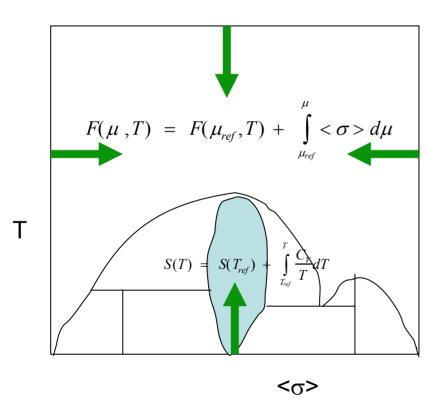
3.320: Lecture 19 (4/14/05)



Free Energies and physical Coarse-graining

Non-Boltzmann sampling and Umbrella sampling

Simple Sampling

Importance Sampling

Sample randomly

$$\langle A \rangle = \sum_{\nu=1}^{M} \frac{\exp(-\beta H_{\nu})}{\sum_{\nu=1}^{M} \exp(-\beta H_{\nu})} A_{\nu}$$



Sample with Boltzmann weight

$$\langle A \rangle = \sum_{\nu=1}^{M} A_{\nu}$$

Non Boltzmann Sampling

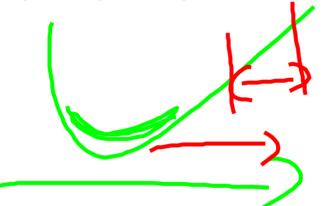
Sample with some Hamiltonian Ho

$$\langle A \rangle = \left(\frac{\sum_{v=1}^{M} \exp(-\beta(H_v - H_v^o))}{\sum_{v=1}^{M} \exp(-\beta(H_v - H_v^o))} \right)$$

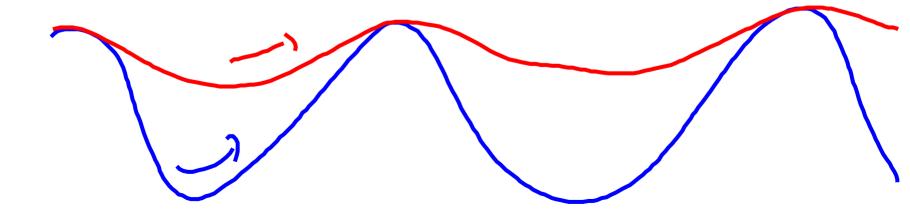
$$\Delta H = H H^{\circ}$$

Cases where non-Boltzmann sampling may be useful

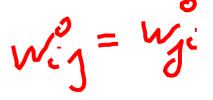
1) To sample part of phase space relevant for a particular property



2) To sample phase space more efficiently



Non-Metropolis Monte Carlo



Allow non-equal a-priori probabilities to get less possible moves that are not accepted

$$\longrightarrow W_{ij}^o = f \left[\Delta H_{ij} \right]$$

$$\longrightarrow$$
 $W_{ji}^{o} = f \Delta H_{jj}$

In Metropolis this is symmetric

Detailed balance

$$P_i W_{ij}^o P_{ij} = P_j W_{ij}^o P_{ji}$$

$$\frac{P_{ij}}{P_{ji}} = \frac{f \Delta H_{ij}}{f \Delta H_{ji}} \exp(-\beta \Delta H_{ij})$$

Example: Force-bias Monte Carlo

$$\delta r_i = AF_i + \delta r_i^{random}$$

Go downhill faster, but requires force calculation

Pangali et al., Chem. Phys. Lett., 55, 413 (1978)

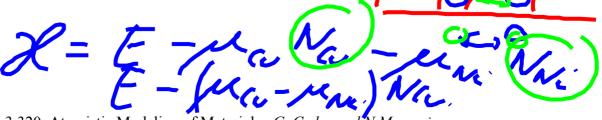
Case Study: Studying Surface segregation in Cu-Ni

See Foiles, S. M. "Calculation of the surface segregation of Ni-Cu alloys with the use of the embedded atom method." *Physical Review B* 32, no. 12 (1985): 7685–7693.

