

Goal: Relation between thermodynamics & ~~entropy~~ information theory
 entropy & Shannon entropy (measure of missing info)
 equilibrium ensembles & maximal entropy principle

Information - theoretical derivation of ensembles

Information content of probability distributions

Problem: Suppose you choose a number $0 \leq n < M$ (say, $M=1000$). How many "binary" questions must I ask to find out n ?

"Binary" question - question with YES/NO answer
 1/0

Solution: Write n in binary representation

$$n = \sum_{k=0}^{\dots} n_k 2^k \quad n_k = 0 \text{ or } 1 \quad 0 \leq k < k_{\max}$$

	binary	decimal	
	... 000	= \emptyset	$\underbrace{\hspace{10em}}_{0 \leq n < 2^{k_{\max}}}$
... $n_2 n_1 n_0$... 001	= 1	
	... 010	= 2	
	... 011	= 3	
	... 100	= 4	
	... 101	= 5	

\Rightarrow Number of questions = (smallest number of bits needed to represent any number $0 \leq n < M$) = $\log_2 M$

Disclosure of n has information content = $\log_2 M$ bits
 $= \log_2 \frac{1}{p}$,

$$p = \frac{1}{M} \text{ - probability of event } n.$$

General case:

* $i = 1, 2, \dots, M$ disjoint outcomes (events),

* p_i - probability of event i

* message that event ~~event~~ i has occurred has information content $-\log p_i$

* Information content of a randomly picked outcome (out of the distribution) = $\langle -\log p_i \rangle$

average information we gain from a trial

↓

$$H = - \sum_i p_i \log p_i$$

 - can be viewed as missing information about the state of the system (before any trial)

= "Shannon entropy"

= "information - theoretical entropy"

Examples

1) $p_{i_0} = 1, p_{i \neq i_0} = 0$ } \Rightarrow any outcome is i_0 , so do not need to try anything to know the state

$H = 0$ - consistent with the expectation of no new information learned

2) $p_i = \frac{1}{M}$ \Rightarrow

$H = \log M$

 - compare w entropy in the microcanonical ensemble

Maximal information gain because all events are equally likely.

Indeed, maximize $H = - \sum_i p_i \log p_i$ subject to only $\sum_i p_i = 1$
Lagrange multiplier λ
 $- \sum_i p_i \log p_i - \lambda (\sum_i p_i - 1)$ - maximize over λ & p_i indep.

$$\frac{\delta}{\delta \lambda} = 0 \Rightarrow \sum_i p_i = 1$$

$$\frac{\delta}{\delta p_i} = 0 \quad - \log p_i - 1 - \lambda = 0, \quad p_i = e^{-1-\lambda} = \text{const indep of } i$$

$$\Rightarrow p_i = \frac{1}{M}$$

$p_i = \frac{1}{M}$ - natural subjective choice when we do not have any other information - least biased choice

\Rightarrow Probability distribution $\{p_i\}$ is "least biased" or

Shannon entropy (Shannon's argument)

M possible outcomes : $i=1,2,\dots,M$

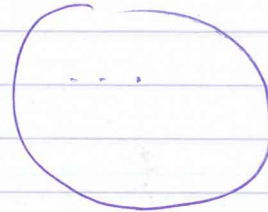
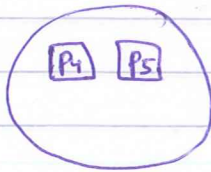
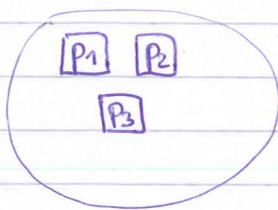
p_i - probability of outcome i

Shannon asks: how to quantify the uncertainty inherent in the distribution $\{p_i\}$

$H_s(p_1, p_2, \dots, p_M)$ - Shannon entropy
("missing information")

