

# Brief Review of Statistical Mechanics

## Introduction

Statistical mechanics: “a branch of physics which studies macroscopic systems from a microscopic or molecular point of view” (McQuarrie, 1976)

Also see (Hill, 1986; Chandler, 1987)

Stat mech will inform us about

- how to set up and run a simulation algorithm
- how to estimate macroscopic properties of interest from simulations

Two important postulates

- in an isolated system with constant  $E$ ,  $V$ , and  $N$ , all *microstates* are equally likely.
- time averages are equivalent to *ensemble* averages (principle of ergodicity).

The *ensemble* formalism allows extension of these postulates to more useful physical situations.

## Ensembles

Ensemble: “the (virtual) assembly of all possible microstates (that are) consistent with the constraints with which we characterize the system macroscopically” (Chandler, 1987)

Microstate: the complete specification of a system at the most detailed level.

In the most rigorous sense, the microstate of a system is its quantum state, which is obtained by solving the Schrodinger equation. Quantum states are discrete and have discrete probabilities.

However, the microstate of a *classical* system is completely specified by the positions ( $\mathbf{r}$ ) and momenta ( $\mathbf{p}$ ) of all particles. Such microstates are part of a continuum and must be described with probability density functions.

Note: We will sometimes use quantum notation for compactness, but the focus of this part of the course is on classical systems.

Macroscopic constraints: generally, these are thermodynamic properties (energy, temperature, pressure, chemical potential, ...)

## Role of simulation

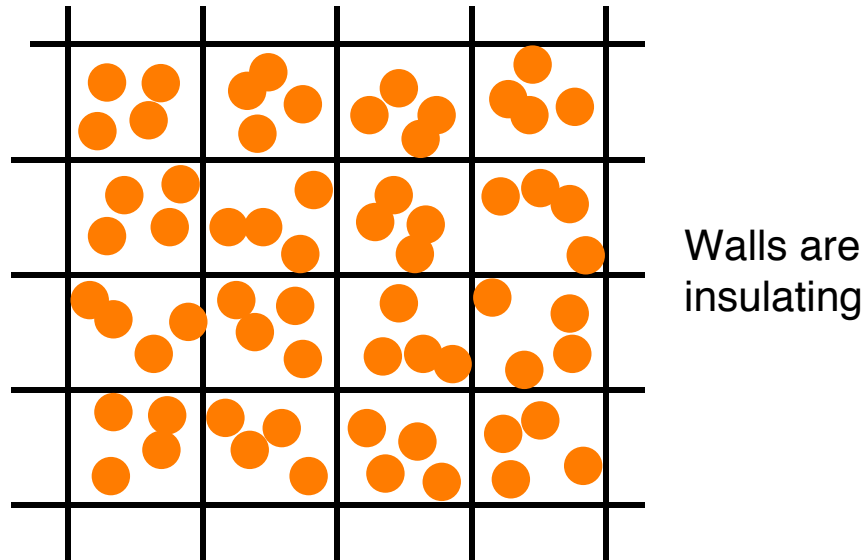
For a given model system, the tasks of a molecular simulation are to:

- (1) Sample microstates within an ensemble, with the appropriate statistical weights
- (2) During the sampling, calculate and collect molecular-level information that aids in understanding the physical behavior of the system
- (3) Employ a large enough sample size to ensure that the collected information is meaningful

(Note: even with today's powerful computers, it is generally impossible to sample all of the microstates of a model system.)

## ***Microcanonical ensemble.***

Constant E, V, N.



According to the first postulate, all of these states are equally likely.

$$\Omega_i = \frac{1}{\Omega}$$

Properties that can be measured over a simulation:

T, p. And, with more effort,  $\mu$ .