Embedded atom for energy model

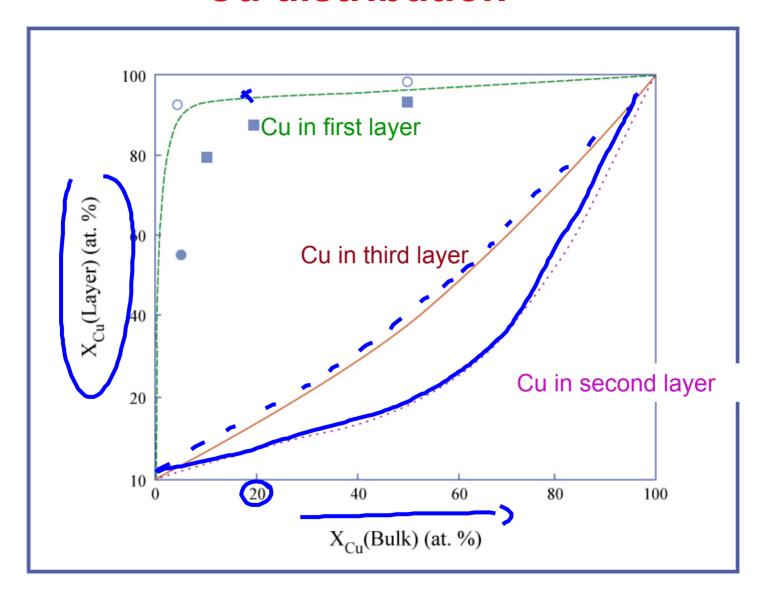
Supercells that are 24x15 to 48x25 atoms with vacuum

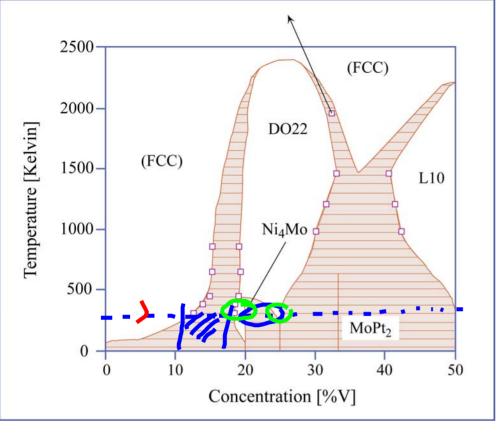
Grand canonical Hamiltonian

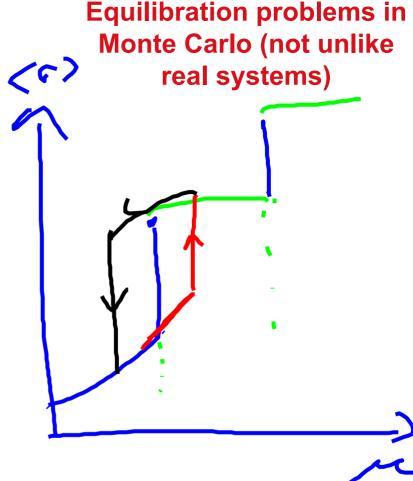


3.320 Atomistic Modeling of Materials G. Ceder and N Marzar

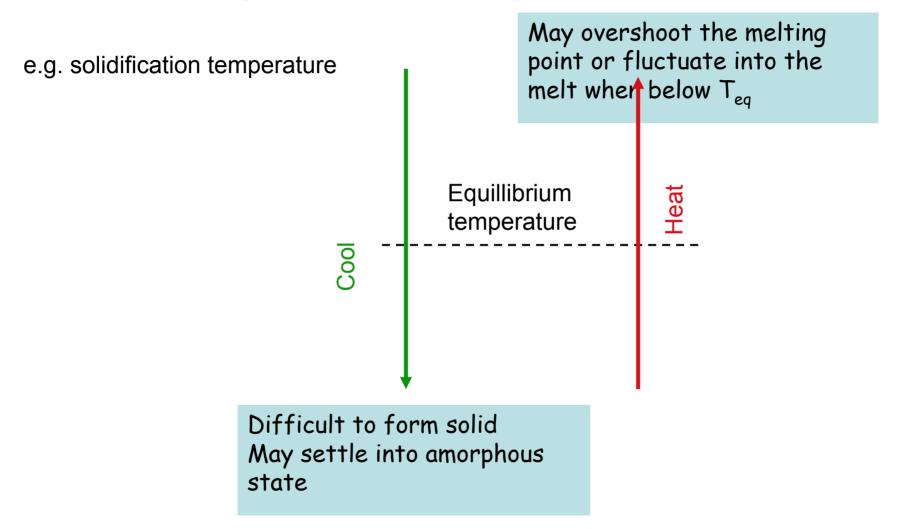
Cu distribution







This problem is similar to problems in MD



Could get free phase transitions from free energies, but F and S are difficult to compute ...