Desirable to satisfy composition rule :

for any breaking into groups



$$q_1 = p_1 + p_2 + p_3, \quad q_2 = p_4 + p_5, \quad q_3 = \dots \text{ etc.}$$

$$H_s(p_1, p_2, \dots, p_M) = H_s(q_1, q_2, \dots) + q_1 H_s\left(\frac{p_1}{q_1}, \frac{p_2}{q_1}, \dots, \frac{p_a}{q_1}\right) + q_2 H_s\left(\frac{p_{a+1}}{q_2}, \dots, \frac{p_{a+b}}{q_2}\right) + \dots$$

measure of information from knowing which group

measure of info from knowing within group

prob. of group 1

Can prove that, up to overall constant factor,

$$H_s(\{p_i\}) = - \sum_i p_i \ln p_i$$

Check: $-q_1 \ln q_1 + q_1 \left(- \sum_{i=1}^a \frac{p_i}{q_1} \ln \left(\frac{p_i}{q_1} \right) \right) =$
 $= -q_1 \ln q_1 + q_1 \left(-\frac{1}{q_1} \sum_{i=1}^a p_i (\ln p_i - \ln q_1) \right) = - \sum_{i=1}^a p_i \ln p_i$

Schematic proof:

⊗ ~~Consider~~ Consider special case $p_1 = p_2 = \dots = p_M = \frac{1}{M}$
and denote

$$H_s\left(\frac{1}{M}, \frac{1}{M}, \dots, \frac{1}{M}\right) = J(M)$$

Consider B groups, with $\frac{M}{B}$ in each

$$q_i = \frac{1}{B} ; \quad \frac{p_j}{q_i} = \frac{1/M}{1/B} = \frac{B}{M}$$

X · Y
"

$$\begin{aligned} J(M) &= H_s\left(\frac{1}{M}, \frac{1}{M}, \dots\right) = H_s\left(\frac{1}{B}, \frac{1}{B}, \dots\right) + B \times \frac{1}{B} H_s\left(\frac{B}{M}, \frac{B}{M}, \dots\right) \\ &= J(B) + J\left(\frac{M}{B}\right) \\ &\quad \text{"} \quad \quad \quad \text{"} \\ &\quad X \quad \quad \quad Y \end{aligned}$$

$$J(X \cdot Y) = J(X) + J(Y) \Rightarrow J(X) = \ln X$$

$$\otimes H_s(q_1, q_2, \dots) = H_s(p_1, p_2, \dots, p_M) - \sum_i q_i H_s\left\{\frac{p_j}{q_i}\right\}$$

↑
with $p_i = \frac{1}{M}$

$$= J(M) - \sum_i q_i J\left(\frac{\text{[scribble]}}{M \cdot q_i}\right) = \ln M - \sum_i q_i \ln(M \cdot q_i)$$

$$= - \sum_i q_i \ln q_i \quad \text{— Shannon entropy.}$$

Imagine starting with all $p_i = \frac{1}{M}$; grouping into

groups $\frac{q_i}{(1/M)} = q_i \cdot M$ in group i

— this is "engineering" of $\{q_i\}$ by grouping equally-distributed events.

"most likely" (among all distributions consistent with given data) when missing information H about the system

is maximal

We are led to consider

⇒ Maximal Entropy Principle

Suppose we know only the expectation values $\langle A^{(\nu)} \rangle$ of the observables $A^{(\nu)}$ ($\nu = 1 \dots m; m \ll N$). Then the "least biased" distribution $\{p_i\}$ consistent with the given expectation values of the observables is given by

maximizing

$$S(p_1, \dots, p_N) = -k_B \sum_i p_i \ln p_i$$

subject to conditions

$$0 \leq p_i \leq 1,$$

$$\sum_i p_i = 1$$

$$\sum_i p_i A_i^{(\nu)} = \langle A^{(\nu)} \rangle, \nu = 1, \dots, m$$

Theorem 1. The solution of maximal entropy principle is given by

$$p_i = \frac{1}{Z} e^{-\sum_{\nu} \lambda^{(\nu)} A_i^{(\nu)}}$$

- generalized Boltzmann distribution

$$Z = \sum_i e^{-\sum_{\nu} \lambda^{(\nu)} A_i^{(\nu)}}$$

where the $\lambda^{(\nu)}$ are determined by the equations

$$-\frac{\partial \ln Z}{\partial \lambda^{(\nu)}} = \langle A^{(\nu)} \rangle - \text{given data}$$

The covariances of $A^{(1)}, \dots, A^{(v)}, \dots, A^{(m)}$ are given by

$$\begin{aligned} \left\langle [A^{(v)} - \langle A^{(v)} \rangle] [A^{(v')} - \langle A^{(v')} \rangle] \right\rangle &= \sum_i p_i (A_i^{(v)} - \langle A^{(v)} \rangle) (A_i^{(v')} - \langle A^{(v')} \rangle) = \\ &= \frac{\partial^2 \ln Z}{\partial \lambda^{(v)} \partial \lambda^{(v')}} \end{aligned}$$

