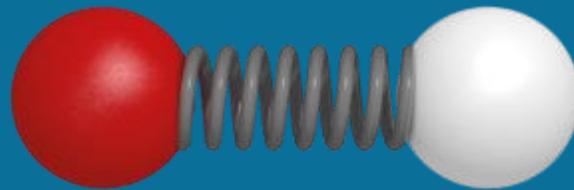


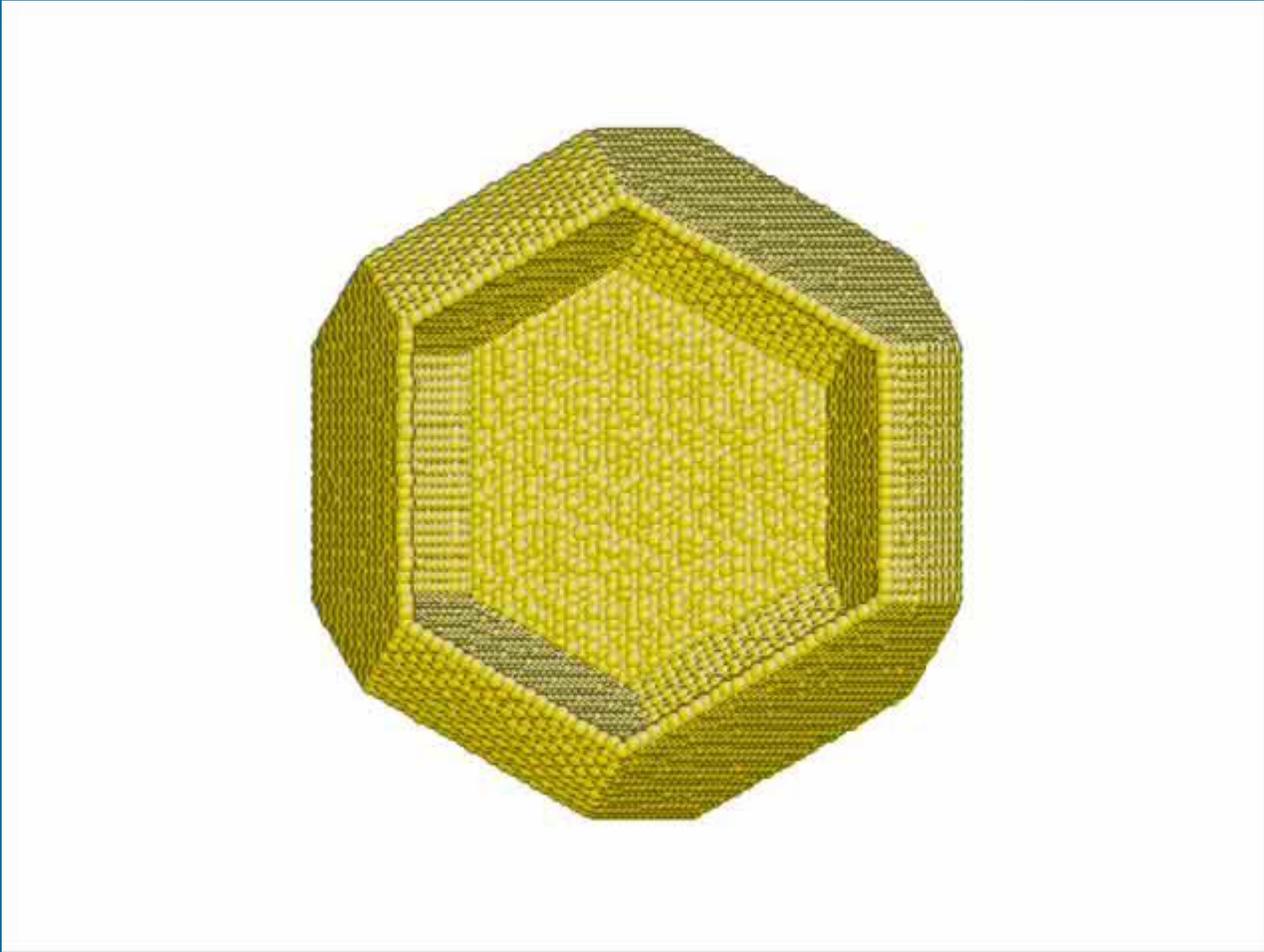
INTERATOMIC POTENTIALS FOR MOLECULAR DYNAMICS SIMULATION



Alex Li

UC San Diego

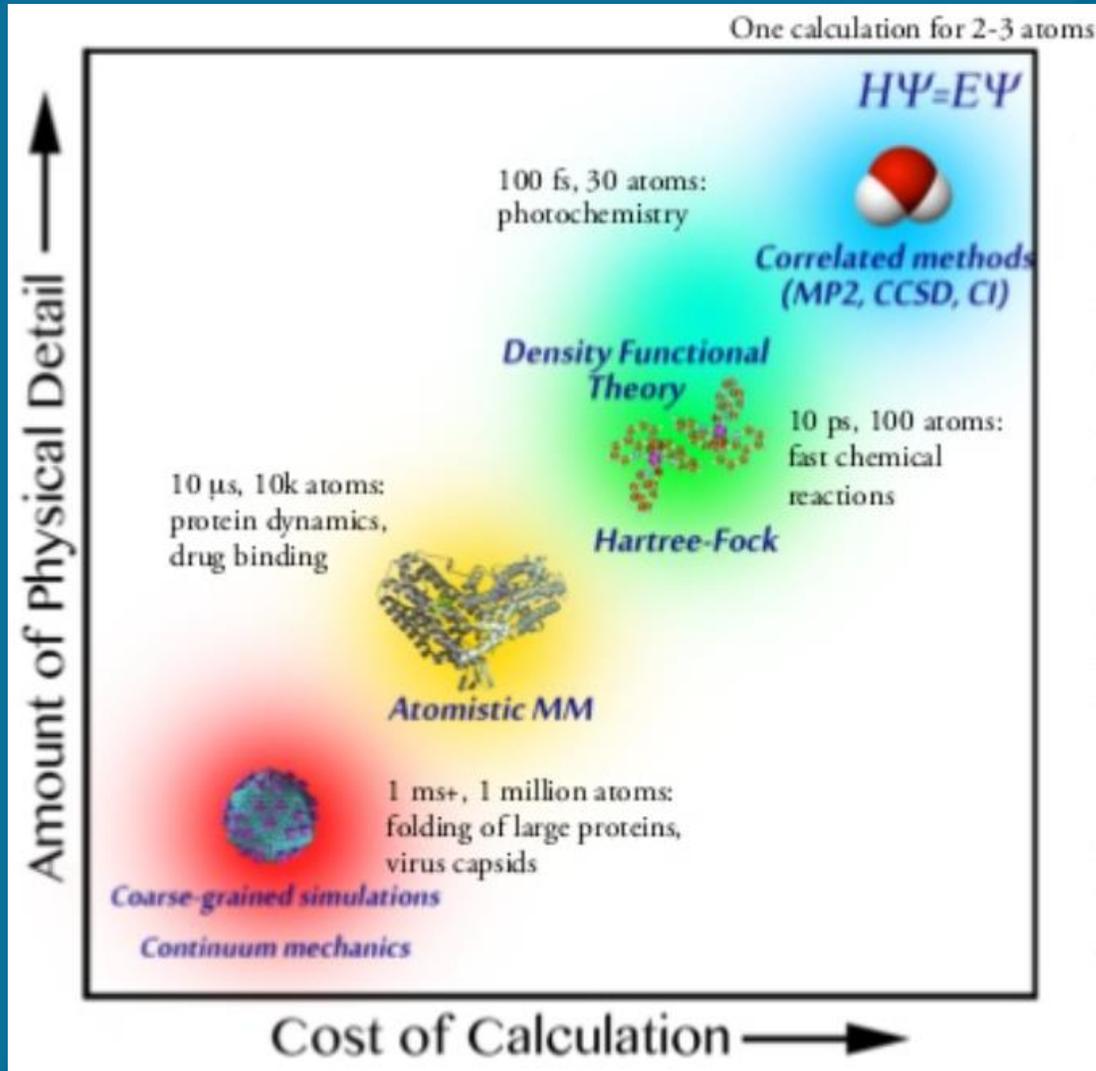
Introduction – Molecular Dynamics and Potentials



Dislocation Nucleation in Metallic Nanoparticles

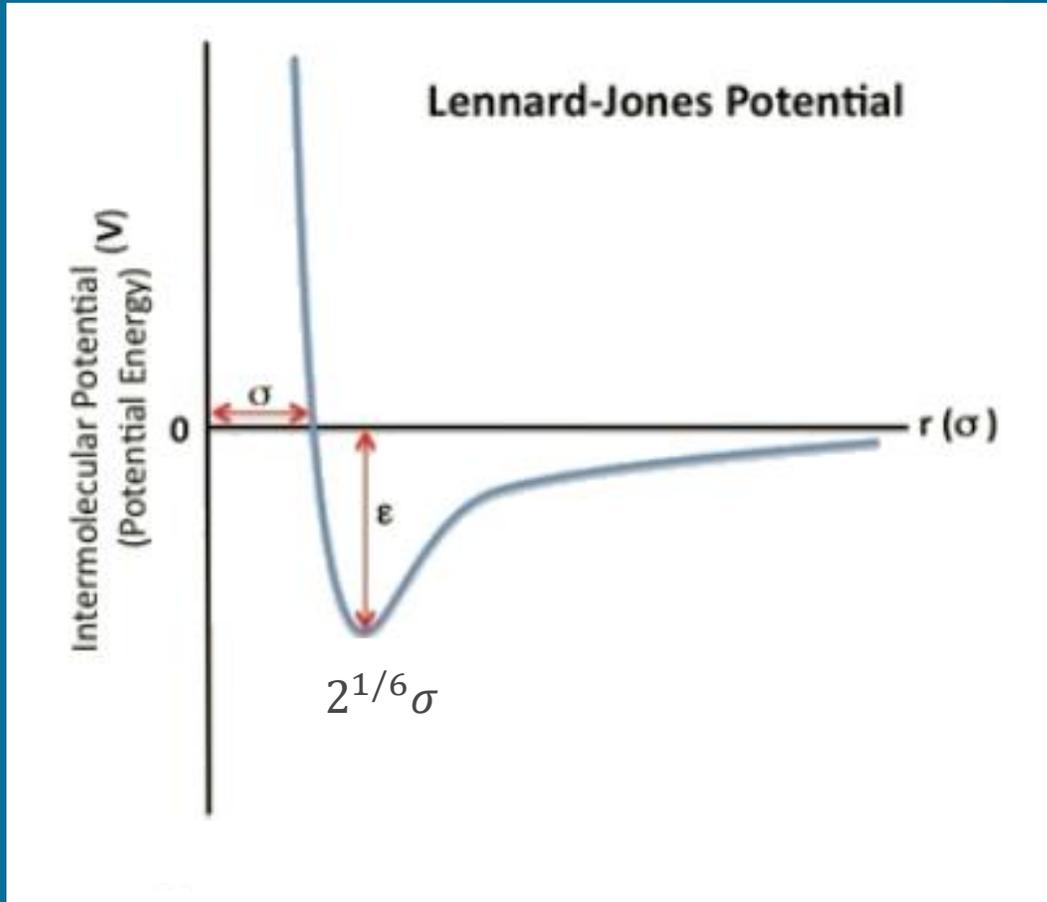
- Molecular Dynamics
 - A simulation tool for analyzing the physical behavior of a system of particles
- $F = ma$
 - Newton's laws applied to individual atoms
- Interatomic Potentials
 - Describe the energy between particles, from which the forces can be derived
 - The accuracy of the potential translates to the accuracy of the simulation

Types of Interatomic Potentials



- Interatomic Potentials describe the potential energy of a system of atoms
- There are many different Types of potentials with different resolution and computational load
 - Empirical Potentials
 - Ab Initio Methods
 - Machine Learning Potentials
- Multiscale Modeling
 - A method of bridging the scales from continuum mechanics to atomistic modeling

Lennard-Jones Potential

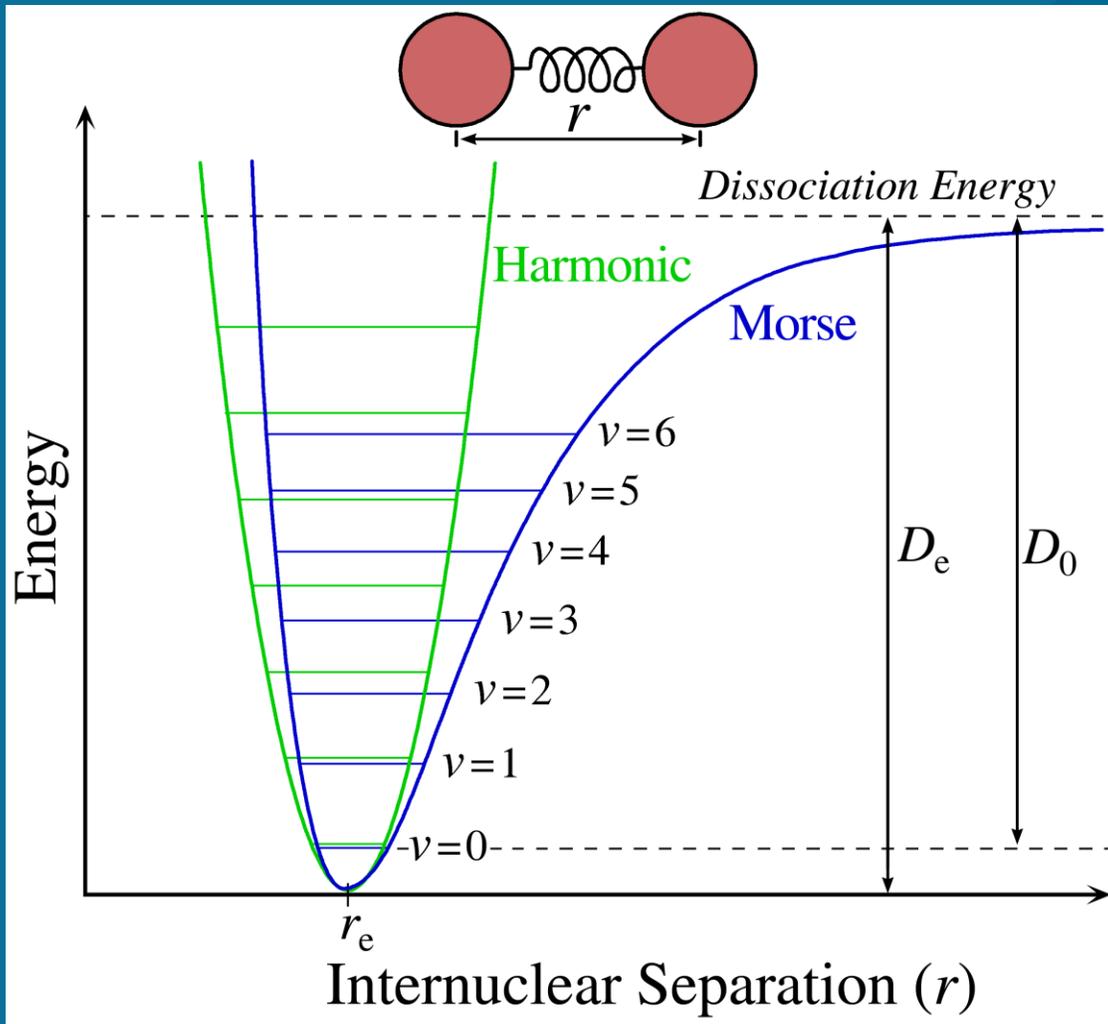


The deeper the well depth ϵ , the stronger the interaction between the two particles. When the bonding potential energy is equal to zero, the distance of separation, r , will be equal to σ . Minimum energy distance occurs at $2^{1/6}\sigma$.

$$V(r) = 4\epsilon \left[\left(\frac{\sigma}{r} \right)^{12} - \left(\frac{\sigma}{r} \right)^6 \right]$$

- Sometimes parameterized as
 - $V(r) = \frac{A}{r^{12}} - \frac{B}{r^6}$
 - Where $A = 4\epsilon\sigma^{12}$, $B = 4\epsilon\sigma^6$
- Widely known two-body potential
- Used as a basis for the two-body interaction in many higher order potentials

Other Pair Potentials



<https://commons.wikimedia.org/wiki/File:Morse-potential.png>

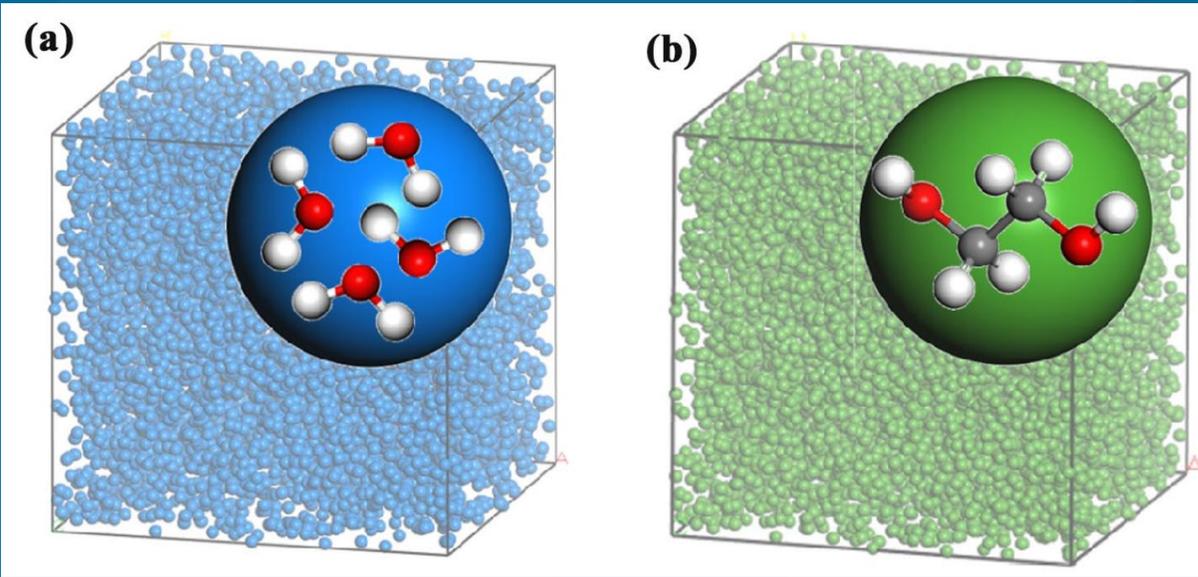
$$V(r) = D_e \left(e^{-2a(r-r_e)} - 2e^{-a(r-r_e)} \right)$$

- Morse Potential
 - Similarly composed of a repulsive and attractive term
- Buckingham Potential

$$\Phi_{12} = A \exp(Br) \frac{C}{r^6}$$

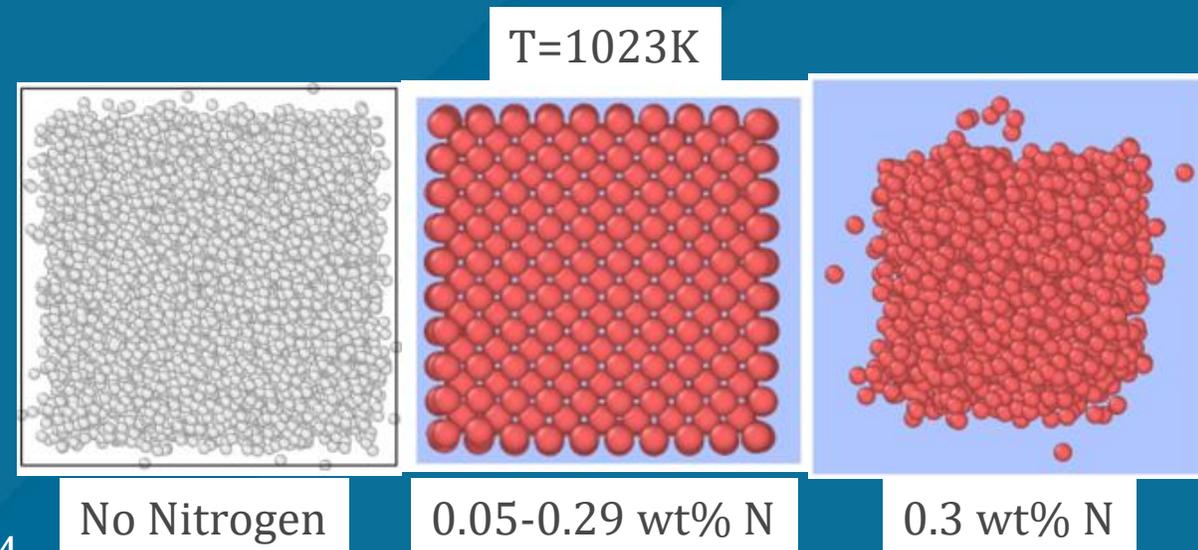
- Considered a simplified LJ Potential

Lennard-Jones Potential - Applications



- Using the LJ to match physical properties of larger clusters of molecules for speeding up computation

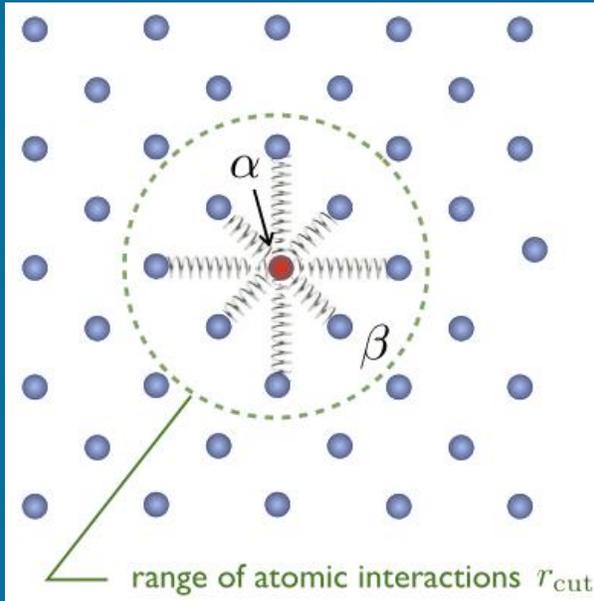
Cha, J., Lee, W., Shin, E. *et al.*, *Multiscale Sci. Eng.*, 2020



- Using LJ to derive properties of iron in molten lead for investigation of corrosion inhibition in nuclear reactors using Nitrogen

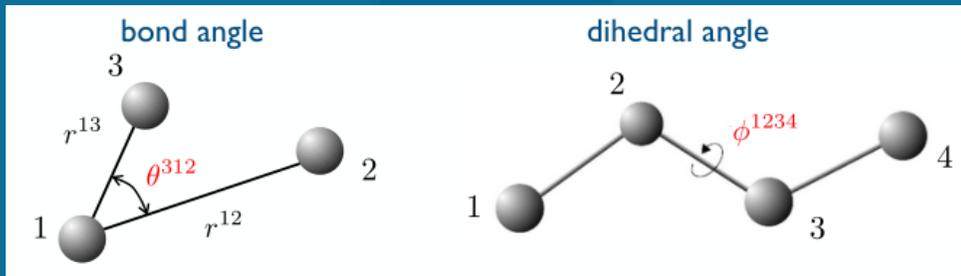
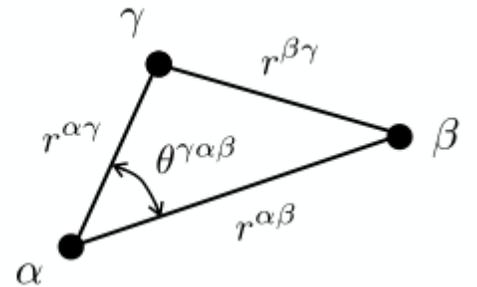
Triwardani *et al.*, *AIP Conference Proceedings*, 2020

