

Exceptional service in the national interest



Predictive Atomistic Simulations of Materials Using LAMMPS

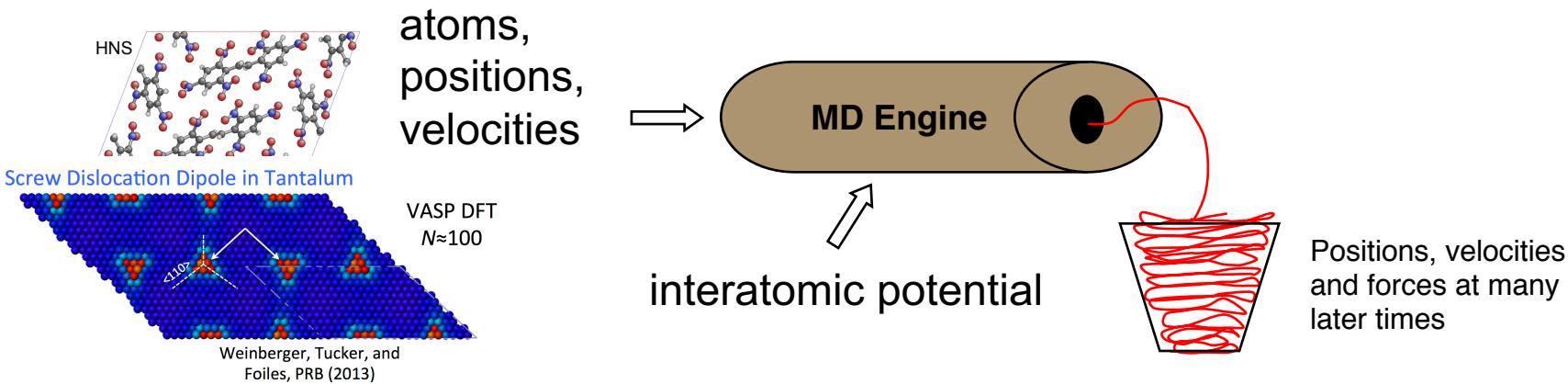
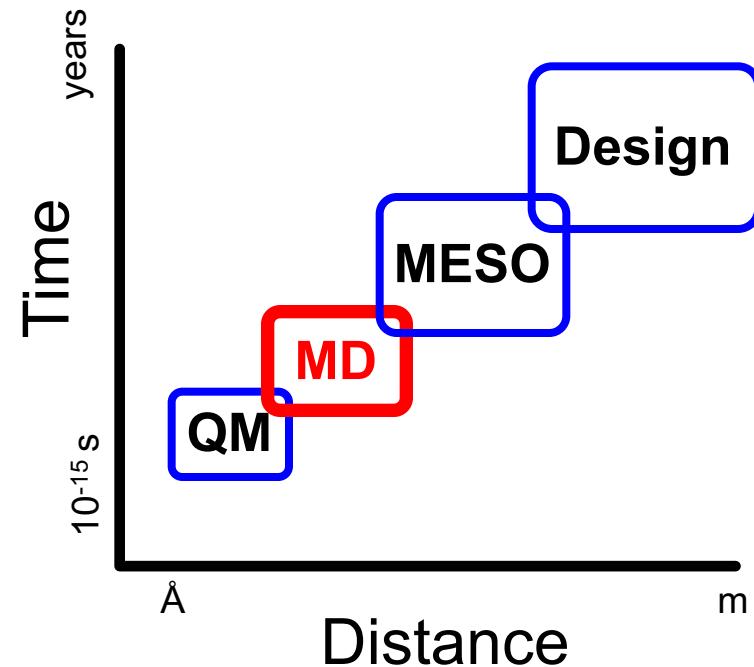
Aidan P. Thompson
Center for Computing Research
Sandia National Laboratories