Proof: Use method of Lagrange multipliers for the constrained maximization problem:

$$S(\{p_i\}) - k_B \lambda^{(0)} \left(\sum_i p_i - 1 \right) - k_B \sum_v \lambda^{(v)} \left(\sum_i p_i A_i^{(v)} - \langle A^{(v)} \rangle \right)$$

- unconstrained minimization over $p_i, \lambda^{(v)}, v=0,1,\dots,m$

$$\frac{\delta}{\delta \lambda^{(0)}} = 0 \Rightarrow \sum_i p_i = 1$$

$$\frac{\delta}{\delta \lambda^{(v)}} = 0 \Rightarrow \sum_i p_i A_i^{(v)} = \langle A^{(v)} \rangle$$

$$\frac{\delta}{\delta p_i} = 0 \Rightarrow -\ln p_i - 1 - \lambda^{(0)} - \sum_v \lambda^{(v)} A_i^{(v)} = 0$$

$$\begin{aligned} p_i &= \exp(-1 - \lambda^{(0)} - \sum_v \lambda^{(v)} A_i^{(v)}) = \\ &= \text{const} \cdot e^{-\sum_v \lambda^{(v)} A_i^{(v)}} \end{aligned}$$

$$\sum_i p_i = 1 \Rightarrow Z = \sum_i e^{-\sum_v \lambda^{(v)} A_i^{(v)}}$$

$$p_i = \frac{1}{Z} e^{-\sum_v \lambda^{(v)} A_i^{(v)}}$$

Require $\sum_i p_i A_i^{(v)} = \langle A^{(v)} \rangle$ ← specified values

$$\frac{1}{Z} \sum_i A_i^{(v)} e^{-\sum_{\mu} \lambda^{(\mu)} A_i^{(\mu)}} = \frac{1}{Z} \cdot \frac{-\partial}{\partial \lambda^{(v)}} Z = -\frac{\partial \ln Z}{\partial \lambda^{(v)}}$$

$\lambda^{(v)}$ are determined from $-\frac{\partial \ln Z}{\partial \lambda^{(v)}}(\lambda^{(1)}, \lambda^{(2)}, \dots) = \langle A^{(v)} \rangle$

Consider

$$\begin{aligned} \frac{\partial^2 \ln Z}{\partial \lambda^{(v)} \partial \lambda^{(v')}} &= \frac{\partial}{\partial \lambda^{(v)}} \left(\frac{1}{Z} \frac{\partial Z}{\partial \lambda^{(v')}} \right) = \frac{1}{Z} \frac{\partial^2 Z}{\partial \lambda^{(v)} \partial \lambda^{(v')}} - \\ &- \frac{1}{Z^2} \frac{\partial Z}{\partial \lambda^{(v)}} \frac{\partial Z}{\partial \lambda^{(v')}} = \frac{1}{Z} \sum_i A_i^{(v)} A_i^{(v')} e^{-\sum_{\mu} \lambda^{(\mu)} A_i^{(\mu)}} - \langle A^{(v)} \rangle \langle A^{(v')} \rangle \\ &= \langle A^{(v)} A^{(v')} \rangle_P - \langle A^{(v)} \rangle_P \langle A^{(v')} \rangle_P \\ &= \langle (A^{(v)} - \langle A^{(v)} \rangle) (A^{(v')} - \langle A^{(v')} \rangle) \rangle \\ &= \langle A^{(v)} A^{(v')} \rangle - \underbrace{\langle A^{(v)} \rangle \langle A^{(v')} \rangle} - \underbrace{\langle \langle A^{(v)} \rangle A^{(v')} \rangle + \langle A^{(v)} \rangle \langle A^{(v')} \rangle}_{\langle A^{(v)} \rangle \langle A^{(v')} \rangle + \langle A^{(v)} \rangle \langle A^{(v')} \rangle} \end{aligned}$$

- covariance of $A^{(v)}$ and $A^{(v')}$ ▲

Theorem 2

Maximum of the entropy is given by

$$\begin{aligned} S &= k_B \ln Z - k_B \sum_{\nu} \lambda^{(\nu)} \frac{\partial \ln Z}{\partial \lambda^{(\nu)}} \quad (S \text{ as a function of } \lambda \text{'s}) \\ &= k_B \ln Z + k_B \sum_{\nu} \lambda^{(\nu)} \langle A^{(\nu)} \rangle \quad (S \text{ as a function of } \langle A \rangle \text{'s}) \\ &\quad \underbrace{\quad \quad \quad}_{\text{functions of } \langle A \rangle \text{'s}} \end{aligned}$$