F and S are not simple averages

$$F = U - TS$$

$$U = \sum_{\nu} P_{\nu} E_{\nu}$$
Need relative probabilities

$$S = -k_B \sum_{\nu} P_{\nu} \ln(P_{\nu})$$

Need absolute probabilities

F as an integrated quantity

$$F = \sum_{v} P_{v} [E_{v} + k_{B} T \ln(P_{v})]$$

$$\Rightarrow F = \sum_{v} P_{v} [-k_{B} T \ln(Z)]$$

Quantity that needs to be integrated is flat (but unknown)

Could we get the free energy?

Problem: F is not an average. Free energy does not exist in a microstate, it is a property of the distribution function. Same for entropy

$$F = -kT \ln(Q) = -kT \ln \left[\sum_{v \in e} \exp(-\beta H_v) \right]$$

Can write F as an average, but not over the important states

$$F = -kT \ln \left[\frac{1}{\left(\exp(\beta H_{\nu}) \right)} \right] - kT \ln[M]$$

Proof

$$\langle \exp(\beta H_{\nu}) \rangle = \sum_{\nu \in e} \frac{\exp(-\beta H_{\nu})}{Q} \exp(\beta H_{\nu})$$

$$= \frac{1}{Q} \sum_{\nu \in e} 1 = \frac{M}{Q}$$

Methods to Obtain Free Energy *Differences*

- 1) Free energy integration (including λ -integration)
- 2) Overlapping distribution methods
- 3) Others

Overlapping Distribution Methods

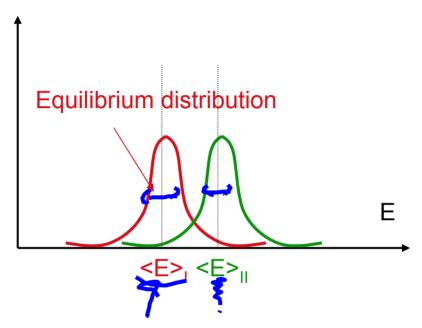
$$\Delta F = -kT \ln \frac{Q_{II}}{Q_{I}} = -kT \ln \frac{\sum_{v \in e}^{l} \exp(-\beta H_{v}^{II})}{\sum_{v \in e}^{l} \exp(-\beta H_{v}^{I})}$$

$$\Delta F = -kT \ln \left[\sum_{v \in e} \exp(-\beta (H_v^{II} - H_v^{I})) \right] \frac{\exp(-\beta H_v^{I})}{Q_I} \rightarrow 0$$

$$\Delta F = -kT \ln \left[\exp(-\beta (H_{\nu}^{II} - H_{\nu}^{I})) \right]$$

Forward projecting: Using the states sampled in state I to get the free energy difference with II.

Example: free energy difference between two different temperature



Overlapping distribution methods will fail when the distributions do not overlap much. E.g. Low temperature simulation may not sample much of the excitations that would be present at high temperature

Thermodynamic Integration: You will be so proud you remember thermodynamics

And now for an important message ...

$$- \lambda (\lambda_1 \lambda_2) - A(\lambda_1) = \int_{\lambda_1}^{\lambda_2} \frac{\partial A}{\partial \lambda} d\lambda$$

