle$

$$\begin{aligned}
 &= -\log e^{-\beta \langle E \rangle} - \log Z \\
 &= -\log \frac{e^{-\beta \langle E \rangle}}{Z} \\
 &\quad \left(\begin{array}{l} \text{W}_n = \frac{e^{-\beta E_n}}{Z} \\ \rightarrow = -\log W(\langle E \rangle) \end{array} \right) \\
 &\quad \left(\begin{array}{l} a = \log e^a \\ = -\log e^{-a} \end{array} \right) \\
 &\quad \left(\begin{array}{l} W(\langle E \rangle) = \frac{e^{-\beta \langle E \rangle}}{Z} \\ \rightarrow \text{Probability for a state} \\ \text{with its energy equal to } \langle E \rangle. \end{array} \right)
 \end{aligned}$$

$W(\langle E \rangle) = W_n$ with $E_n = \langle E \rangle$.
 Because energy E is additive, its variance scales with the system size linearly.

$$E = \sum_{i=1}^N \varepsilon_i, \quad \text{sum over } N \text{ subsystems.}$$

$\text{Var}(E) \sim N$, statistical independence.

$$\frac{\sqrt{\text{Var}(E)}}{E} \sim \frac{\sqrt{N}}{N} \sim N^{-\frac{1}{2}} \rightarrow 0 \text{ for macroscopic system.}$$

for macroscopic system, E 's fluctuation is approaching zero relative to energy itself.

$$\sqrt{N} \text{ vs } N$$

$$\text{Variance} \sim N$$

$$\text{S.D.} \sim \sqrt{N}, \quad E \sim N.$$

Energy at $\langle E \rangle$ is representative.
Distribution in energy is very concentrated near $\langle E \rangle$.

$$\frac{\sqrt{N}}{N} \sim \frac{1}{\sqrt{N}} \rightarrow 0. \quad \text{Peaked distribution.}$$

$W(\langle E \rangle)$: Probability for a representative state.

$$\sum_n W_n = 1$$

Important states : E_n close to $\langle E \rangle$.

Number of important states $\frac{1}{W(\langle E \rangle)}$

$$\frac{1}{W(\langle E \rangle)} \quad W(\langle E \rangle) = 1 = \sum_n W_n$$

Sum over states with $E_n \sim \langle E \rangle$.

over all states.

$$S = -\log W(\langle E \rangle) = \log \frac{1}{W(\langle E \rangle)}$$

= $\log (\text{Number of important states})$

Meaning of S .

Tombstone formula.

Boltzmann.

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$$f \sim e^{-\frac{1}{k_B T} E(g, p)}$$

in phase space.

$$\langle Q(g, p) \rangle = \int dq dp Q(g, p) f(g, p)$$

Computationally, mission impossible
 (g, p) space $\sim 6N$

Monte Carlo method.

Effectively, only a very small part of phase space contributes to the integral.

M.C. \rightarrow capture this small & effective part.

\hookrightarrow high distribution density.

① Integral to compute for $\langle Q \rangle$

② Phase space is high-dimensional.

③ $f(g, p)$ is very singular.

Markov chain:

A sequence of microscopic states

$s_1 \rightarrow s_2 \rightarrow s_3 \rightarrow s_4 \rightarrow \dots$

using random "walkers" in phase space.

s_{n+1} depends on s_n only.
 No memory.

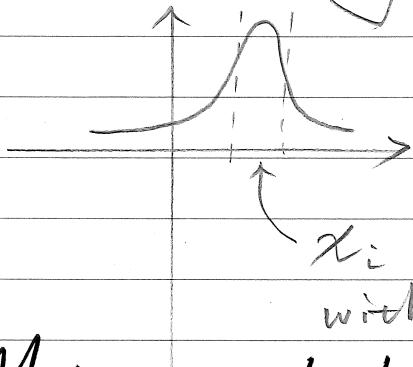
$$I = \int_{-\infty}^{\infty} Q(x) f(x) dx = \langle Q \rangle$$

$$\int_{-\infty}^{\infty} f(x) dx = 1 \text{ PDF.}$$

$X: x_1 \rightarrow x_2 \rightarrow x_3 \rightarrow x_4 \rightarrow x_5 \dots$

A markov chain (x_{n+1} from x_n only),
say, x_4 by x_3 ONLY.

A sequence of values for x : PDF $f(x)$.
Histogram of $x_i \rightarrow$ PDF of x .



x_i in this interval will appear
with large frequency.