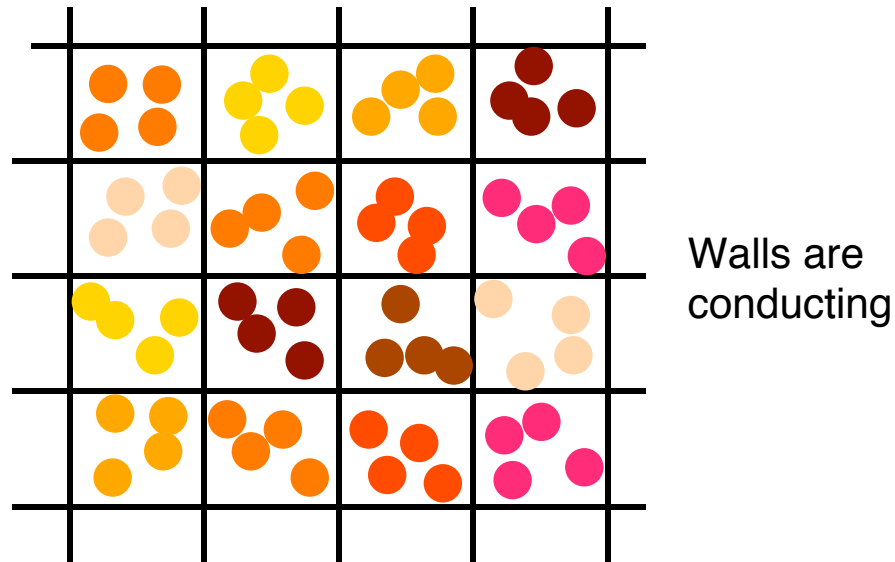
Note: The conjugate variables are the ones that can be “measured” as outcomes.

$$dE = TdS - pdV + \mu dN$$

$$dS = \frac{1}{T}dE + \frac{p}{T}dV - \frac{\mu}{T}dN$$

## Canonical ensemble.

Constant  $T$ ,  $V$ ,  $N$ .



Now the boxes may have different energies!

Can show (Hill, 1986; McQuarrie, 1976) that the probability of a state is

$$\Omega_i(E_i) = \frac{e^{-\beta E_i}}{Q}, \quad \text{where } \beta = \frac{1}{k_B T}$$

Properties that can be measured:

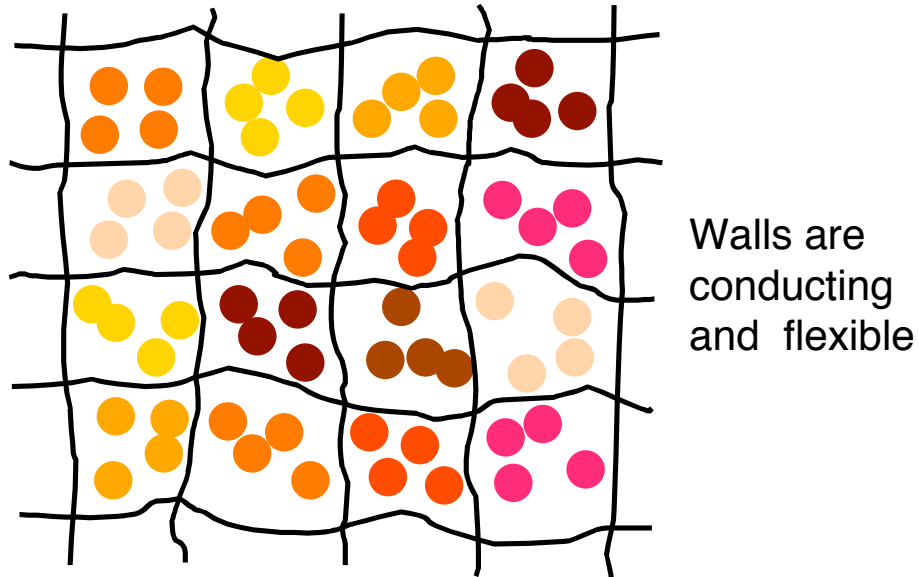
$E$ ,  $p$ . And, with more effort,  $\chi$ .

The governing equation is

$$d\left(\frac{S}{T}\right) = \frac{E}{T^2} dT + \frac{p}{T} dV + \frac{\chi}{T} dN$$

## ***Isothermal-isobaric ensemble.***

Constant  $T$ ,  $p$ ,  $N$ .



