

High-throughput computational thermodynamics

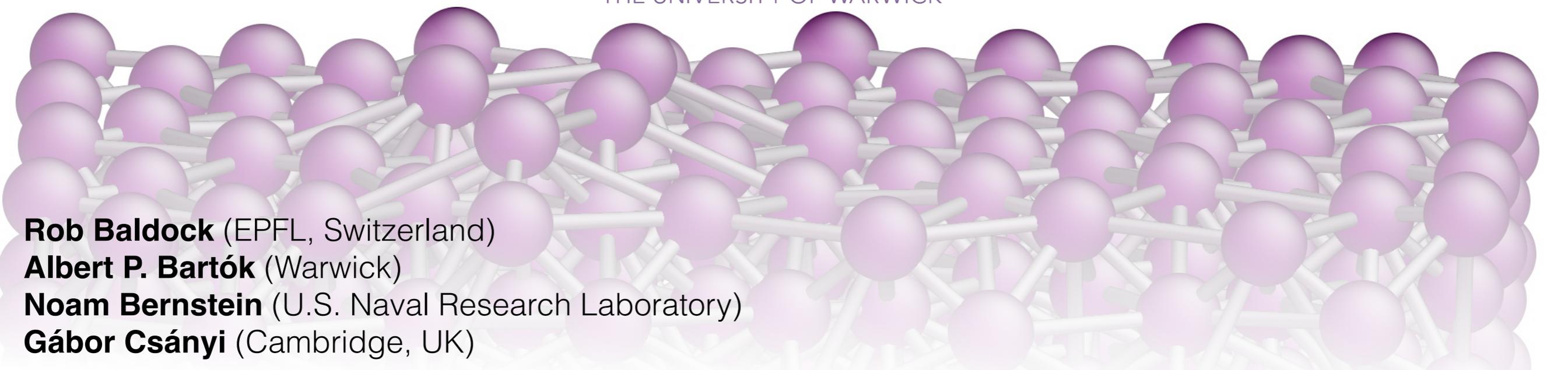
* exploring potential energy landscapes with Nested Sampling *

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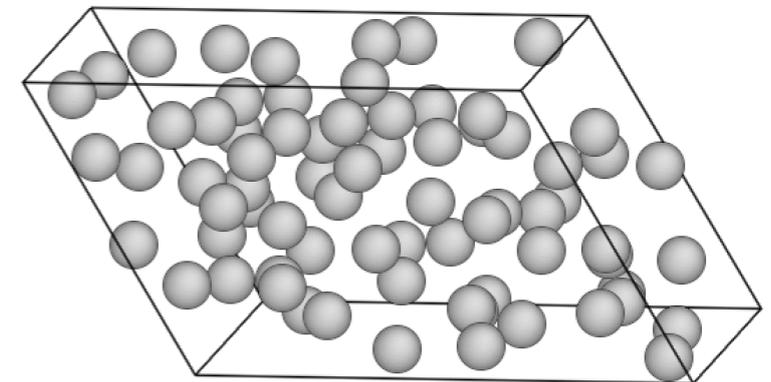
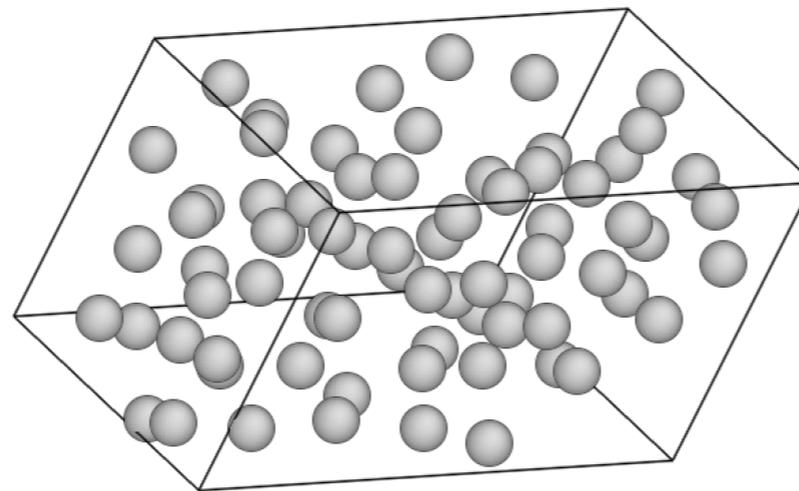
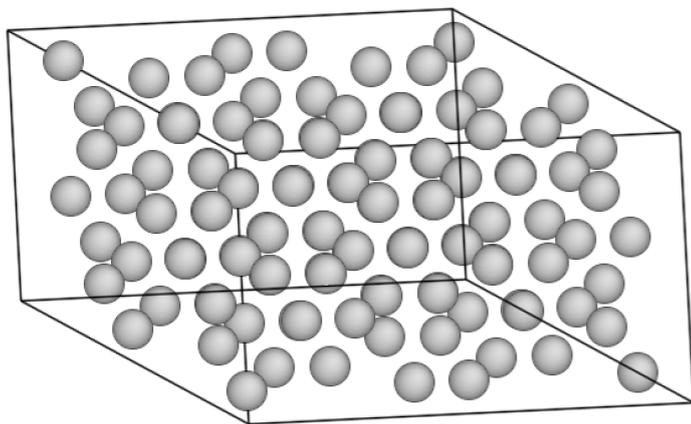
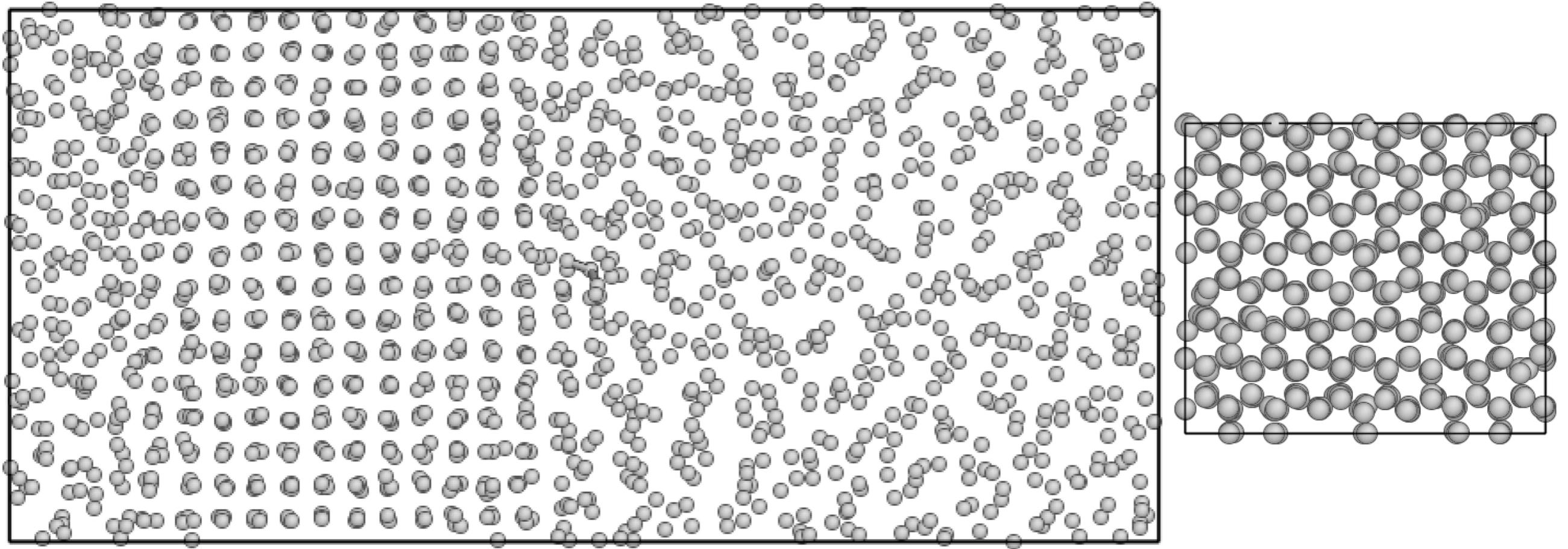


WARWICK
THE UNIVERSITY OF WARWICK



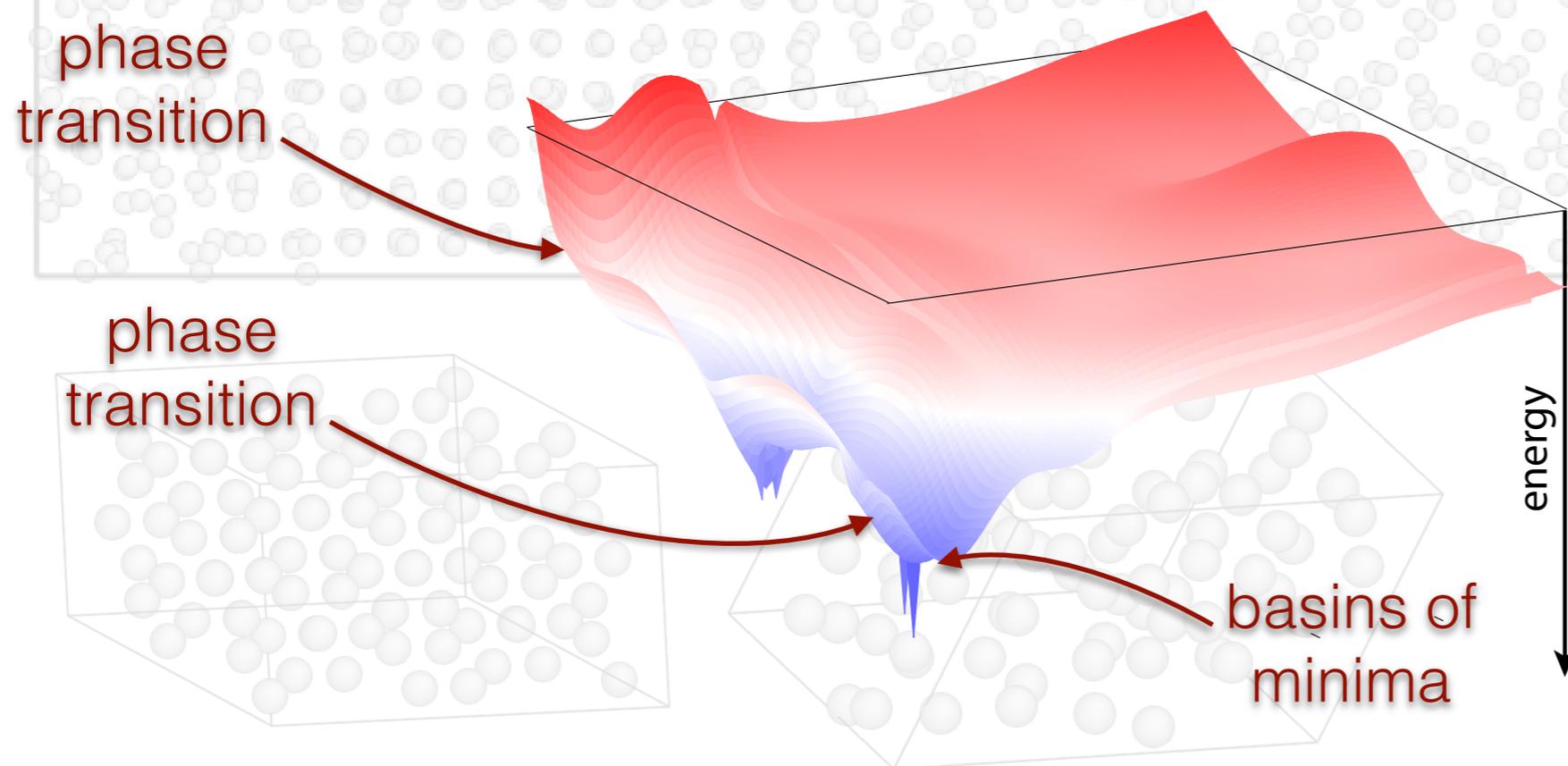
Rob Baldock (EPFL, Switzerland)
Albert P. Bartók (Warwick)
Noam Bernstein (U.S. Naval Research Laboratory)
Gábor Csányi (Cambridge, UK)

How to generate relevant atomic configurations?



How to generate relevant atomic configurations?

Aim: To have an unbiased sampling technique which can give an overview of the entire PES (**THERMODYNAMICS**), and can be automated: not specific to a given part of the PES (**GENERAL**), where no prior knowledge of structures are necessary (**PREDICTIVE**).



Outline

- nested sampling algorithm
- example applications: p - T phase diagram of metals, alloys and carbon

How much can we trust potential models?

John Skilling, 2004, Bayesian statistics

“...to sample probability densities in **high-dimensional** spaces where the regions contributing most of the probability mass are **exponentially localised**.”

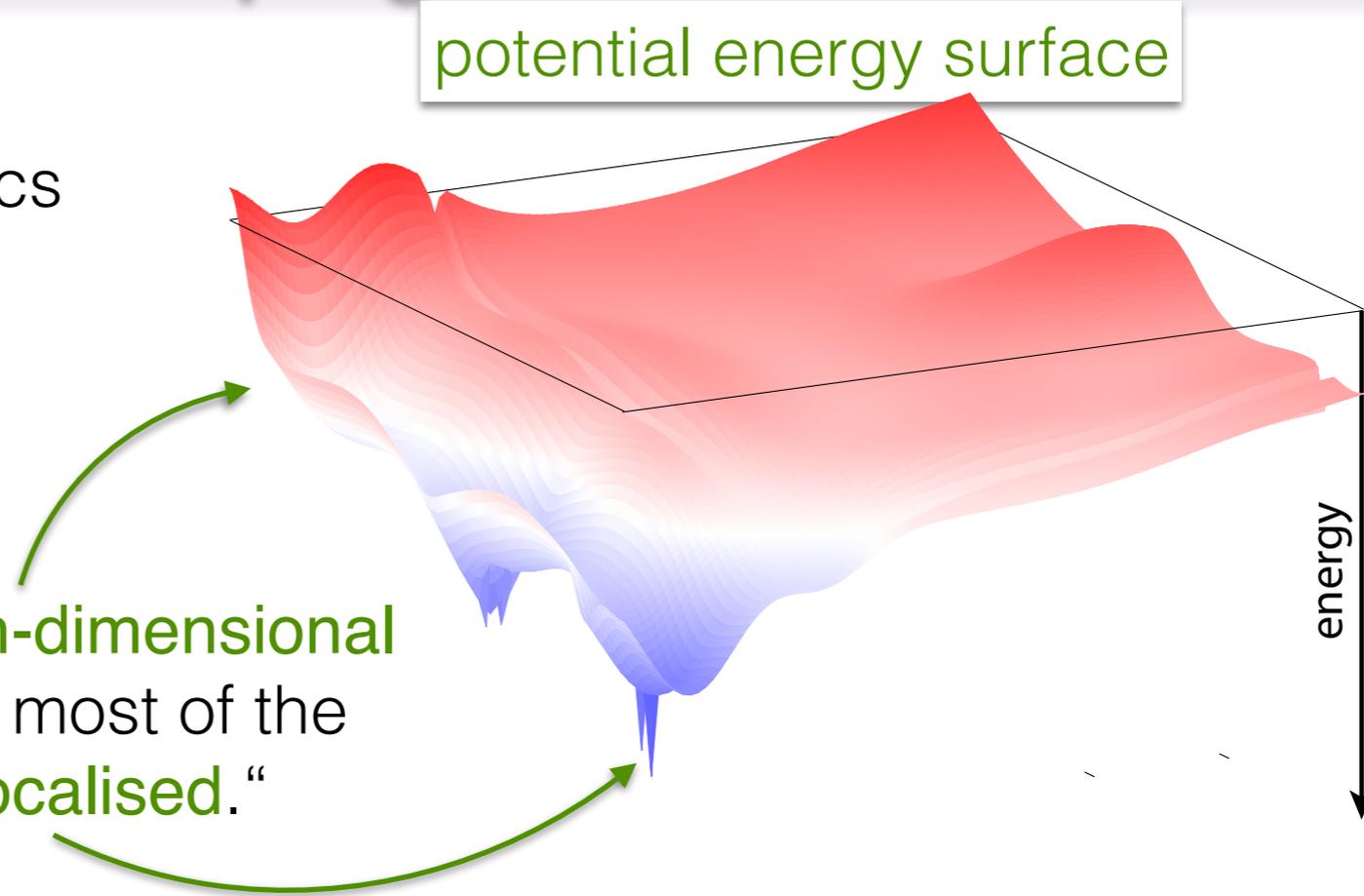
evidence (Z) likelihood (L) proportion of the prior distribution

$$Z = \int_0^1 L(X) dX$$

Nested Sampling

John Skilling, 2004, Bayesian statistics

“...to sample probability densities in **high-dimensional** spaces where the regions contributing most of the probability mass are **exponentially localised**.”



potential energy surface

basins of minima, Boltzmann-factor

evidence (Z)

likelihood (L)

proportion of the prior distribution

$$Z = \int_0^1 L(X) dX$$

partition function

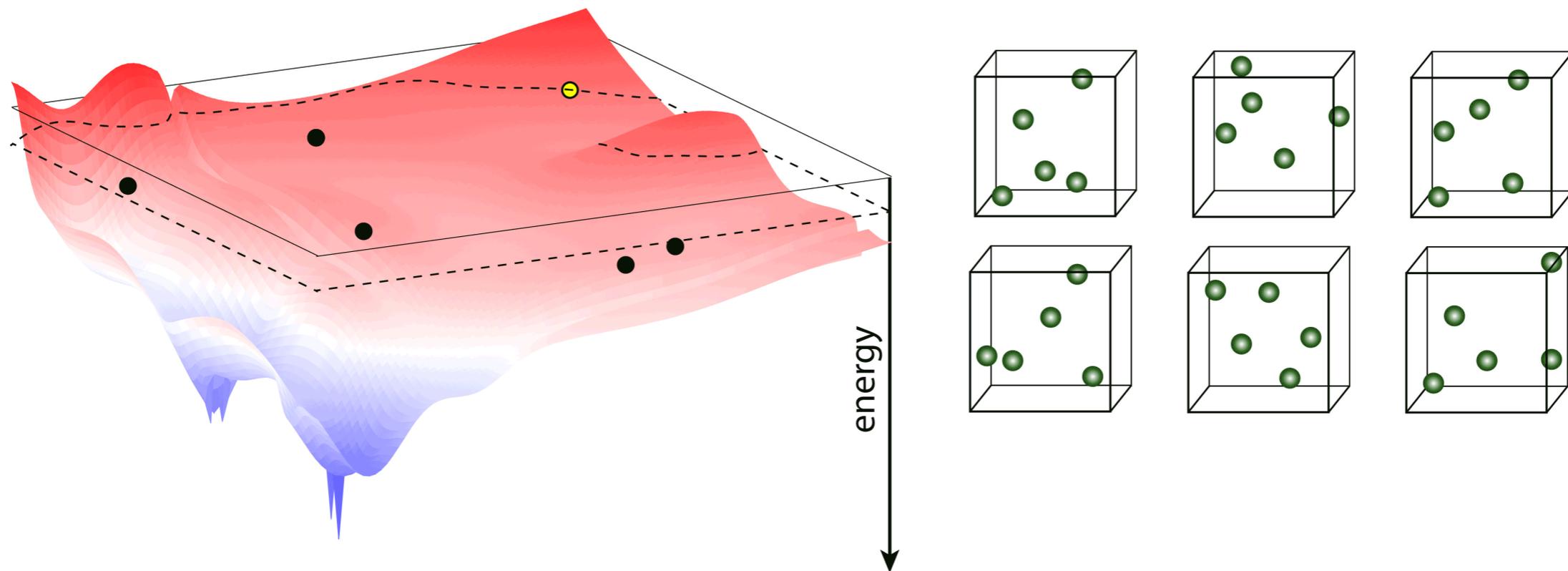
Boltzmann-factor
(energy)

phase space volume
(prior distribution is uniform)

Nested Sampling Algorithm

Iterative algorithm, starting from the “top” (ideal gas) and going towards the “bottom” (global minimum), through a series of nested energy “contours”.