Talk Outline

- **Molecular Dynamics**
- Interatomic Potentials
- ReaxFF
- SNAP
- Outlook

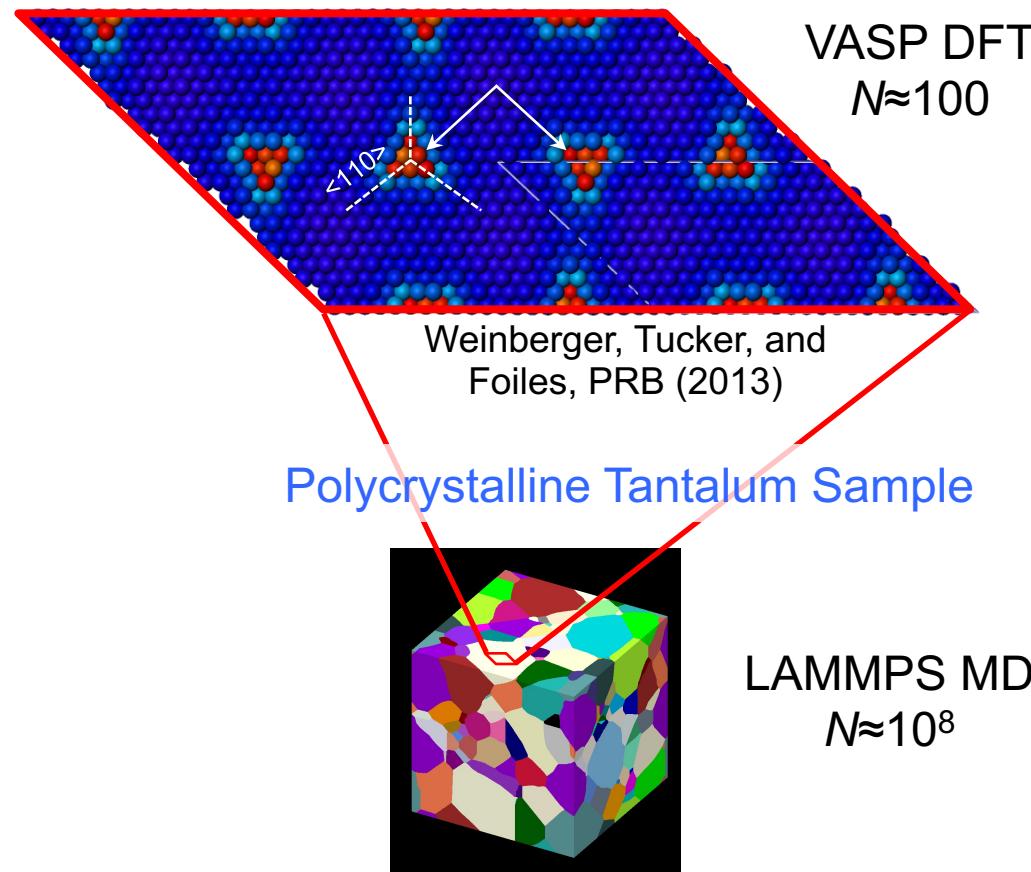
What is Molecular Dynamics Simulation?

- Continuum models require underlying models of the materials behavior
- Quantum methods can provide very complete description for 100s of atoms
- Molecular Dynamics acts as the “missing link”
 - Bridges between quantum and continuum models
 - Moreover, extends quantum accuracy to continuum length scales; retaining atomistic information



Example: Plasticity in BCC Metals

Screw Dislocation Motion in BCC Tantalum

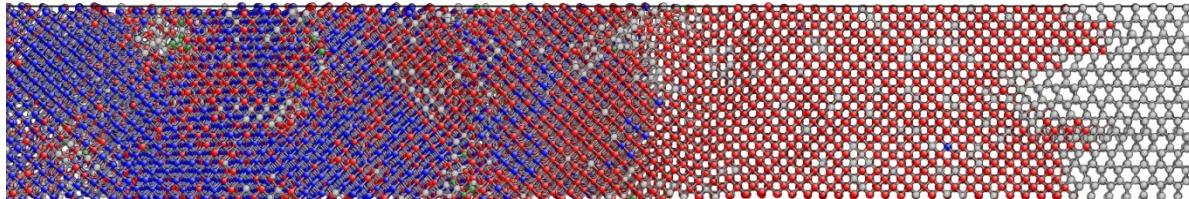
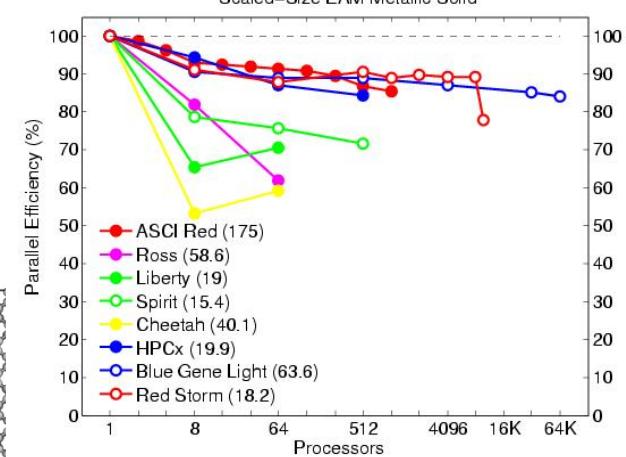
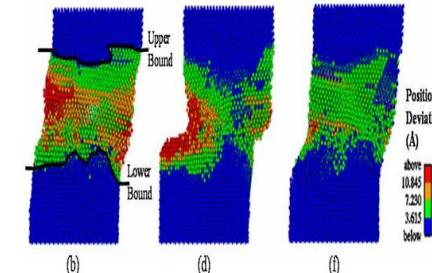
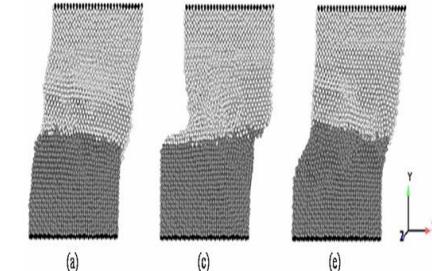
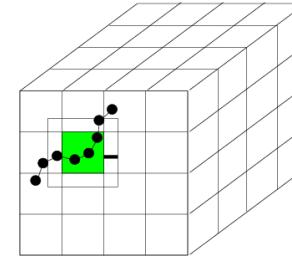


What is LAMMPS?