Example: Entropy as function of T

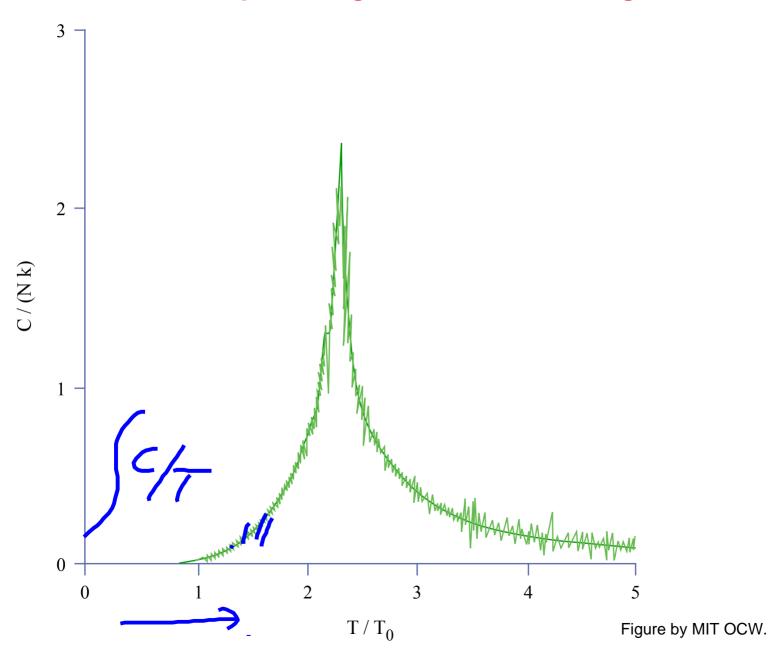
S(T) =
$$S(T_{ref})$$
 + $\int_{T_{ref}}^{T_2} \frac{\partial S}{\partial T} dT$ = $\int_{T_1}^{T_2} \frac{C_V}{T} dT$ Can be obtained from Monte Carlo

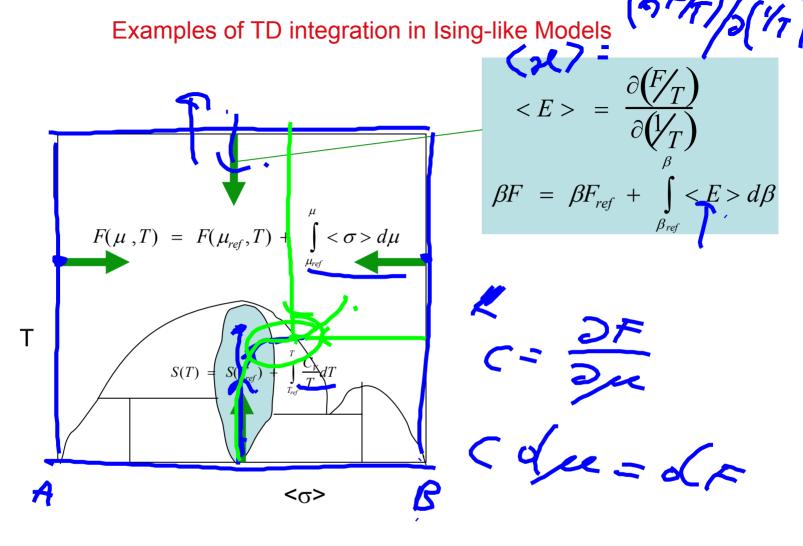
$$S(T) = S(T_{ref}) + \int_{T_{ref}}^{T} \frac{C_V}{T} dT$$

Need to find reference state in which we know entropy

Example: Ising model from T = 0

Example: Integrate from T=0 in Ising model





Issues with Thermodynamic Integration

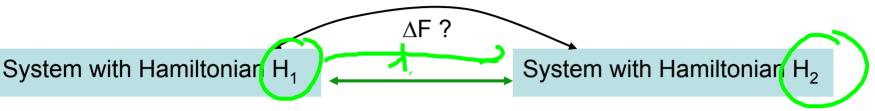
Disadvantages

- 1) Need to have a reference state
- 2) Need to simulate along path from reference state to desired state
- 3) Error accumulates along path
- 4) Need path to be in equilibrium

Advantages

- 5) Highly accurate
- 6) All approximations are under control and error be reduced by longer simulations.

Why stop at integrating with physical parameters; The wonders of computations



Any parameter in Hamiltonian could be different

Turn on additional interaction

Add a particle

Change temperature

$$H(\lambda) = H_I + \lambda (H_{II} - H_I) \longrightarrow F(\lambda)$$

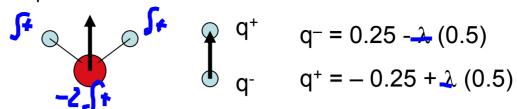
$$\frac{\partial (F)}{\partial \lambda} = \frac{\partial}{\partial \lambda} \left[-\frac{1}{\beta} \ln \sum_{\nu \in e} \exp(-\beta H_{\nu}(\lambda)) \right]$$

$$\frac{\partial \lambda}{\partial \lambda} = \frac{1}{\partial \lambda} \left[-\frac{1}{\beta} \ln \sum_{v \in e} \exp(-\beta H_v(\lambda)) \right]$$
$$= \left[-\frac{1}{2} \ln \sum_{v \in e} \left(-\beta H_v(\lambda) \right) \exp(-\beta H_v(\lambda)) \right]$$

$$\left(= \left\langle \frac{\partial H(\lambda)}{\partial \lambda} \right\rangle \right)$$