Starting set: generate K random samples **uniformly** in the total phase space volume

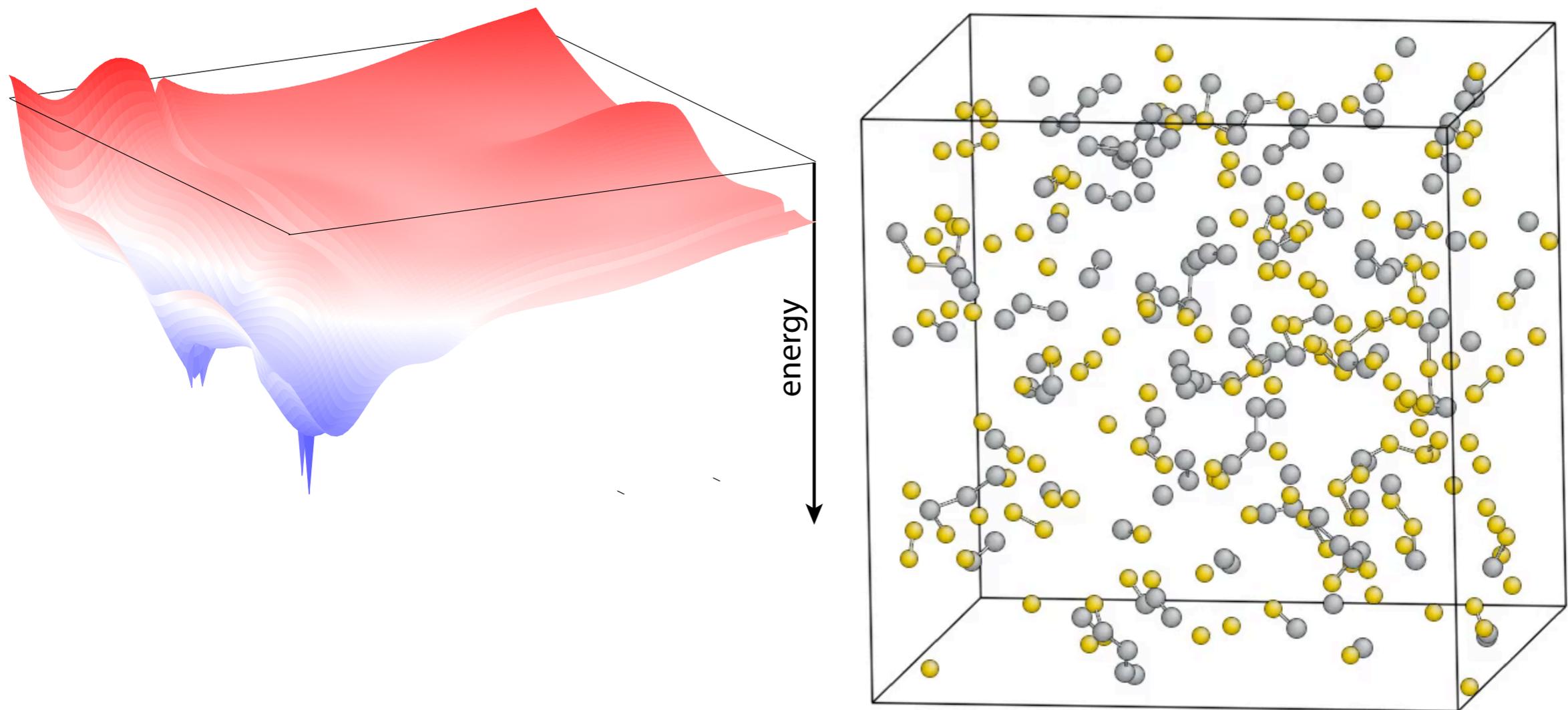


- Choose the sample (configuration) with the highest energy (the phase space volume within the contour is $K/(K+1)$ fraction of the previous)
- Generate a new point within the current contour (uniformly)
- Repeat until the “bottom” is found

Nested Sampling Algorithm

Iterative algorithm, starting from the “top” (ideal gas) and going towards the “bottom” (global minimum), through a series of nested energy “contours”.

Starting set: generate K random samples **uniformly** in the total phase space volume



309 atoms (Cu and Pt) in fixed cell:
cluster

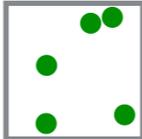
Nested Sampling Algorithm

At the end we have a set of energies $\{E_i\}$, corresponding volumes $\{[K/(K+1)]^i\}$ and configurations

E_1	$K/(K+1)$	
E_2	$K/(K+1) * K/(K+1)$	
E_3	$K/(K+1) * K/(K+1) * K/(K+1)$	
...		
E_i	$\{K/(K+1)\}^i$	
E_{i+1}	$\{K/(K+1)\}^{i+1}$	
...		
E_n	$\{K/(K+1)\}^n$	

Nested Sampling Algorithm

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Partition function:

$$Z(\beta) = Z_p \sum_i w_i e^{-\beta E_i}$$

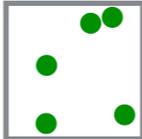
$$= Z_p(\beta) \sum_i [(K/(K+1))^i - (K/(K+1))^{i+1}] e^{-\beta E_i}$$



Heat capacity
Free energy
Compressibility
...etc.

Nested Sampling Algorithm

At the end we have a set of energies $\{E_i\}$, corresponding volumes $\{[K/(K+1)]^i\}$ and configurations

E_1	$K/(K+1)$	
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Partition function:

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$$= Z_p(\beta) \sum_i [(K/(K+1))^i - (K/(K+1))^{i+1}] e^{-\beta E_i}$$

Advantages

- Entire PES is sampled - not specific or limited to a region
- Sampling itself independent from temperature
- Can be done with both (N, V, T) and (N, ρ, T)
- Easy control parameter of the sampling is K , called the “walkers” (is the resolution of the PES)
- No need for prior knowledge of the structures

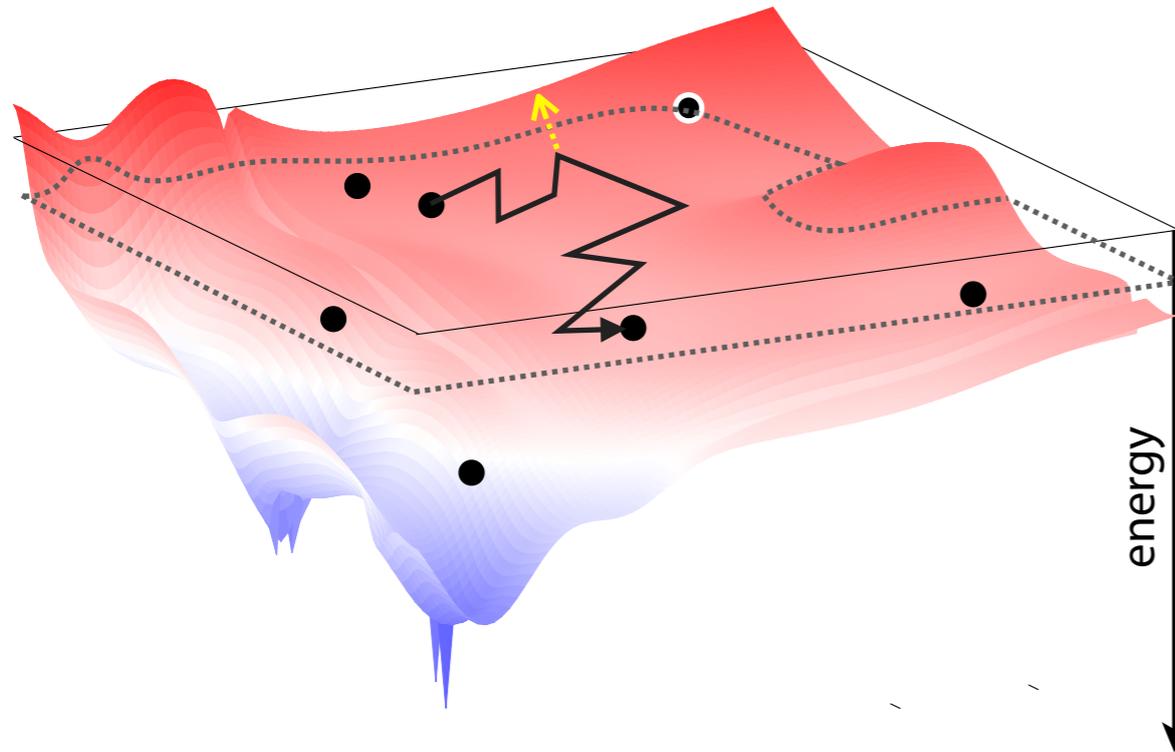
Typical K : ~1000-2000
Typically 10^6 iterations

PREDICTIVE!

found new, more stable structure for...

- * NiTi (EAM)
- * Li (EAM)
- * Lennard-Jones

Generating a new sample configuration



Clone a randomly selected sample and perform a random walk until it is independent from its parent configuration:

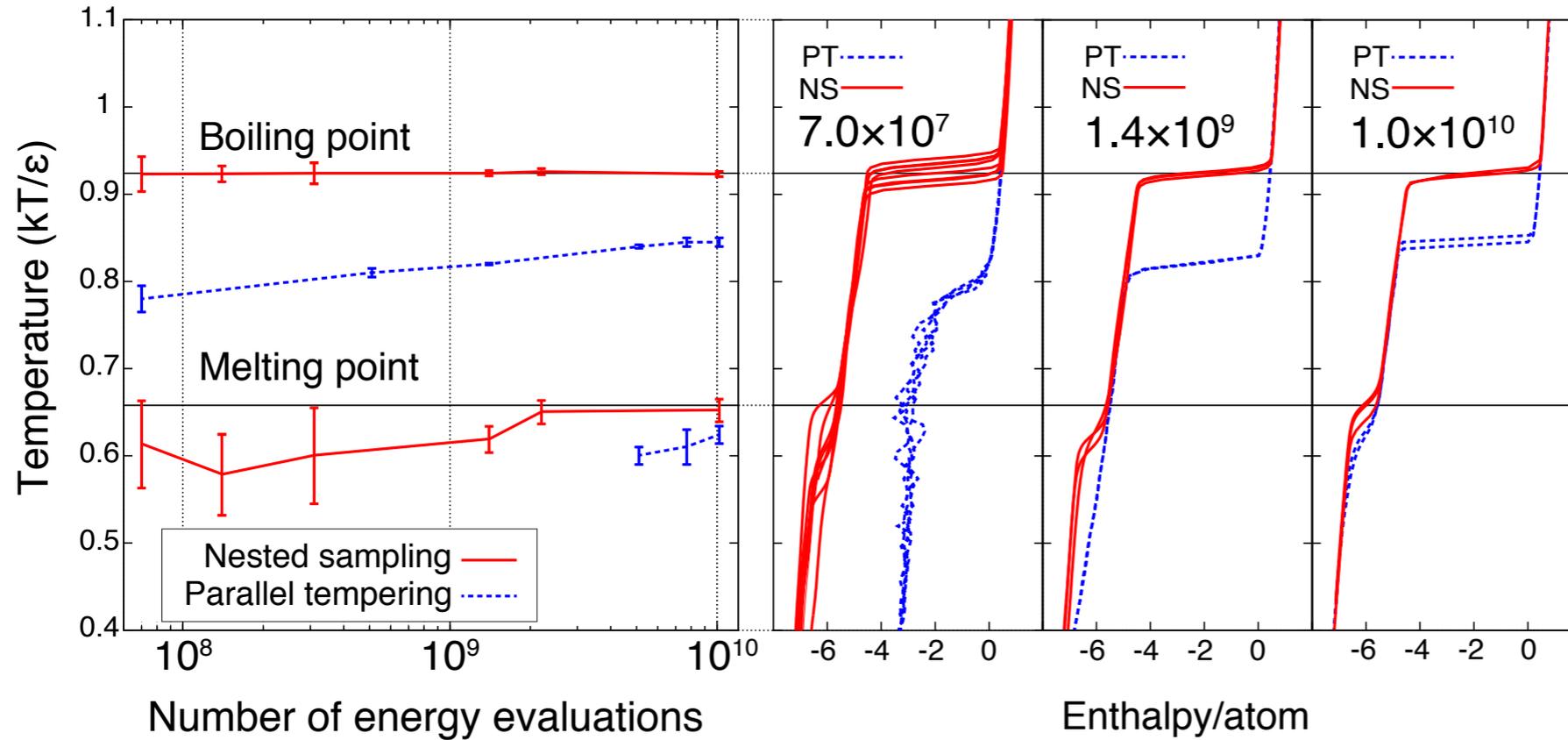
- atomic coordinates
- cell shape
- cell volume
- swap types

- **Markov Chain Monte Carlo (MCMC):**
single particle and cell moves (volume, shear, stretch)
- **Total Enthalpy Hamiltonian Monte Carlo (TE-HMC)**
short constant total energy MD trajectories
- **Galilean Monte Carlo (GMC)**
all-atoms moves, along straight lines between elastic collisions (reflect the velocities to redirect the sample to allowed phase space region)

Length of the random walk, L , is the other control parameter.