Now the boxes may have different energies and volumes!

Can show (Hill, 1986; McQuarrie, 1976) that the probability of a state is

$$\Omega_i(E_i, V_i) = \frac{e^{-\beta E_i} e^{-\beta p V_i}}{\Omega}$$

Properties that can be measured:

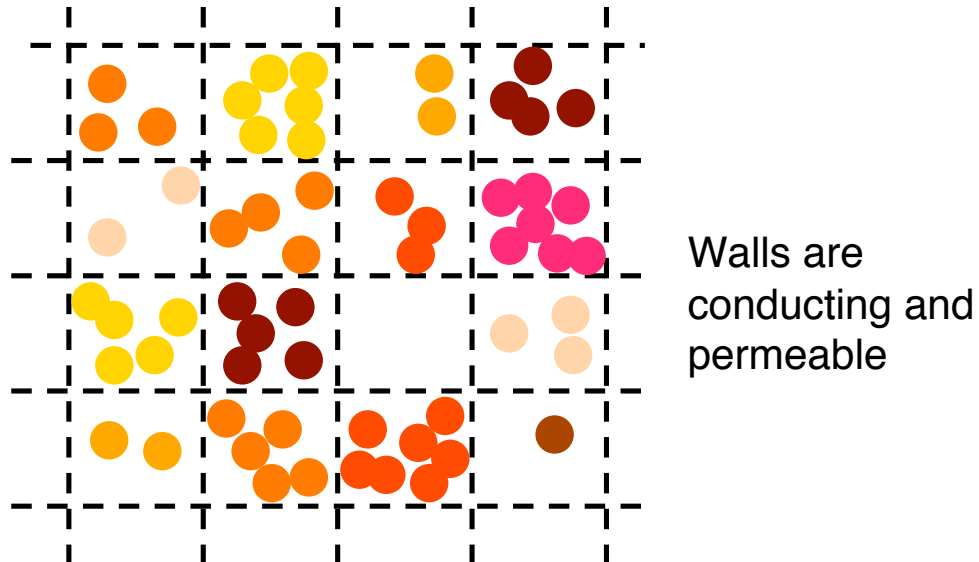
$E$ ,  $V$ . And, with more effort,  $\Omega$ .

The governing equation is

$$dS = \frac{E}{T} d\beta + \frac{pV}{T} d\beta + \frac{1}{T} dV + \frac{p}{T} dV + \frac{1}{T} dN$$

## Grand canonical ensemble.

Constant  $T, V, \mu$ .



Now the boxes may have different energies and numbers of molecules!

Can show (Hill, 1986; McQuarrie, 1976) that the probability of a state is

$$\Omega_i(E_i, N_i) = \frac{e^{-\beta E_i} e^{-\beta \mu N_i}}{\Omega}$$

Properties that can be measured:

$E, p,$  and  $N$ .

The governing equation is

$$d\left(\frac{S}{T}\right) + \frac{N}{T} d\left(\frac{1}{T}\right) + \frac{p}{T} dV + Nd\left(\frac{\mu}{T}\right)$$

## Bridges to macroscopic thermodynamics

### *Partition functions.*

The normalization constants are referred to as partition functions, and they have (macroscopic) physical significance.

Summary, in “quantum” notation:

Ensemble	Partition Function	Bridge Equation
Micro-canonical	$\Omega(E, V, N) = \sum_i 1$	$\frac{S}{k_B} = \ln \Omega$
Canonical	$Q(T, V, N) = \sum_i e^{-\beta E_i}$	$\beta A = \ln Q$
Isothermal-Isobaric	$\Omega(T, p, N) = \sum_V e^{-\beta pV} \sum_i e^{-\beta E_i(V)}$ $= \sum_V e^{-\beta pV} Q(T, V, N)$	$\beta G = \ln \Omega$
Grand canonical	$\Omega(T, V, \mu) = \sum_N e^{-\beta \mu N} \sum_i e^{-\beta E_i(N)}$ $= \sum_N e^{-\beta \mu N} Q(T, V, N)$	$\beta pV = \ln \Omega$



We can translate these quantum formulas into quasi-classical expressions that are appropriate for our force-field-based molecular modeling approach.