 $=\langle H_{II}-H_{I}\rangle_{1}$ Quantity that needs to be integrated

dipole moment



Effect of dipole in water

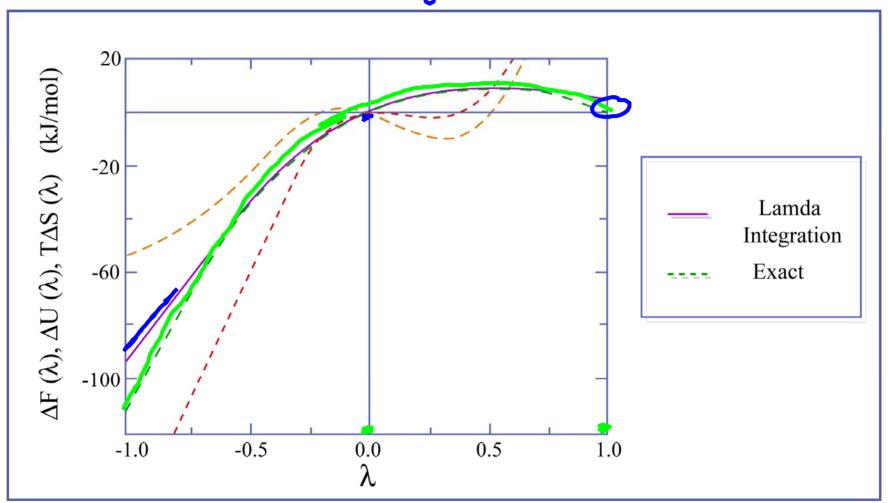
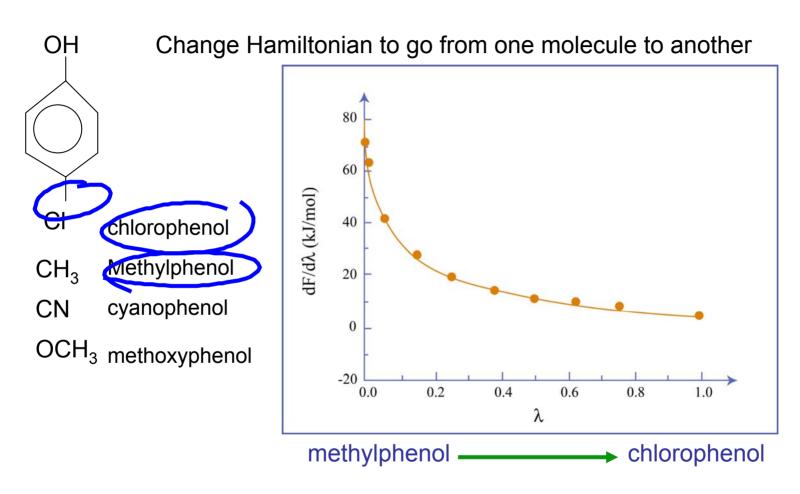


Figure by MIT OCW.

See Liu, H. et al, *J. Phys. Chem* **100**, 9485 (1996)

Turn Lead into Gold?



Monte Carlo

Advantages

- Conceptually simple
- •Easy to implement
- Can Equilibrate any degree of freedom/No Dynamics needed
- Accurate Statistical Mechanics

Disadvantages

- No Kinetic Information
- Requires many Energy Evaluations
- Stochastic nature gives noise in data
- Not easy to get entropy/free energy

References

D. Frenkel and B. Smit, "Understanding Molecular Simulation", Academic Press.

Fairly recent book. Very good background and theory on MD, MC and Stat Mech. Applications are mainly on molecular systems.