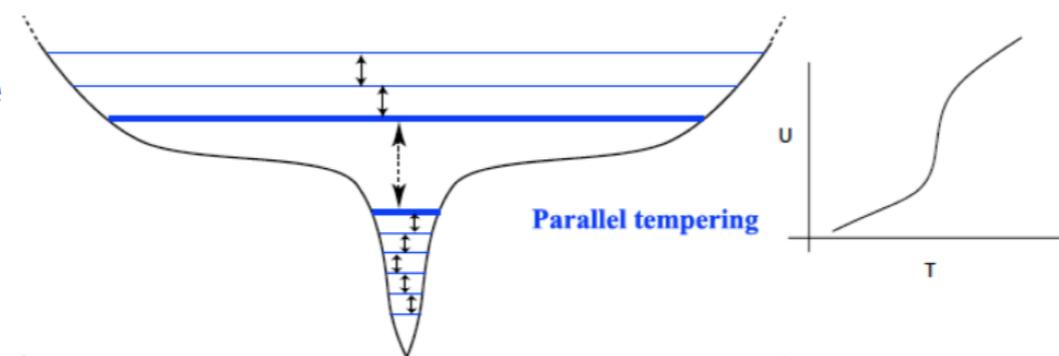
Computational cost comparison

64 LJ atoms at constant pressure



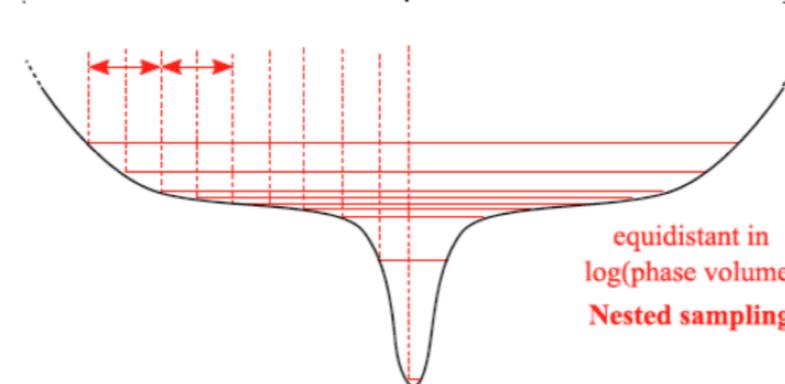
Nested Sampling vs. Parallel Tempering

levels equidistant in temperature



Parallel tempering

levels equidistant in log(phase volume)



equidistant in log(phase volume)
Nested sampling

N, P, T (periodic systems)

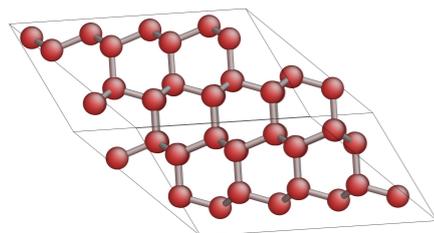
Aluminium [PRB (2016),93:174108]

Iron [Comp.Mat.Sci. (2018),149:153]

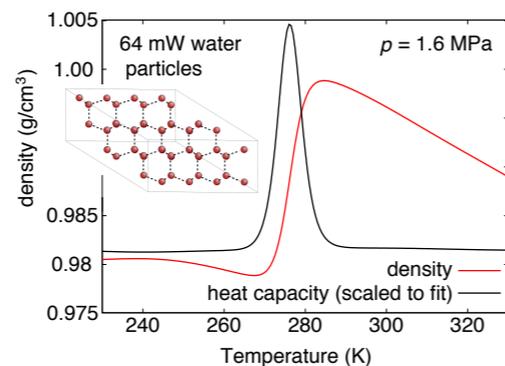
Lithium [J.Phys.Chem.B (2020), in press]

Hard sphere model system [PRE (2014),89, 022302]

coarse grain water: mW [PRE (2016),96:043311]



$\rho = 1.6$ MPa

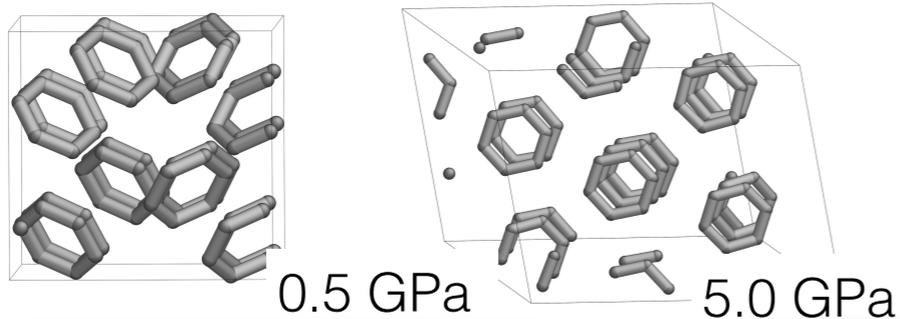


Binary Lennard-Jones [PRE (2016),96:043311]

NiTi shape memory alloy [PRB (2016),93:174108]

single bead (LJ) spring polymer [PRE (2016),96:043311]

Benzene



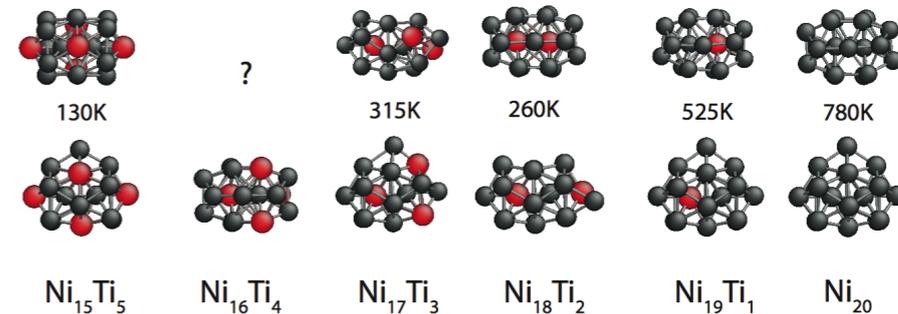
Nested transition path sampling

[PRL (2018),120:250601]

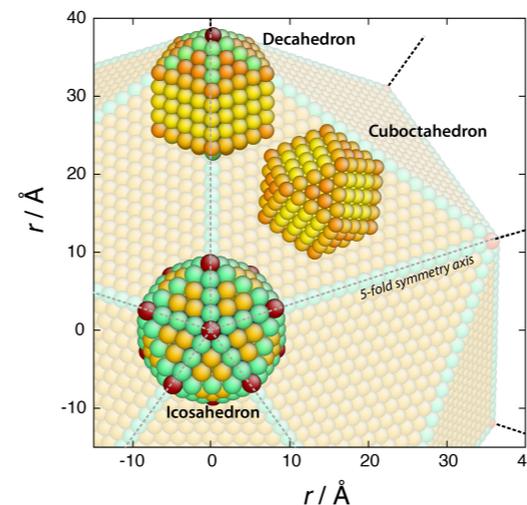
N, V, T (clusters)

Lennard-Jones (LJ₅ - LJ₃₈) [JPC (2010),114:10502]

Ni_xTi_y binary clusters



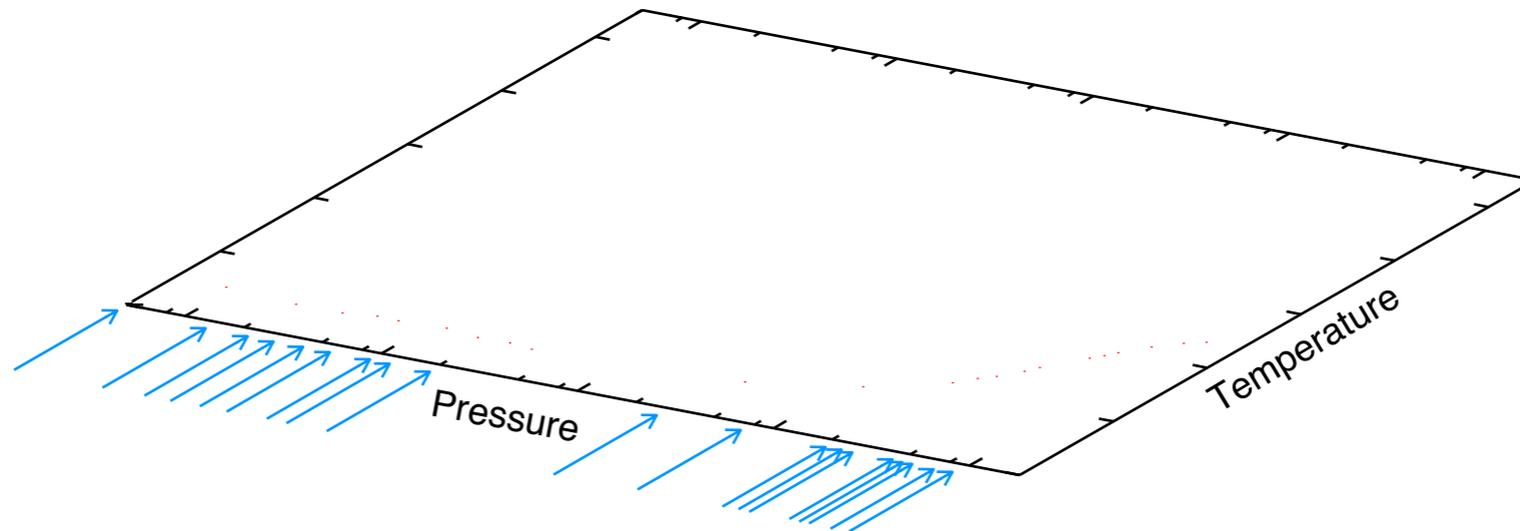
CuPt nanocluster [Sci.Rep. (2018),8:9150]



mW and TIP3P water clusters [PCCP(2019),21:7305]

Quantum partition function

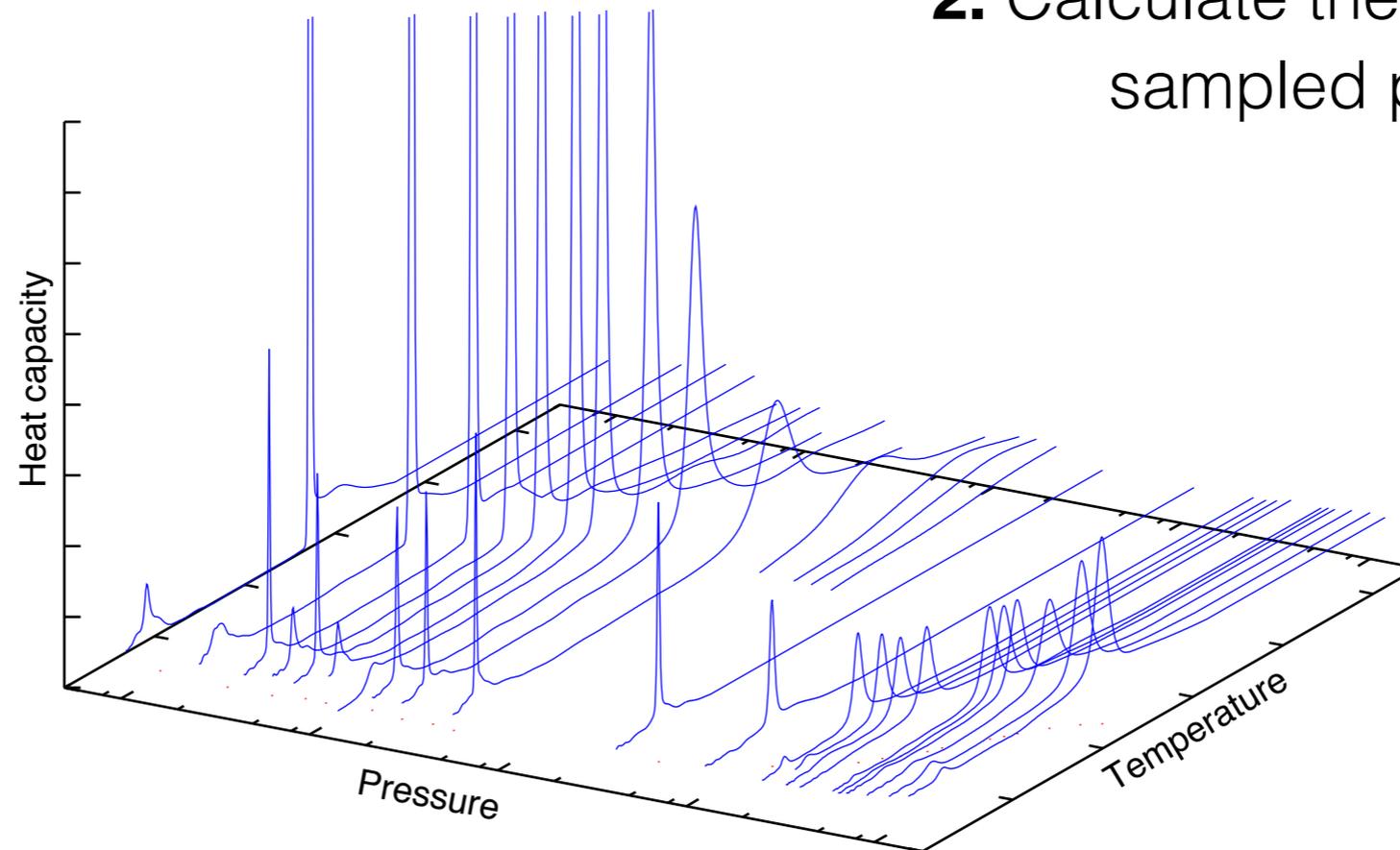
[JCTC (2018),14:4353]



1. Choose a system (potential model) and a set of pressures. Perform a *nested sampling* calculation for each.

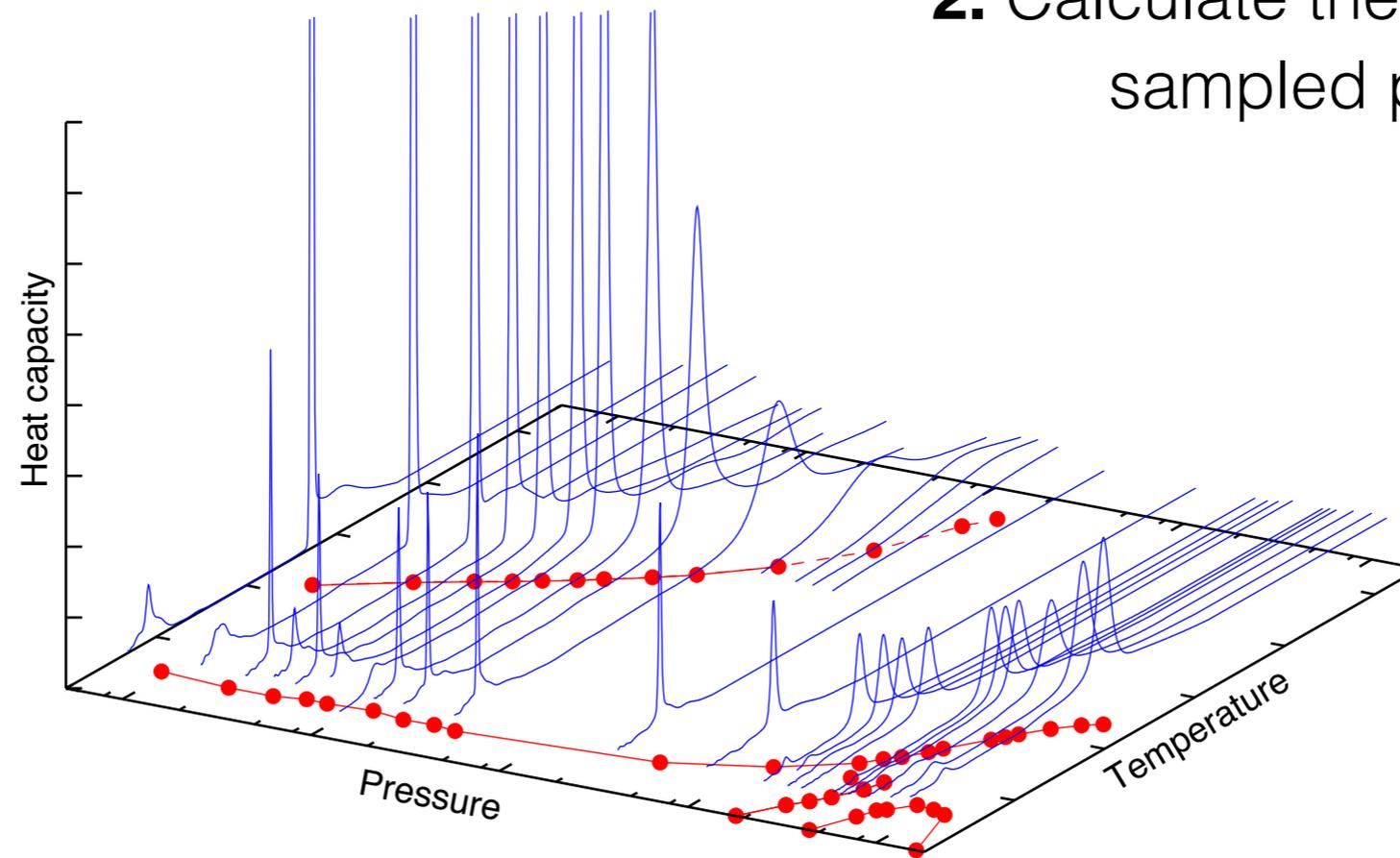
p - T phase diagram “in three steps”

2. Calculate the $c_p(T)$ for every sampled pressure.



1. Choose a system (potential model) and a set of pressures. Perform a *nested sampling* calculation for each.

p - T phase diagram “in three steps”



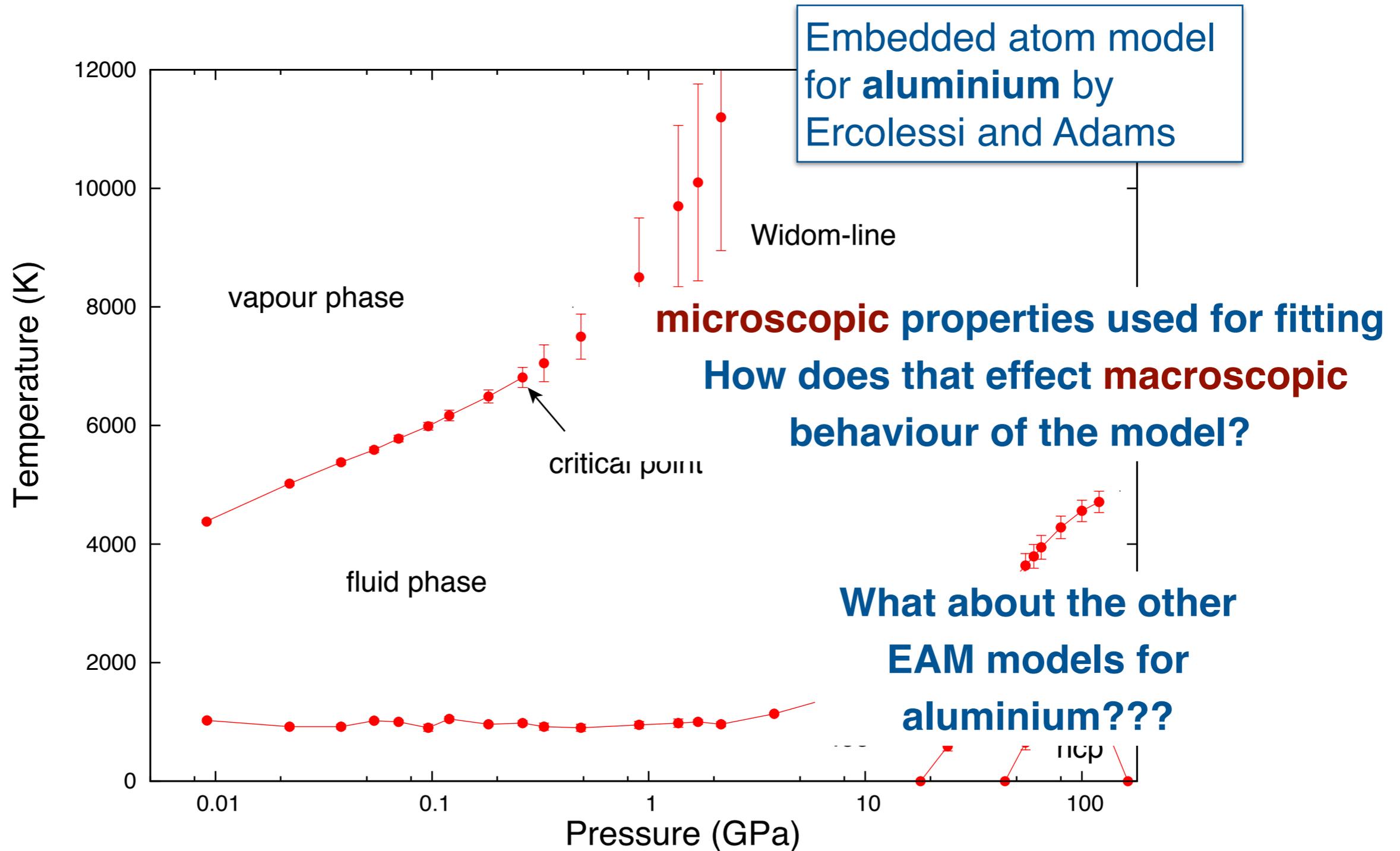
- 1.** Choose a system (potential model) and a set of pressures. Perform a *nested sampling* calculation for each.