Three Body Potentials



$$V = \sum_{\alpha} V^{\alpha} = \frac{1}{2} \sum_{\substack{\alpha, \beta \\ \alpha \neq \beta}} \phi(r^{\alpha\beta})$$

$$V = \frac{1}{2!} \sum_{\substack{\alpha, \beta \\ \alpha \neq \beta}} \phi_2(r^{\alpha\beta}) + \frac{1}{3!} \sum_{\substack{\alpha, \beta, \gamma \\ \alpha \neq \beta \neq \gamma}} \phi_3(r^{\alpha\beta}, r^{\alpha\gamma}, r^{\beta\gamma})$$



$$V = \frac{1}{2} \sum_{\alpha, \beta \neq \alpha} \phi_2(r^{\alpha\beta}) + \frac{1}{6} \sum_{i, j} \phi_3(r^{\alpha\beta}, r^{\alpha\gamma}, \theta^{\gamma\alpha\beta})$$

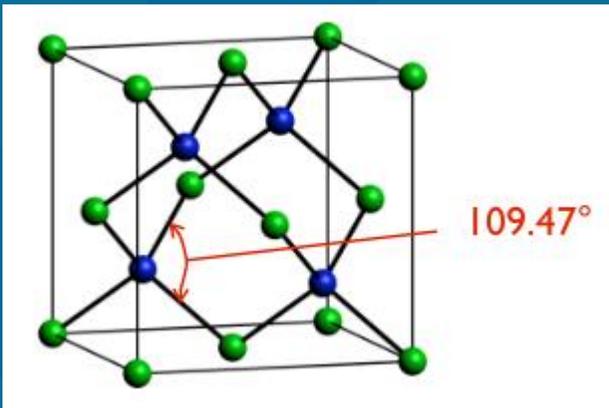
Stillinger Weber

$$V = \frac{1}{2} \sum_{\alpha, \beta \neq \alpha} \phi_2(r^{\alpha\beta}) + \frac{1}{3!} \sum_{i,j} \phi_3(r^{\alpha\beta}, r^{\alpha\gamma}, \theta^{\beta\alpha\gamma})$$

$$\phi_2(r) = f_c(r) [A_1 r^{-\lambda_1} - A_2 r^{-\lambda_2}]$$

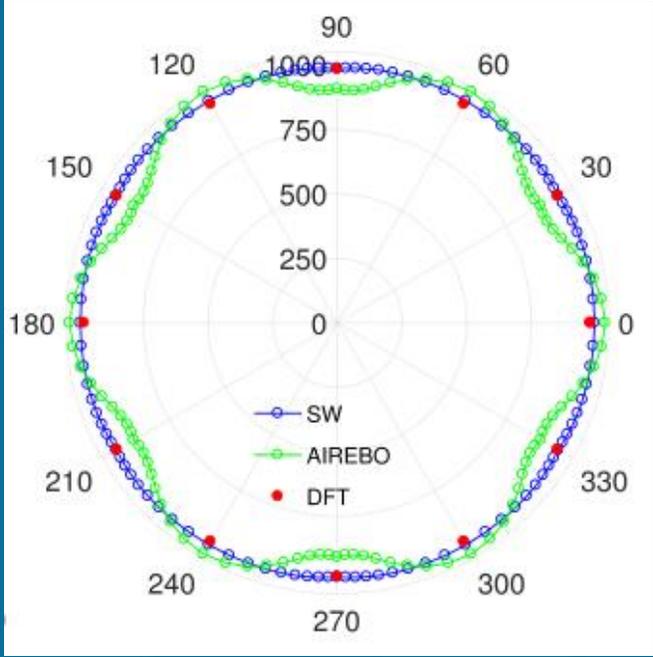
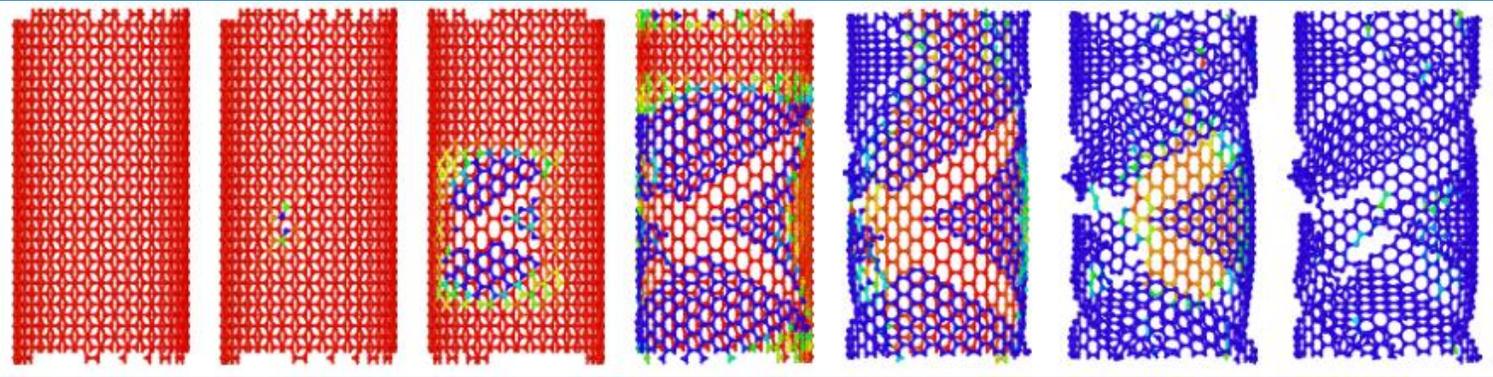
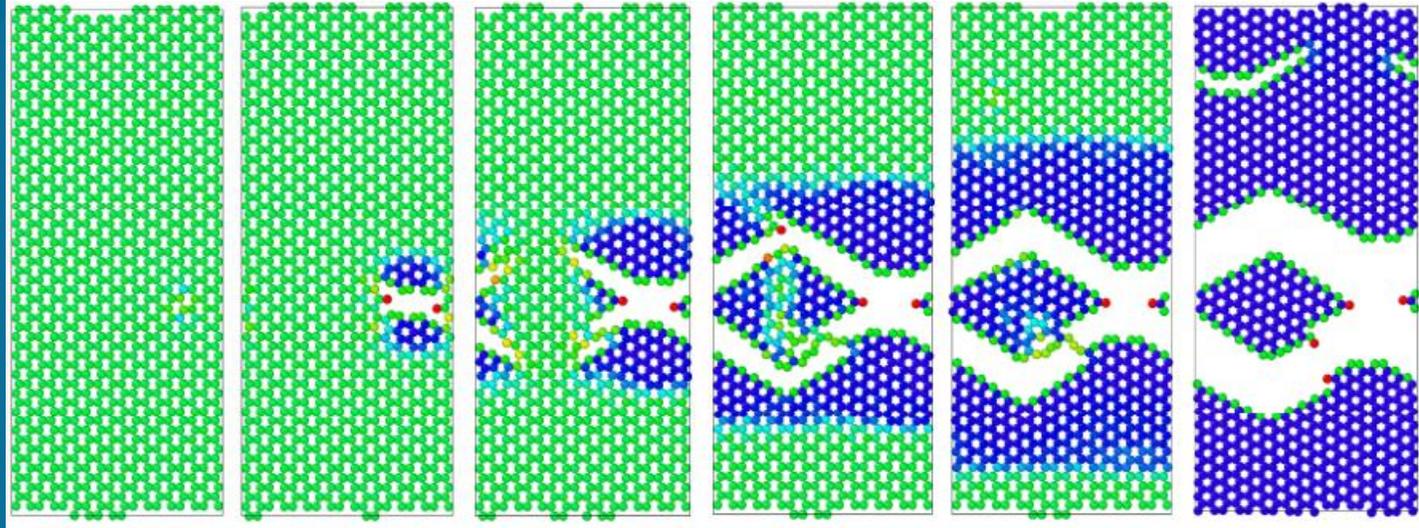
$$f_c(r) = \begin{cases} e^{\mu/(r-r_{cut})} & \text{if } r < r_{cut} \\ 0 & \text{otherwise} \end{cases}$$

$$\phi_3(r^{\alpha\beta}, r^{\alpha\gamma}, \theta^{\beta\alpha\gamma}) = Z [f_c(r^{\alpha\beta}) f_c(r^{\alpha\gamma})] \left(\cos \theta^{\beta\alpha\gamma} + \frac{1}{3} \right)^2$$



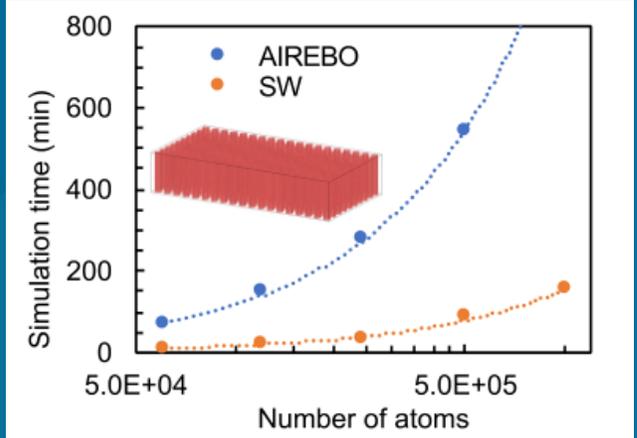
- Designed for Silicon
- Keating potential for pair-potential
- $\cos \theta^{\beta\alpha\gamma} + \frac{1}{3}$
 - This term is specific to the tetrahedral form of silicon, where $\theta_t = 109.47^\circ$
 - $\cos \theta_t = -\frac{1}{3}$
 - This minimizes the energy in the tetrahedral configuration
- Parameters Used
 - $Z = 21, \mu = 1.20, r_{cut} = 1.80$
 - $A_1 = 7.049556277, A_2 = 0.6022246684$
 - $\lambda_1 = 4, \lambda_2 = 0$

Stlinger Weber – Modeling Fracture in Graphene and CNT



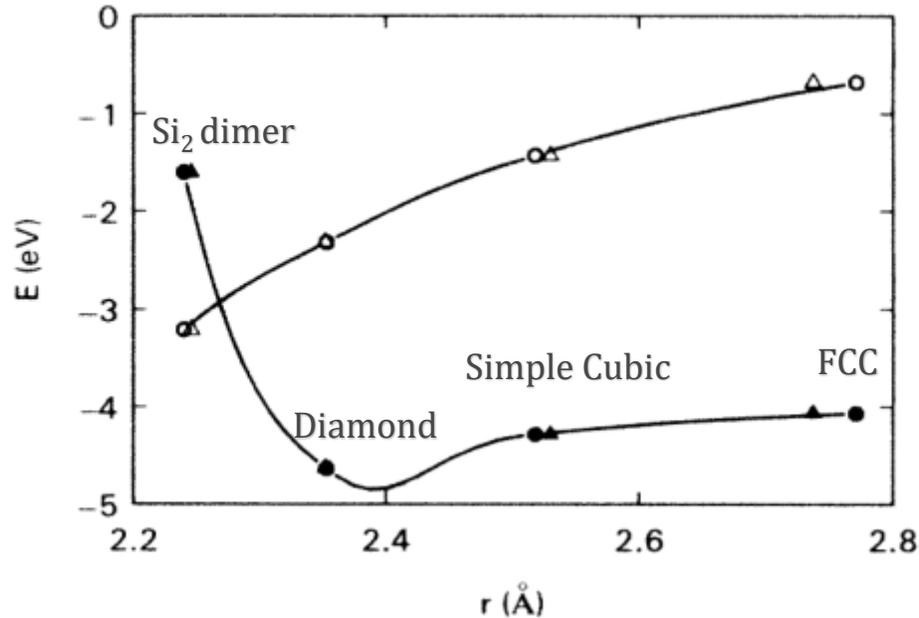
Young's Modulus vs Crystallographic Direction

- Other empirical potentials did not exhibit glass-like brittle
- (ReaxFF, Tersoff, EDIP, AIREBO)



Tersoff Potential

A Modified Two Body Potential



Silicon Energy vs Bond length
 Open: Cohesive energy per bond
 Closed: Cohesive energy per atom

$$E_{ij} = \sum_i E_i = \frac{1}{2} \sum_{i,j \neq i} V_{ij}$$

$$V_{ij} = f_c(r_{ij}) [A \exp(-\lambda_1 r_{ij}) - B_{ij} \exp(\lambda_2 r_{ij})]$$

Tersoff Trial Potential

$$B_{ij} = B_0 \exp(-z_{ij}/b)$$

$$z_{ij} = \sum_{k \neq i,j} [w(r_{ik})/w(r_{ij})]^n \times [c + \exp(-d \cos \theta_{ijk})]^{-1}$$

$$w(r) = f_c(r) \exp(-\lambda_2 r)$$

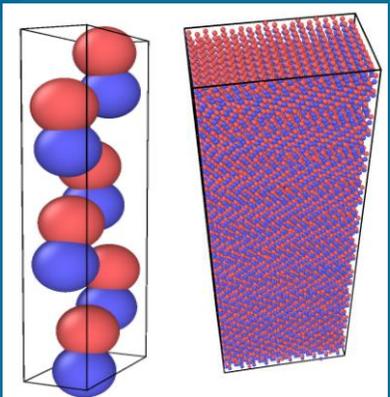
$$A = 2280 \text{ eV}, \quad B_0 = 171 \text{ eV}, \quad \lambda_1 = 2\lambda_2, \quad \lambda_2 = 1.465 \text{ \AA}^{-1}$$

$$b = 1.324, \quad c = 6.5, \quad d = 6.02, \quad n = 4,$$

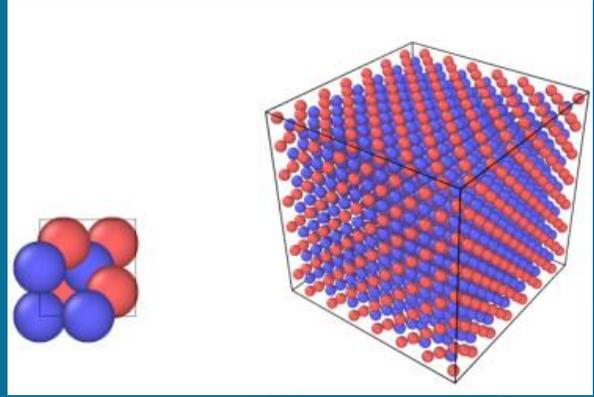
$$f_c = \begin{cases} 1, & r < R - D, \\ \frac{1}{2} - \frac{1}{2} \sin[\frac{1}{2}\pi(r - R)/D], & R - D < r < R + D, \\ 0, & r > R + D, \end{cases}$$

$$R = 3.0 \text{ \AA}, \quad D = 0.2 \text{ \AA}$$

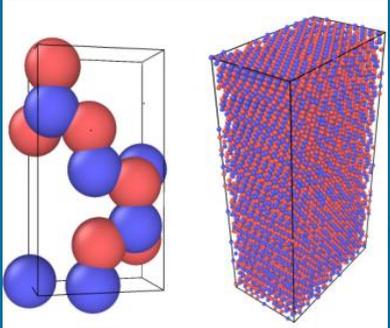
Tersoff Potential – Modeling Mechanical Behavior in CMCs



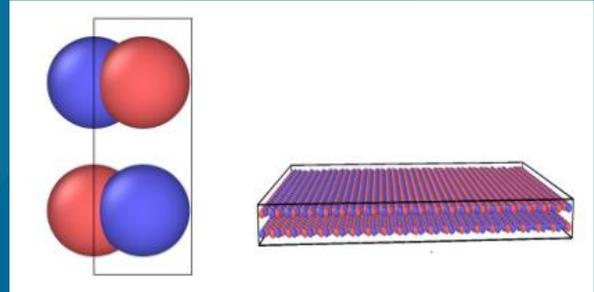
6H SiC



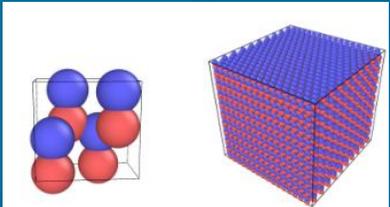
β -SiC (3H)



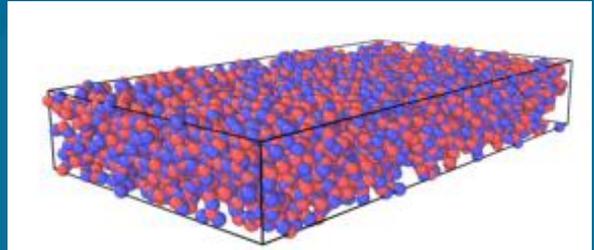
4H SiC



Bilayer h-BN



2H SiC



Amorphous BN

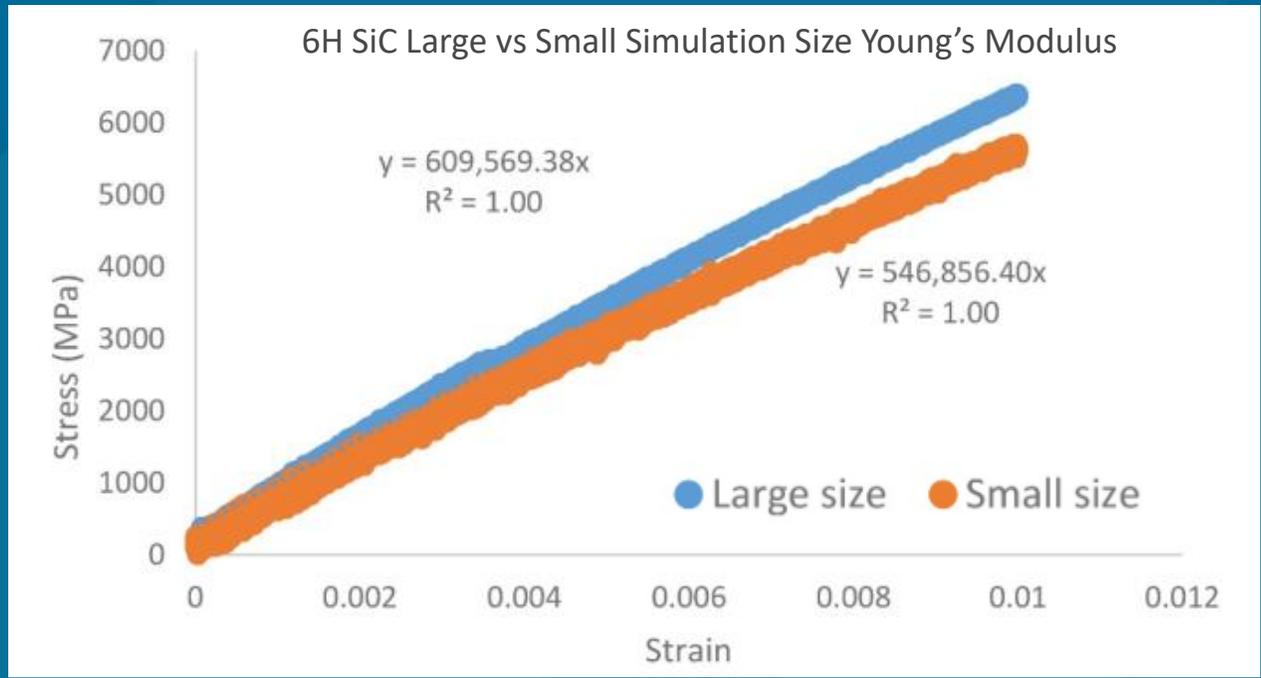
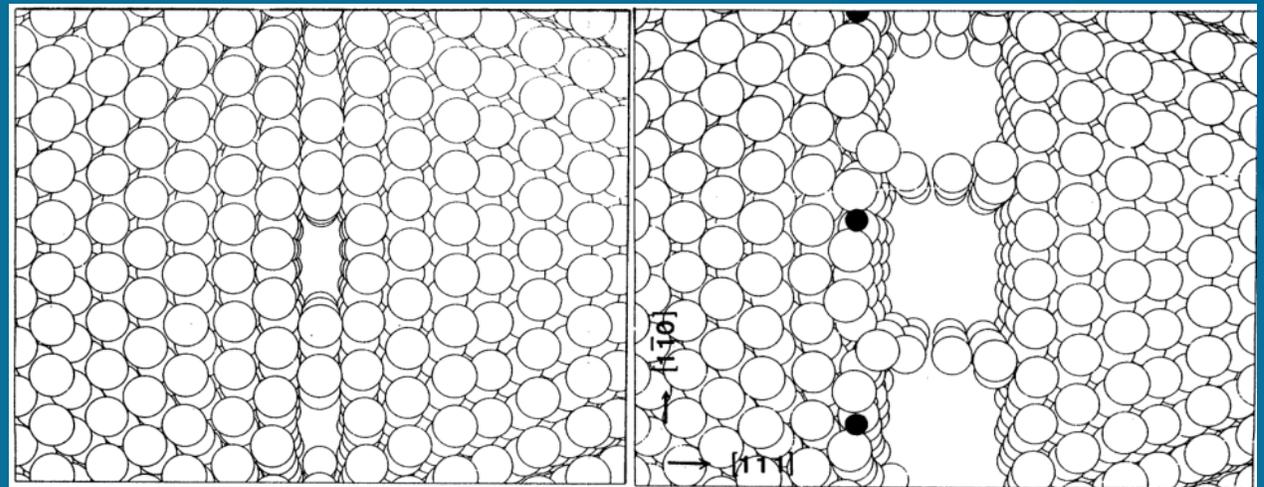
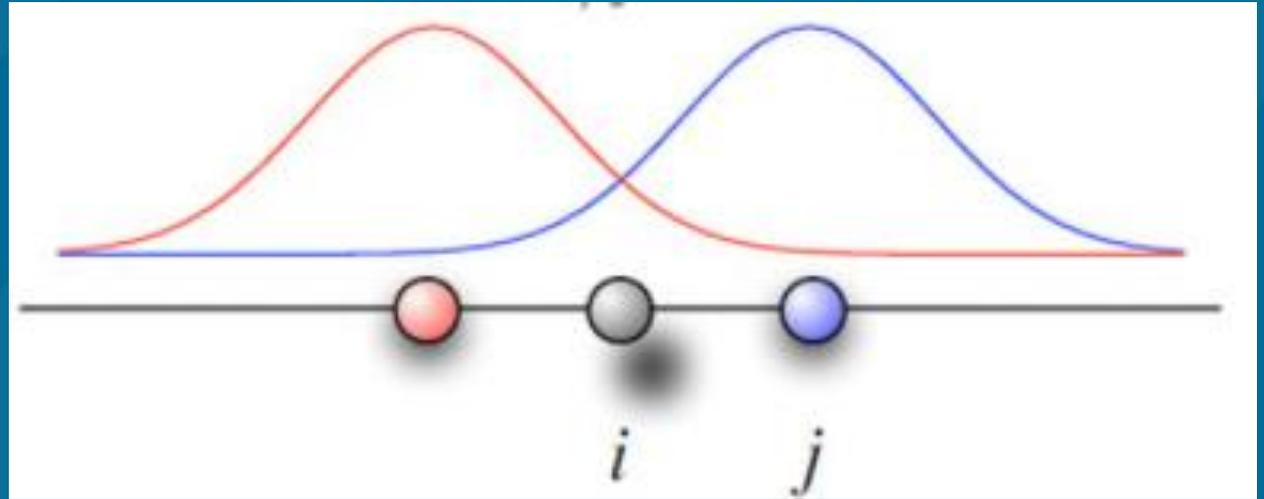
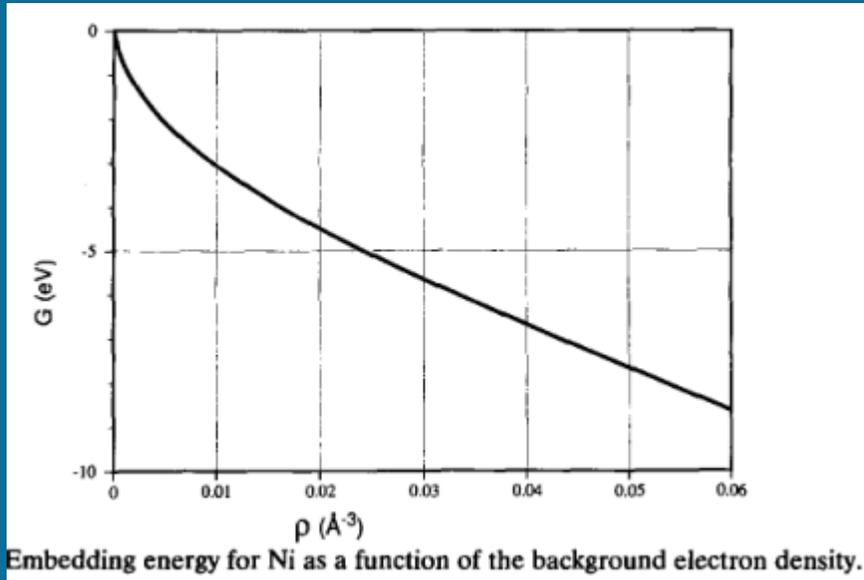