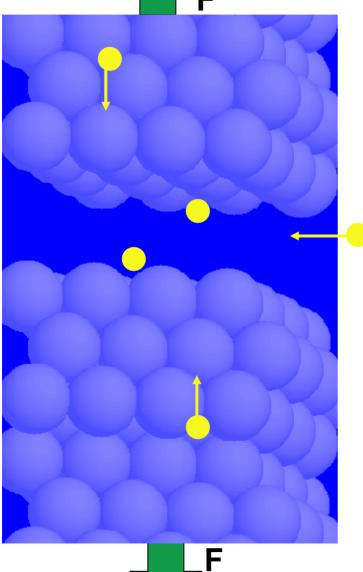
A.R. Leach, "Molecular Modeling Principles and Applications", Chapter 7

M.E.J. Newman and G.T. Barkema, "Monte Carlo Methods in Statistical Physics"

K. Binder and D.W. Heerman, "Monte Carlo Simulation in Statistical Physics"

Methods with multiple time scales: Coarse-grain fast one away

Equilibration of Chemical Composition and Structure: A slow time-scale problem

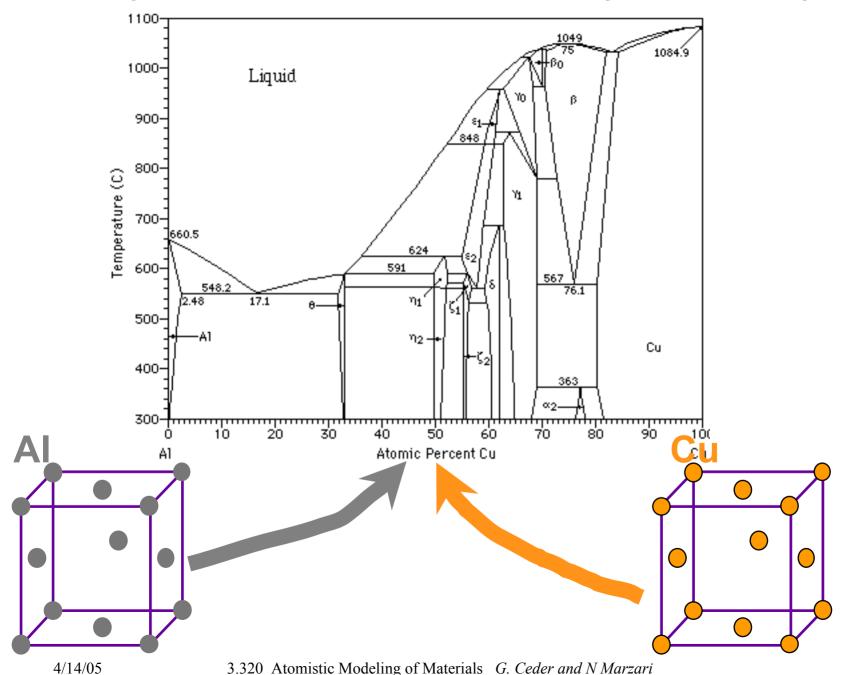


Cracking of Al with hydrogen impurities in the material

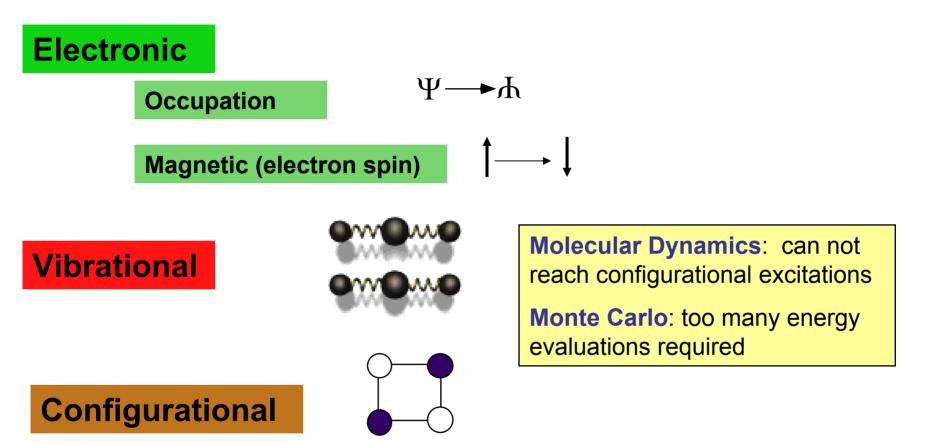
Hydrogen can flow into the opening crack and reduce the cohesion there

Need to equilibrate both amount and arrangement of H on Al(111) for each separation

Case Study: First Principles Predication of Alloy Phase Stability



Need to Equilibrate all Time Scales -> Free Energy



We can use lattice models for studying mixing and ordering or atoms in crystalline materials. But why is this a good approximation?