- 2.** Calculate the $c_p(T)$ for every sampled pressure.

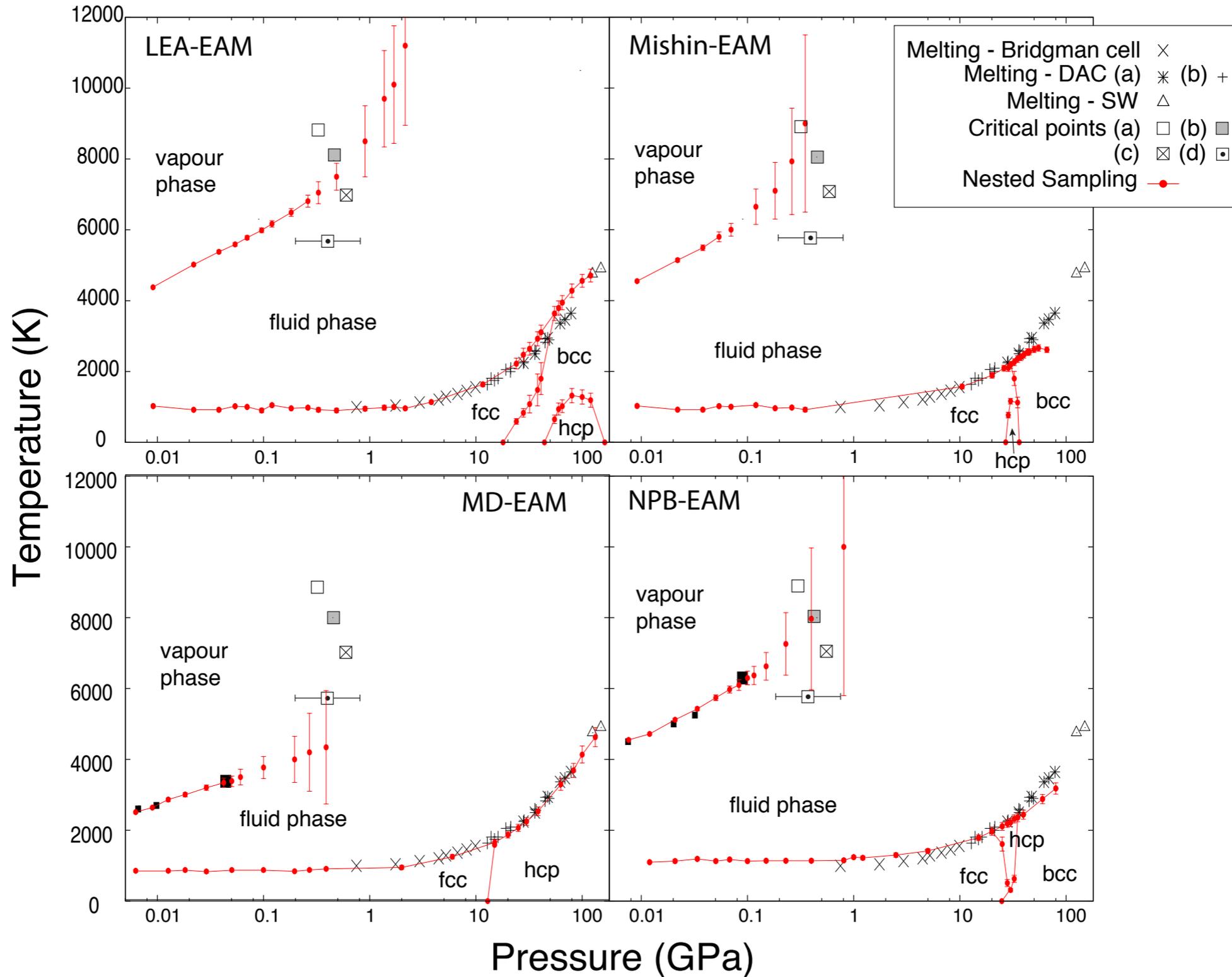
- 3.** Determine the location of maxima on the $c_p(T)$ curve, showing the phase transitions.

p - T phase diagram!

p - T phase diagram “in three steps”



Phase Diagram of Aluminium





Cold melting and solid structures of dense lithium

Christophe L. Guillaume¹, Eugene Gregoryanz^{1*}, Olga Degtyareva¹, Malcolm I. McMahon¹, Michael Hanfland^{2*}, Shaun Evans², Malcolm Guthrie³, Stanislav V. Sinogeikin⁴ and H-K. Mao^{3,4}

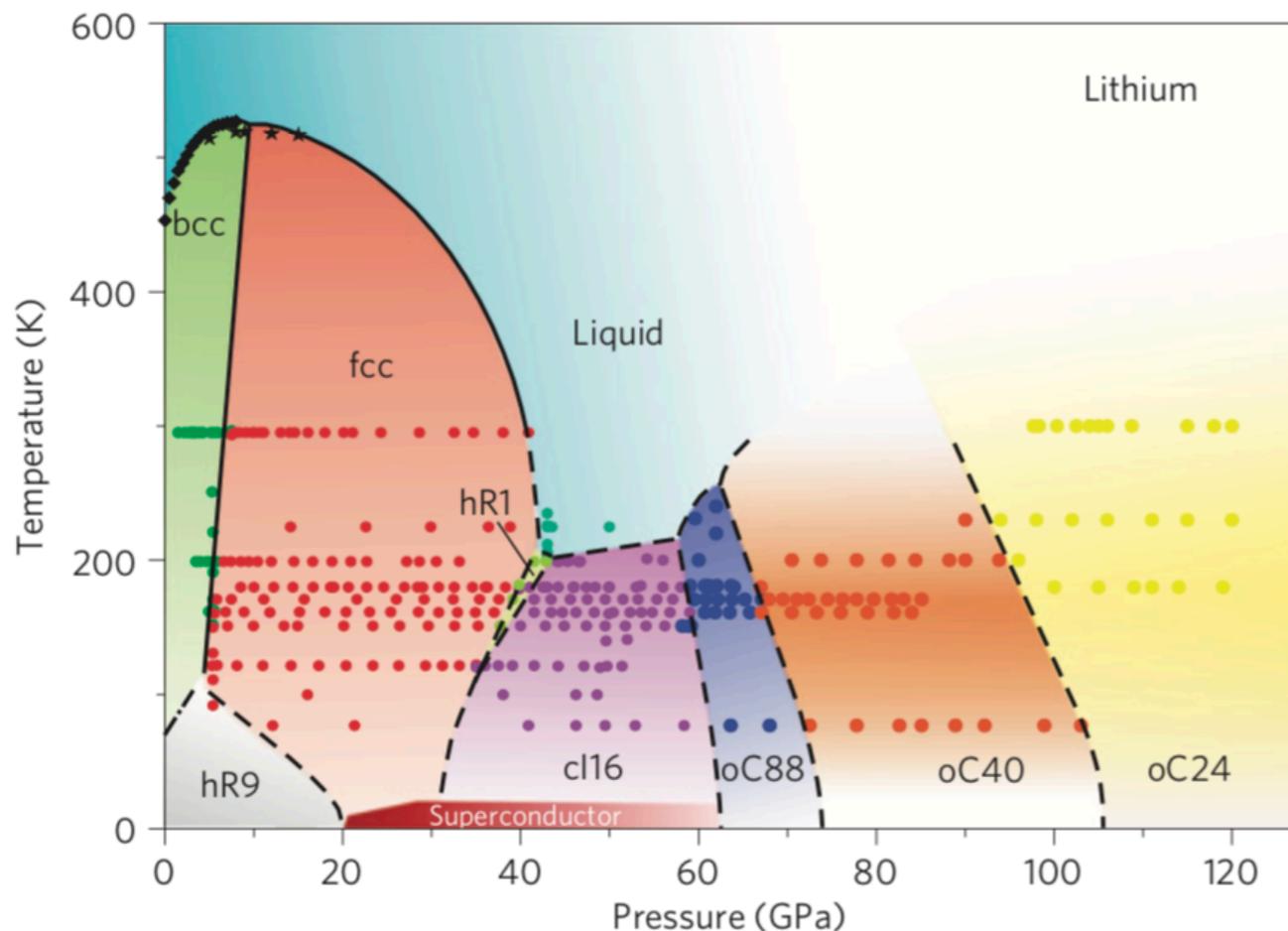


Figure 1 | Proposed phase diagram of lithium over a wide pressure-temperature range. Apart from bcc and fcc, the phases are

Nested sampling calculations:

with 64 and 60 atoms
1000-3000 walkers

EAM by Belashchenko

bcc lattice parameter, elastic constants, vacancy formation energy, surface properties, liquid and solid density, high pressure properties

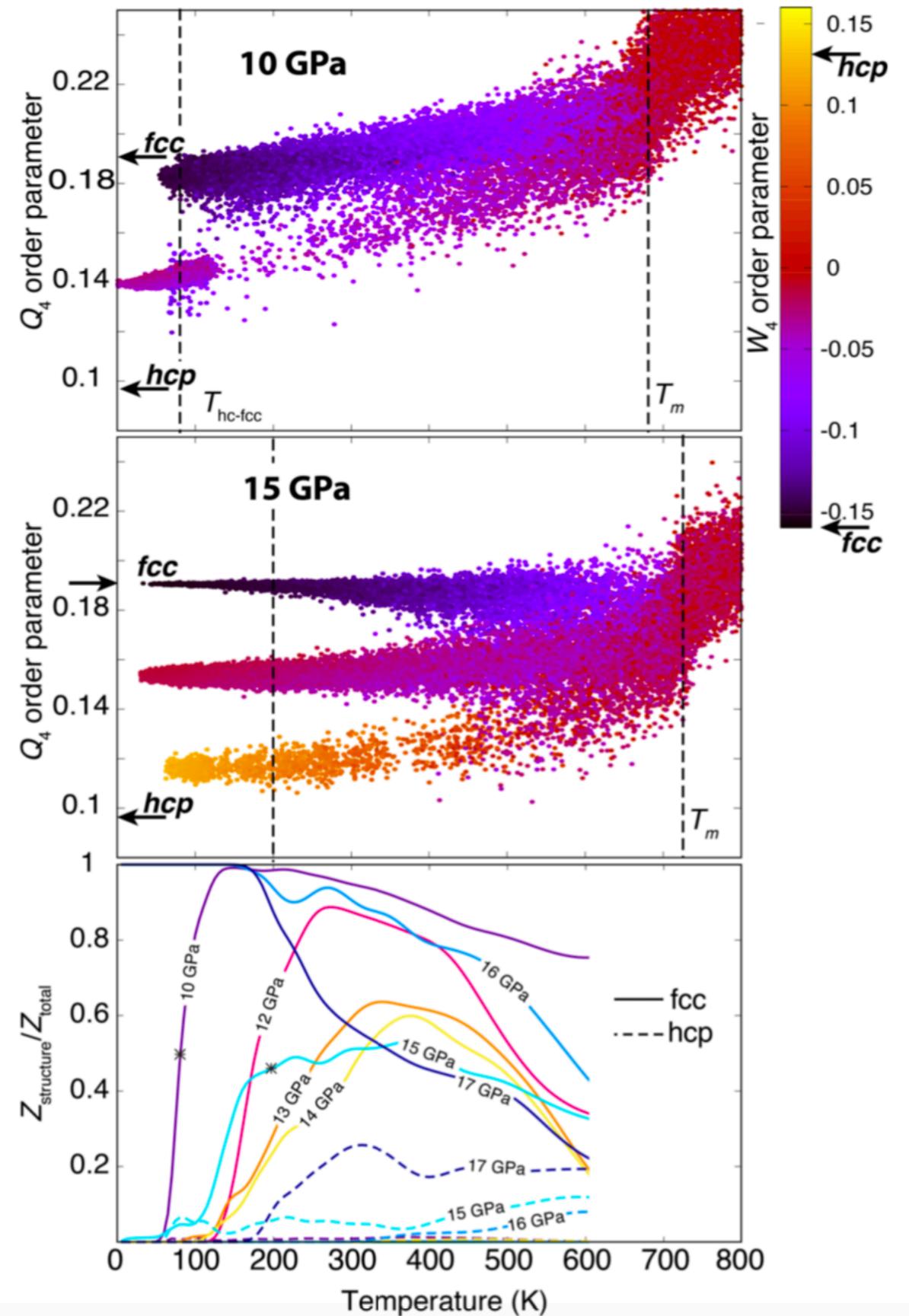
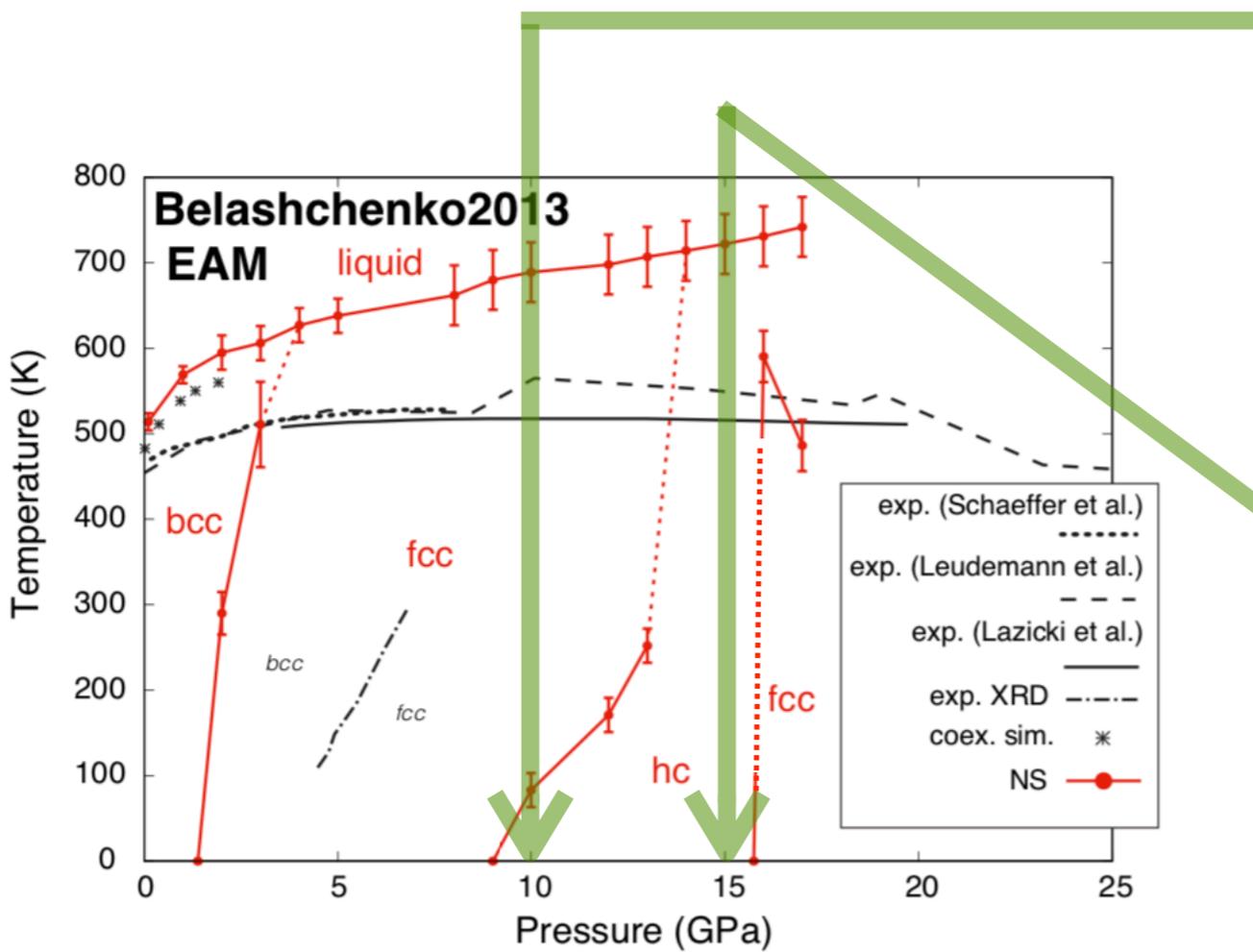
EAM by Nichol and Ackland

bcc lattice parameter, elastic constants, cohesive energy, unrelaxed vacancy formation energy