Proof :

$$\begin{aligned}
 \boxed{S} &= -k_B \sum_i p_i \ln p_i = -k_B \sum_i p_i \ln \left(\frac{1}{Z} e^{-\sum_\nu \lambda^{(\nu)} A_i^{(\nu)}} \right) \\
 &= k_B \ln Z + k_B \sum_i p_i \left(\sum_\nu \lambda^{(\nu)} A_i^{(\nu)} \right) = \\
 &= \boxed{k_B \ln Z + k_B \sum_\nu \lambda^{(\nu)} \langle A^{(\nu)} \rangle} \quad \blacktriangle
 \end{aligned}$$

Remark: meaning of λ -s

Suppose we solve for $\lambda^{(\nu)}$ from $-\frac{\partial \ln Z}{\partial \lambda^{(\nu)}} = \langle A^{(\nu)} \rangle$ and thus express S as a function of $\langle A^{(\nu)} \rangle$.

$$\Rightarrow \boxed{\frac{\partial S}{\partial \langle A^{(\nu)} \rangle}} = k_B \sum_\mu \frac{\partial \ln Z}{\partial \lambda^{(\mu)}} \cdot \frac{\partial \lambda^{(\mu)}}{\partial \langle A^{(\nu)} \rangle} + \\
 + k_B \sum_\mu \frac{\partial \lambda^{(\mu)}}{\partial \langle A^{(\nu)} \rangle} \cdot \langle A^{(\mu)} \rangle + k_B \lambda^{(\nu)} = \boxed{k_B \lambda^{(\nu)}}$$

\Rightarrow meaning of λ 's

Remark: connection with Legendre transforms; meaning of $\ln Z$

Consider function $f(\lambda^{(1)}, \dots) = k_B \ln Z(\lambda^{(1)}, \lambda^{(2)}, \dots)$ and consider Legendre transformation

$$\begin{aligned}
 \phi(x^{(1)}, x^{(2)}, \dots) &= \min_{\lambda^{(1)}, \lambda^{(2)}, \dots} \left\{ f(\lambda^{(1)}, \lambda^{(2)}, \dots) - \right. \\
 &\quad \left. - \sum_\nu \lambda^{(\nu)} \cdot \underbrace{(-k_B x^{(\nu)})}_{\substack{\uparrow \\ \text{new vars}}} \right\} \\
 &\quad \uparrow \\
 &\quad \text{new variables} \qquad \qquad \qquad \uparrow \\
 &\quad \qquad \qquad \qquad \qquad \qquad \text{old vars}
 \end{aligned}$$

$$\left. \begin{aligned}
 \frac{\partial}{\partial \lambda^{(\nu)}} &= 0 \Rightarrow \frac{\partial \ln Z}{\partial \lambda^{(\nu)}} + x^{(\nu)} = 0 \\
 -k_B x^{(\nu)} &= \frac{\partial}{\partial \lambda^{(\nu)}} (k_B \ln Z)
 \end{aligned} \right\} \text{equations for } \lambda^{(1)}, \lambda^{(2)}, \dots$$

Inverse Legendre transform: $\lambda^{(\nu)} = - \frac{\partial \phi(x)}{\partial (-k_B x^{(\nu)})}$

$$\left. \begin{array}{l} \text{Compare } x^{(v)} = -\frac{\partial}{\partial \lambda^{(v)}} \ln Z \\ \text{with } \langle A^{(v)} \rangle = -\frac{\partial}{\partial \lambda^{(v)}} \ln Z \end{array} \right\} \Rightarrow x^{(v)} = \langle A^{(v)} \rangle$$

$$\text{Compare } \phi(x^{(1)}, x^{(2)}, \dots) = k_B \ln Z + k_B \sum_v \lambda^{(v)} x^{(v)}$$

$$\text{with } S = k_B \ln Z + k_B \sum_v \lambda^{(v)} \langle A^{(v)} \rangle$$

$$\Rightarrow \phi(x^{(1)}, x^{(2)}, \dots) = S(\langle A^{(1)} \rangle, \langle A^{(2)} \rangle, \dots)$$