Recall that the microstate of a classical system is not defined by a quantum state, but rather by the position and momentum of each particle. To get a partition function, we must sum (actually integrate, for the classical case) over all possible microstates.

Example: canonical partition function

$$Q = \frac{1}{N!} \frac{1}{h^{3N}} \int \dots \int d\mathbf{p}_1 \dots d\mathbf{p}_N d\mathbf{r}_1 \dots d\mathbf{r}_N e^{-\beta H}$$

where

$$H(\mathbf{p}^{\{N\}}, \mathbf{r}^{\{N\}}) = K(\mathbf{p}^{\{N\}}) + U(\mathbf{r}^{\{N\}})$$

If we could evaluate this partition function for a model system at various temperatures and volumes, we could obtain thermodynamic properties via

$$\beta A(\beta, V, N) = \ln Q$$

$$E = \left. \frac{\partial(\beta A)}{\partial \beta} \right|_{V, N}$$

$$\beta p = \left. \frac{\partial(\beta A)}{\partial V} \right|_{T, N}$$

However, it is *not even close* to practical to calculate the partition function for a typical system.

Example:

Say we have a system with  $N=100$  atoms, and we wish to evaluate the configurational ( $\mathbf{r}$ ) part of the canonical partition function. We have  $3N=300$  coordinates over which to integrate.

Try a Simpson's rule integration, where 10 function evaluations per coordinate are employed (a fairly coarse grid).

$$\# \text{ of function evaluations} = (10)(10)^L (10) = 10^{300}$$

$$\begin{aligned} (10^{300} \text{ operations}) \left( \frac{\text{sec}}{5 \times 10^{12} \text{ ops}} \right) &= 10^{288} \text{ sec} \\ &= 10^{280} \text{ yrs} \end{aligned}$$

Not likely in the foreseeable future!

Instead, we focus on obtaining averages of properties of interest.

### ***Formalism for simple averages.***

One can easily define the average of any property that has a simple dependence on the microstate variables.

For example, in quantum notation

$$\langle B \rangle = \sum_i B_i \rho_i$$

In the canonical ensemble, for example, we have

$$\langle B \rangle = \frac{\sum_i B_i e^{-\beta E_i}}{Q}$$

In classical notation, a similar expression can be written for any quantity that has a simple, direct functional dependence on molecular positions and momenta.

$$\langle B \rangle = \frac{\frac{1}{N!} \frac{1}{h^{3N}} \int \dots \int dp_1 \dots dp_N dr_1 \dots dr_N B(\mathbf{p}^{\{N\}}, \mathbf{r}^{\{N\}}) e^{-\beta H}}{Q}$$

This seems no better than before – we can't calculate the numerator or denominator!

But...

## ***Obtaining simple averages from simulation.***

Recall that it is the task of a simulation algorithm to generate microstates in an ensemble, in proportion to their statistical weights (probabilities).

This can be done

- probabilistically (Monte Carlo)
- deterministically (molecular dynamics)\*

\* actually a time average – we'll revisit this issue

Either way, given a set of  $n_{\text{obs}}$  representative microstates, we can write the average of B as

$$\langle B \rangle = \frac{1}{n_{\text{obs}}} \prod_{i=1}^{n_{\text{obs}}} B(\mathbf{p}_i^{\{N\}}, \mathbf{r}_i^{\{N\}})$$

*as long as those microstates were generated according to the appropriate weighting function  $\square$  for that ensemble!*

The quality of the result that you obtain depends on  $n_{\text{obs}}$ .

### ***Separation of the energy.***

In the classical limit, the kinetic energy (K) and potential energy (U) can be considered as separable in the Hamiltonian.