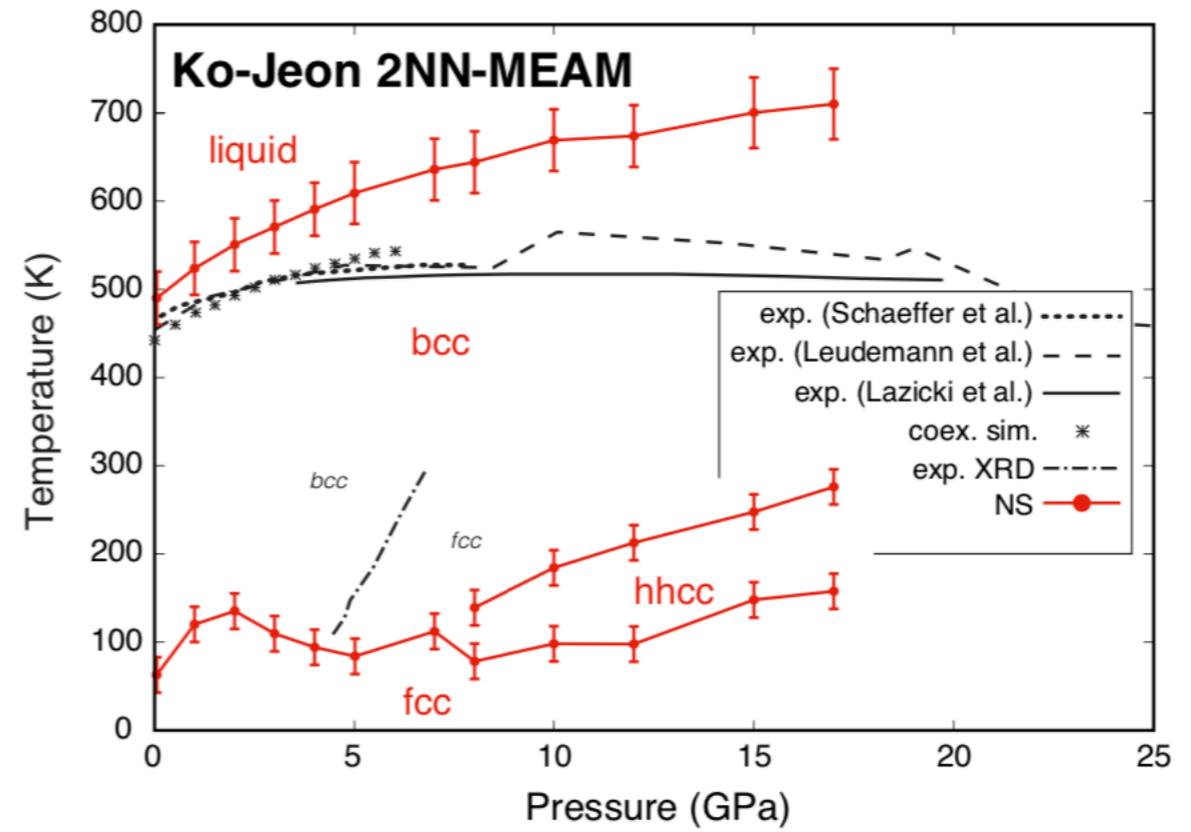
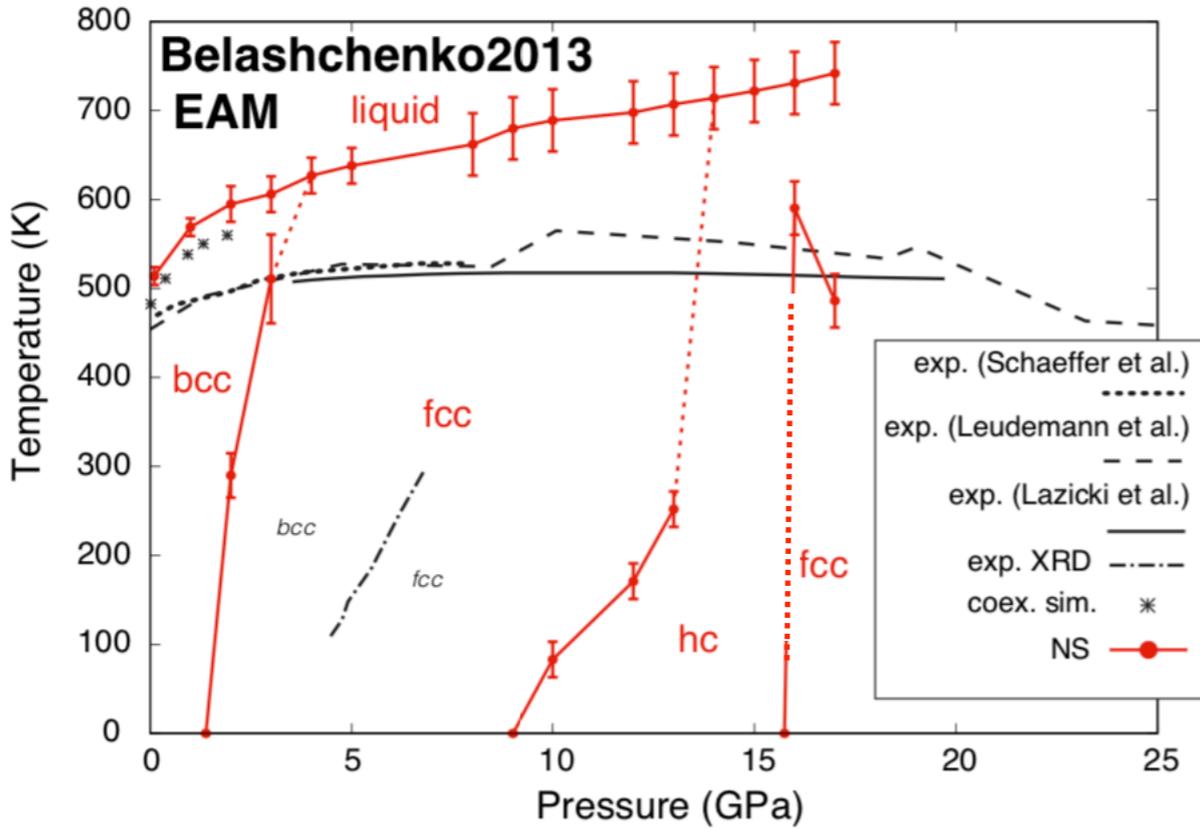
2NN-MEAM by Ko and Jeon

force matching algorithm - DFT database of fcc, bcc, hcp configuration 0K and finite temperature

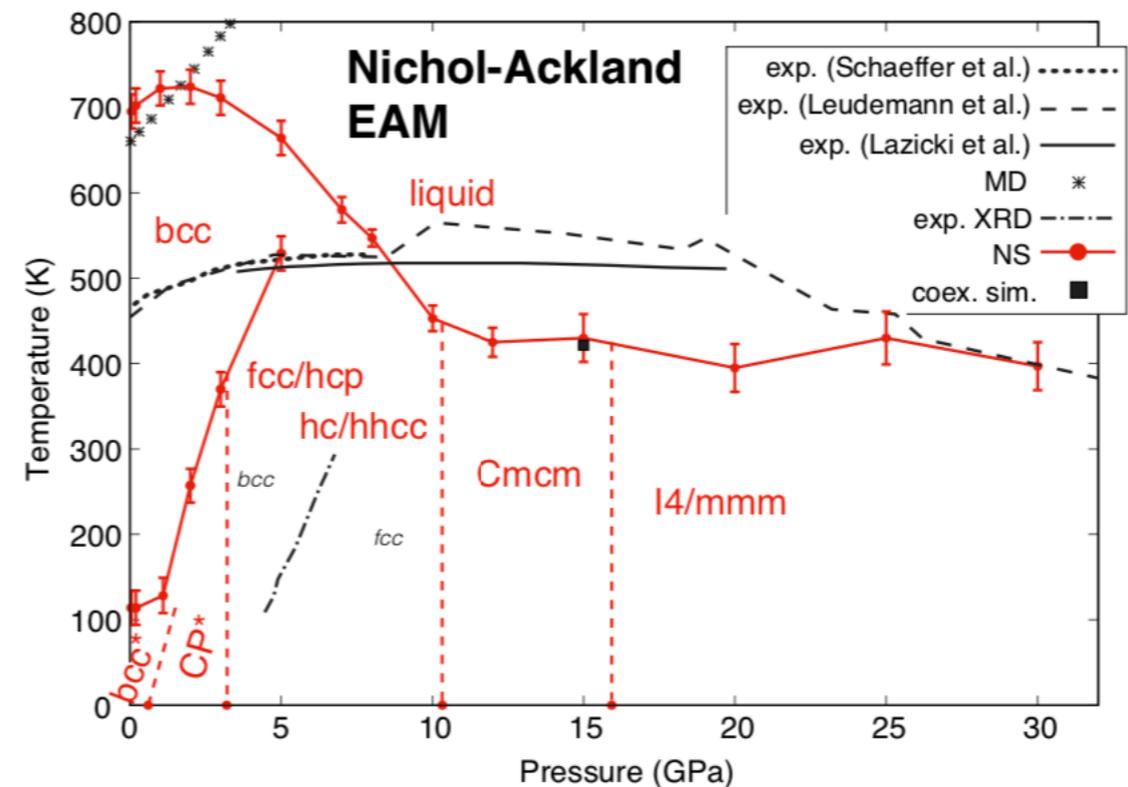
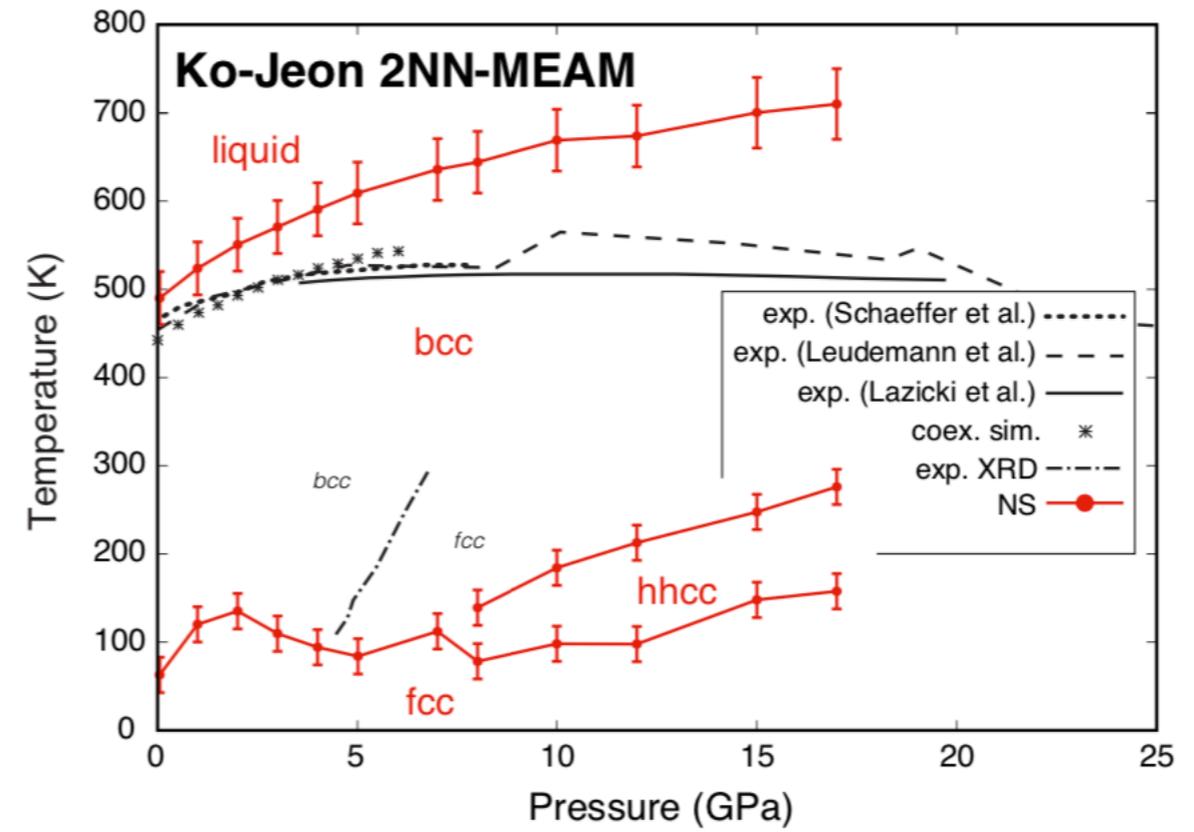
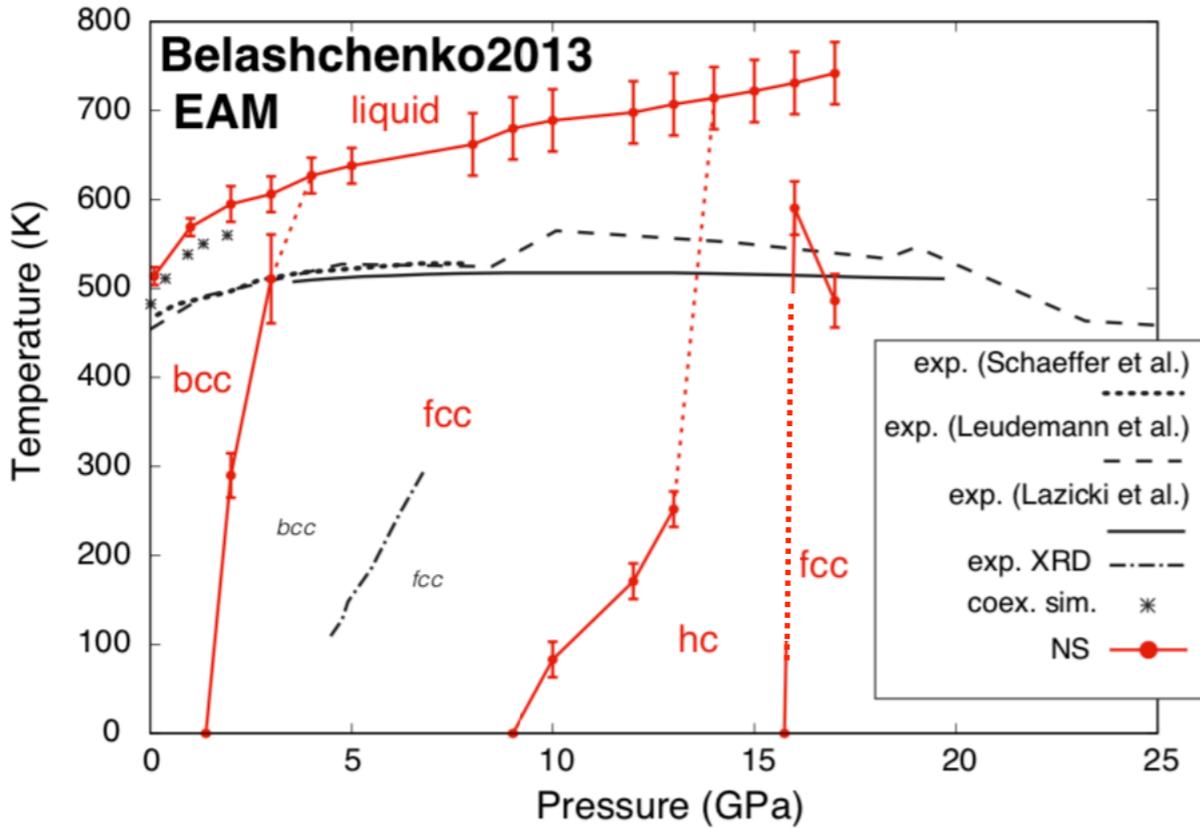
Phase Diagram of Lithium