In particular,

$$\Rightarrow \boxed{k_B \lambda^{(v)} = \frac{\partial S}{\partial \langle A^{(v)} \rangle}}$$

Earlier in thermodynamics we were Legendre-transforming energy rather than entropy. The connection with the above is as follows:

$$\text{Thermodynamics: } U(S, V, N) \quad , \quad T = \left(\frac{\partial U}{\partial S} \right)_{V, N}$$

$$F(T, V, N) = U - TS = U - S \left(\frac{\partial U}{\partial S} \right)_{V, N}$$

$$-\frac{F}{\left(\frac{\partial U}{\partial S} \right)_{V, N}} = S - \frac{U}{\left(\frac{\partial U}{\partial S} \right)_{V, N}} = S - \left(\frac{\partial S}{\partial U} \right)_{V, N} \cdot U$$

Thus, $-\frac{F}{\left(\frac{\partial U}{\partial S} \right)_{V, N}}$ is Legendre transform of S with respect to U

$$\underbrace{k_B \ln Z}_{\text{Legendre transform of } S} = S - S \cdot \frac{\partial S}{\partial \langle E \rangle}$$

precisely as above in the maxEnt derivation of ensembles

Application to Statistical Mechanics

Relation between information theory and thermodynamics:

- 1) Thermodynamic quantities = ~~averages~~ averages with respect to probability distribution $\{p_i\}$
- 2) Thermodynamic entropy ~~is missing information about the system~~
 \sim Shannon entropy = missing information about the system (relative to what we know from macroscopic measurements)
- 3) Equilibrium \Leftrightarrow maximum missing information

Derivation of ensembles

Microcanonical: fixed $E \leq E_i \leq E + \delta E$
 $N_i = N$

No macro-condition of type $\sum_i p_i A_i^{(v)} = \langle A^{(v)} \rangle$
(only $\sum_i p_i = 1$) \Rightarrow no $\lambda^{(v)}$ for $v=1,2,\dots$; only $\lambda^{(0)}$

$$\Rightarrow \bullet p_i = \frac{1}{\mathcal{Z}} \cdot e^0 = \frac{1}{\mathcal{Z}}$$

$$\bullet \mathcal{Z} = \sum_i e^0 = \Omega$$

\bullet No Lagrange params $\lambda^{(1)}, \dots$

$$\bullet \text{entropy } S = k_B \ln \mathcal{Z}$$

\bullet entropy as a function of macroscopic data

$$S(E, V, N)$$

\bullet meaning of \mathcal{Z} : $k_B \ln \mathcal{Z}(E, V, N) = S(E, V, N)$

Canonical ensemble

"fixed"

Macroscopic conditions of parametric type: $N_i = N$
(fixed N)

Macroscopic conditions of "on average" type:

$$\sum_i p_i E_i = \langle E \rangle$$

- probability $p_i = \frac{1}{Z} e^{-\beta E_i}$
- partition function $Z = \sum_i e^{-\beta E_i}$
- Lagrange parameter β for $\langle E \rangle$
- Entropy $S = k_B \ln Z + k_B \beta \cdot \langle E \rangle$
- S as a function of macroscopic data $S(\langle E \rangle, V, N)$
- meaning of Lagrange parameter:

$$k_B \beta = \frac{\partial S}{\partial \langle E \rangle} = \frac{1}{T}$$

from $dS = \frac{1}{T} dU + \frac{P}{T} dV - \frac{\mu}{T} dN$

- $S = k_B \ln Z + \frac{\langle E \rangle}{T}$
- compare with thermodynamic relations

$$S = -\frac{F}{T} + \frac{U}{T} \quad (F = U - TS)$$

⇒ gives meaning of Z :