This allows Q to be factored

$$Q = \frac{1}{N!} \frac{1}{h^{3N}} \left( \int \dots \int dp_1 \dots dp_N e^{-\beta K} \right) \left( \int \dots \int dr_1 \dots dr_N e^{-\beta U} \right)$$

and the momentum part will drop out of averages that depend only on positions.

$$\begin{aligned} \langle B \rangle &= \frac{\frac{1}{N!} \frac{1}{h^{3N}} \left( \int \dots \int dp_1 \dots dp_N e^{-\beta K} \right) \left( \int \dots \int dr_1 \dots dr_N B(\mathbf{r}^{\{N\}}) e^{-\beta U} \right)}{\frac{1}{N!} \frac{1}{h^{3N}} \left( \int \dots \int dp_1 \dots dp_N e^{-\beta K} \right) \left( \int \dots \int dr_1 \dots dr_N e^{-\beta U} \right)} \\ &= \frac{\int \dots \int dr_1 \dots dr_N B(\mathbf{r}^{\{N\}}) e^{-\beta U}}{\int \dots \int dr_1 \dots dr_N e^{-\beta U}} \end{aligned}$$

This is why Monte Carlo, where there is no time, can still be useful in obtaining thermodynamic properties.

## ***Examples of simple averages.***

Kinetic energy.

The classical definition is

$$K = \sum_{i=1}^N \frac{1}{2m_i} |\mathbf{p}_i|^2$$

So we have

$$\langle K \rangle = \frac{1}{n_{\text{obs}}} \sum_{i=1}^{n_{\text{obs}}} K(\mathbf{p}_i^{\{N\}}) = \frac{1}{n_{\text{obs}}} \sum_{i=1}^{n_{\text{obs}}} \sum_{j=1}^N \frac{1}{2m_j} |\mathbf{p}_i|^2$$

Temperature.

Start with the rigorous definition of  $\langle K \rangle$

$$\langle K \rangle = \frac{\frac{1}{N!} \frac{1}{h^{3N}} \left( \int \dots \int d\mathbf{p}_1 \dots d\mathbf{p}_N K(\mathbf{p}^{\{N\}}) e^{-\beta K} \right) \left( \int \dots \int d\mathbf{r}_1 \dots d\mathbf{r}_N e^{-\beta U} \right)}{\frac{1}{N!} \frac{1}{h^{3N}} \left( \int \dots \int d\mathbf{p}_1 \dots d\mathbf{p}_N e^{-\beta K} \right) \left( \int \dots \int d\mathbf{r}_1 \dots d\mathbf{r}_N e^{-\beta U} \right)}$$

$$= \frac{\int \dots \int d\mathbf{p}_1 \dots d\mathbf{p}_N K(\mathbf{p}^{\{N\}}) e^{-\beta K}}{\int \dots \int d\mathbf{p}_1 \dots d\mathbf{p}_N e^{-\beta K}}$$

Can show that for  $K = \sum_{i=1}^N \frac{1}{2m_i} |\mathbf{p}_i|^2$ , this reduces to

$$\langle K \rangle = \frac{3}{2} N k_B T$$

*The equipartition principle:* any contribution to the Hamiltonian that is additive and quadratic will contribute  $(k_B T/2)$  to the energy. (McQuarrie, 1976 pp. 121-123)

So the average temperature is

$$T = \frac{2}{3Nk_B} \langle K \rangle$$

Potential energy.

This is simply the interaction potential within and between molecules (intramolecular and intermolecular, respectively). It depends only on the atomic coordinates, not the momenta.

So we may write

$$\langle U \rangle = \frac{1}{n_{\text{obs}}} \prod_{i=1}^{n_{\text{obs}}} U(\mathbf{r}_i^{\{N\}})$$

We may write a similar relationship for any particular component of the potential energy. For example, for a polymeric system we may be interested in the torsional component of the potential:

$$\langle U_{\text{tors}} \rangle = \frac{1}{n_{\text{obs}}} \prod_{i=1}^{n_{\text{obs}}} U_{\text{tors}}(\mathbf{r}_i^{\{N\}})$$



Pressure.