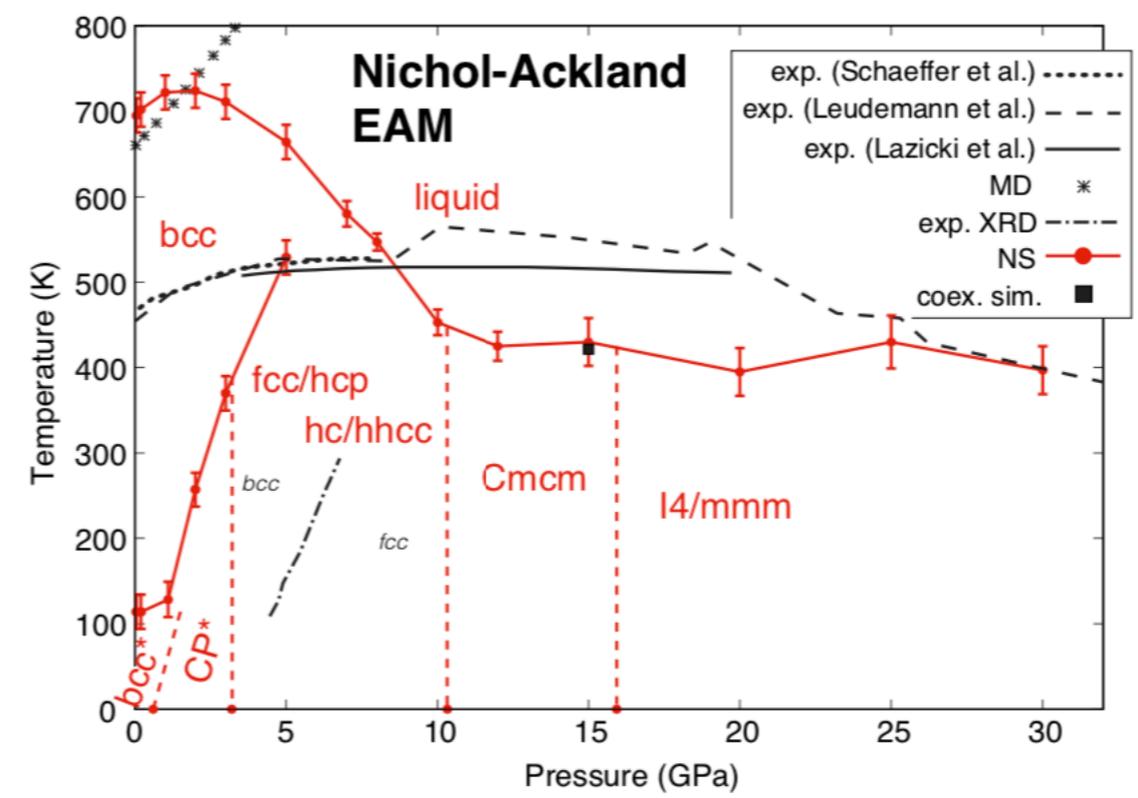
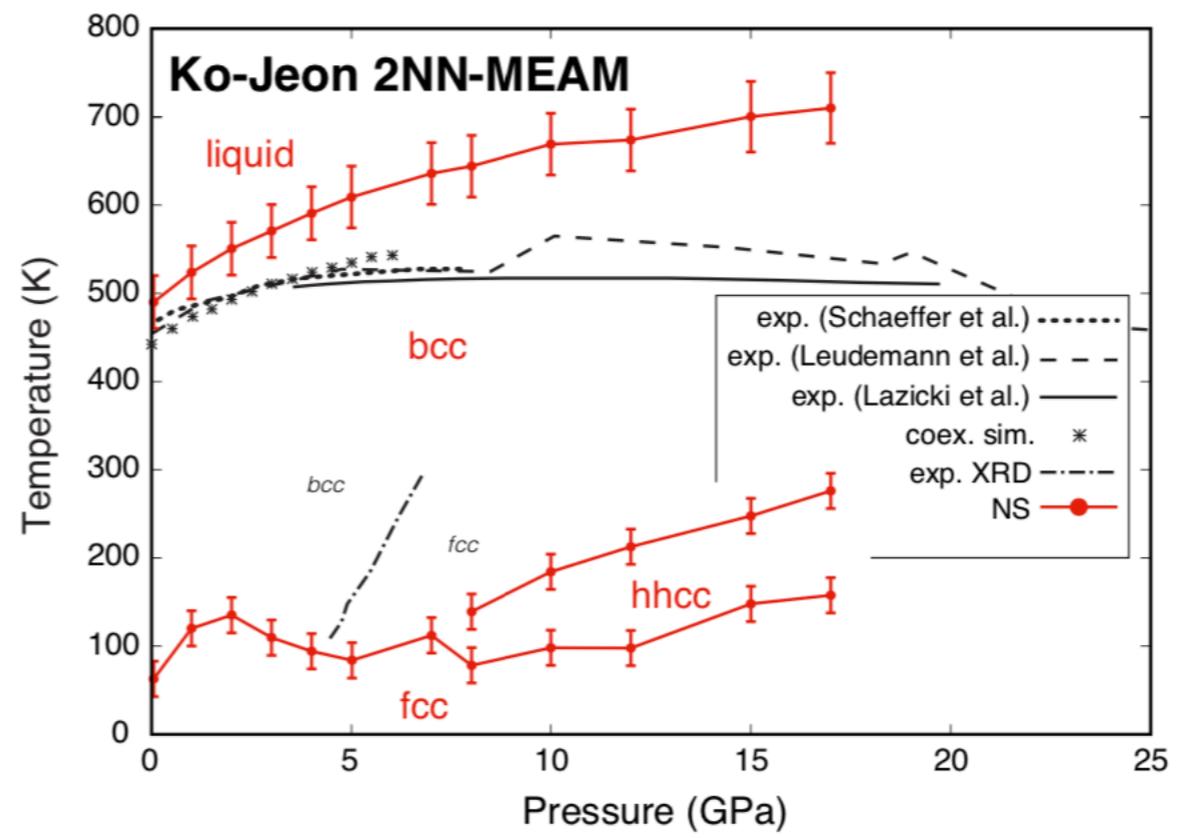
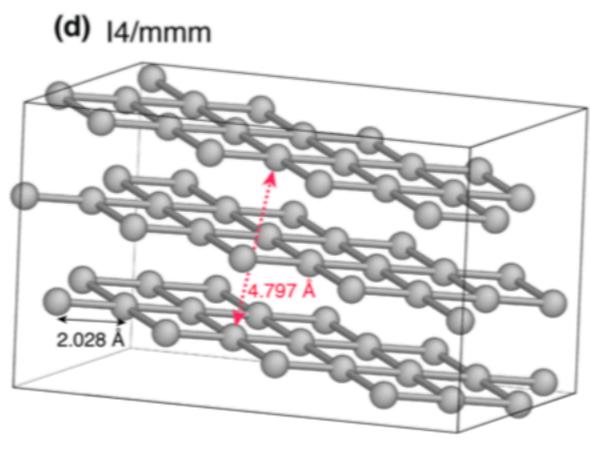
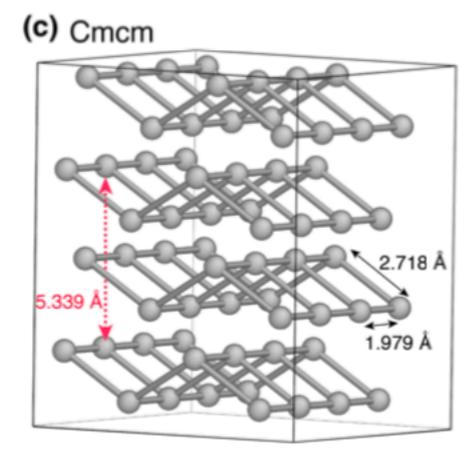
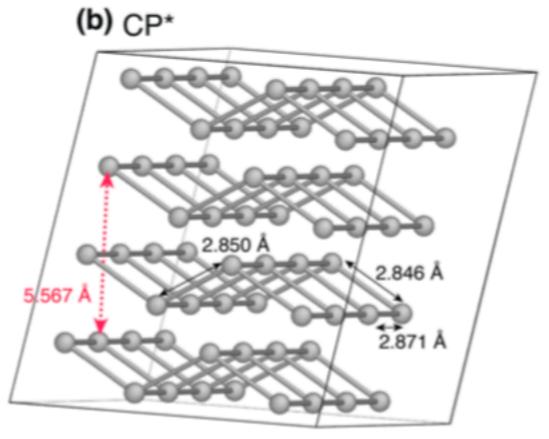
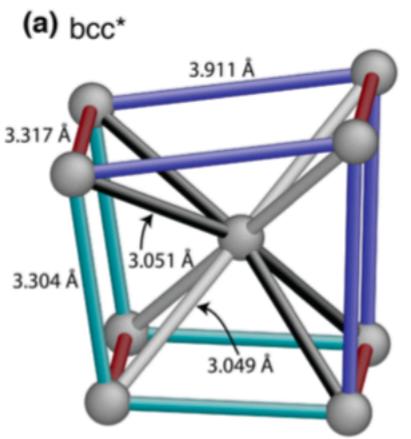
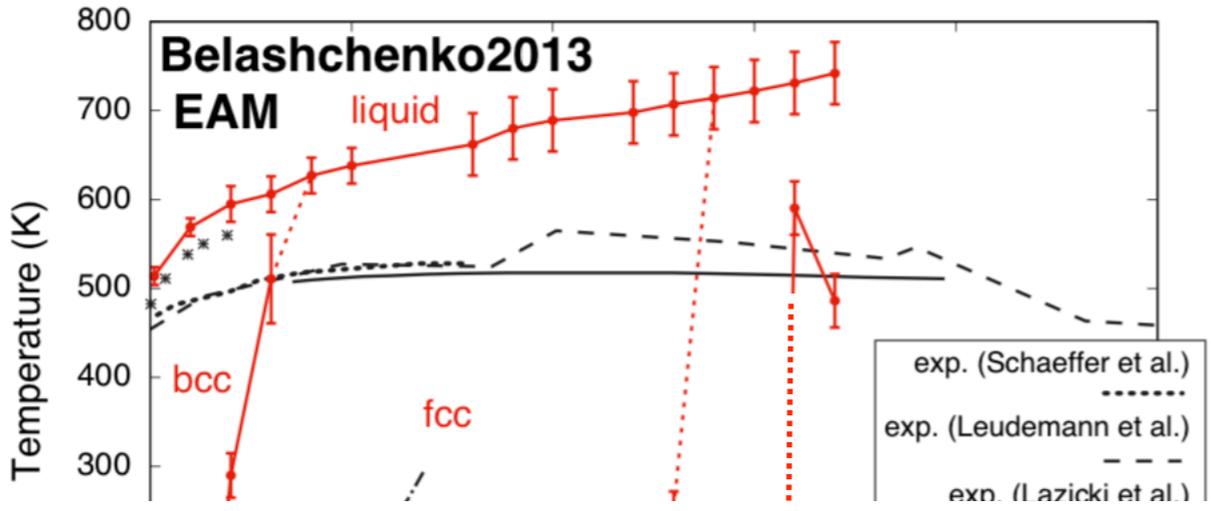
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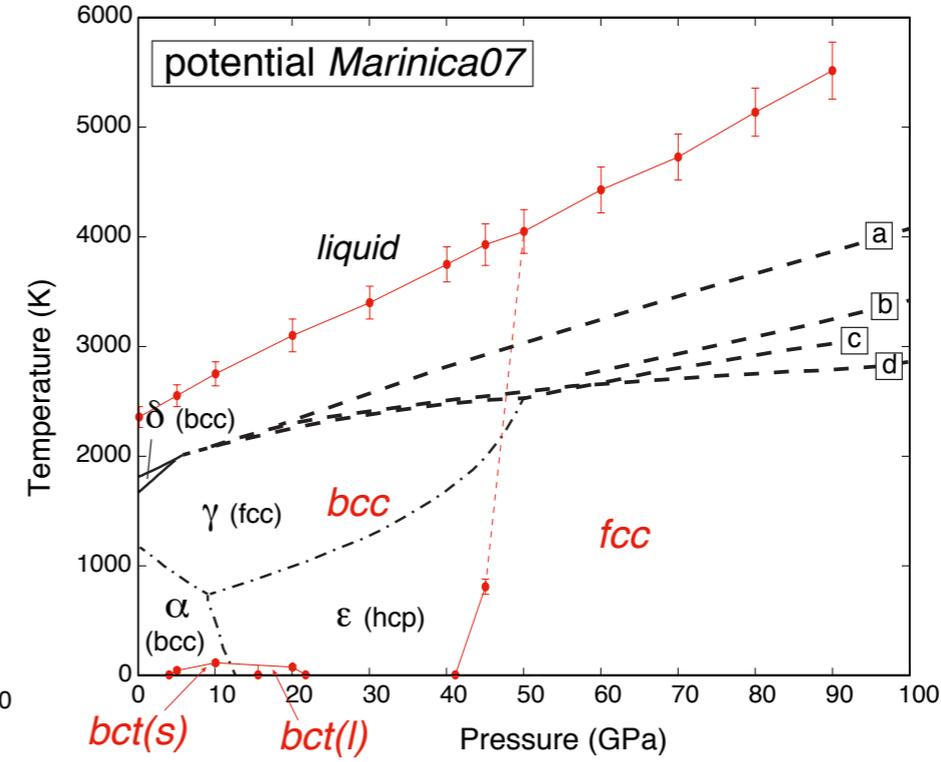
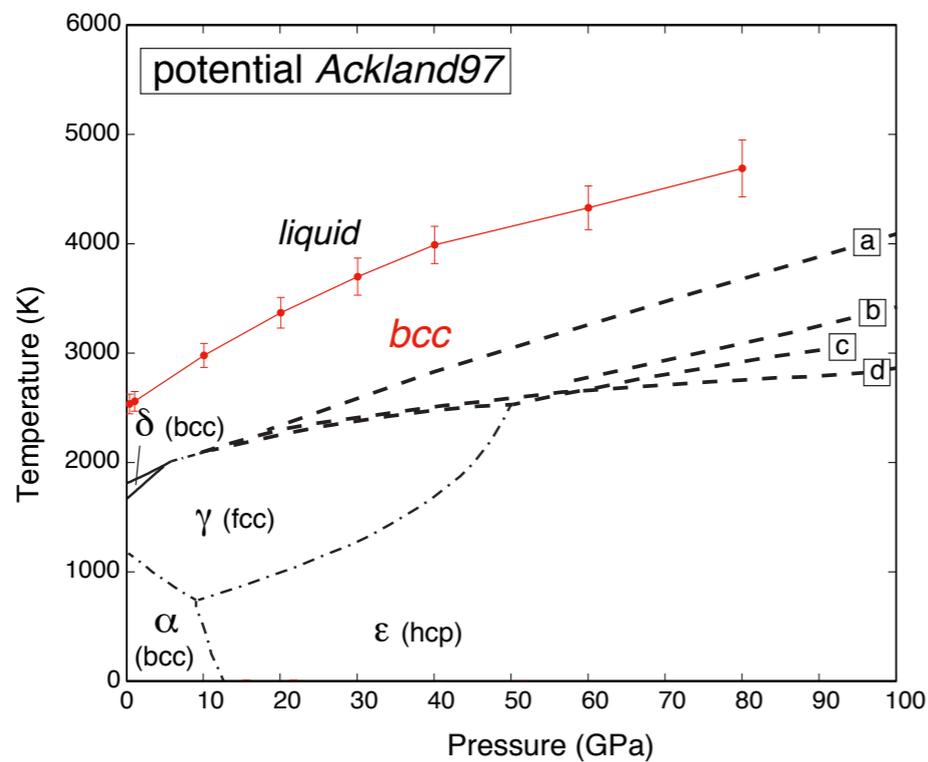
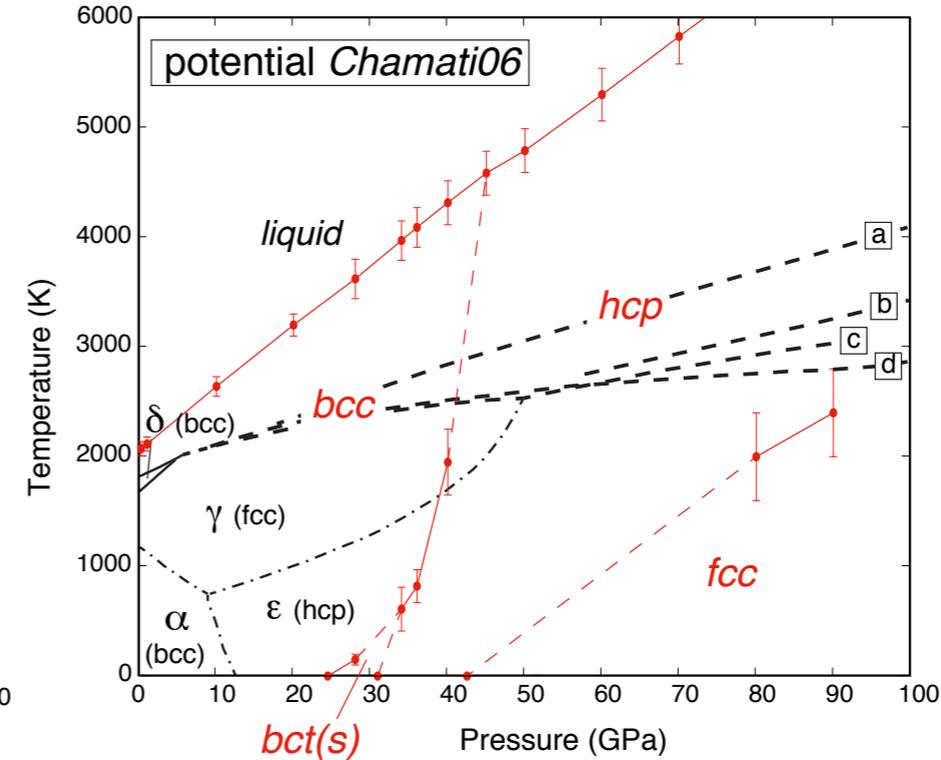
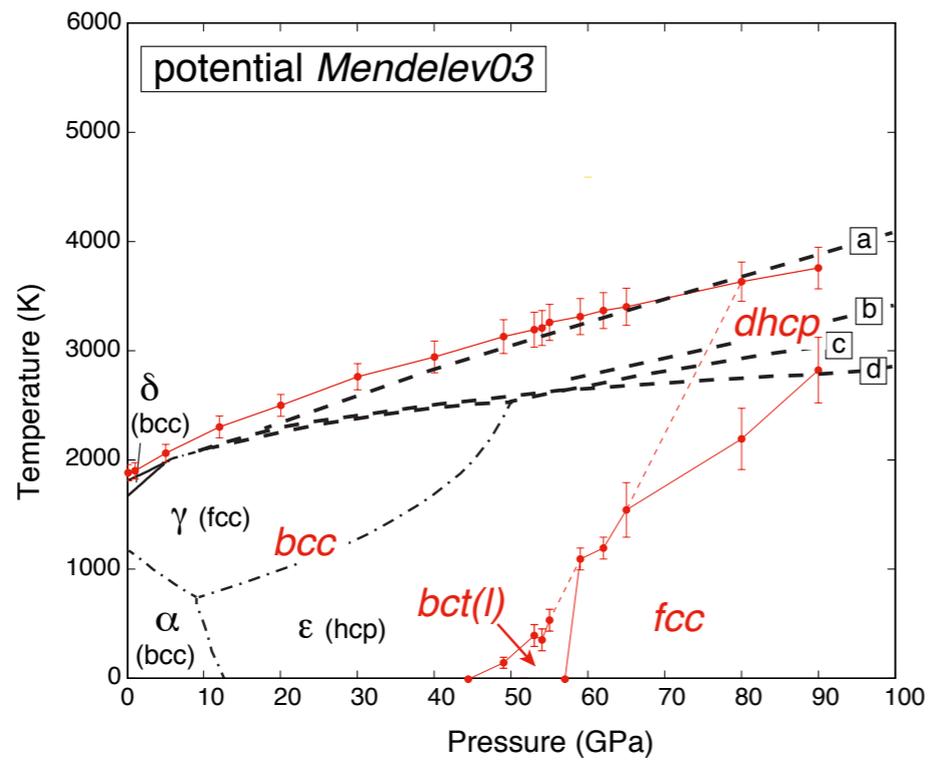