TABLE 1.—ELASTIC RESPONSE OF 6H SiC USING TERSOFF AT $\dot{\epsilon} = 10^7/s$

Property	Sample 1	Sample 2	Sample 3	Average	Expt (Ref. 13)
E_x (GPa)	546.8560	537.768	544.946	543.19	473.417
E_y (GPa)	539.4410	536.8980	543.946	539.933	473.417
E_z (GPa)	612.0060	608.1430	633.749	617.966	544.188
G_{xy} (GPa)	252.7710	249.9730	254.459	252.401	195
G_{xz} (GPa)	225.9860	229.8690	221.512	225.789	163
G_{yz} (GPa)	219.4410	217.3560	219.582	218.793	163
ν_{xy}	0.23040	0.2188	0.2378	0.2290	0.2139
ν_{xz}	0.0840	0.0799	0.0797	0.0812	0.0739
ν_{yz}	0.0988	0.0941	0.0954	0.0961	0.0739

Embedded Atom Model

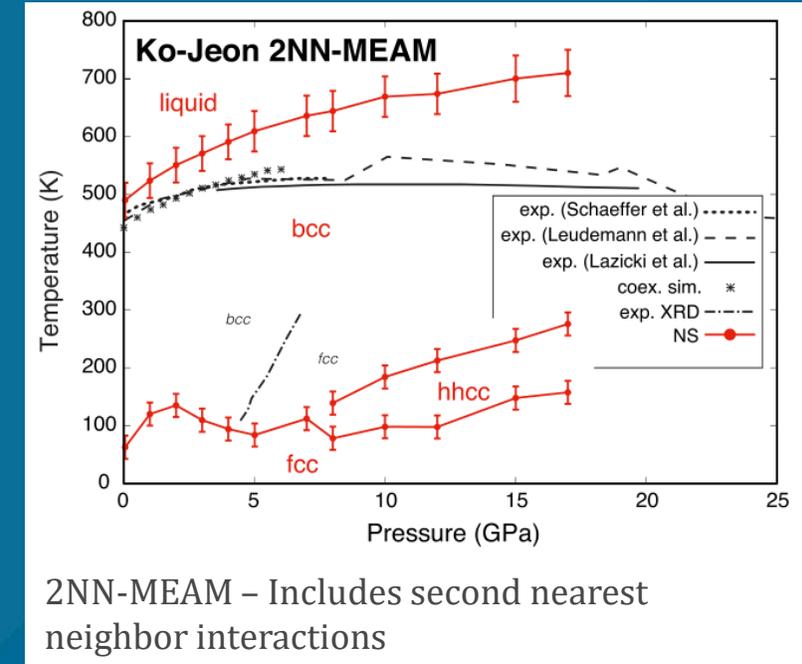
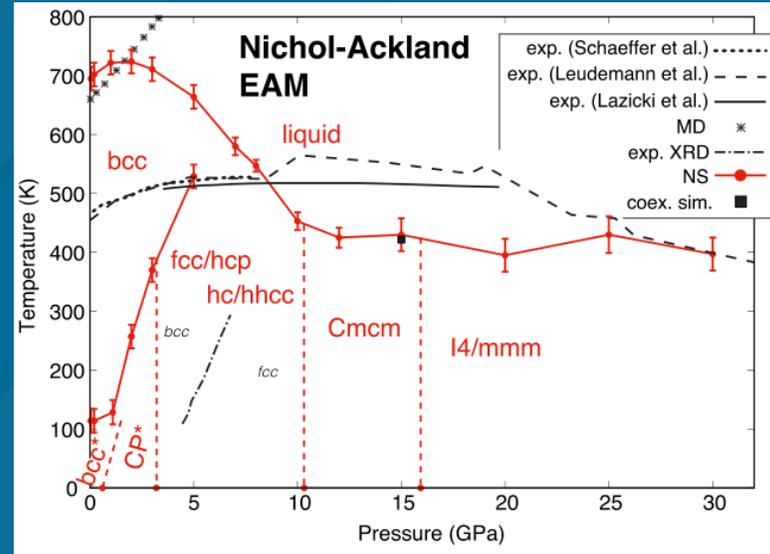
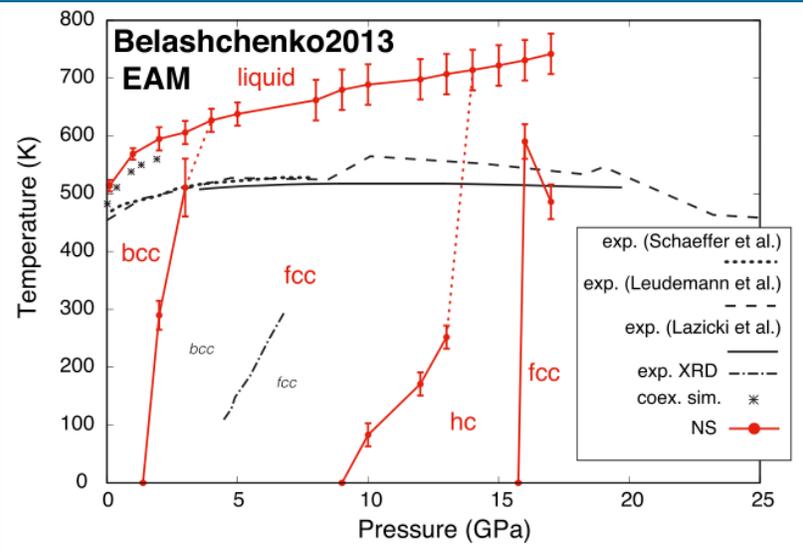


$$E_{coh} = \sum_i G_i \left(\sum_{j \neq i} \rho_j^a(R_{ij}) \right) + \frac{1}{2} \sum_{i,j (j \neq i)} U_{ij}(R_{ij})$$

G is embedding energy, ρ^a is the spherically averaged atomic electron density, and U is an electrostatic, two-atom interaction

Ni Slab with defects. Hydrogen adsorption promotes fracture on the right side image

Embedded Atom Model - Applications



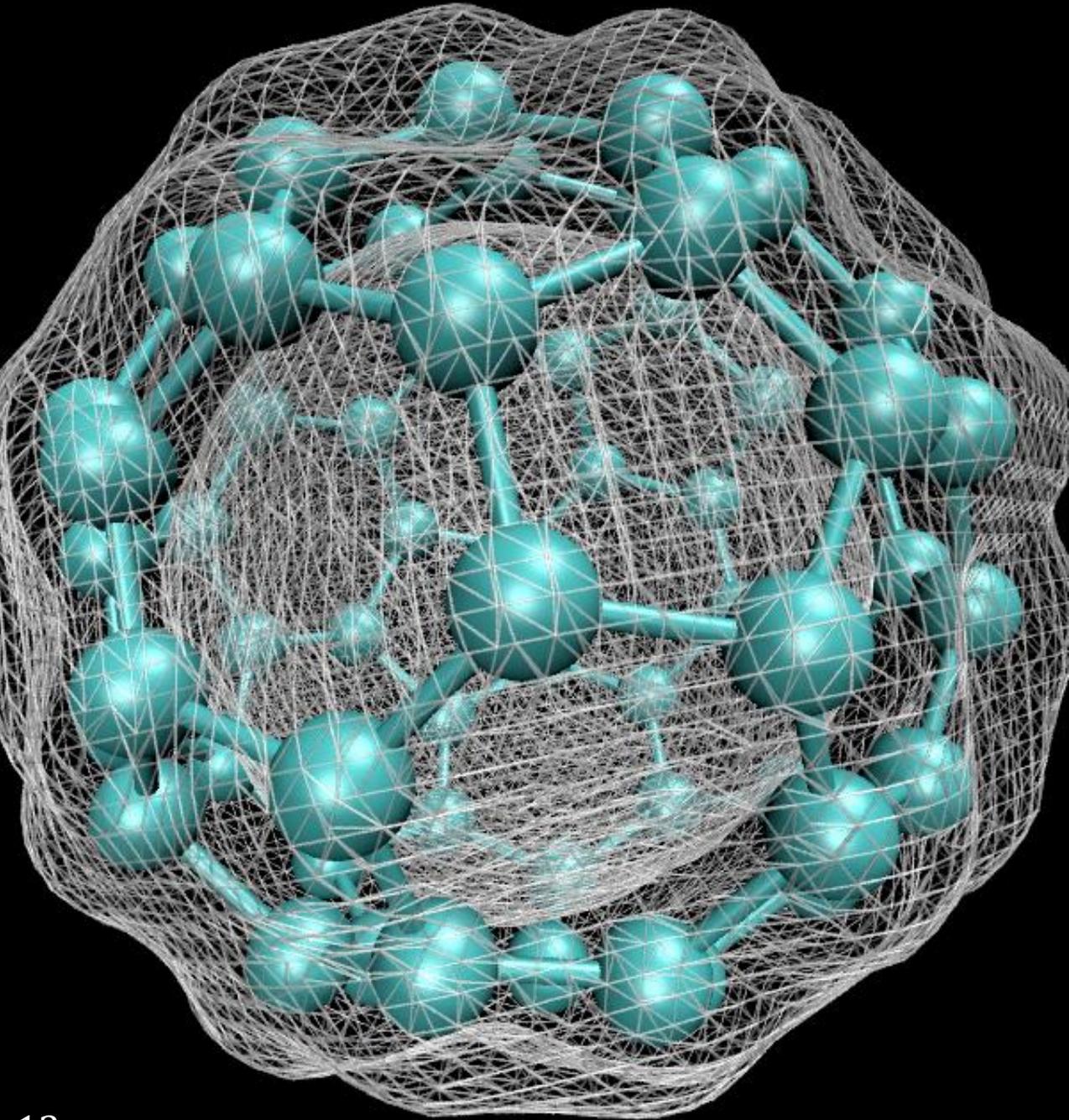
- Comparison of 3 phase diagrams constructed from different EAM models for Lithium
 - Fitted to different microstructural properties and using different procedures
 - Show differences in melting points, critical points, and phase transformations

Wide Selection of Empirical Potentials

Silicon IMs since the 1980s:

1. Keating (Valence), *Phys. Rev.*, **145**, 637 (1966).
2. Altmann, ..., Tomassini (Valence), *J. Phys. C*, **15**, 5581 (1982).
3. Pearson, Takai, Halicioglu, Tiller (PTHT), *J. Cryst. Growth*, **70**, 33 (1984).
4. Stillinger-Weber (SW), *PRB*, **31**, 5262 (1985).
5. Tersoff (T1), *PRL*, **56**, 632 (1986).
6. Brenner, Garrison, *PRB*, **34**, 1304 (1986).
7. Dodson (DOD), *PRB*, **35**, 2795 (1987).
8. Biswas, Hamann (BH), *PRB*, **36**, 6434 (1987).
9. Baskes (EAM-Si), *PRL*, 2666 (1987).
10. Tersoff (T2), *PRB*, **37**, 6991 (1988).
11. Tersoff (T3), *PRB*, **38**, 9902 (1988).
12. Khor, Das Sarma, *PRB*, **38**, 3318 (1988).
13. Kaxiras, Pandey, *PRB*, **38**, 12736 (1988).
14. Baskes, Nelson, Wright (MEAM-Si), *PRB*, **40**, 6085 (1989).
15. Ackland, *PRB*, **40**, 10351 (1989).
16. Chelikowsky, Phillips, Kamal, Strauss, *PRL*, **62**, 292 (1989).
17. Mistriotis, Flytzanis, Farantos (4-body), *PRB*, **39**, 1212 (1989).
18. Erkoç, *Phys. Stat. Sol. (b)*, **152**, 447 (1989).
19. Bolding, Anderson, *PRB*, **41**, 10568 (1990).
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21. Murrell, Mottram, *Mol. Phys.*, **69**, 571 (1990).
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24. Li, Johnson, Murrell, *Chem. Soc. Faraday Trans.*, **88**, 1229 (1992).
25. Gong, *PRB*, **47**, 2329 (1993).
26. Liu, *Thermocem. J. Molec. Struct.*, **341**, 253 (1995).
27. Omote, Waseda (Pair Potential), *Jap. J. Appl. Phys. I*, **35**, 151 (1996).
28. Stephenson, Radny, Smith (modified SW), *Surf. Sci.*, **366**, 177 (1996).
29. Bazant, Kaxiras, Justo (EDIP), *PRB*, **56**, 8542 (1997).
30. Cai, *Phys. Stat. Sol. B*, **212**, 9 (1999).
31. Lenosky, ..., Kress (MEAM), *Mod. Sim. Mater. Sci. Eng.*, **8**, 825 (2000).
32. van Duin, ..., Goddard (ReaxFF), *J. Phys. Chem. A* **107**, 3803 (2003).
33. Erhart, Albe (Bond Order), *PRB*, **71**, 035211 (2005).
34. Kumagai, Izumi, Hara, Sakai, *Comp. Mat. Sci*, **39**, 457 (2007).
35. Lee, *Calphad-Comp. Coupling Phase Diag. Thermochem.*, **31**, 95 (2007).
36. Yu, Sinnott, Phillpot, *PRB*, **75**, 085311 (2007).
37. Timonova, Lee, Thijssse (MEAM), *Nuc. Inst. Meth. Phys. Res. B*, **255**, 195 (2007).
38. Gillespie, ..., Pettifor (Bond Order), *PRB*, **75**, 155207 (2007).
39. Behler and Parrinello (NN), *Phys. Rev. Lett.* **98**, 146401 (2007).
40. Vashishta et al. (3-body), *J. Appl. Phys.* **101**, 103515 (2007).
41. Sanville (NN), *J. Phys. Cond. Matt.* **20**, 285219 (2008).
42. Schelling (Bond order), *Comp. Mat. Sci.* **44**, 274-279 (2008).
43. Malshe et al. (NN), *J. Chem. Phys.* **129**, 044111 (2008).
44. Ohta et al. (SW), *Jap. J. Appl. Phys.* **48**, 020225 (2009).
45. Hossain et al. (DFT-ArSi), *Nucl. Inst. & Meth. Phys. Res. B* **267**, 1061 (2009).
46. Lucas et al. (EDIP), *J. Phys. Cond. Matt.* **22**, 035802 (2010).
47. Ryu and Cai (MEAM), *J. Phys. Cond. Matt.* **22**, 055401 (2010).
48. Timonova and Thijssse (MEAM), *Comp. Mat. Sci.* **48**, 609-620 (2010).
49. Grochia et al. (MEAM), *Chem. Phys. Lett.* **493**, 57-60 (2010).
50. Du et al. (MEAM), *Phys. Stat. Solidi B* **248**, 2050-2055 (2011).
51. Tewary (Phenomenological), *Phys. Lett. A* **375**, 3811-3816 (2011).
52. Lee and Hwang (FM-SW), *Phys. Rev. B* **85**, 125204 (2012).
53. Dongare et al. (A-EAM), *MSMSE* **20**, 035007 (2012).
54. Cui et al. (MEAM), *J. Power Sources* **207**, 150-159 (2012).
55. da Cruz et al. (MEAM), *J. Heat Trans.* **134**, 062402 (2012).
56. Briquet et al., (reactive) *J. Phys.: Condens. Matter.* **24**, 395004 (2012).
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60. Takamoto et al. (Tersoff), *J. Appl. Phys.* **120**, 165109 (2016).
61. Pun and Mishin (Tersoff), *PRB* **95**, 224103 (2017).
62. Bartok et al. (machine learning), *PRX* **8**, 041048 (2018).

Density Functional Theory



Density Functional Theory



Walter Kohn



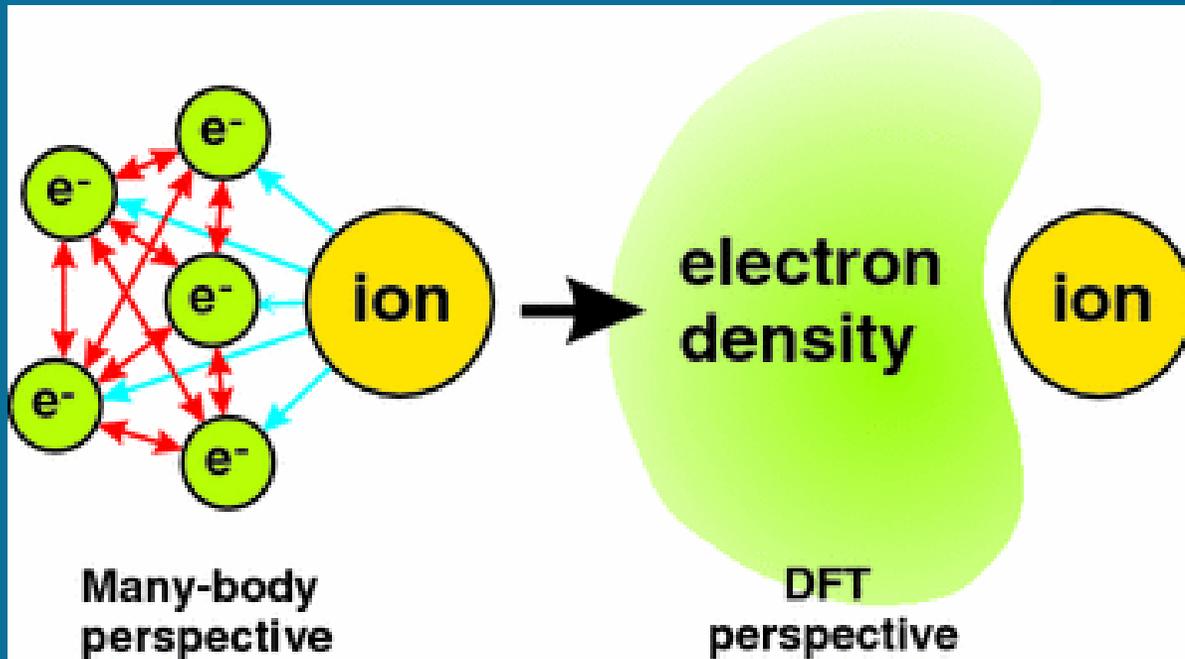
Lu Jeu Sham

$$-\frac{1}{2}\nabla^2\phi_i(\vec{r}) + \left[V_{ext}(\vec{r}) + \underbrace{\int d\vec{r}' \frac{n(\vec{r}')}{|\vec{r}-\vec{r}'|}}_{V_H} + \underbrace{\epsilon_{xc}[n] + n(\vec{r})\frac{\delta\epsilon_{xc}[n]}{\delta n(\vec{r})}}_{V_{xc}} \right] \phi_i(\vec{r}) = \epsilon_i\phi_i(\vec{r})$$

Kohn – Sham Equation

- The Schrodinger Equation:
 $\hat{H}|\Psi\rangle = E|\Psi\rangle$
- Governs dynamics of a time-independent system
- Ψ is the many electron wave function
 - Contains $3N$ degrees of freedom, where N is the number of electrons
- Density Functional Theory reduces the complexity of the system from a $3N$ Body problem to N single body problems
 - Theorem 1 - The external potential is a unique functional of the electron density only. Thus the Hamiltonian, and hence all ground state properties, are determined solely by the electron density.
 - Theorem 2 - The groundstate energy may be obtained variationally: the density that minimizes the total energy is the exact groundstate density.