$$k_B \ln Z(T, V, N) = -\frac{F(T, V, N)}{T}$$

	microcanonical ensemble	canonical ensemble	grand-canonical ensemble	pressure ensemble
macroscopic conditions of parametric type	$E \leq E_i \leq E + \delta E$ $V_i = V$ $N_i = N$	$V_i = V$ $N_i = N$	$V_i = V$	$N_i = N$
macroscopic conditions of "on-average" type	—	$\sum_i p_i E_i = \langle E \rangle$	$\sum_i p_i E_i = \langle E \rangle$ $\sum_i p_i N_i = \langle N \rangle$	$\sum_i p_i E_i = \langle E \rangle$ $\sum_i p_i V_i = \langle V \rangle$
probability P_i	$\frac{1}{Z} e^{\phi}$	$\frac{1}{Z} e^{-\beta E_i}$	$\frac{1}{Z} e^{-\beta E_i - \delta N_i}$	$\frac{1}{Z} e^{-\beta E_i - \lambda V_i}$
partition function Z	$\sum_i e^{\phi} = \Omega$	$\sum_i e^{-\beta E_i}$	$\sum_i e^{-\beta E_i - \delta N_i}$	$\sum_i e^{-\beta E_i - \lambda V_i}$
Lagrange parameters	—	β ($\delta \langle E \rangle$)	β ($\delta \langle E \rangle$), δ ($\delta \langle N \rangle$)	β ($\delta \langle E \rangle$) λ ($\delta \langle V \rangle$)
entropy S	$k_B \ln Z$	$k_B \ln Z + k_B \beta \langle E \rangle$	$k_B \ln Z + k_B \beta \langle E \rangle + k_B \delta \langle N \rangle$	$k_B \ln Z + k_B \beta \langle E \rangle + k_B \lambda \langle V \rangle$
S as a function of mac. data	$S(E, V, N)$	$S(\langle E \rangle, V, N)$	$S(\langle E \rangle, V, \langle N \rangle)$	$S(\langle E \rangle, \langle V \rangle, N)$
meaning of Lagrange Params	—	$k_B \beta = \frac{\partial S}{\partial \langle E \rangle} = \frac{1}{T}$	$k_B \delta = \frac{\partial S}{\partial \langle N \rangle} = -\frac{\mu}{T}$	$k_B \lambda = \frac{\partial S}{\partial \langle V \rangle} = -\frac{P}{T}$
		$\{ dS(E, V, N) = \frac{1}{T} dE + \frac{P}{T} dV - \frac{\mu}{T} dN \}$		

	microcanonical ensemble	canonical ensemble	grand-canonical ensemble	pressure ensemble
entropy	$S = k_B \ln Z$	$S = k_B \ln Z + \frac{\langle E \rangle}{T}$	$S = k_B \ln Z + \frac{\langle E \rangle - \mu N}{T}$	$S = k_B \ln Z + \frac{\langle E \rangle}{T} + \frac{PV}{T}$
Compare with thermodynamic relations	—	$S = -\frac{E}{T} + \frac{U}{T}$	$S = -\frac{\Omega}{T} + \frac{U}{T} - \frac{\mu N}{T}$ $\Omega = -PV$ (Gibbs-Duhem)	$S = \frac{PV}{T} + \frac{U}{T} - \frac{\mu N}{T}$ "Gibbs potential" $\rightarrow G/T$
gives meaning of Z	$k_B \ln Z(E, V, N) = S(E, V, N)$	$k_B \ln Z(T, V, N) = -\frac{F(T, V, N)}{T}$	$k_B \ln Z(T, \mu) = -\frac{\Omega(T, \mu, N)}{T} = -\frac{PV}{T}$	$k_B \ln Z(T, P, N) = -\frac{G(T, P, N)}{T}$
Z yields all other therm. quantities	$\left(\frac{\partial S}{\partial E}\right)_{V, N} = \frac{1}{T}$ $\left(\frac{\partial S}{\partial V}\right)_{E, N} = \frac{P}{T}$ $\left(\frac{\partial S}{\partial N}\right)_{E, V} = -\frac{\mu}{T}$	$\left(\frac{\partial F}{\partial T}\right)_{V, N} = -S$ $\left(\frac{\partial F}{\partial V}\right)_{T, N} = -P$ $\left(\frac{\partial F}{\partial N}\right)_{T, V} = +\mu$ $\left(\frac{\partial \ln Z}{\partial \left(\frac{1}{k_B T}\right)}\right)_{V, N} = -U$	$\left(\frac{\partial \ln Z}{\partial \left(\frac{1}{k_B T}\right)}\right)_{\mu, N} = -U + \mu N$ $\left(\frac{\partial \ln Z}{\partial \left(\frac{\mu}{k_B}\right)}\right)_{T, V} = \frac{N}{T}$ $\left(\frac{\partial \ln Z}{\partial \beta}\right)_{\mu} = -U$	$\left(\frac{\partial G}{\partial T}\right)_{P, N} = -S$ $\left(\frac{\partial G}{\partial P}\right)_{T, N} = V$ $\left(\frac{\partial G}{\partial N}\right)_{T, V} = \mu$ $\left(\frac{\partial \ln Z}{\partial \left(\frac{1}{k_B T}\right)}\right)_{P, N} = -U - PV$ $\left(\frac{\partial \ln Z}{\partial \left(\frac{P}{k_B}\right)}\right)_{T, N} = -\frac{V}{T}$
ensemble convenient	when Ω (# of microstates) is easy to compute [rare]; when molecular dynamics simulations are performed	for interacting systems when fixed N poses no problem	when fixed N yields unphysical conditions; when phase equilibria at issue (common μ)	when fixed V yields unphysical constraints (rare); when Monte Carlo simulations at const. P are performed