Pressure can be obtained from the *virial formula* (Allen and Tildesley, 1987)

$$PV = Nk_B T + \langle W \rangle$$

where  $W$  is the *virial*

$$W = \frac{1}{3} \sum_{i=1}^N \mathbf{r}_i \cdot \mathbf{f}_i$$

Usually this is reduced into a form that is independent of origin before application. For example, for pairwise forces, the virial takes the form

$$W = \frac{1}{3} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \mathbf{r}_{ij} \cdot \mathbf{f}_{ij} \equiv \frac{1}{3} \sum_i \sum_{j>i} \mathbf{r}_{ij} \cdot \mathbf{f}_{ij}$$

Three-body and higher forces are more complicated, but similar formulas can be derived.

## Chemical potential.

Chemical potential is not a “mechanical variable” – it does not have a “simple, direct functional dependence on molecular positions and momenta.”

Calculating the chemical potential of a species from a molecular simulation can be quite challenging; we will discuss this in detail later.

For now, the following definition (in the canonical ensemble) provides a clue on how it might be calculated

$$\mu = \left. \frac{\partial(\beta A)}{\partial N} \right|_{\beta, V}$$

## Ergodicity

### ***Ergodic hypothesis.***

“...a large number of observations made on a single system at  $n$  arbitrary instants of time have the same statistical properties as observing  $n$  arbitrarily chosen systems at the same time from an ensemble...”

(McQuarrie, 1976)

time average  $\Leftrightarrow$  ensemble average

We believe that it “holds for all many-body systems in nature.” (Chandler, 1987)

### ***Implications for molecular simulation.***

(Allen and Tildesley, 1987; Frenkel and Smit, 1996)

molecular dynamics

simulation in time

average over snapshots in time

Monte Carlo

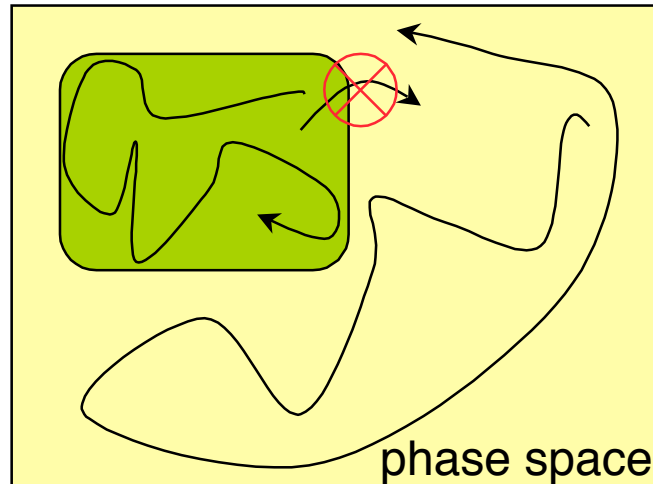
probabilistic walk through configurations

average over (properly weighted) configurations

When we simulate a given model system under a given set of macroscopic constraints, we should get statistically identical results from MD and MC.

## ***Ergodic problems in molecular simulation.***

It is possible for your simulation to become effectively “stuck” in certain regions of phase space ( $\mathbf{r}^{\{N\}}, \mathbf{p}^{\{N\}}$ ) and not explore other regions of importance.



(Figure by D.A. Kofke)

This can happen because of

- effective (kinetic) barriers
- true disconnects in phase space of model

When it happens

- the simulated system is effectively (or truly) *non-ergodic*
- you may have *phase space sampling problems*
  - fail to achieve a representative sampling of microstates
  - calculated averages are not true averages of your model system.

Phase-space sampling problems can occur with both MD and MC algorithms. There are several ways to look for, and avoid, such problems.

### Molecular dynamics

- increase simulation time
- vary starting conditions
- use annealing

### Monte Carlo

- same remedies as MD, plus...
- use special (bolder) algorithms

## Role of simulation, re-visited

For a given model system, the tasks of a molecular simulation are to:

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(Note: even with today's powerful computers, it is generally impossible to sample all of the microstates of a model system.)