Density Functional Theory



Bechstedt F. (2015) Density Functional Theory

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$$-\frac{1}{2}\nabla^2\phi_i(\vec{r}) + \left[V_{ext}(\vec{r}) + \underbrace{\int d\vec{r}' \frac{n(\vec{r}')}{|\vec{r}-\vec{r}'|}}_{V_H} + \underbrace{\epsilon_{xc}[n] + n(\vec{r})\frac{\delta\epsilon_{xc}[n]}{\delta n(\vec{r})}}_{V_{xc}} \right] \phi_i(\vec{r}) = \epsilon_i\phi_i(\vec{r})$$

Kohn – Sham Equation

Density Functional Theory in MD – Car-Parrinello

$$\mathcal{L}_{\text{CP}} = \frac{1}{2} \sum_I M_I \dot{\mathbf{R}}_I^2 + \frac{\mu}{2} \sum_i \langle \dot{\Phi}_i | \dot{\Phi}_i \rangle - E(\mathbf{R}, \{\Phi\}) + \sum_{ij} \lambda_{ij} (\langle \Phi_i | \Phi_j \rangle - \delta_{ij}),$$

Lagrangian (Kinetic minus Potential Energy)

$$M_I \ddot{\mathbf{R}}_I = - \frac{\partial E(\mathbf{R}, \{\Phi\})}{\partial \mathbf{R}_I} + \sum_{ij} \lambda_{ij} \frac{\partial}{\partial \mathbf{R}_I} \langle \Phi_i | \Phi_j \rangle,$$

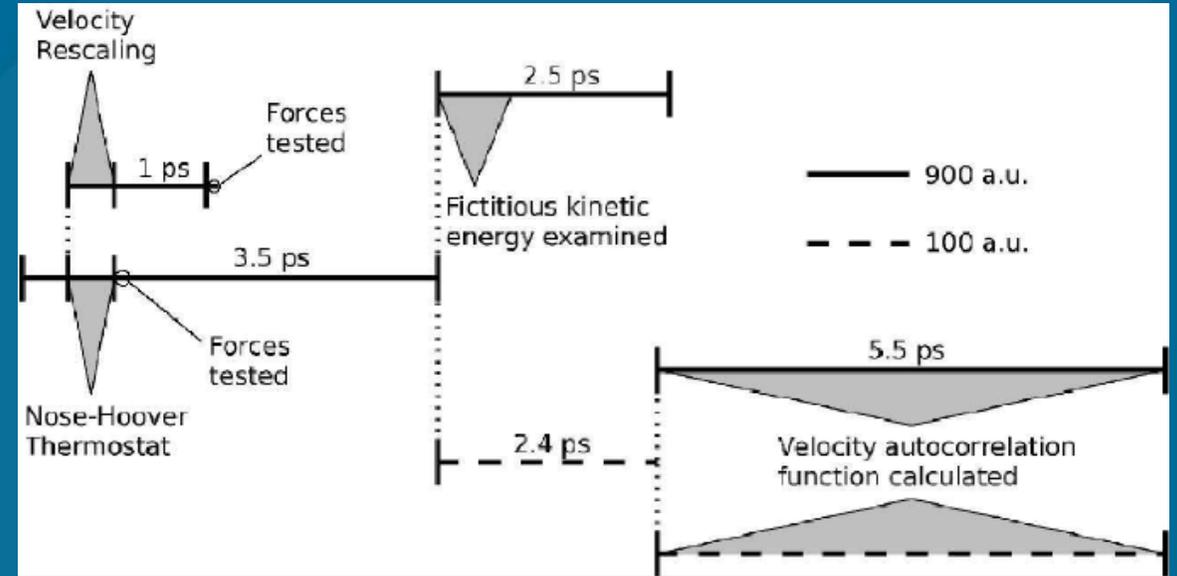
$$\mu \ddot{\Phi}_i = -\mathcal{H}(\mathbf{R}, \{\Phi\}) \Phi_i + \sum_j \lambda_{ij} \Phi_j,$$

Equations of Motion

$$E_{\text{const}} = \frac{1}{2} \sum_I M_I \dot{\mathbf{R}}_I^2 + \frac{\mu}{2} \sum_i \langle \dot{\Phi}_i | \dot{\Phi}_i \rangle + E(\mathbf{R}, \{\Phi\}),$$

$$= E_{\text{phys}} + \frac{\mu}{2} \sum_i \langle \dot{\Phi}_i | \dot{\Phi}_i \rangle = E_{\text{phys}} + T_e.$$

Constant of Motion



- Lagrangian form assigns Newtonian dynamics to both the ionic nuclei and the electron orbitals themselves
- A fictitious mass parameter is assigned to the electron orbitals
 - Large enough to allow large timesteps
 - Small enough not to affect nuclei

Density Functional Theory in MD – Born-Oppenheimer

$$\mathcal{L}(\mathbf{q}, \dot{\mathbf{q}}, \mathbf{x}, \dot{\mathbf{x}}) = \frac{1}{2}M\dot{\mathbf{q}}^2 + \frac{1}{2}\mu\dot{\mathbf{x}}^2 - E(\mathbf{q}, \mathbf{y}) + k\mu G(\|\mathbf{x} - \mathbf{y}\|),$$

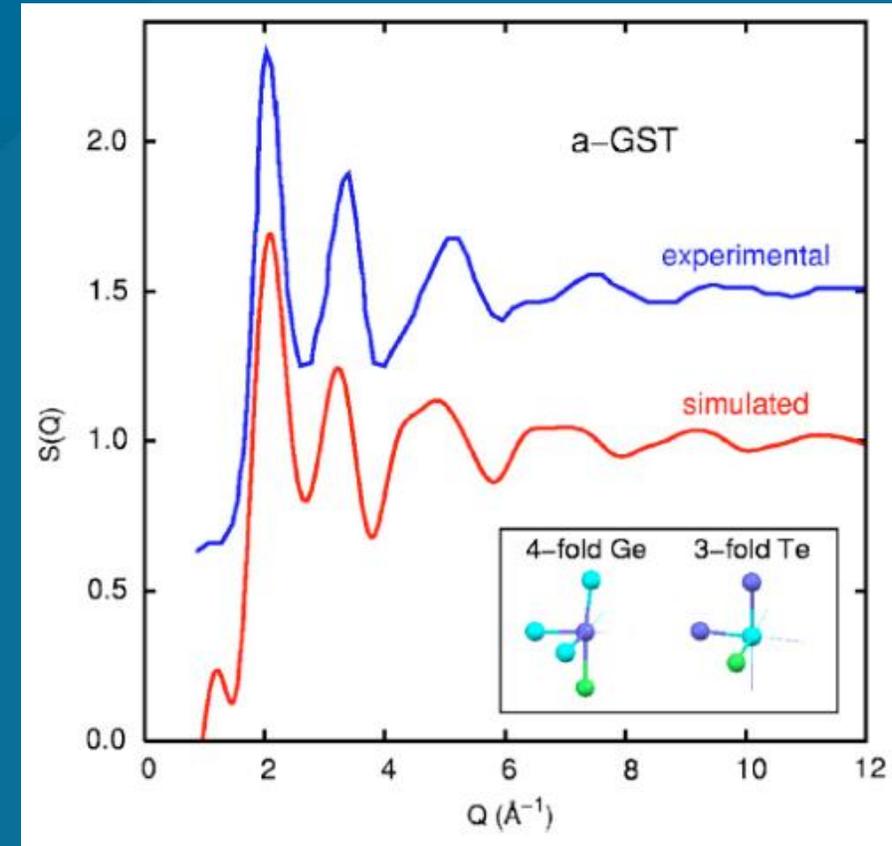
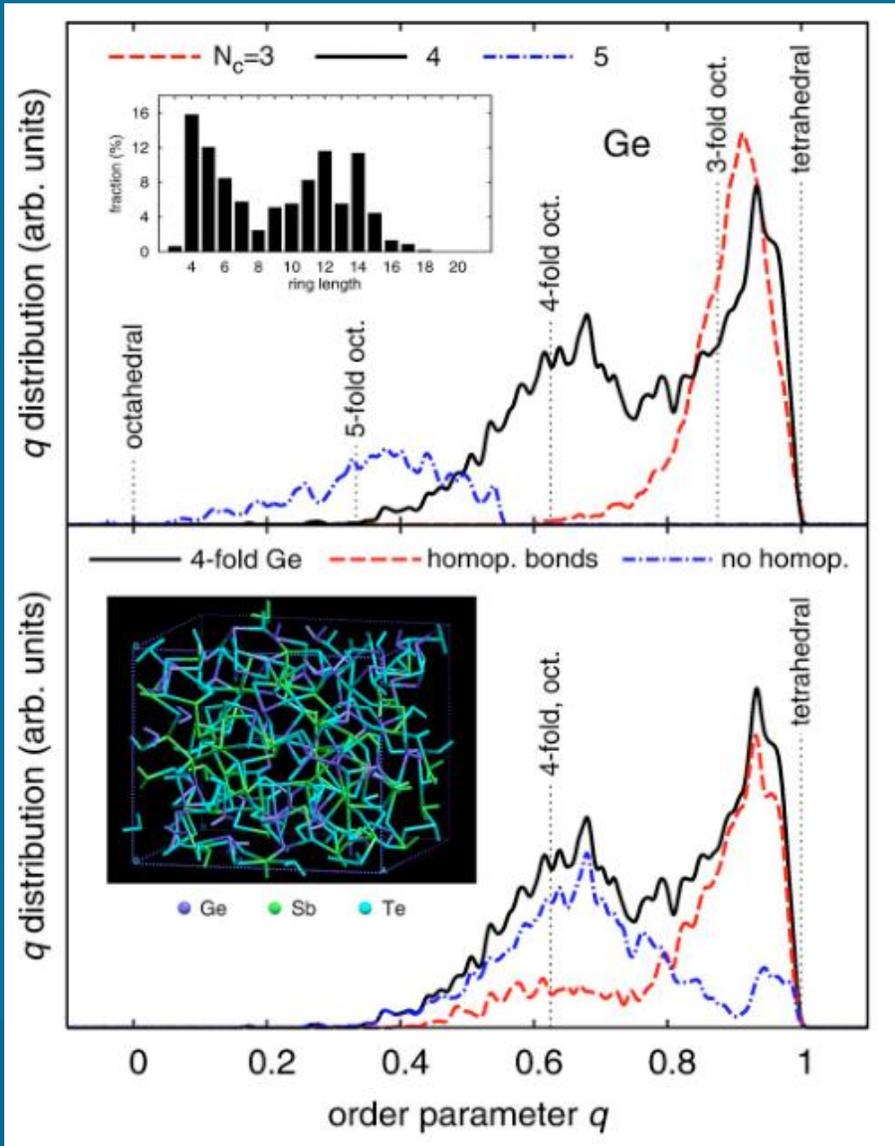
$$\mathcal{L}_{\text{BO}}(\mathbf{R}, \dot{\mathbf{R}}) = \frac{1}{2}M\dot{\mathbf{R}}^2 - E(\mathbf{R}),$$

$$E(\mathbf{R}) = \min_{\{\Phi\}} \left[E_{\text{KS}}(\mathbf{R}, \{\Phi\}) - \sum_{ij} \lambda_{ij} (\langle \Phi_i | \Phi_j \rangle - \delta_{ij}) \right],$$

$$\mathcal{L}_{\psi}(\psi, \dot{\psi}) = \frac{1}{2} \sum_i \dot{\psi}_i^2 + kG(\{\psi\}, \{\Phi\}).$$

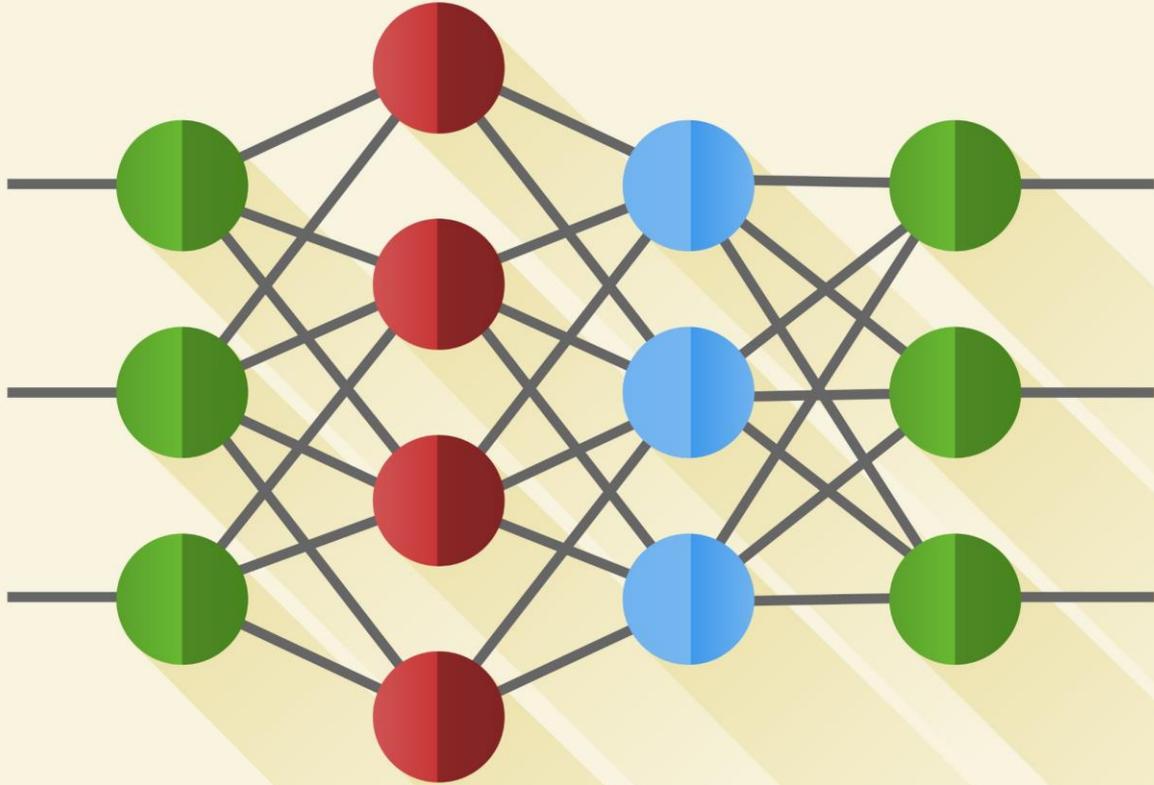
- Born-Oppenheimer Molecular Dynamics are very similar to Car-Parinello
 - Lagrangian representation of system energy dynamics
 - Electronic waveform remains on the Born-Oppenheimer potential energy surface
- Born Oppenheimer calculates the electronic wave function differently
 - Car-Parinello uses fictitious dynamics to propagate
 - Born-Oppenheimer solves the wave function at each time step
- Born Oppenheimer has larger timesteps but more costly computation
 - Higher accuracy
- More used as computational power has increased

Ab initio Molecular Dynamics in action



- Experimental and simulated XRD for amorphous GST
- Order Parameters for different coordinations

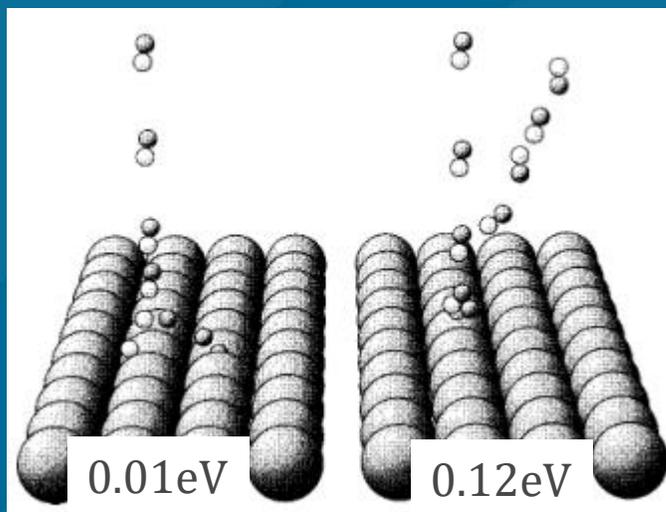
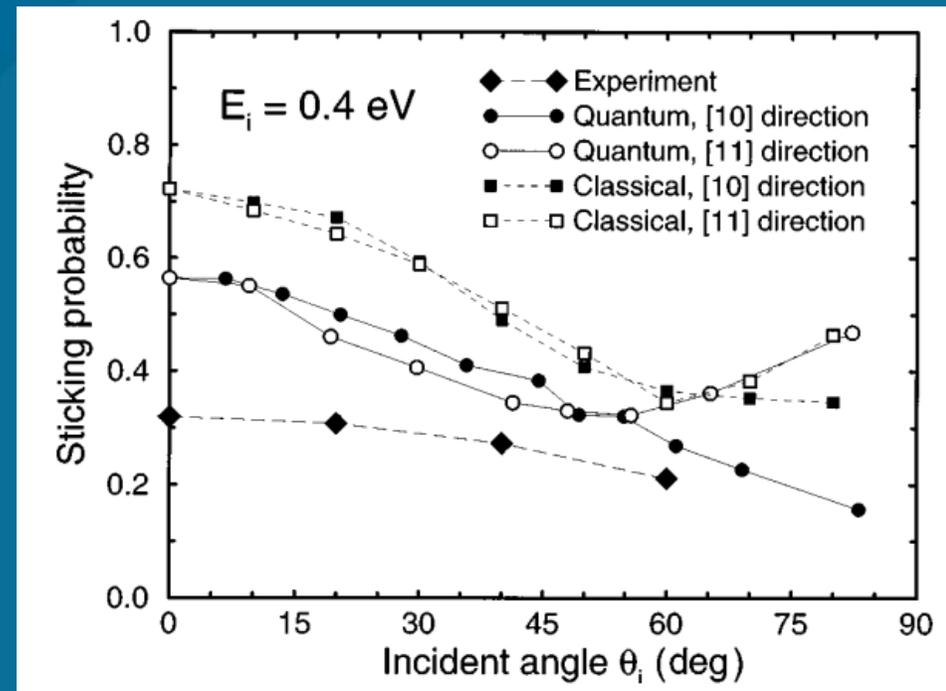
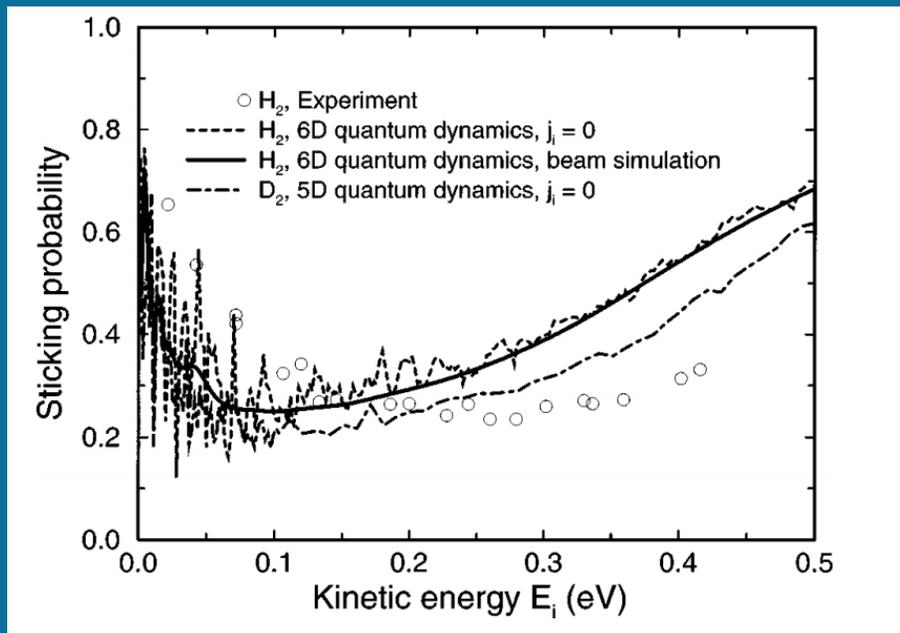
Machine Learning and Interatomic Potential Development



The underlying physical laws necessary for the mathematical theory of a large part of physics and the whole of chemistry are thus completely known, and the difficulty is only that the exact application of these laws leads to equations much too complicated to be soluble. It therefore becomes desirable that approximate practical methods of applying quantum mechanics should be developed.

~Paul A.M. Dirac

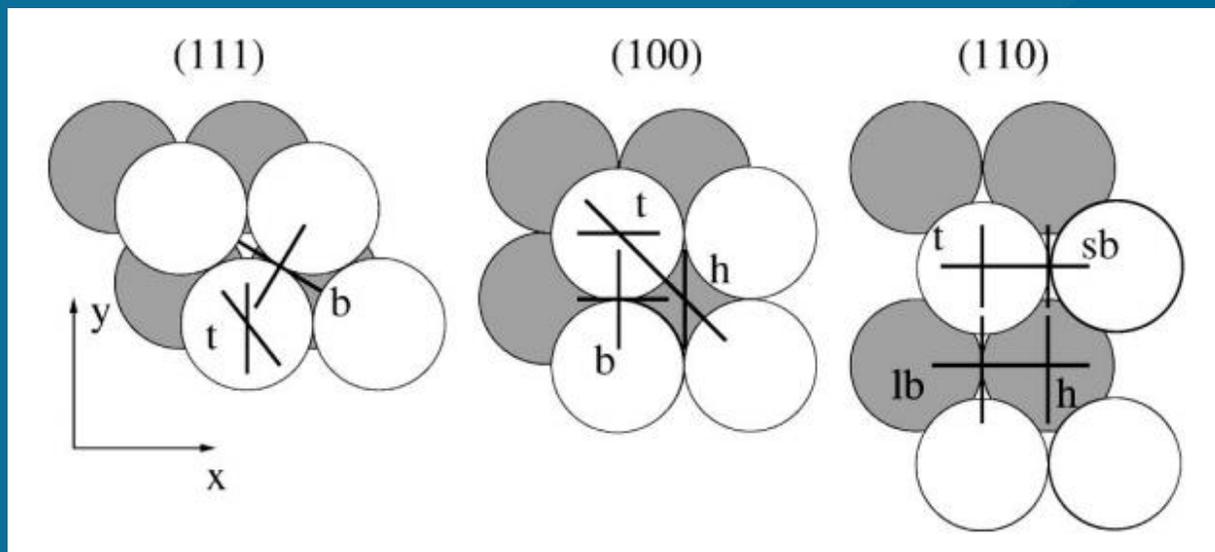
Analytical Representations of Potential Energy Surfaces



Ab initio quantum and molecular dynamics of the dissociative adsorption of hydrogen on Pd(100)

- 6D analytical model that interpolated between different calculated potential energy surfaces
- Results compared with DFT calculations

Analytical Representations of Potential Energy Surfaces



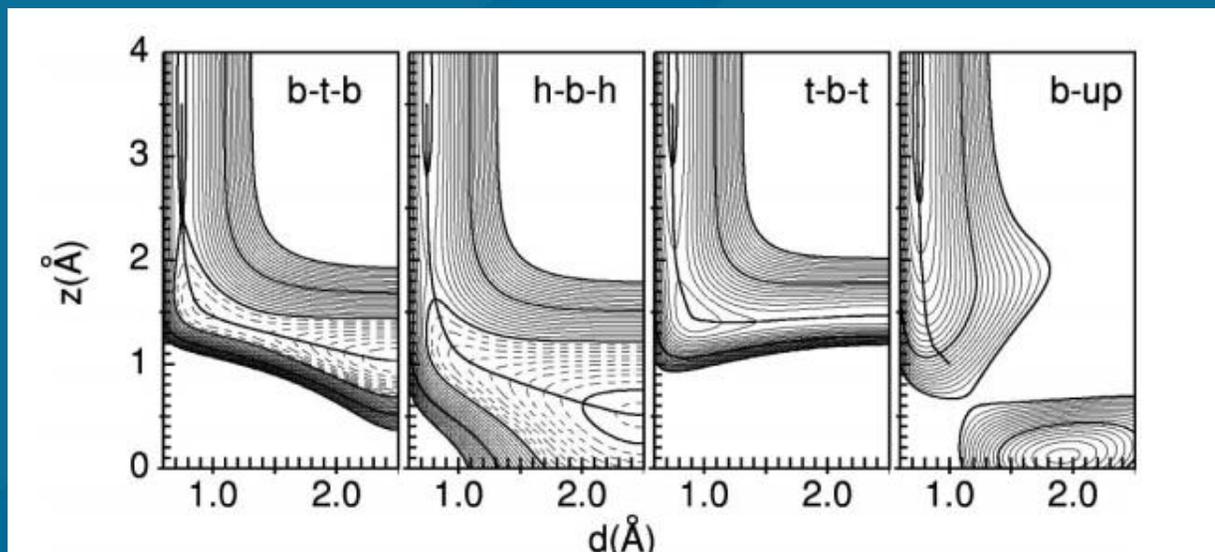
2D PES calculated for high symmetry sites and molecular orientations