Phase Diagram of Lithium



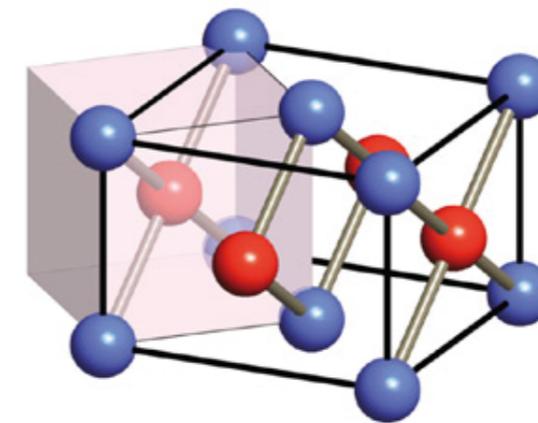
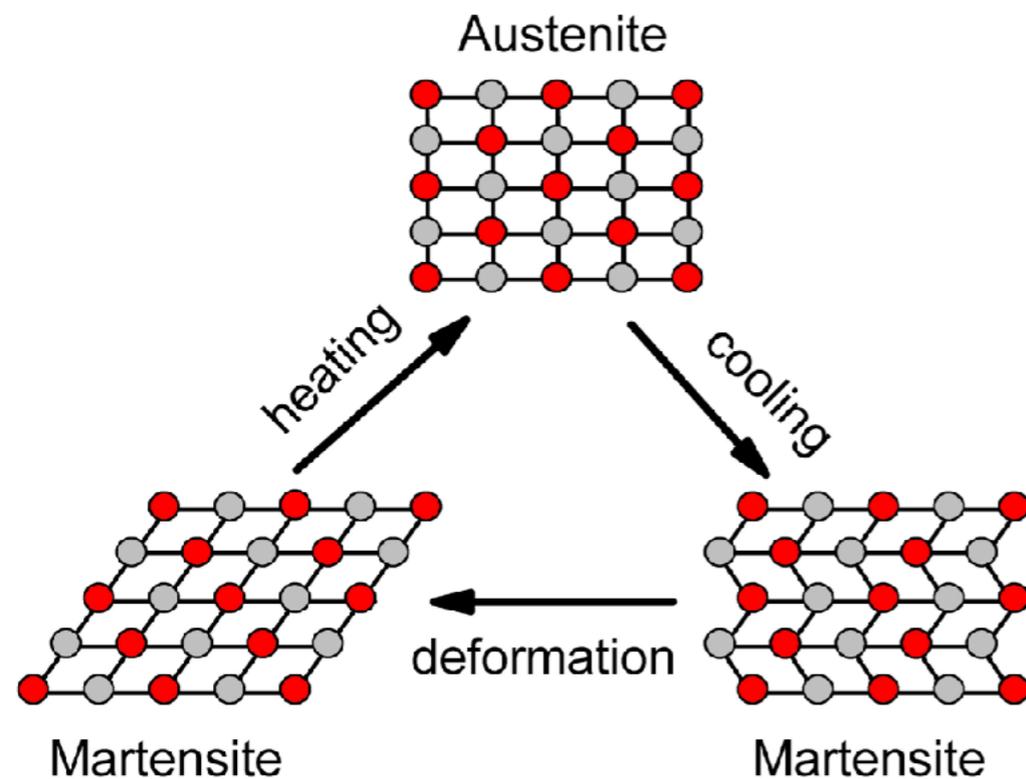
Phase Diagram of Iron

Embedded atom model of iron, 64 atoms in a simulation cell with variable size and shape

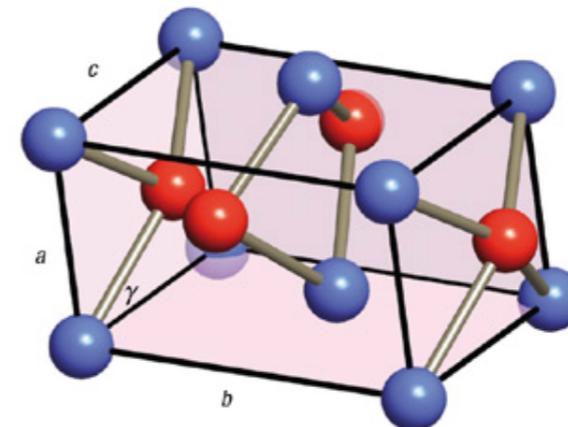


Martensitic Transition in NiTi alloys

shape memory alloy: “remembers” its original shape when deformed, and returns to it when heated



B2



B19'

(from Huang et.al. *Nat.Mat.*2003)

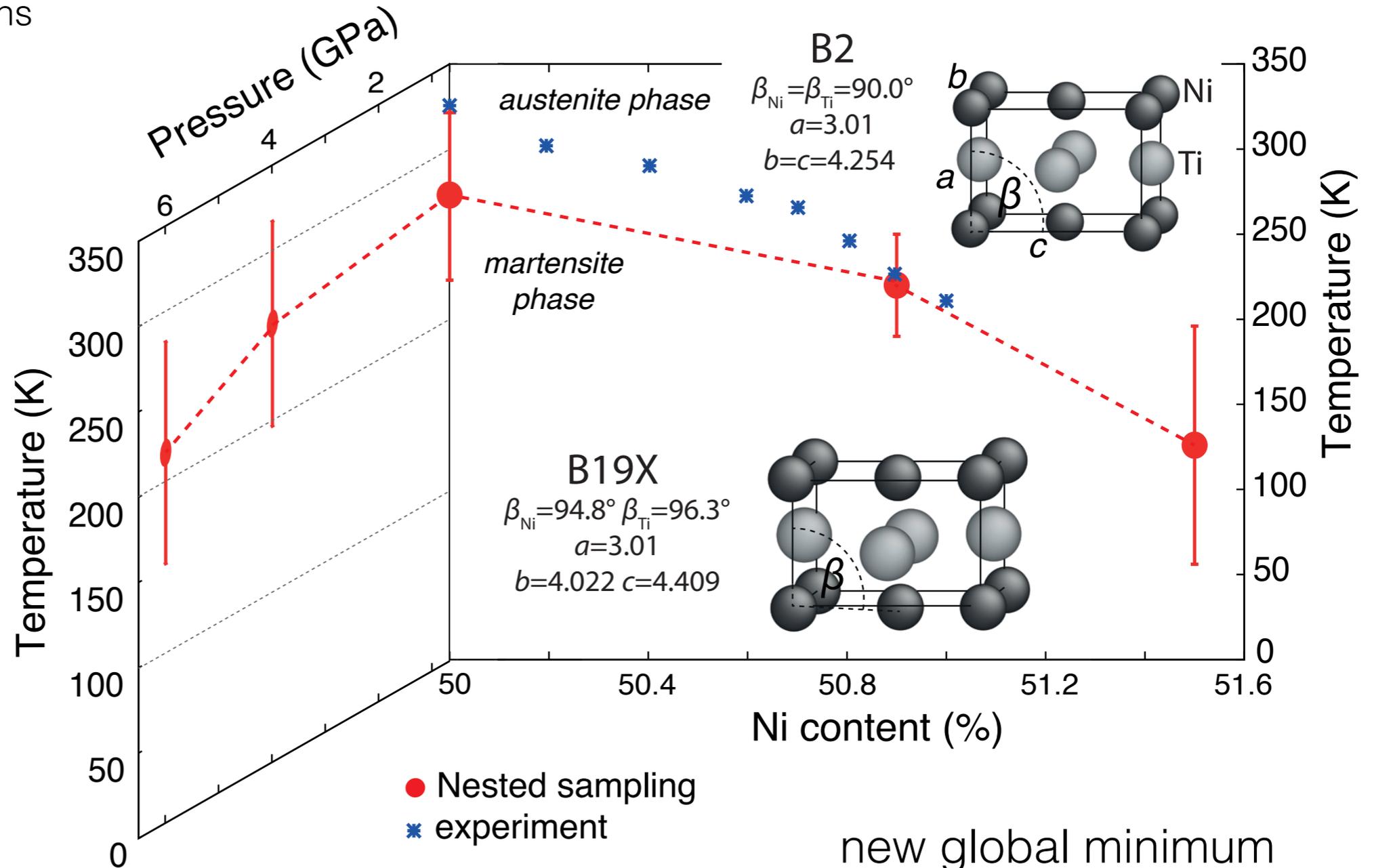
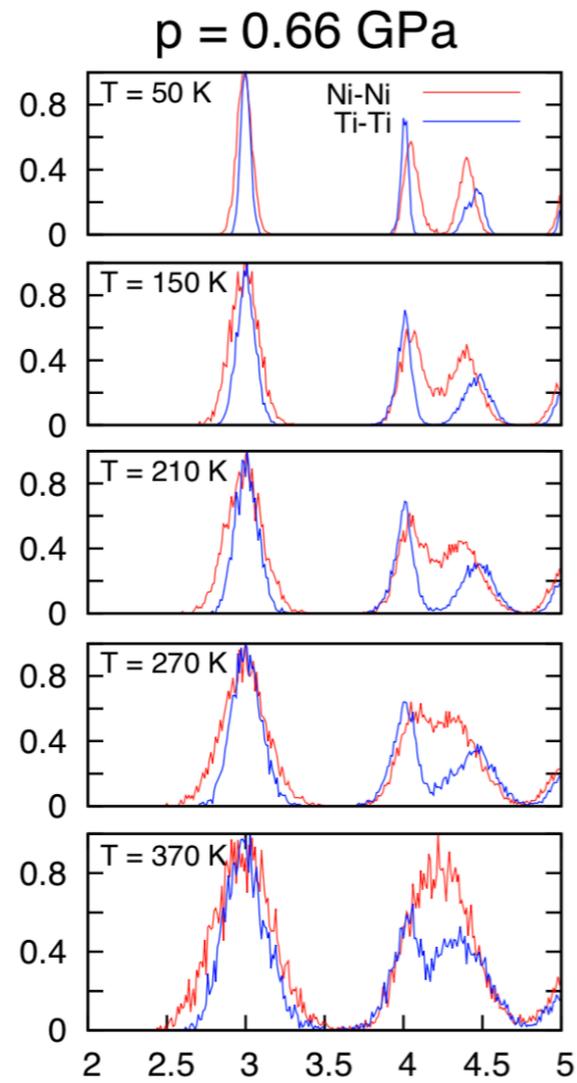
Martensitic Transition in NiTi alloys

pressure-temperature-composition phase diagram

Embedded atom model by Zhong et al.

64 and 108 atoms in a simulation cell with variable size and shape

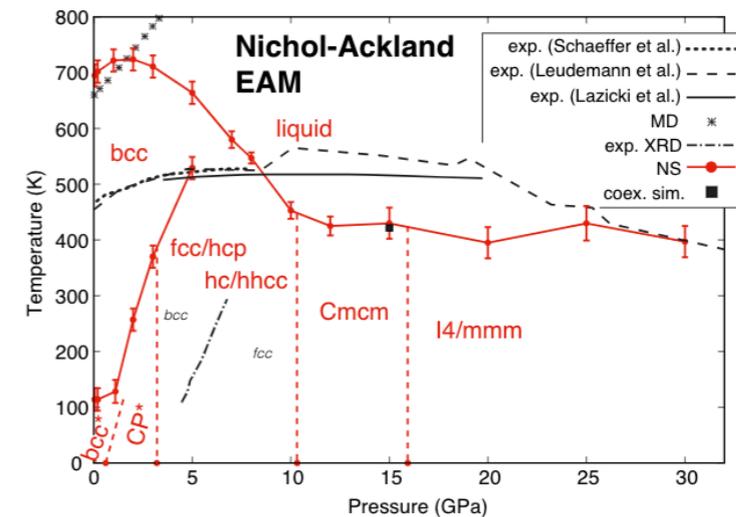
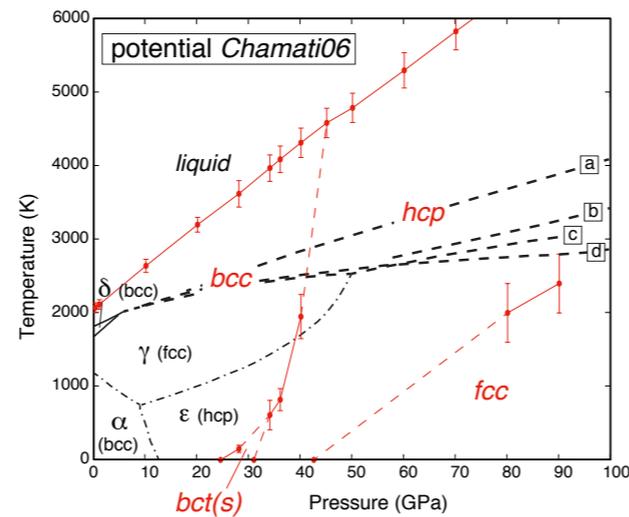
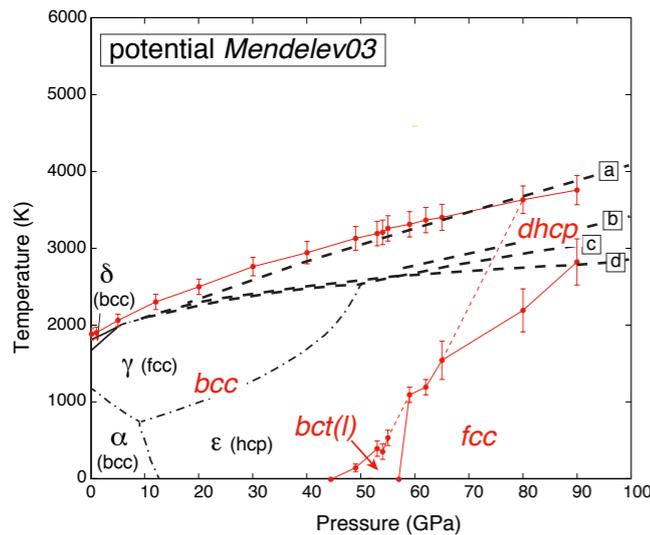
NS weighted radial distribution functions



new global minimum structure found!

Phase Diagram of... models?

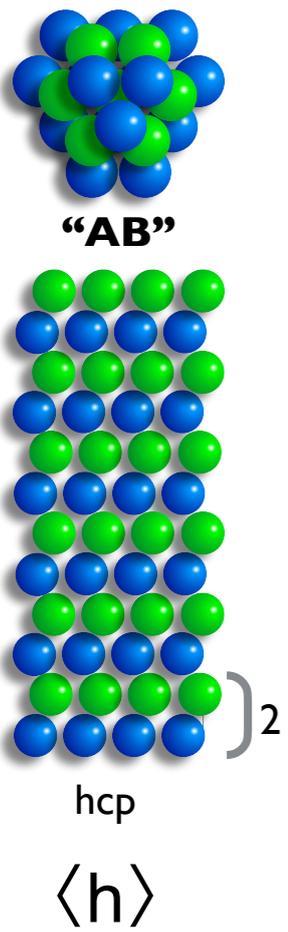
Aim: To have an unbiased sampling technique which can give an overview of the entire PES (**THERMODYNAMICS**), and can be automated: not specific to a given part of the PES (**GENERAL**), where no prior knowledge of structures are necessary (**PREDICTIVE**).



What do we know about the reliability of these models?
 How do they perform on reproducing macroscopic behaviour?
 How to choose the model we want use for a specific study?
 What information to use in the fitting procedure?

What is the global minimum of the Lennard-Jones model?