Coarse-graining: The concept

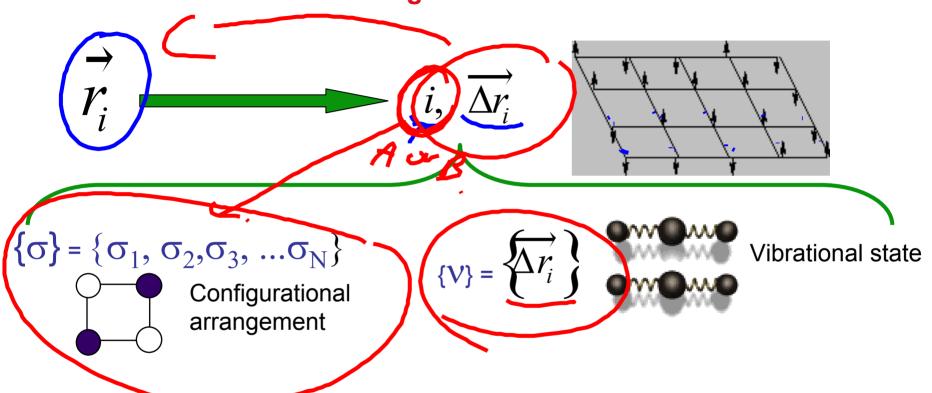
Can we integrate partition function over fast degrees of freedom to obtain an effective Hamiltonian for the slower degrees of freedom?

e.g. for an alloy: Can we find an effective free energy function for the substitutional arrangement of an alloy that includes the entropic effect of vibrations and electronic excitations?

YES

Use Monte Carlo, Molecular Dynamics, or analytical methods to integrate effect of temperature on fast degrees of freedom

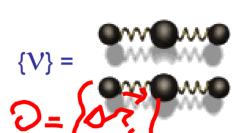
Change coordinates



Coarse-graining by reduction of degrees of freedom

$$\{\sigma\} = \{\sigma_1, \sigma_2, \sigma_3, ...\sigma_N\}$$
Configurational arrangement





Vibrational state

$$Q = \sum_{\{\sigma\}} \sum_{\upsilon} \exp(-\beta E(\{\sigma\}, \upsilon(\{\sigma\})))$$

$$Q = \sum_{\{\sigma\}} \exp(-\beta F(\{\sigma\}))$$

Partition Function of an Ising-like Model

Two approximations for F

$$F(\{\sigma\} = -kT \ln \left[\sum_{\{\upsilon\}} \exp(-\beta E(\upsilon(\{\sigma\}))) \right]$$

F is Effective Hamiltonian for $\{\sigma\}$ degree of freedom

Approximations to $F({\sigma})$ determine which excitations (entropies) are included in the total free energy

1. Approximate
$$F(\{\sigma\})$$
 by $E(\{\sigma\})$

$$F(\{\sigma\} = -kT \ln \left[\sum_{\{\upsilon\}} \exp(-\beta E(\upsilon(\{\sigma\}))) \right]$$

when doing Monte Carlo and free energy integration, only get configurational entropy

- 2. Approximate $F(\{\sigma\})$ by $E(\{\sigma\})$ -TS_{electronic} ($\{\sigma\}$) when doing Monte Carlo and free energy integration, get configurational entropy and electronic
- 3. $F(\lbrace \sigma \rbrace) = E(\lbrace \sigma \rbrace) TS_{electronic} (\lbrace \sigma \rbrace) TS_{vib} (\lbrace \sigma \rbrace)$

when doing Monte Carlo and free energy integration, get configurational entropy + electronic + vibrational

Summary so far

The model on the time scale of the substitutional excitations is an Ising-like model (i.e. excitations are changes of occupation variables)

The Hamiltonian of the Ising-like model is the free energy of the faster excitations (e.g. vibrations, electronic excitations).

Only approximation is separation of time scales



But need a practical form for the Ising-like Hamiltonian