Only the distance between Hydrogen atoms and the height of the atoms from the surface are varied for these 2D PESs

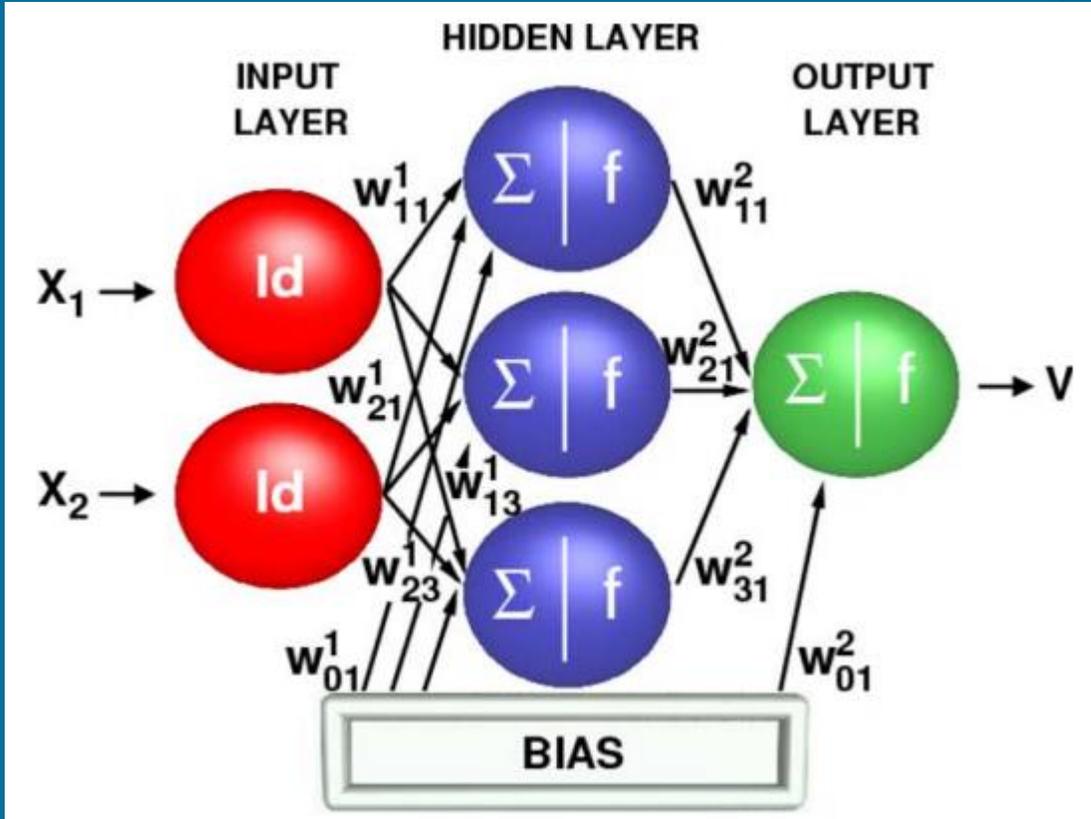
6D Potential obtained by interpolating between the 2D sites

Important Experimental trends captured
Deviation in surface

Inflexible and grows complex very quickly with increased problem dimensionality



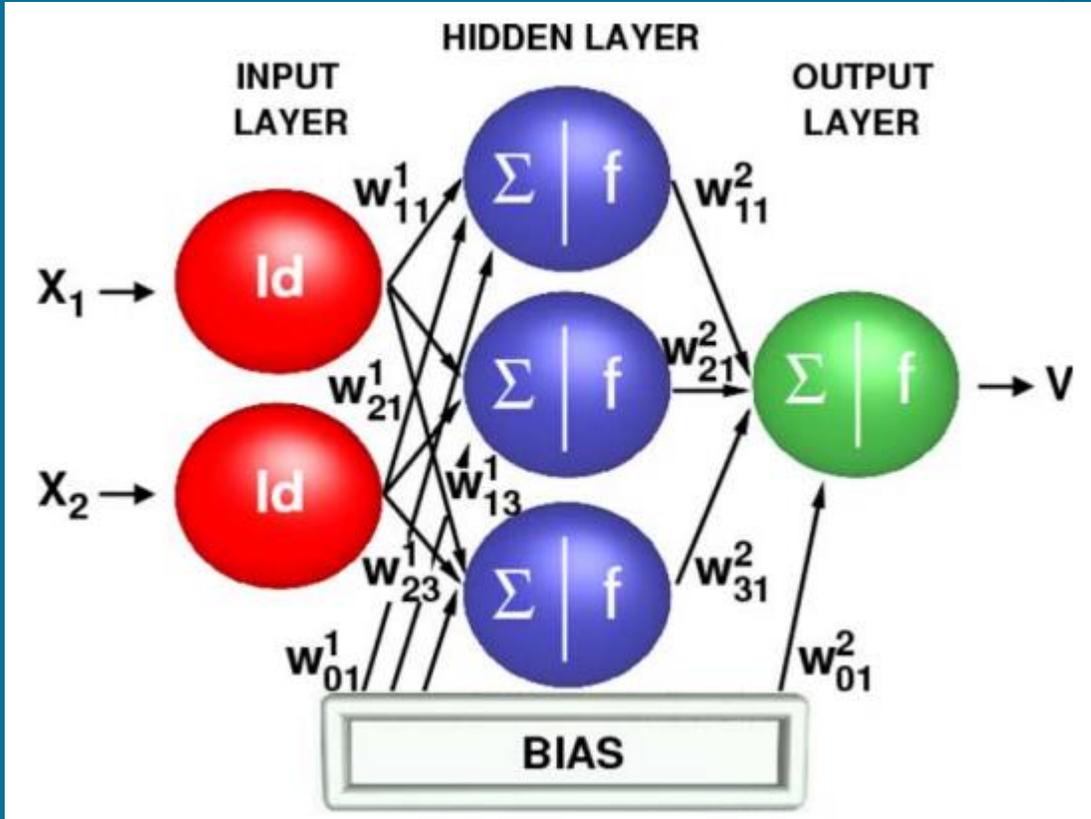
Neural Network Representation of Potential Energy Surfaces



$$V_{mn}(\mathbf{x}) = f_2 \left(w_{01}^2 + \sum_j w_{j1}^2 f_1 \left(w_{0j}^1 + \sum_{i=1}^6 w_{ij}^1 x_i \right) \right),$$

- Highly flexible, nonlinear model that can approximate any continuous function
- Artificial 'neurons' or nodes are arranged in layers and interconnected via links
- Each link is multiplied by a weight before being supplied to a new node
- Only the Input Layer and Output Layer are interacted with
 - Hidden layers not visible from the outside
- Every node is connected to every node in adjacent layers.
 - Nodes within the same layer are not connected
 - Information is only transmitted forward
 - Multilayer Feed-Forward Neural Network

Neural Network Representation of Potential Energy Surfaces



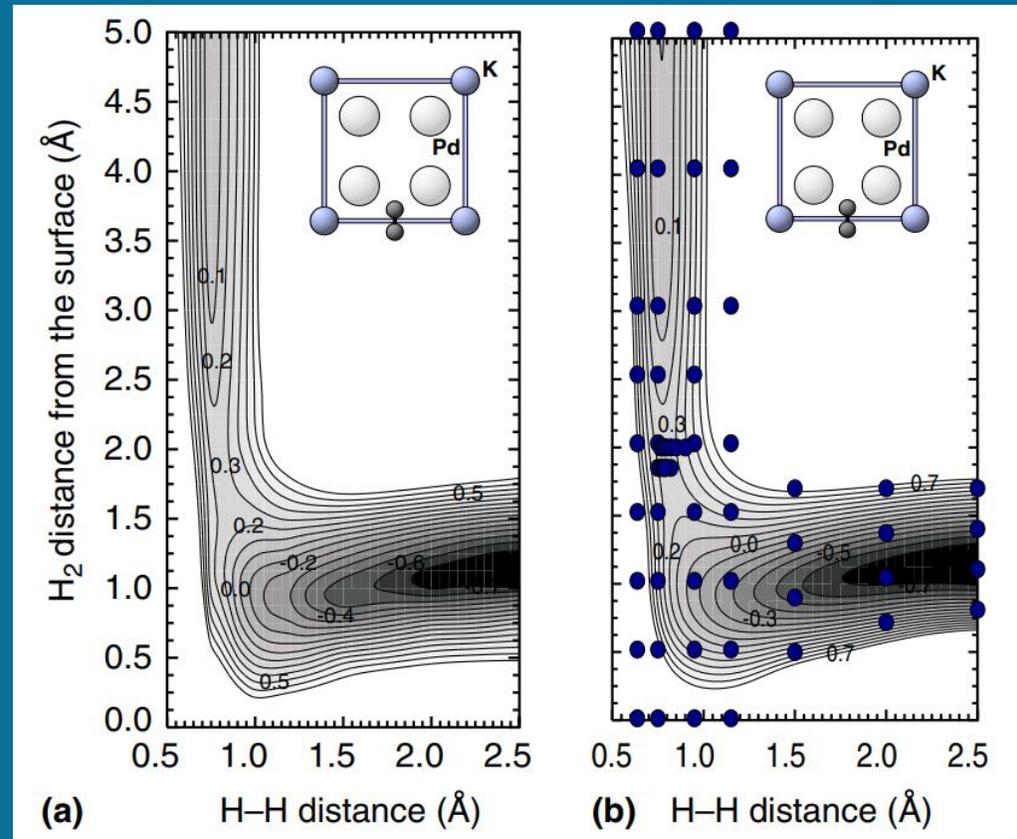
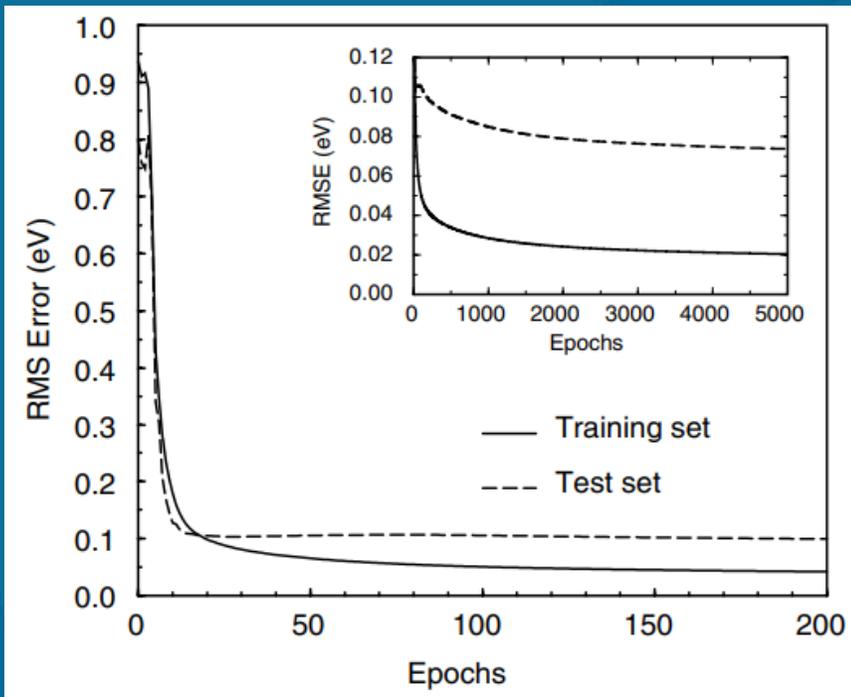
- The Neural Network is minimized via the Cost Function
 - The square root of this function is the Root Mean Square Error (RMSE)
- For each new training data input, the Cost Function is minimized by adjusting the weights of the links in the neural network
- This minimization is called 'learning'
 - Typically done via gradient-based learning such as
 - Steepest Descent
 - Conjugate Gradients
 - Other algorithms
 - Global Extended Kalman Filter used in this paper
- Tested on a H_2 adhesion on Pd surface

$$E(\{\mathbf{x}\}) = \frac{\sum_{i=1}^n u_i (V_{nn}(\mathbf{x}^{(i)}) - V(\mathbf{x}^{(i)}))^2}{\sum_{i=1}^n u_i}$$

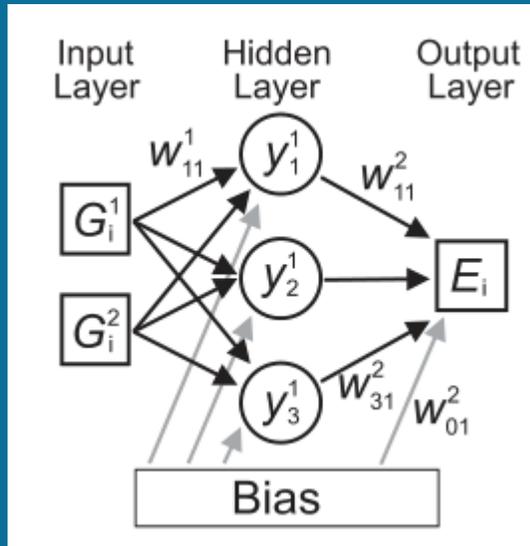
Neural Network Representation of Potential Energy Surfaces

$$\begin{aligned}x_1 &= d, \\x_2 &= e^{Z_c/2}, \\x_3 &= \sin^2\theta \cos 2\phi [\cos GX_c - \cos GY_c]e^{-Z_c/2}, \\x_4 &= \sin^2\theta \cos 2\phi [\cos 2GX_c - \cos 2GY_c]e^{-Z_c/2}, \\x_5 &= \cos^2\theta e^{-Z_c/2}, \\x_6 &= [\cos GX_c + \cos GY_c]e^{-Z_c/2}, \\x_7 &= [\cos 2GX_c + \cos 2GY_c]e^{-Z_c/2}, \\x_8 &= \sin^4\theta \cos 4\phi [\cos 2GX_c + \cos 2GY_c]e^{-Z_c/2}.\end{aligned}$$

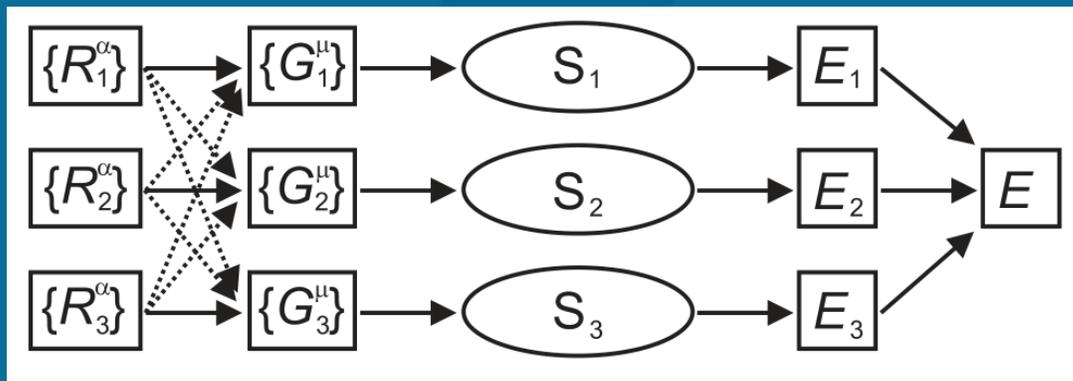
- Eight Symmetry adapted inputs chosen so all fitting is focused on the chemical dynamics of the system
 - 8-24-18-1sl neural network used



Neural Network Representation of Potential Energy Surfaces



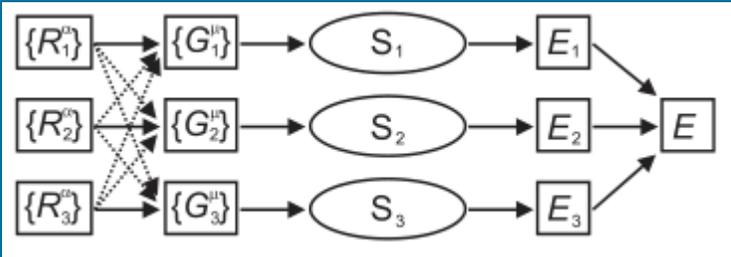
Simple Neural Network



New Topology

- Simple Neural networks are nontransferable
 - They only work for the specific arrangement of input nodes they were optimized for
 - Because weights are different, configuration is not arbitrary
 - Interchanging two atomic coordinates would change the total energy even if the two atoms were the same
 - Cannot be used for a set with a different number of degrees of freedom
 - Different numbers of atoms
- A new topology must be constructed to address these issues
 - Represent total energy as a sum of each atomic energy
 - Transform coordinates of all atoms with symmetry functions to create local environments
- Each atom's environment is fed into a simple NN

Neural Network Representation of Potential Energy Surfaces



$$G_i^1 = \sum_{j \neq i}^{\text{all}} e^{-\eta(R_{ij} - R_s)^2} f_c(R_{ij}).$$

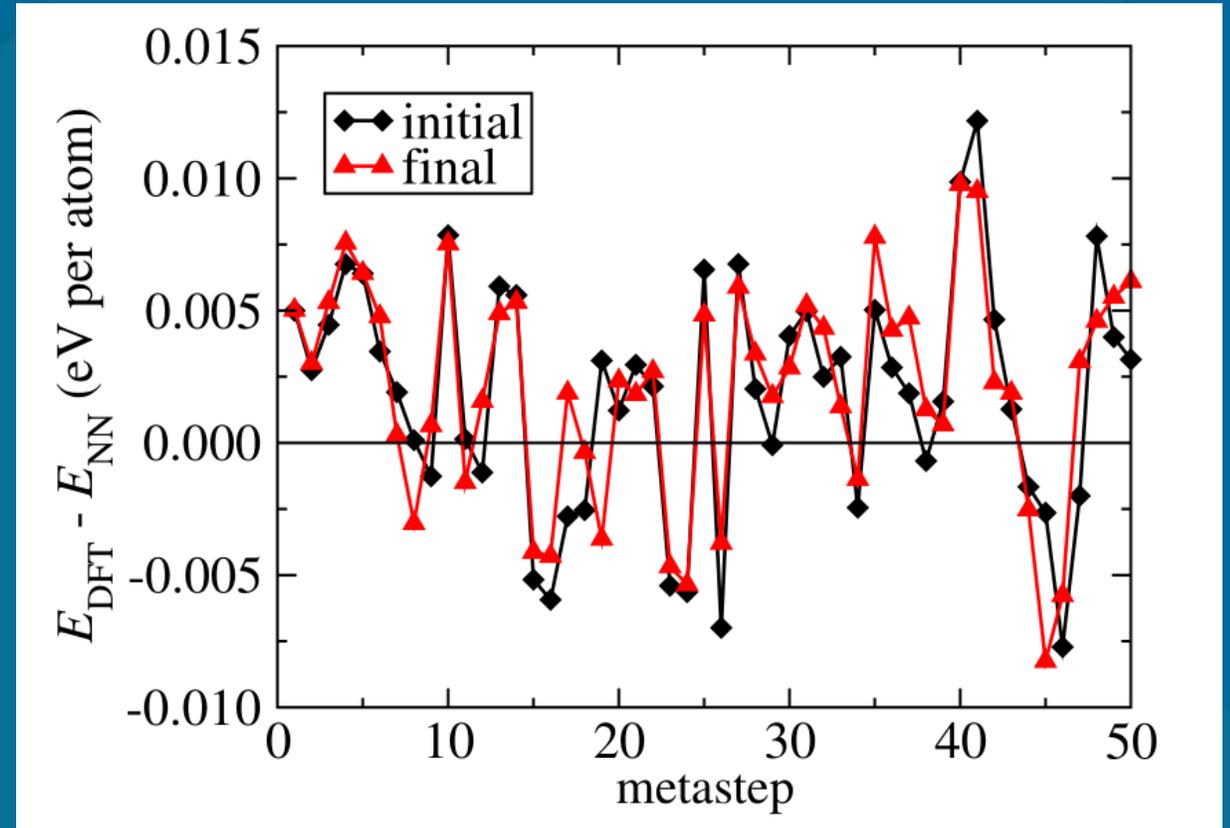
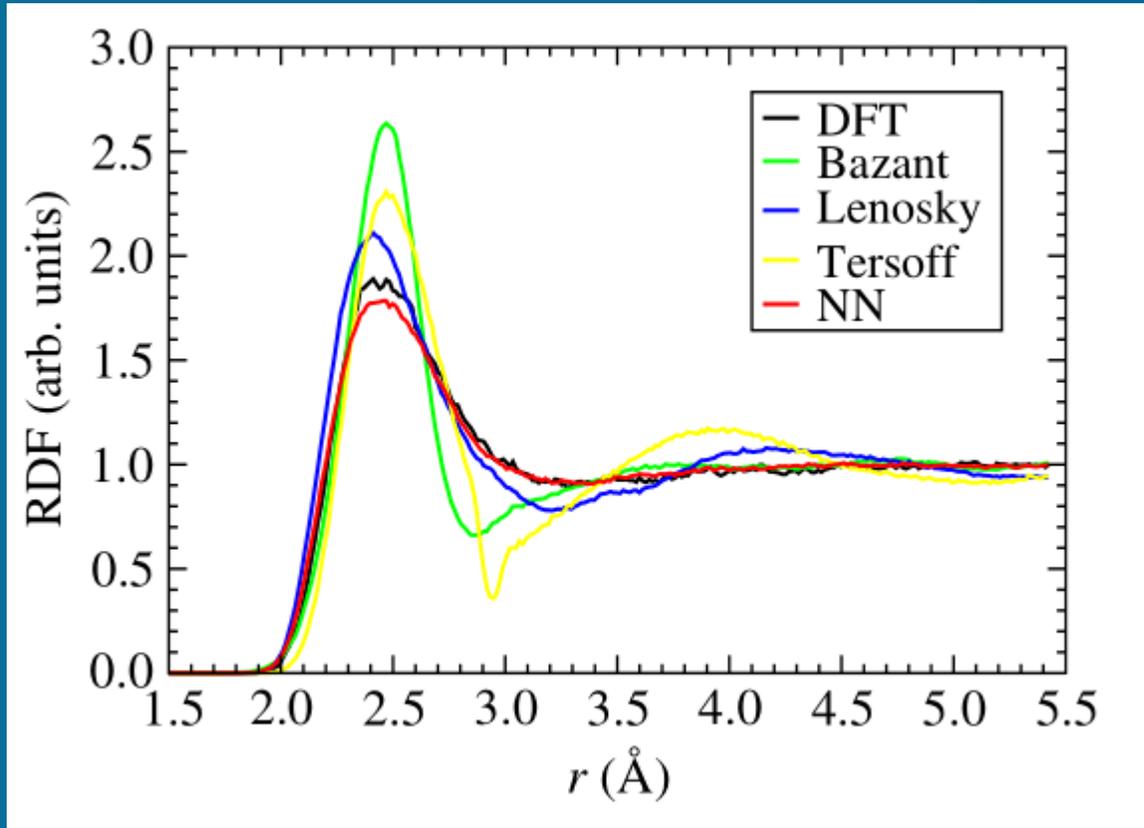
Radial Symmetry Function

$$G_i^2 = 2^{1-\zeta} \sum_{j,k \neq i}^{\text{all}} (1 + \lambda \cos \theta_{ijk})^\zeta \\ \times e^{-\eta(R_{ij}^2 + R_{ik}^2 + R_{jk}^2)} f_c(R_{ij}) f_c(R_{ik}) f_c(R_{jk}),$$