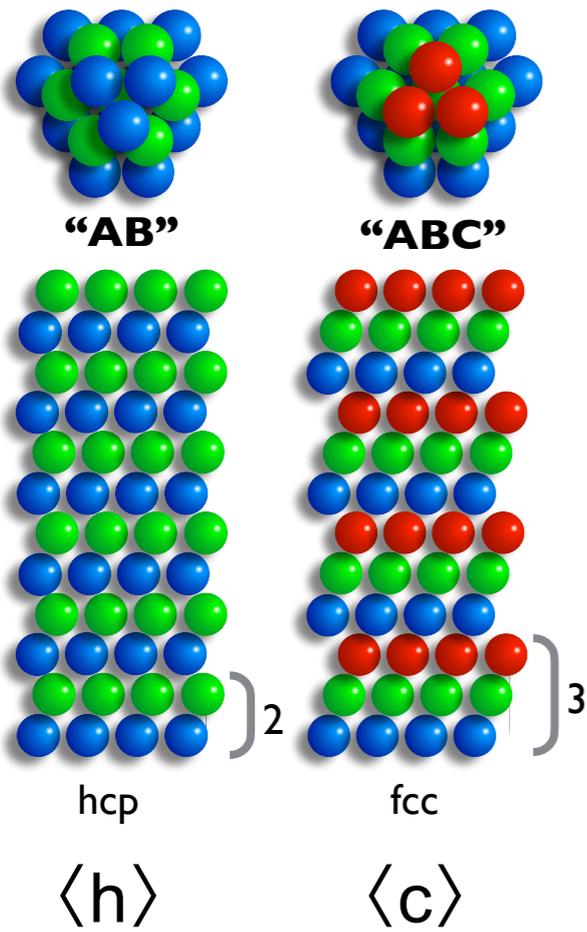
Everyone knows it's **hcp**!



What is the global minimum of the Lennard-Jones model?

Everyone knows it's **hcp**!

Everyone knows it's **fcc**!



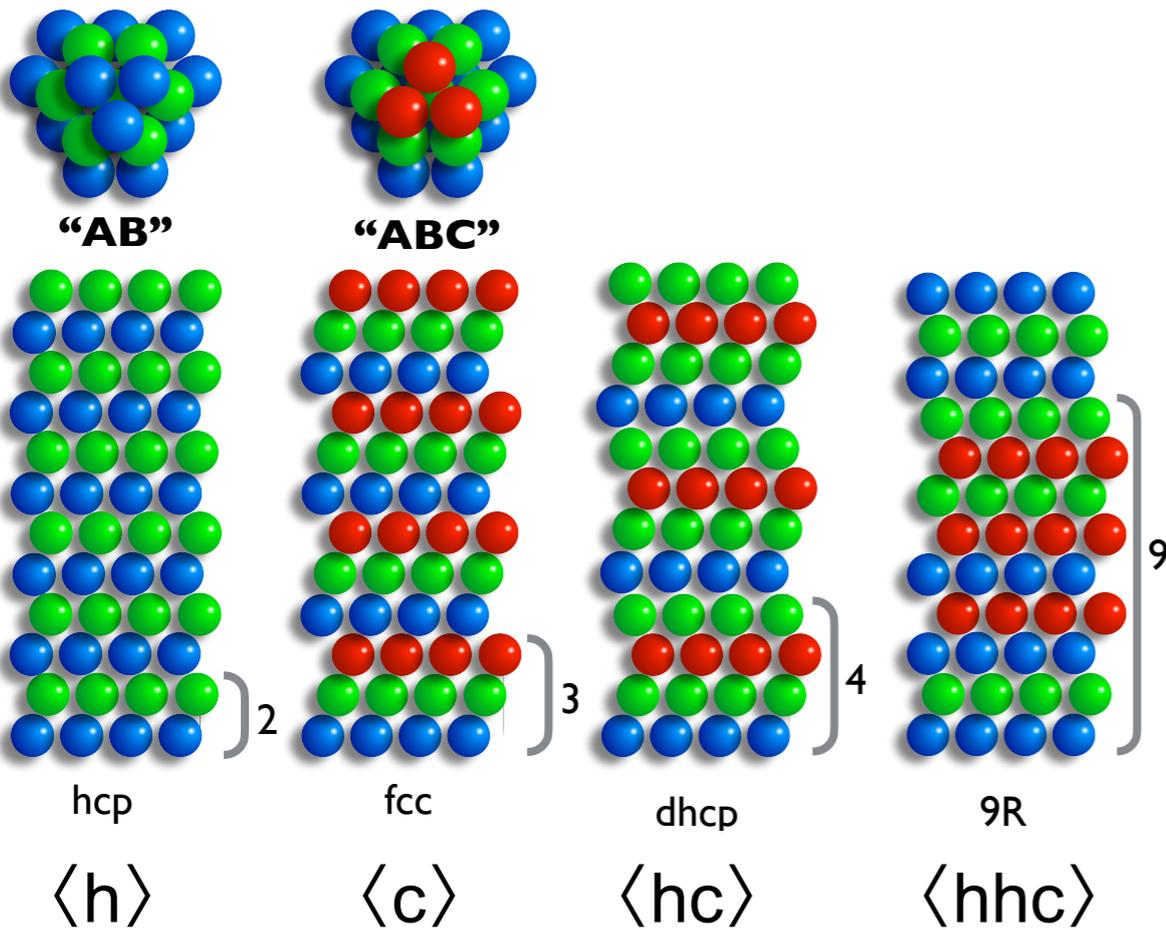
What is the global minimum of the Lennard-Jones model?

Everyone knows it's

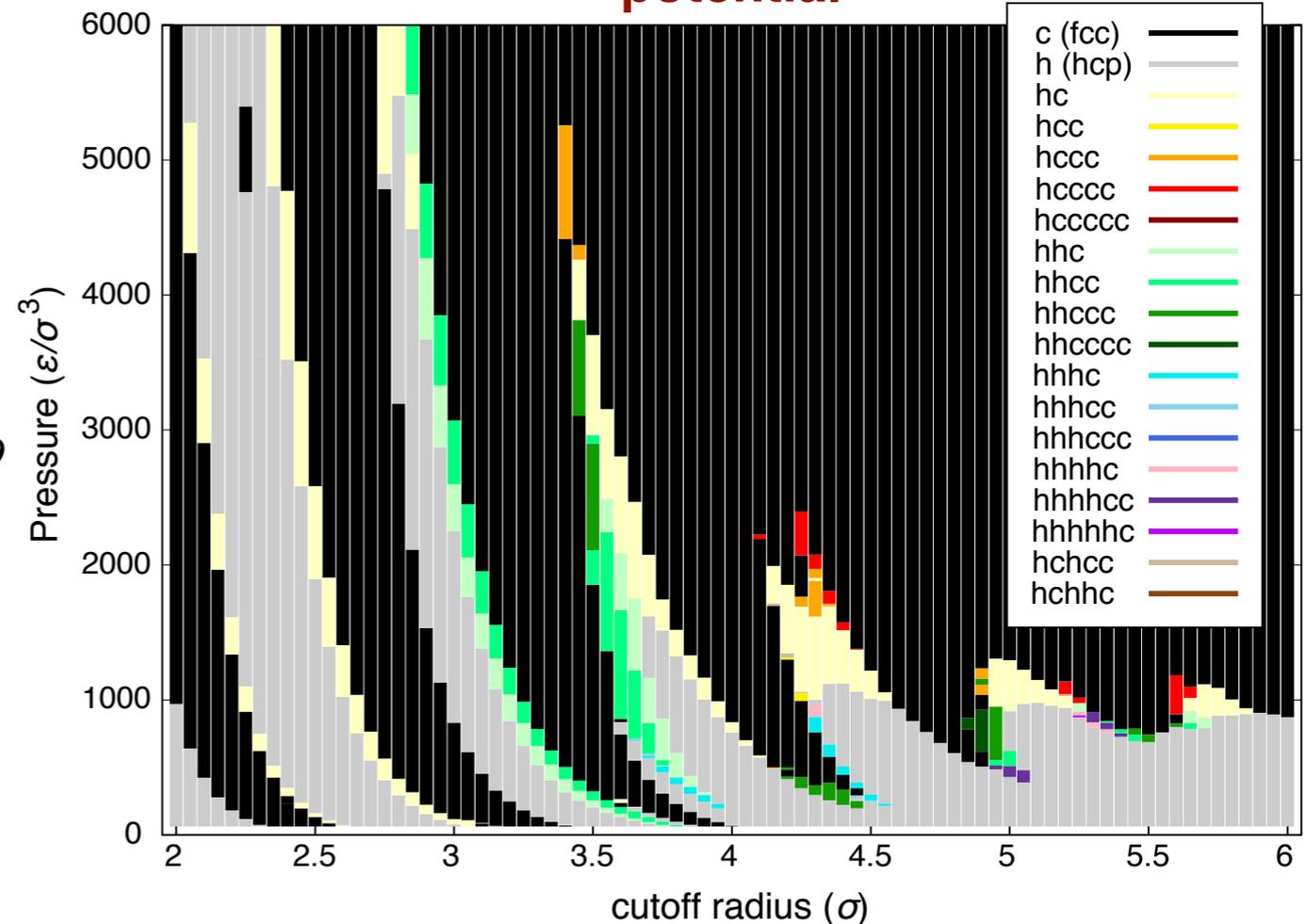
Ev knows

Well, it can be **hcp**, **fcc**, **dhcp**, ... and other close packed **stacking variants!**

depending on the **cutoff distance**, the **smoothness** around the cutoff and the **pressure**, LJ has a ground state of different stacking.



Map of global-minima for energy-shifted LJ potential



GAP model of carbon (Deringer and Csányi, *PRB.* 95. 094203 (2017))

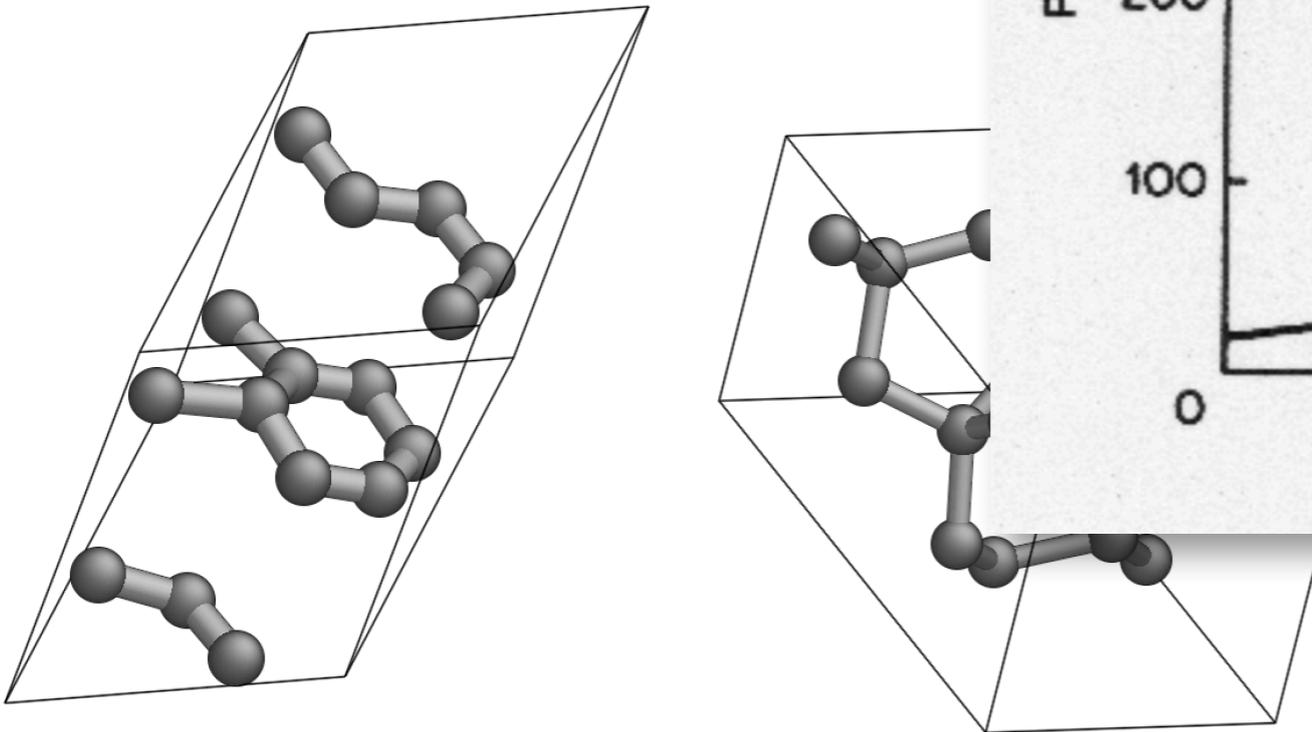
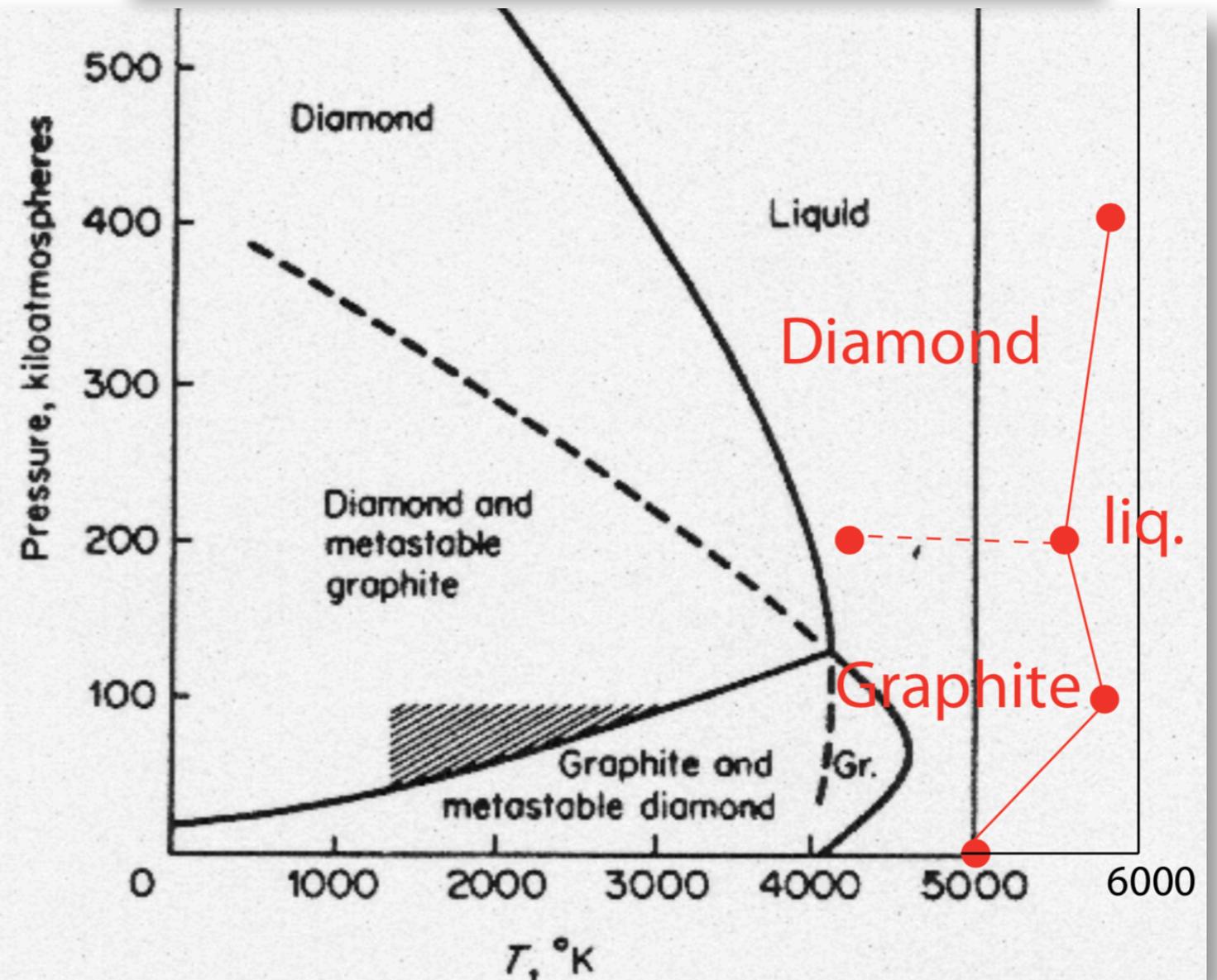
ML Training dataset:

- liquid and amorphous configuration
- amorphous surfaces
- randomly distorted unit cells of graph

Nested sampling:

- 16 atoms/32 atoms
- 600 walkers

Carbon p - T phase diagram



Python code with an interface to **QUIP** and **LAMMPS**

<http://github.com/libAtoms/pymatnest>
<http://libatoms.github.io/pymatnest/>

ns_doc 1 documentation »

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Installation and quick start guide

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Nested sampling method

Authors: Noam, Rob, Gabor, Livia
Date: 2015

Overview

The nested sampling method was first introduced by John Skilling [1] in the field of applied probability and inference to efficiently sample probability densities in high-dimensional spaces where the regions contributing most of the probability mass are exponentially localized. It is an annealing algorithm that creates a sequence of probability distributions, each more concentrated than the previous one near the high-likelihood region of the parameter space - i.e. in the context of materials, the low-energy region of configuration space.

Since its original inception, nested sampling has also been applied to atomistic systems, and its several advantages mean it became a powerful method to sample atomic configuration spaces.

- calculate the partition function, hence all thermodynamic properties become accessible
 - calculate the heat capacity and locate the phase transitions
 - with an order parameter calculate the free energy
- the sampling process itself is independent of temperature, thus the calculation of thermodynamic quantities is a simple post-processing step
- no prior knowledge is needed of the phases or phase transitions
- can be used with both constant volume and constant pressure calculations
- calculate the entire phase diagram in an automated way
- considerable computational gain over parallel tempering

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