More probable x would appear in the
Markov Chain more frequently.

$$\langle Q \rangle = \int Q(x) f(x) dx = \frac{1}{N} \sum_{i=1}^N Q(x_i)$$

Number of x_i values
in $(x, x+dx)$ $\sim f(x) dx$

Key: How to generate a Markov
Chain according to $f(x)$?

frequency of $x \sim f(x)$

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Metropolis importance sampling.

to let x appear with a frequency $\sim f(x)$.

Algorithm for simulation.

No memory S_{n+1} determined from S_n
 only.

Initial state S_1 given,
 Make a trial move from S_1 :

$$S_1 \rightarrow S_c$$

Candidate state.

Compute $E(S_c)$ & $E(S_1)$

If $E(S_c) \leq E(S_1)$, downhill

$$S_1 \rightarrow S_c,$$

then S_c is accepted as S_2 .

Else (Otherwise), $E(S_c) > E(S_1)$,

uphill $S_1 \rightarrow S_c$,

S_c is to be accepted as S_2 ,
 with $P = e^{-(E(S_c) - E(S_1))/k_B T}$

$$< 1$$

In short, candidate state is surely
 accepted if downhill,
 or is accepted with $r < 1$
 (if uphill).

$P = e^{-\Delta E/k_B T}$ for $\Delta E > 0$.
 < 1 .

Given S_1 , trial move $\rightarrow S_c$.

If $E(S_c) \leq E(S_1)$, then $S_2 = S_c$,
i.e., S_c becomes S_2 .
Else ($E(S_c) > E(S_1)$) S_c is accepted
to be S_2 with a probability r ,
 $r = e^{-(E(S_c) - E(S_1))/k_B T} < 1$

How to accept S_c as S_2 with probability $r < 1$?

Generate a random number $\zeta \in [0, 1]$
if $\zeta \leq r$, then acceptance:
 \hookrightarrow probability = r $S_2 = S_c$.

Otherwise, if $\zeta > r$,
probability = $1-r$ $S_2 = S_1$

$$\frac{P_{\text{new}}}{0} \cdot \frac{P_{\text{old}}}{r} \quad \frac{P_{\text{old}}}{1-r} \quad \frac{P_{\text{new}}}{1}$$

S_1 re-used
as S_2 .

How to grow the Markov chain
using the importance sampling.

Consider a system with
two energy states only : H & L
 \hookrightarrow high \hookleftarrow low
energy energy

How to generate a
Markov chain that shows
the Gibbs distribution
by using Importance Sampling.

$$E_H - E_L = \Delta > 0$$

$$w = e^{-\Delta/k_B T} < 1$$

$H \rightarrow S_c = L$: Every trial move
 $L \rightarrow S_c = H$: will change the state .

According to the algorithm, in the M.C.
 H is always followed by L (downhill),
while L is followed by H with probability
 $w < 1$ (uphill) .

$H L H$, w

$H L L H$, $(1-w)w$

$H L L L H$, $(1-w)^2 w$

$H L L L L H$, $(1-w)^3 w$.

Segments
in M.C.

$$\sum \text{probabilities} = w + (1-w)w$$

$$+ (1-w)^2 w$$

$$+ (1-w)^3 w + \dots$$

$$= w (1 + (1-w) + (1-w)^2 + (1-w)^3 + \dots)$$

$$= w \frac{1}{1-(1-w)} = w \cdot \frac{1}{w} = 1 \quad 1-w < 1$$

Normalized.

Let's count the number of L 's following H :

$$n = w + 2(1-w)w + 3(1-w)^2 w + 4(1-w)^3 w + \dots$$

mean

$$= w (1 + 2(1-w) + 3(1-w)^2 + 4(1-w)^3 + \dots)$$

$$= w \frac{1}{1-(1-w)} = w \cdot \frac{1}{w^2} = \frac{1}{w}.$$

Every H is followed by $n = \frac{1}{w}$ L's
on average.

$$P_H : P_L = 1 : \frac{1}{w} = 1 : e^{+\Delta/k_B T} = w : 1$$

desired distribution

$$P_H \sim e^{-E_H/k_B T}$$

$$P_L \sim e^{-E_L/k_B T}$$

$$\frac{P_H}{P_L} = e^{-(E_H - E_L)/k_B T} = e^{-\Delta/k_B T} = w < 1$$

High energy H is less populated than lower energy L.

M. C.

H L L H L L L d H L H L L H ...

Averaging over this M. C.,

we can compute the average according to the Gibbs distribution

$$\frac{P_H}{P_L} = w < 1 \quad \left\{ \begin{array}{l} P_H = \frac{w}{1+w} \\ P_L = \frac{1}{1+w} \end{array} \right.$$