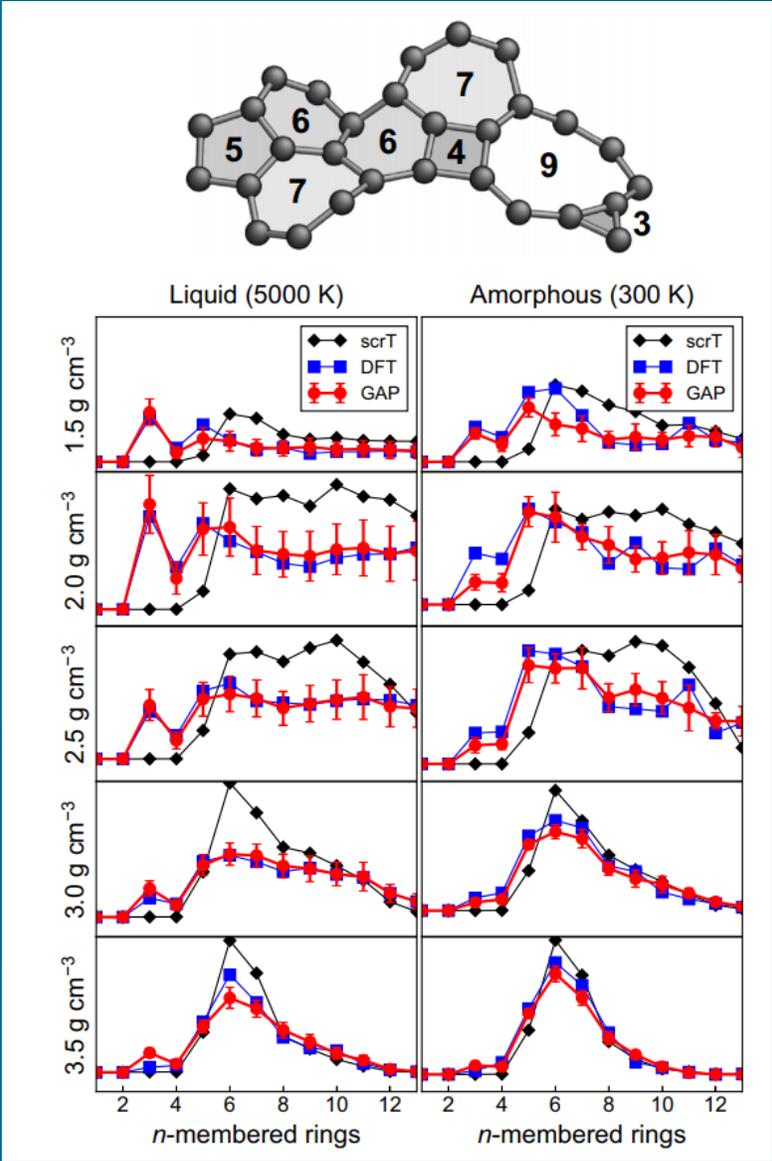
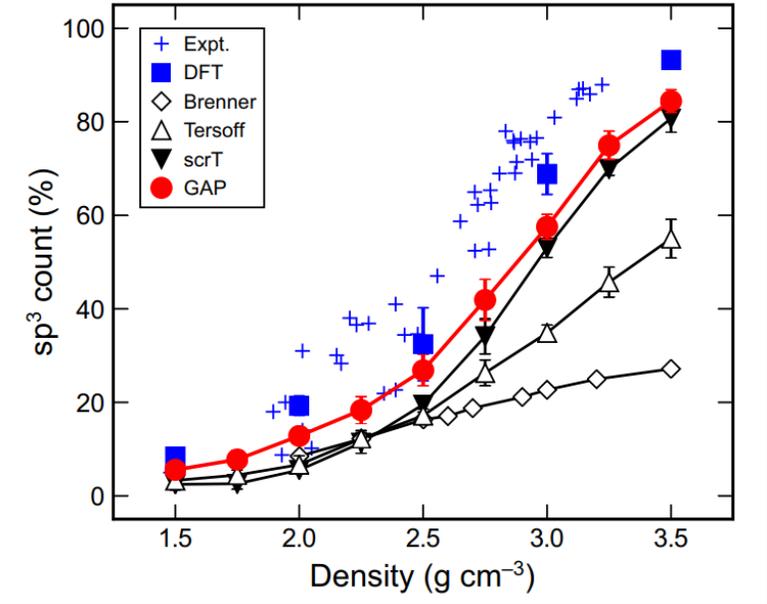
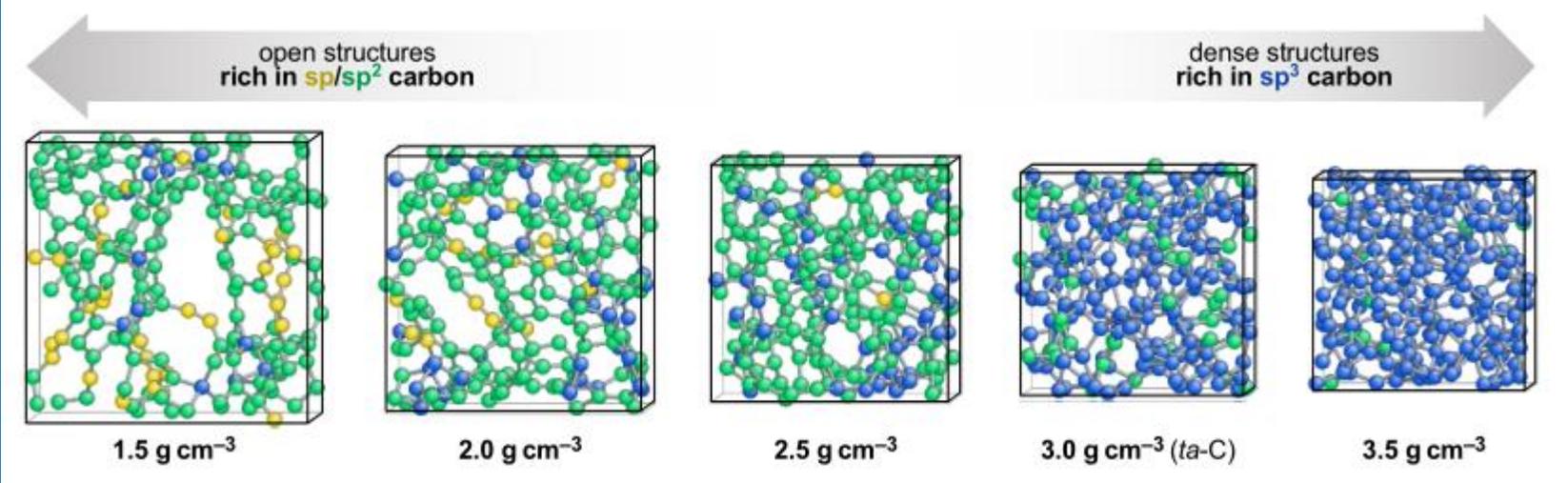
Angular Symmetry Function

- Symmetry Functions convert the positions of all atoms to local environments for each atom
 - Two structures with different energies must yield different symmetry function values
 - Identical structures must yield the same values
 - Must be invariant with respect to translation and rotation
 - Must not be coordination dependents, as coordination can change during simulation
 - Similar to empirical potentials, but describes only structure and not energy
- G1 – Radial Distribution, Sum of Gaussians
- G2 – Angular Distribution, sum of cosines centered on i
 - Any basis that sufficiently describes atomic environment works

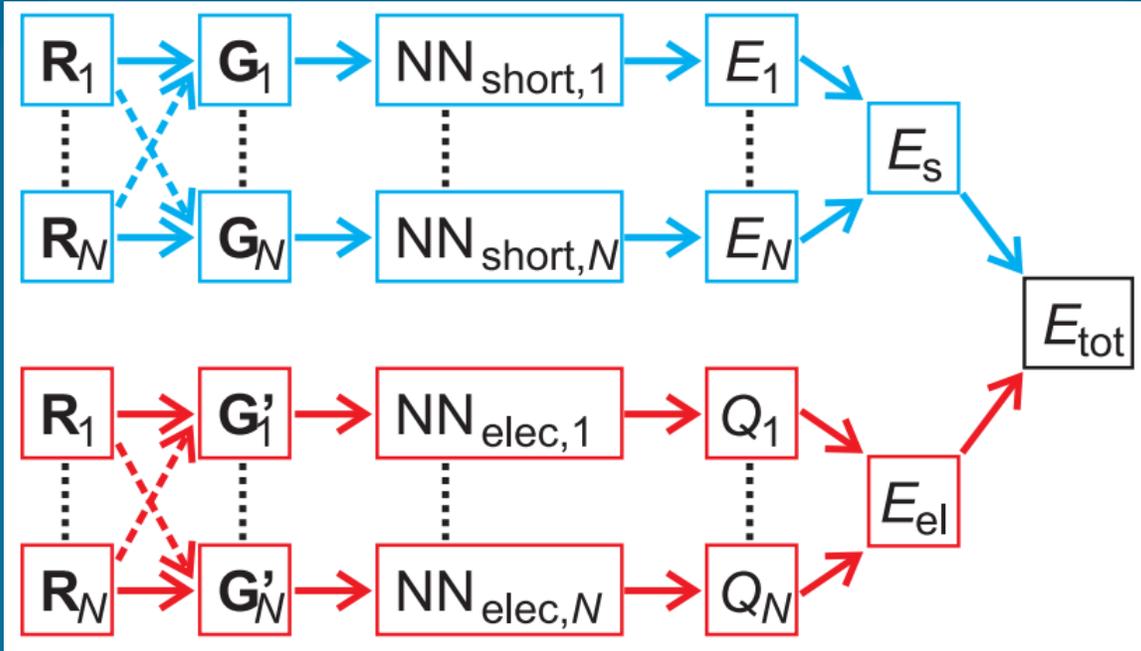
Neural Network Representation of Potential Energy Surfaces



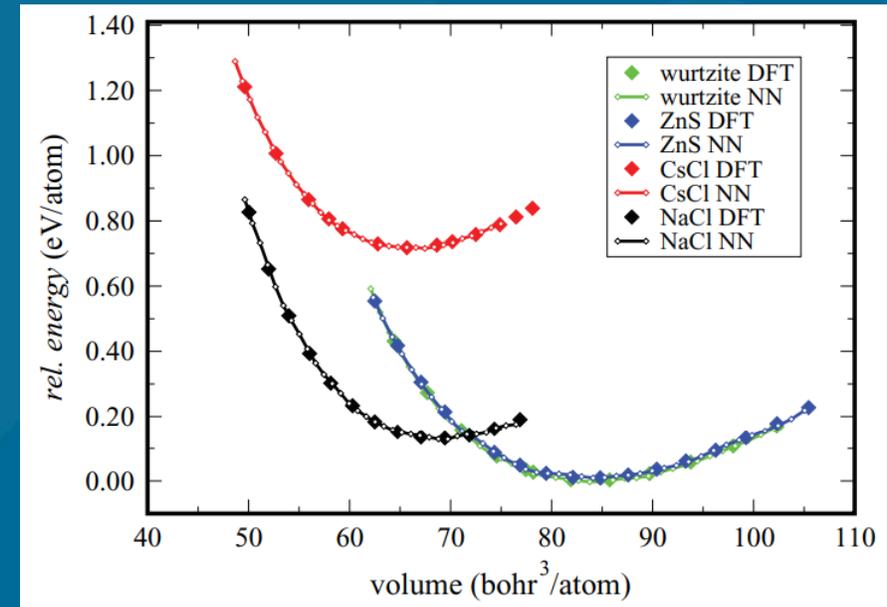
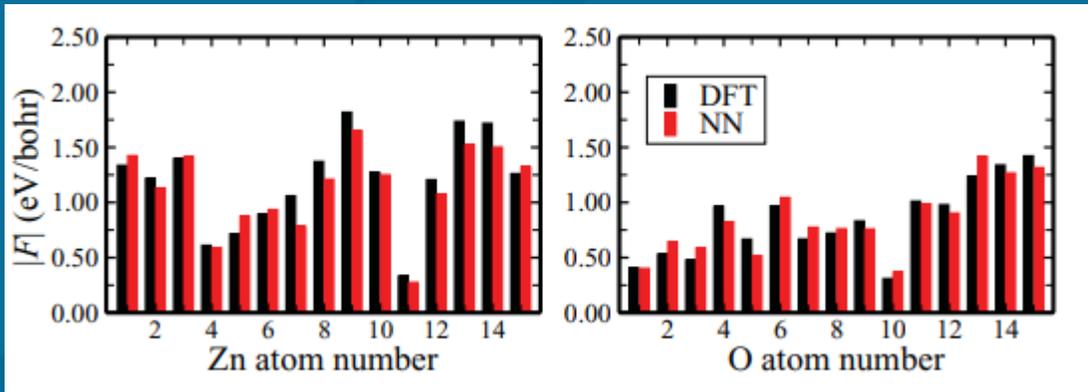
A Machine learning based interatomic potential for amorphous carbon



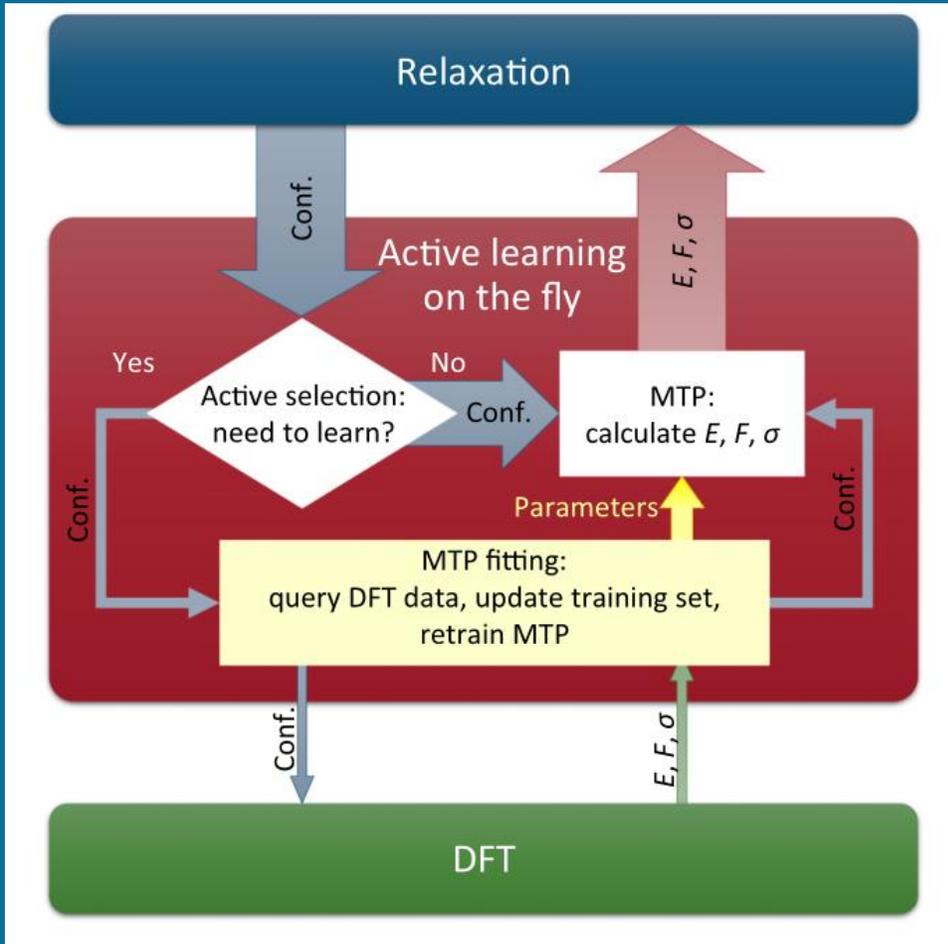
Neural Network Potentials for Multicomponent Systems

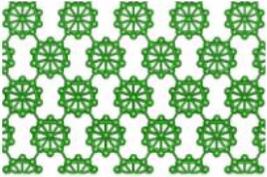
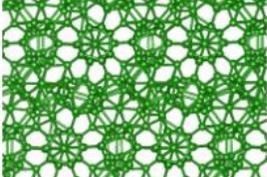
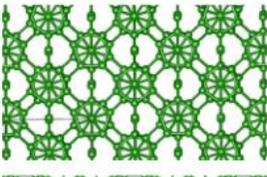
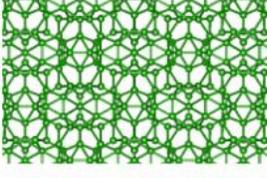
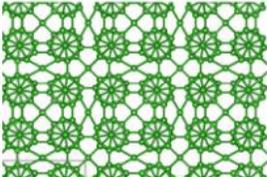
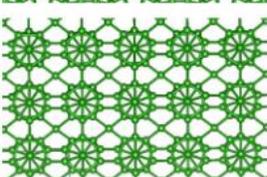


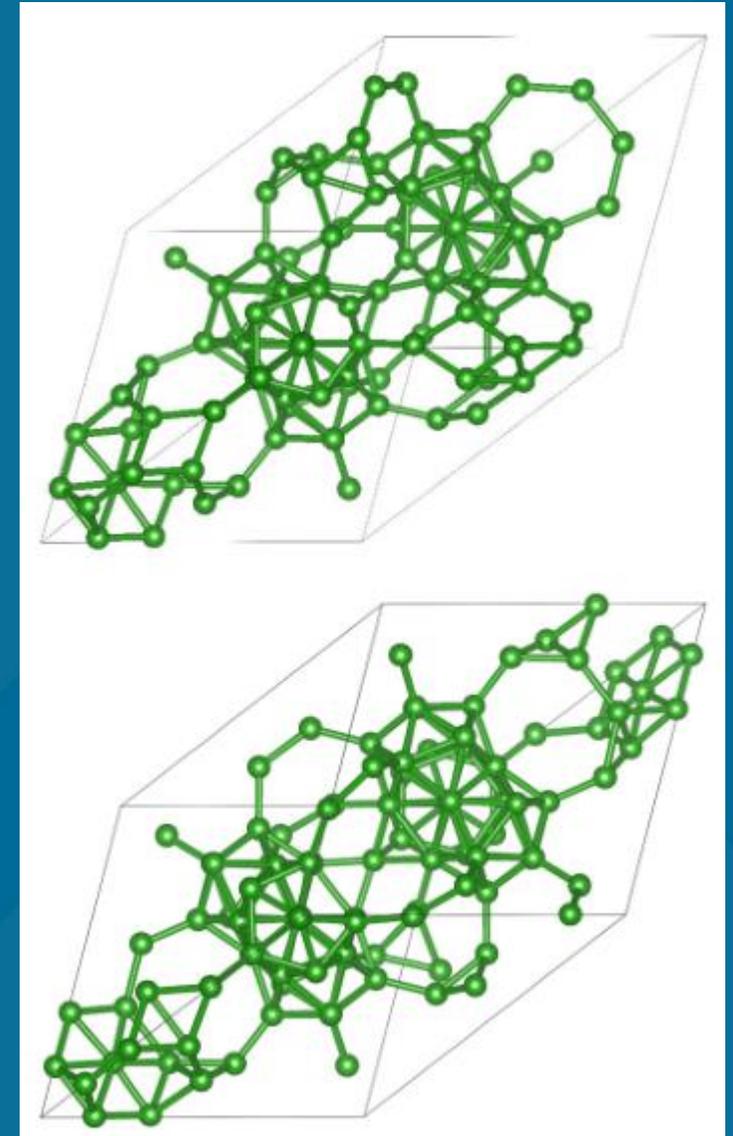
	DFT		NN	
	E_{coh} (eV)	Lattice	E_{coh} (eV)	Lattice
Wurtzite	7.057	$a = 3.278 \text{ \AA}$ $c/a = 1.614$ $u = 0.379$	7.054	$a = 3.278 \text{ \AA}$ $c/a = 1.614$ $u = 0.379$
Zinc blende	7.043	$a = 4.616 \text{ \AA}$	7.041	$a = 4.612 \text{ \AA}$
NaCl	6.747	$a = 4.328 \text{ \AA}$	6.745	$a = 4.344 \text{ \AA}$
CsCl	5.584	$a = 2.688 \text{ \AA}$	5.588	$a = 2.680 \text{ \AA}$



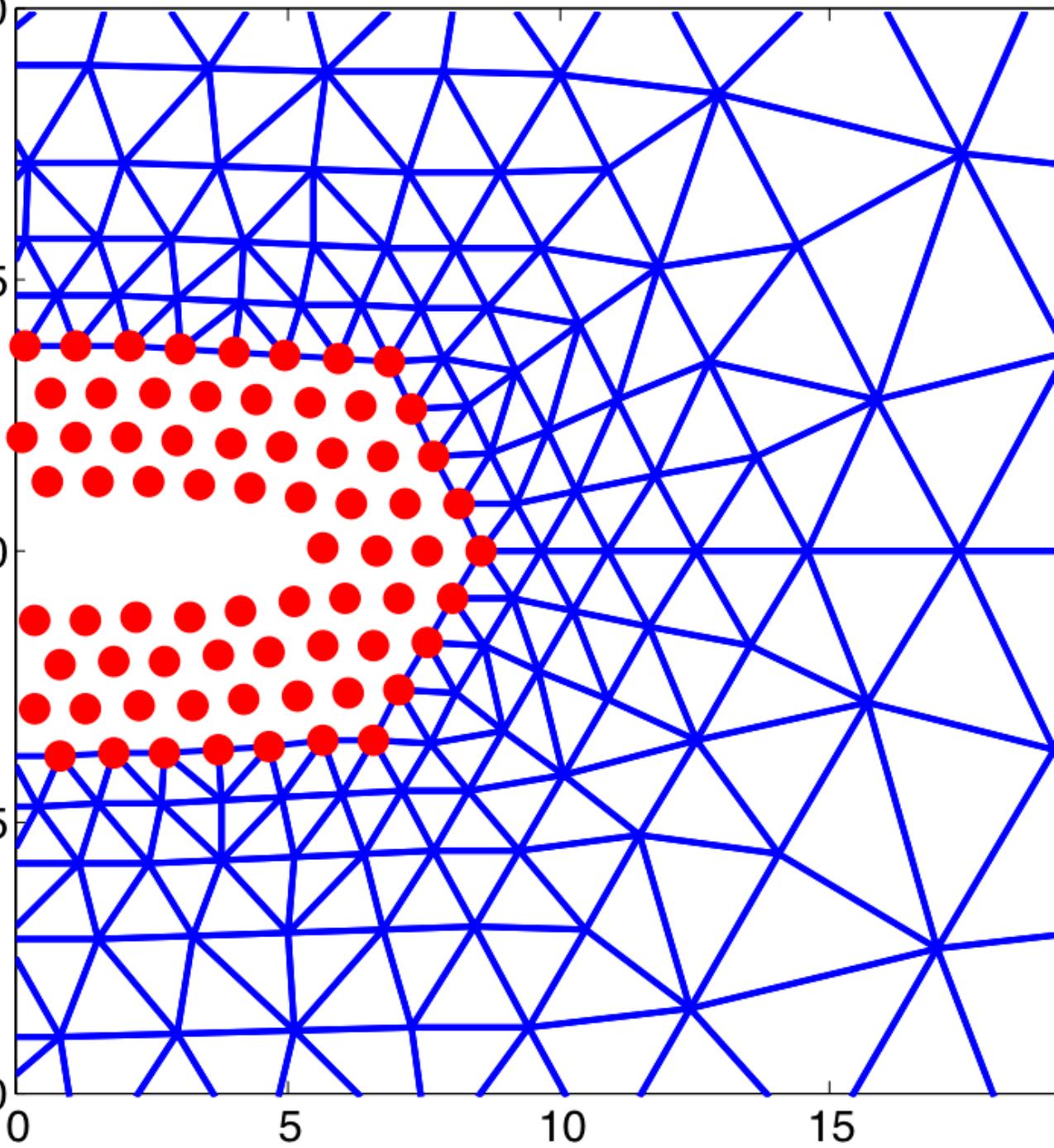
Active Learning Machine Potentials – Structure Prediction