Fluctuations. Equivalences of Ensembles.

3rd law of thermodynamics

Variance

$$\langle (A^{(v)} - \langle A^{(v)} \rangle)^2 \rangle = \frac{\partial^2 \ln Z}{\partial (\lambda^{(v)})^2} = - \frac{\partial \langle A^{(v)} \rangle}{\partial \lambda^{(v)}}$$

↪ change of $\langle A^{(v)} \rangle$ due to change in external parameter $\lambda^{(v)}$

≡ "response function" : gain/loss of $A^{(v)}$ from/to reservoir, i.e. "dissipation"

fluctuation - dissipation theorem

$$\sqrt{\frac{\langle (A^{(v)} - \langle A^{(v)} \rangle)^2 \rangle}{\langle A^{(v)} \rangle^2}} = \frac{1}{\langle A^{(v)} \rangle} \sqrt{-\frac{\partial \langle A^{(v)} \rangle}{\partial \lambda^{(v)}}} \sim \frac{\sqrt{N}}{N} \sim \frac{1}{\sqrt{N}}$$

→ 0 as $N \rightarrow \infty$

Consequences:

* real fluctuations $\sim 10^{-11}$ for $N \sim 10^{22}$

* almost all systems in GCE (grand canonical ensemble) have the same $N \Rightarrow \text{GCE} \Leftrightarrow \text{CE}$

* almost all states in CE (canonical ensemble) have the same $E \Rightarrow \text{CE} \Leftrightarrow \text{MCE}$ (micro-canonical ensemble)

Examples: * $A^{(v)} = E$ in CE or GCE:

$$\langle (E - \langle E \rangle)^2 \rangle = - \frac{\partial \langle E \rangle}{\partial \frac{1}{k_B T}} = k_B T^2 \frac{\partial \langle E \rangle}{\partial T} = k_B T^2 C_V$$

* $A^{(N)} = N$ in GCE

$$\langle (N - \langle N \rangle)^2 \rangle = - \left(\frac{\partial \langle N \rangle}{\partial \left(-\frac{\mu}{k_B T} \right)} \right)_{T, V} = k_B T \left(\frac{\partial \langle N \rangle}{\partial \mu} \right)_{T, V}$$

Third law of thermodynamics

Suppose we work in the canonical ensemble and

$$-\infty < E_1 < E_2 < \dots$$

↑ ↑
energy eigenvalues

Then

$$\begin{aligned} \lim_{T \rightarrow 0} p_i &= \lim_{\beta \rightarrow \infty} \frac{e^{-\beta E_i}}{\sum_j e^{-\beta E_j}} = \lim_{\beta \rightarrow \infty} \frac{e^{-\beta(E_i - E_1)}}{1 + \sum_{j=2}^{\infty} e^{-\beta(E_j - E_1)}} \\ &= \begin{cases} 1 & \text{if } i=1 \\ \emptyset & \text{if } i \neq 1 \end{cases} \end{aligned}$$

⇒ Fluctuations for any observable go to \emptyset as $T \rightarrow \emptyset$

$$\lim_{T \rightarrow 0} U = E_1$$

$$\lim_{T \rightarrow 0} S = 0$$

$$\lim_{T \rightarrow 0} F = E_1$$

- 3rd law of thermodynamics, assuming non-degenerate ground state of a quantum system.

$$S(V, T) = \int_0^T C_V(V, T') \frac{dT'}{T'} \rightarrow 0 \text{ for } T \rightarrow 0 \text{ - this}$$

implies that $C_V(V, T) \rightarrow 0$ as $T \rightarrow 0$.