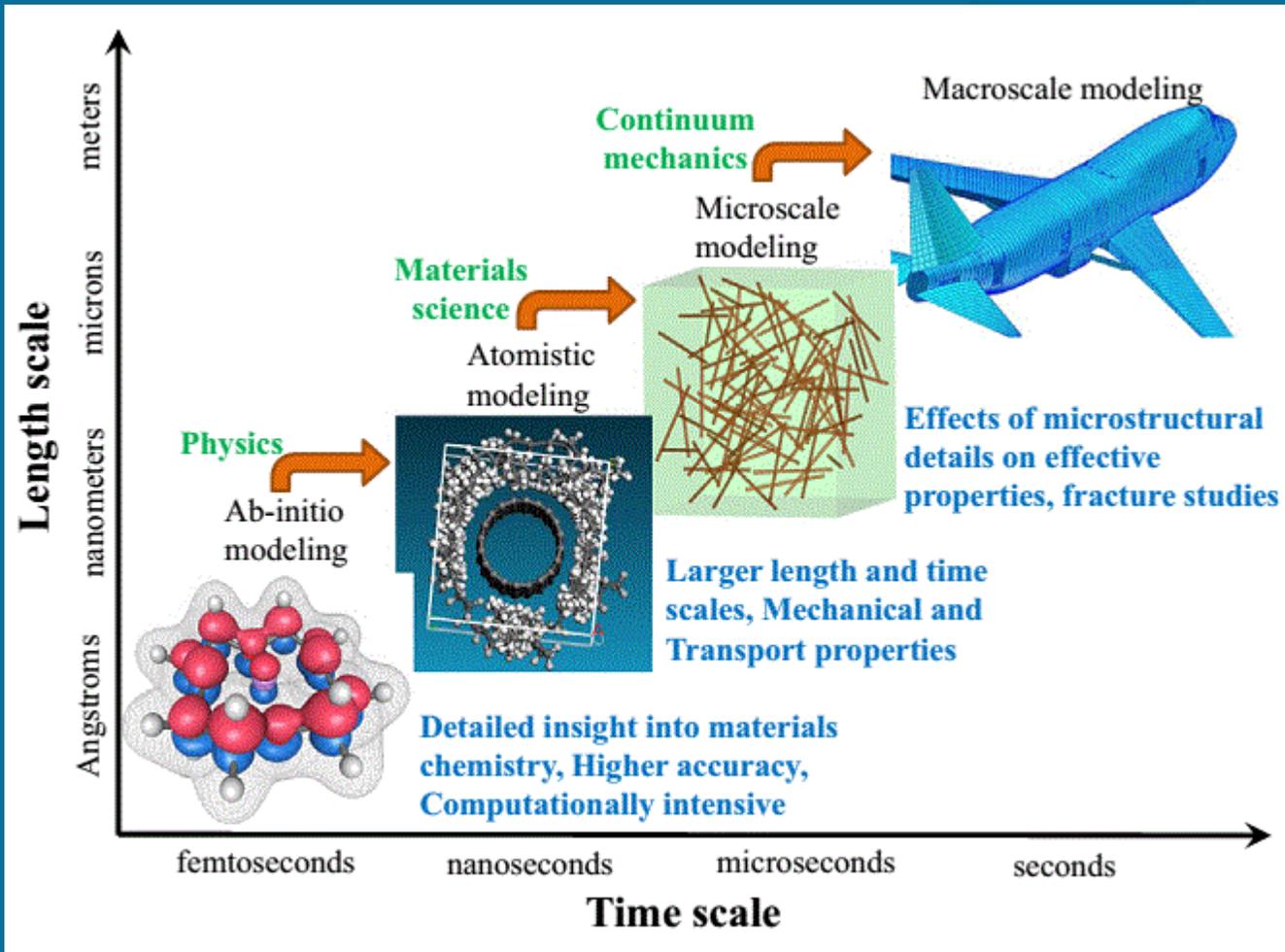
	<p>α-boron $E^{\text{DFT}} = -6.706$ eV/atom Atoms: 12, Space group: $R-3m$, Core-hours: 10^3 AL-MTP vs. $3 \cdot 10^3$ DFT $E^{\text{DFT}} - E^{\text{MTP}} = 28.6$ meV/atom</p>
	<p>β-boron approximant $E^{\text{DFT}} = -6.704$ eV/atom, Atoms: 106, Space group: $P1$, Core-hours: $7 \cdot 10^3$ AL-MTP vs. $6.6 \cdot 10^7$ DFT $E^{\text{DFT}} - E^{\text{MTP}} = 10.1$ meV/atom</p>
	<p>γ-boron $E^{\text{DFT}} = -6.678$ eV/atom Atoms: 28, Space group: $Pnmm$, Core-hours: $2 \cdot 10^3$ AL-MTP vs. $2.5 \cdot 10^4$ DFT $E^{\text{DFT}} - E^{\text{MTP}} = 58.1$ meV/atom</p>
	<p>$E^{\text{DFT}} = -6.667$ eV/atom, Atoms: 54, Space group: $Im-3$, Core-hours: $3 \cdot 10^3$ AL-MTP vs. $3.5 \cdot 10^5$ DFT $E^{\text{DFT}} - E^{\text{MTP}} = 7.3$ meV/atom</p>
	<p>$E^{\text{DFT}} = -6.667$ eV/atom, Atoms: 52, Space group: $P-42m$, Core-hours: $3 \cdot 10^3$ AL-MTP vs. $3.2 \cdot 10^5$ DFT $E^{\text{DFT}} - E^{\text{MTP}} = 37.3$ meV/atom</p>
	<p>$E^{\text{DFT}} = -6.665$ eV/atom, Atoms: 26, Space group: $Cccm$, Core-hours: $2 \cdot 10^3$ AL-MTP vs. $2.1 \cdot 10^4$ DFT $E^{\text{DFT}} - E^{\text{MTP}} = 13.6$ meV/atom</p>



Multiscale Modeling



Bridging Length and Time Scales



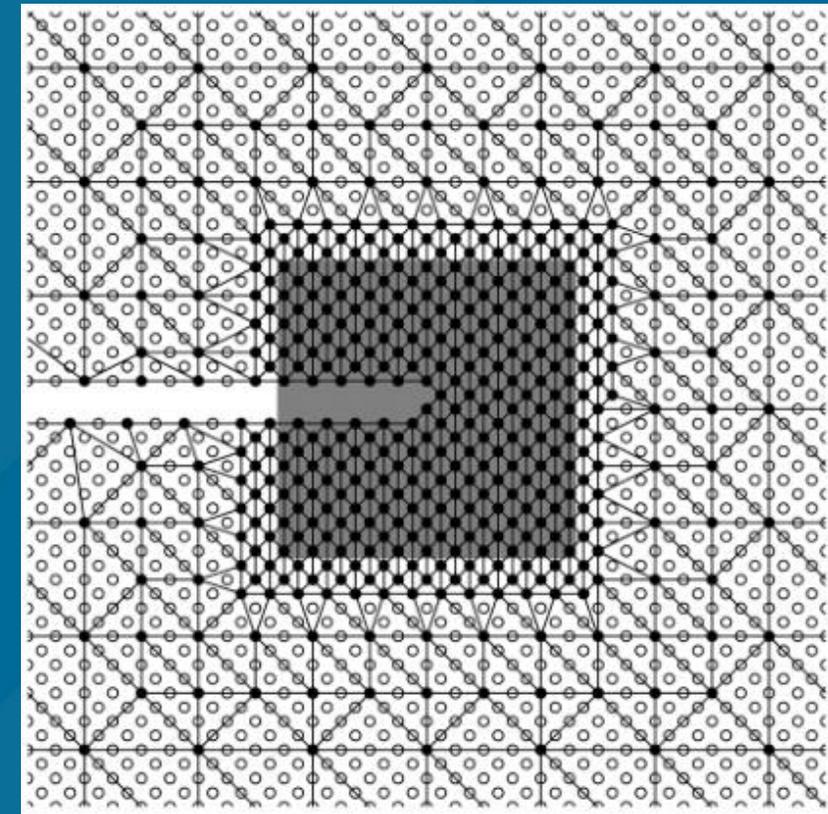
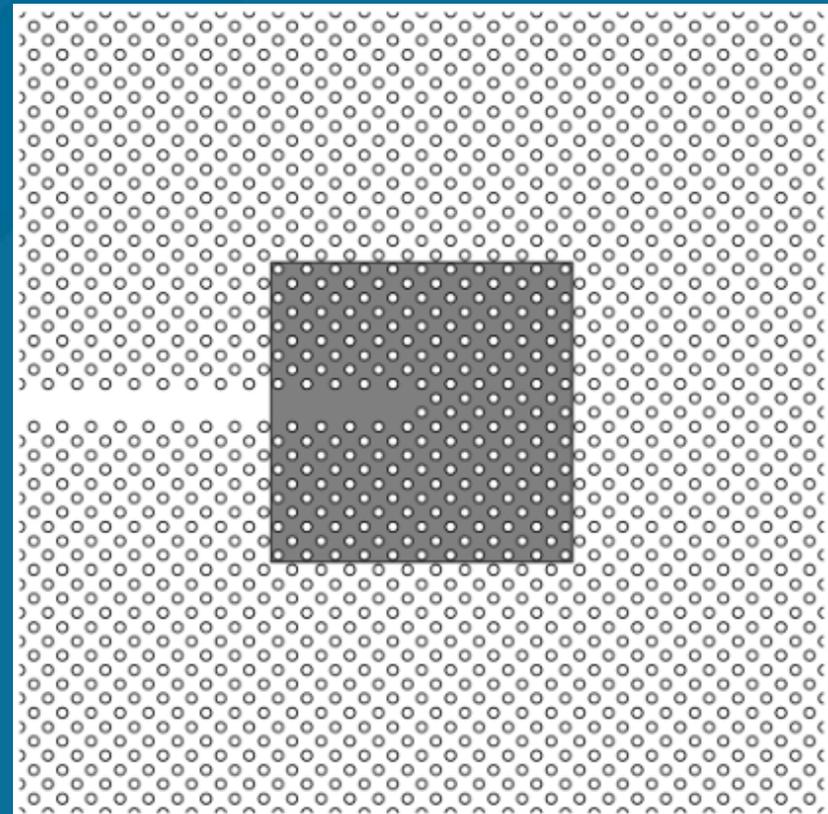
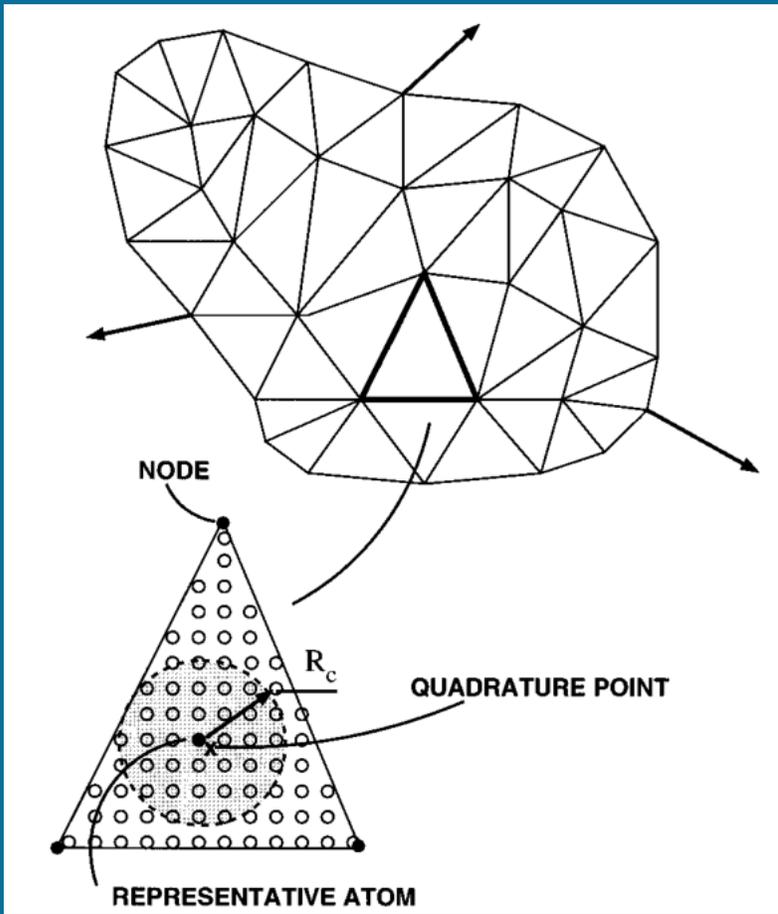
https://www.researchgate.net/publication/328928005_USE_OF_CARBON_NANOTUBE_COMPOSITES_IN_GEARING

- Ab initio calculations of DFT and Molecular Dynamics are still extremely limited in the length and time scales they can simulate with current computational power
- Multiscale modeling attempts to bridge the length and time scales such that simulations can approach the scale of real experiments or beyond

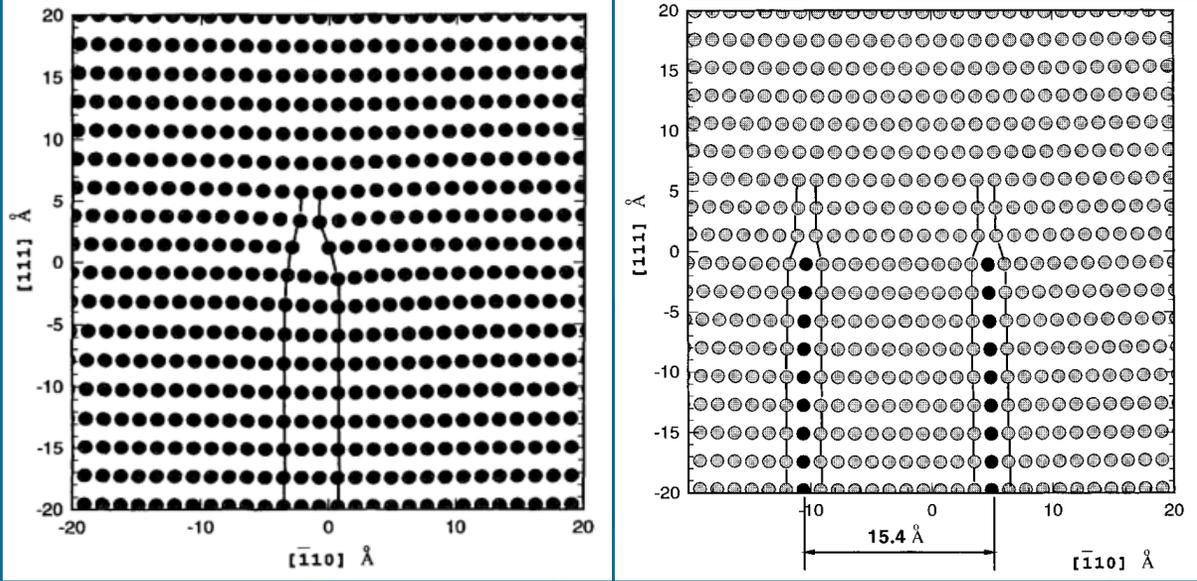
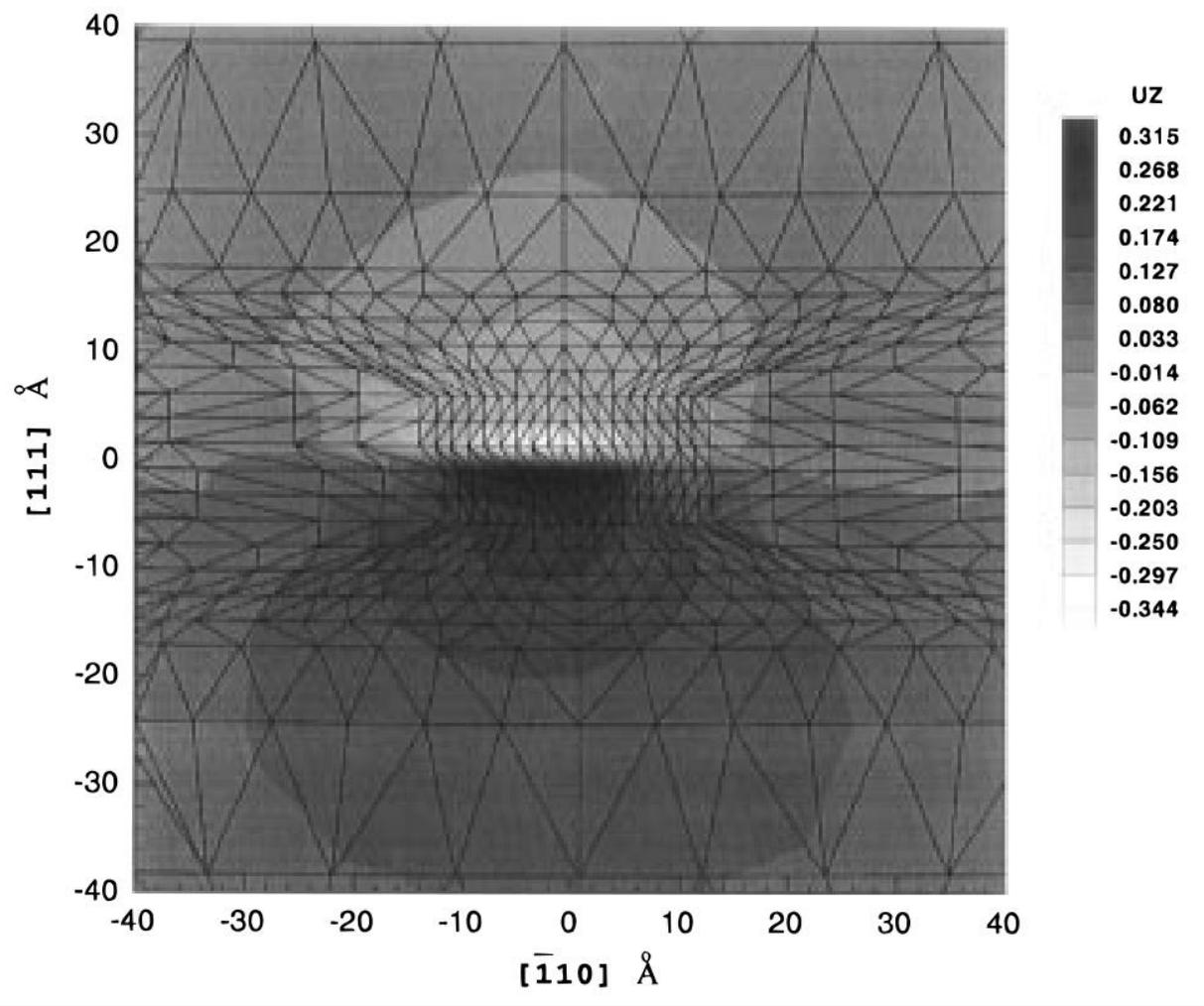
Quasicontinuum Method – Atomistic Simulations in FEA

Cauchy-Born Rule

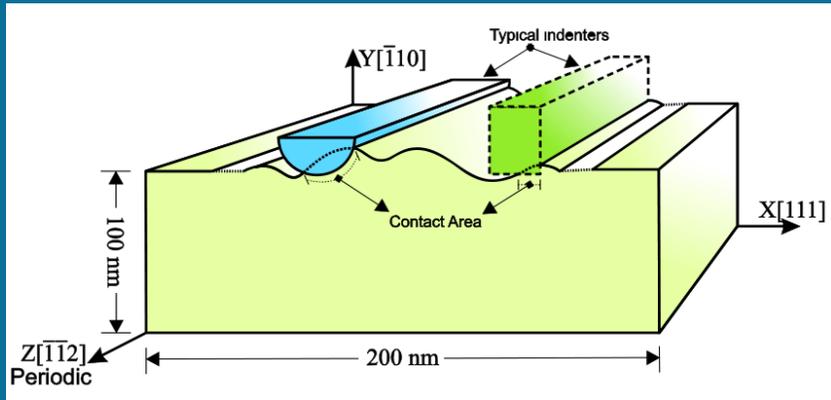
In a crystalline solid subject to a small strain, the positions of the atoms within the crystal lattice follow the overall strain of the medium



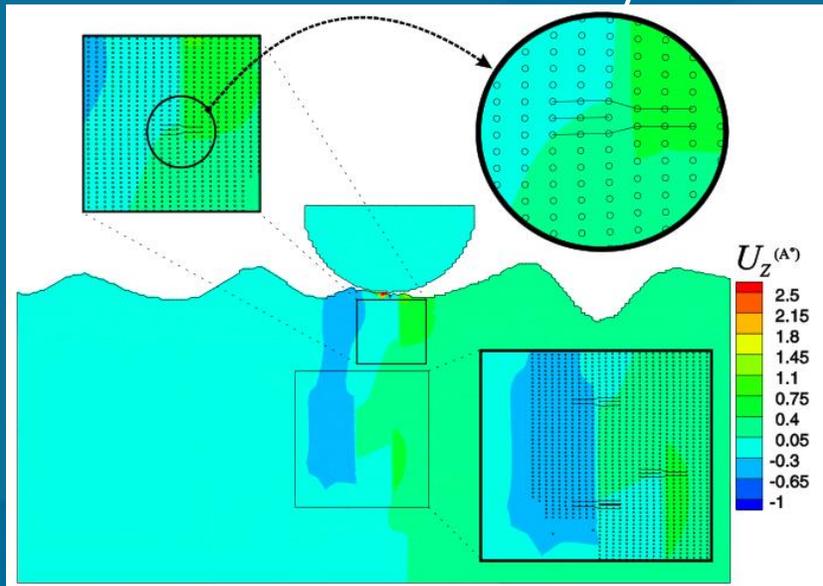
Quasicontinuum Method – Testing Edge Cases



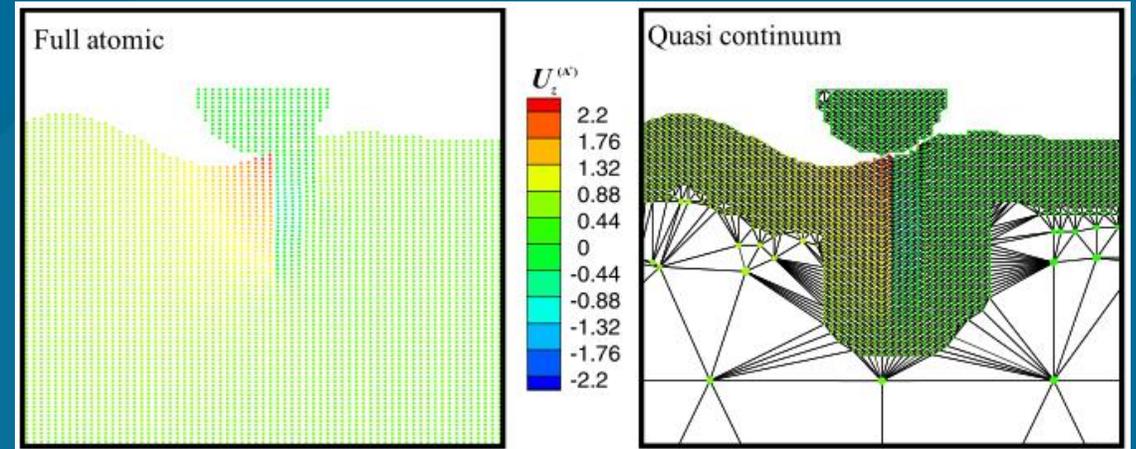
Quasicontinuum Method – Modeling Nanoindentation



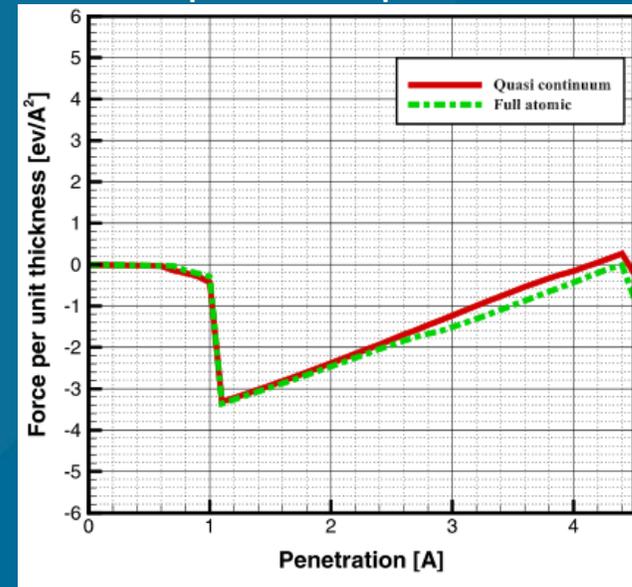
200 x 100 nm Cu FCC Crystal



Z displacement for a R=6.5Å indenter

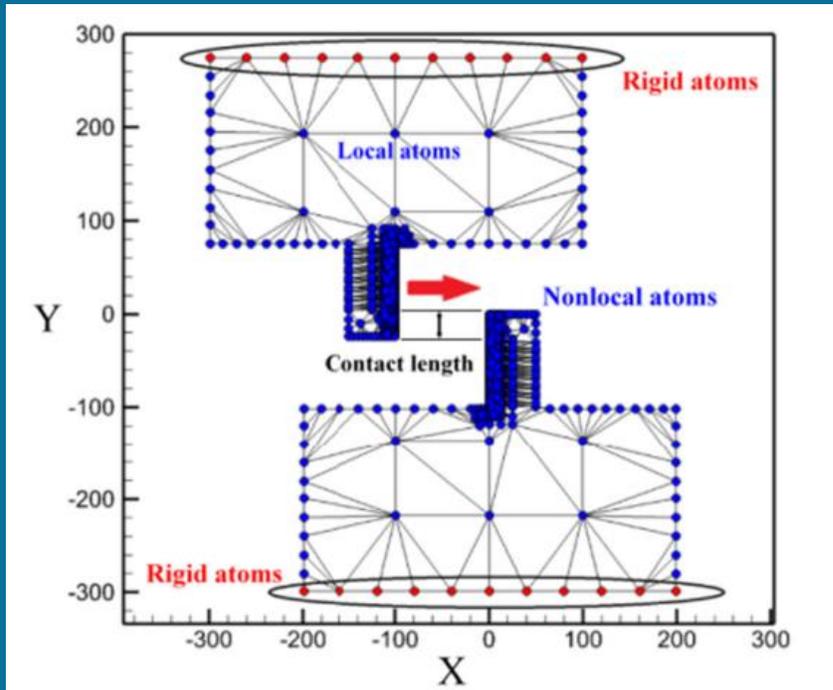


Out of plane displacement

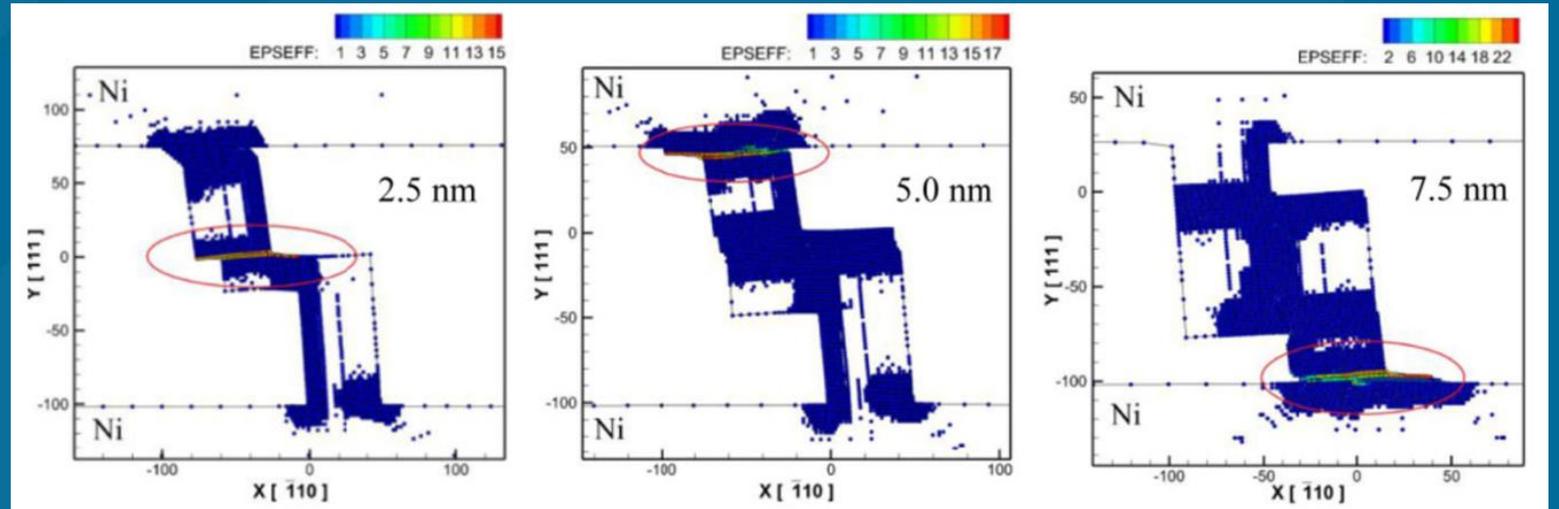


Load Penetration Curves

Quasicontinuum Method – Nanowelding Analysis



Schematic of the QC mesh



Strain may occur at roots of the weld instead of at the contact points

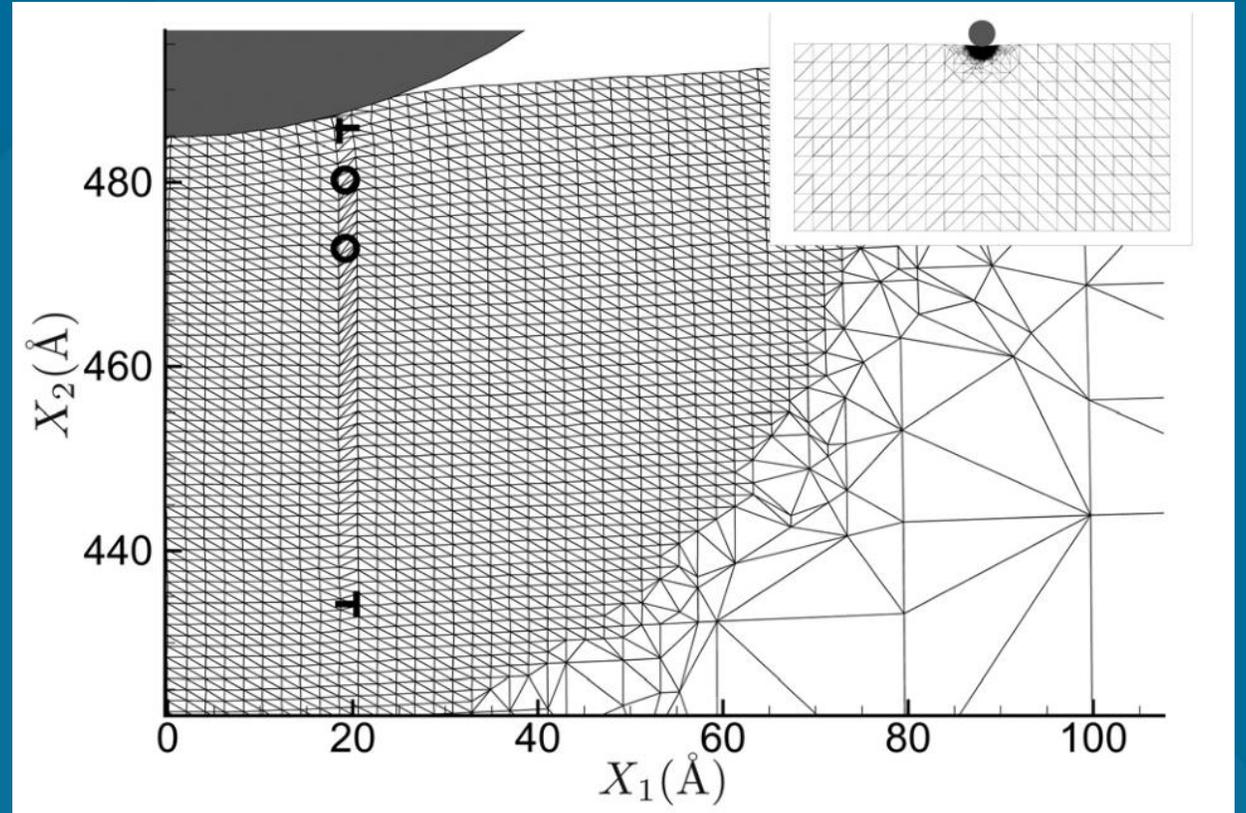
Finite Temperature Quasicontinuum

$$\tilde{\mathcal{H}}^{\text{at}}(\mathbf{q}^{\text{at}}, \mathbf{p}^{\text{at}}, T) = \tilde{\mathcal{V}}^{\text{at}}(\mathbf{q}^{\text{at}}, T) + \mathcal{K}^{\text{at}}(\mathbf{p}^{\text{at}}, T)$$

$$\Psi_{\text{LH}}^{\text{c}}(\mathbf{q}^{\text{at}}, \mathbf{q}^{\text{c}}, T) = \mathcal{V}(\mathbf{q}^{\text{at}}, \mathbf{q}^{\text{c}}) + \frac{k_B T}{2} \sum_{i=1}^{N_c} \ln \left[\frac{h_q^6 \det \Phi_{ii}^{\text{c}}(\mathbf{q}^{\text{at}}, \mathbf{q}^{\text{c}})}{(2\pi k_B T)^3} \right]$$

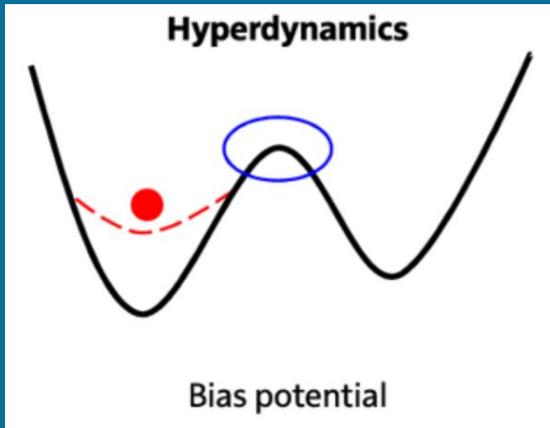
$$\tilde{\mathcal{V}}^{\text{at}}(\mathbf{q}^{\text{at}}, T) = \min_{\mathbf{q}^{\text{c}}} \Psi_{\text{LH}}^{\text{c}}(\mathbf{q}^{\text{at}}, \mathbf{q}^{\text{c}}, T)$$

$$\mathcal{K}^{\text{at}}(\mathbf{p}^{\text{at}}, T) = \sum_{i=1}^{N_{\text{at}}} \frac{\|\mathbf{p}_i^{\text{at}}\|^2}{2m_i^{\text{at}}} - \frac{3k_B T}{2} \sum_{j=1}^{N_c} \ln \frac{2\pi k_B T m_j^{\text{c}}}{h_p^2}$$



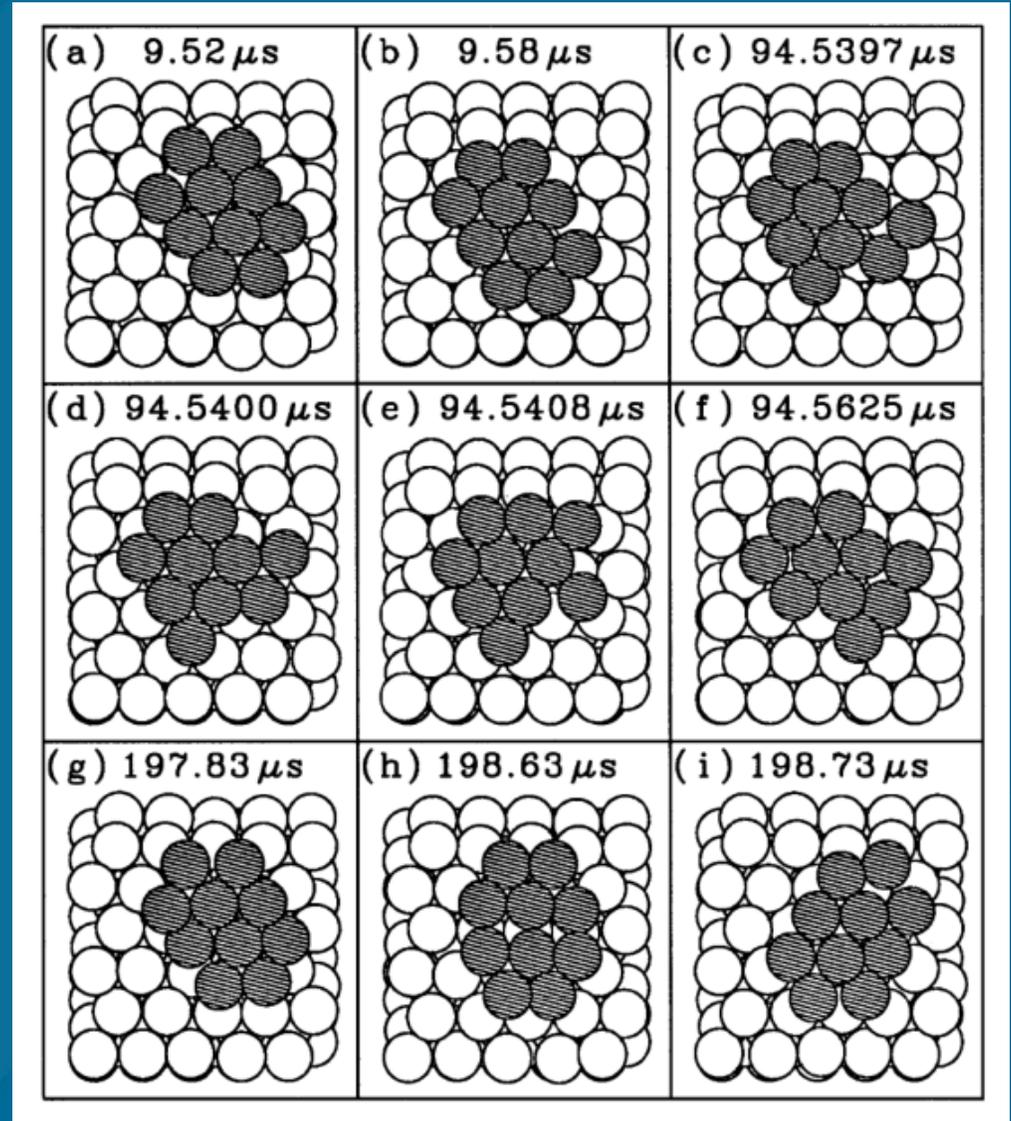
- Finite Temperature Quasicontinuum, or Hot-QC
- Requires a model for the transfer of heat between partitioned domains
- An effective Hamiltonian is derived that adequately approximates the contributions of the unrepresented atoms in the continuum region

Hyperdynamics – Bridging Time scale

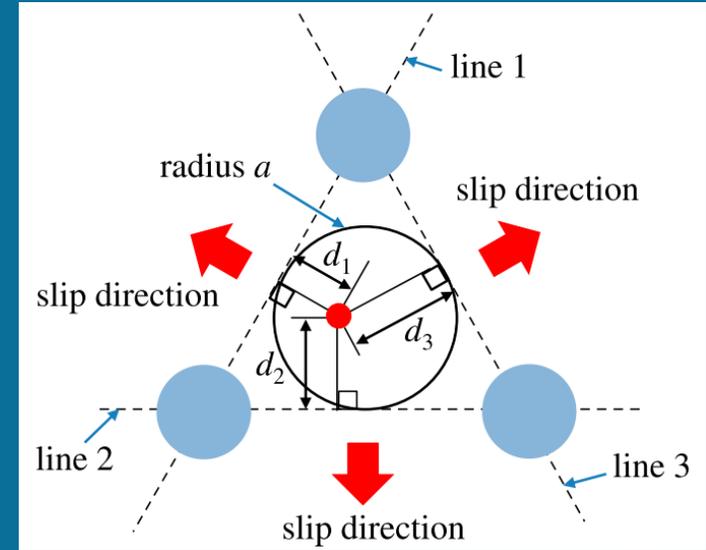
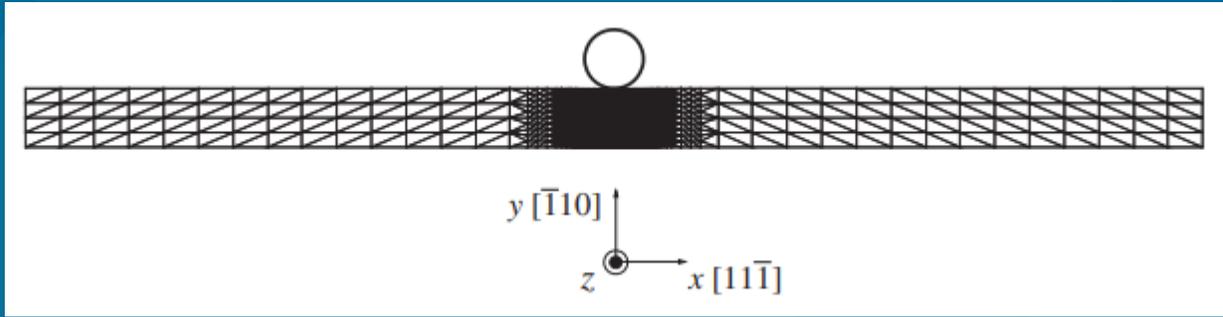


$$\Delta t_{b_i} = \Delta t_{\text{MDE}} e^{\beta \Delta V_b(x(t_i))}; \quad t_b = \sum_i^{n_{\text{tot}}} \Delta t_{b_i}$$

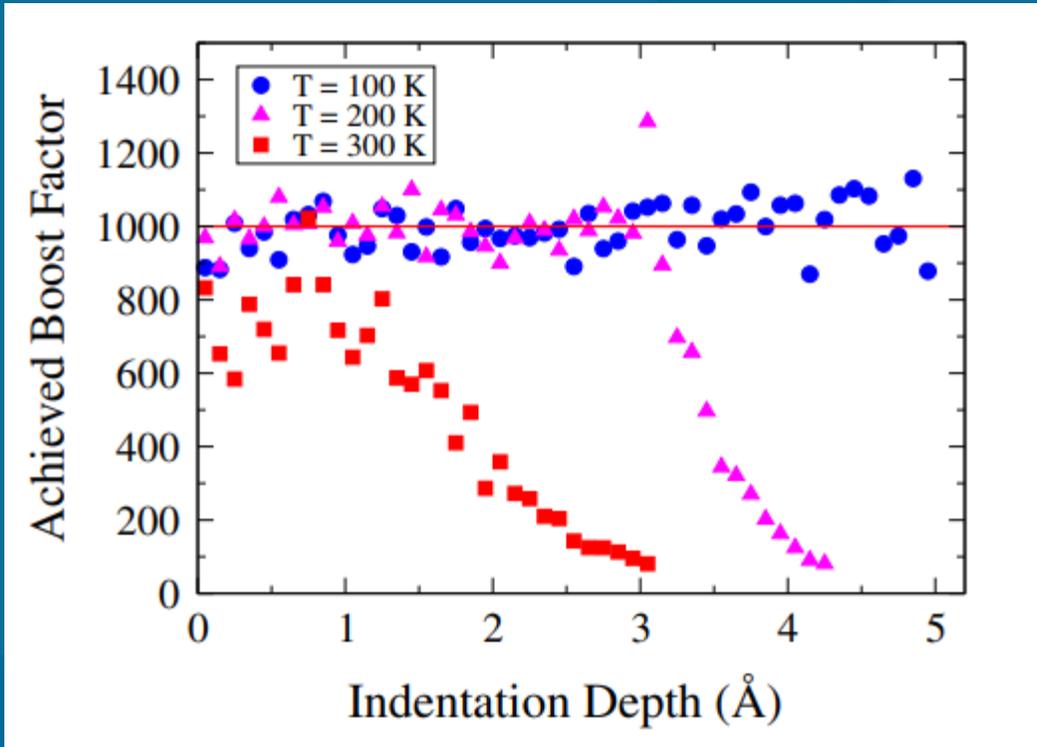
- A Bias potentials raises the energy of the system in areas other than the transition states
- Infrequent events rates boosted proportionally to the magnitude of the bias potential
- Requires no prior knowledge of the transitioning states of the system



HyperQC – Combining Spatial and Temporal Scaling



- Combining the spatial scaling of Quasicontinuum with the temporal scaling of Hyperdynamics
- A mechanism-based bias potential is applied that lowers the energy barrier for slip in fcc crystals
- Speedups between 1000 and 10000 were experienced, lowering as temperature increased



Conclusion

- Empirical Potentials
 - Computationally Inexpensive
 - Based on Physical Models
 - Wide range of performance based on model used and application
- Ab Initio Calculations and Potentials
 - Based on Quantum Mechanical Methods such as Density Functional Theory
 - Extremely computationally expensive
 - Most accurate method available
- Machine Learning Potentials
 - Interpolated potentials based on data sets created from Quantum Mechanical Calculations
 - Combines the accuracy of Ab Initio with the speed of Empirical
 - Possibly the future of Molecular Dynamics Simulations
- Multiscale Methods – Quasicontinuum and Hyperdynamics
 - Bridging the gaps between length and time scales
 - Brings the possibility of simulating real-time and scale experiments

THANK YOU