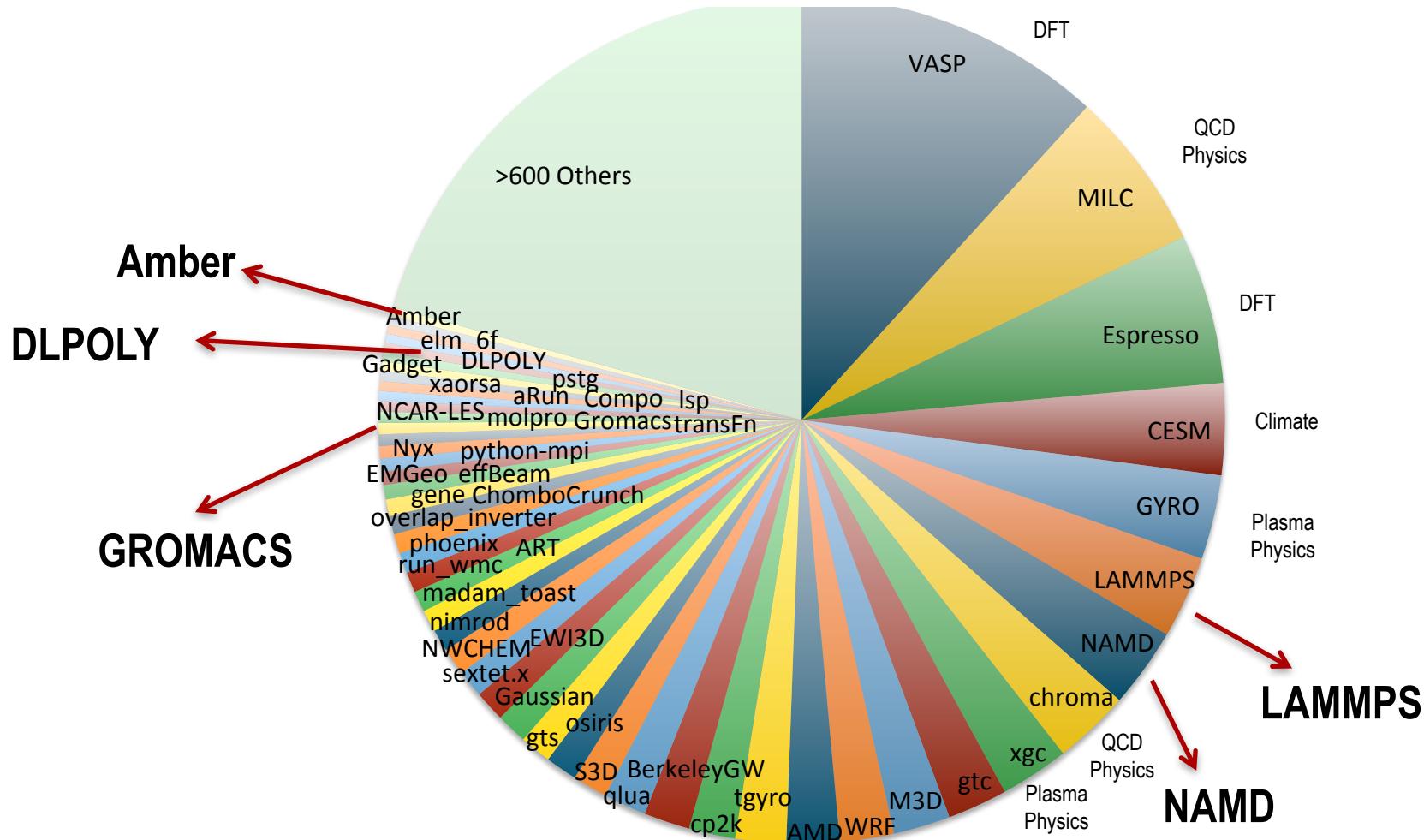
(Large-scale Atomic/Molecular Massively Parallel Simulator)

<http://lammps.sandia.gov>

- Classical MD code.
- Open source, highly portable C++.
- Freely available for download under GPL.
- Easy to download, install, and run.
- Well documented.
- Easy to modify or extend with new features and functionality.
- Active user's e-mail list with over 650 subscribers.
- More than 1000 citations/year
- Users' workshops: 2010, 2011, 2013, 2015
- Spatial-decomposition of simulation domain for parallelism.
- Energy minimization via conjugate-gradient relaxation.
- Atomistic, mesoscale, and coarse-grain simulations.
- Variety of potentials (including many-body and coarse-grain).
- Variety of boundary conditions, constraints, etc.



MD is Big Consumer of Computer Time

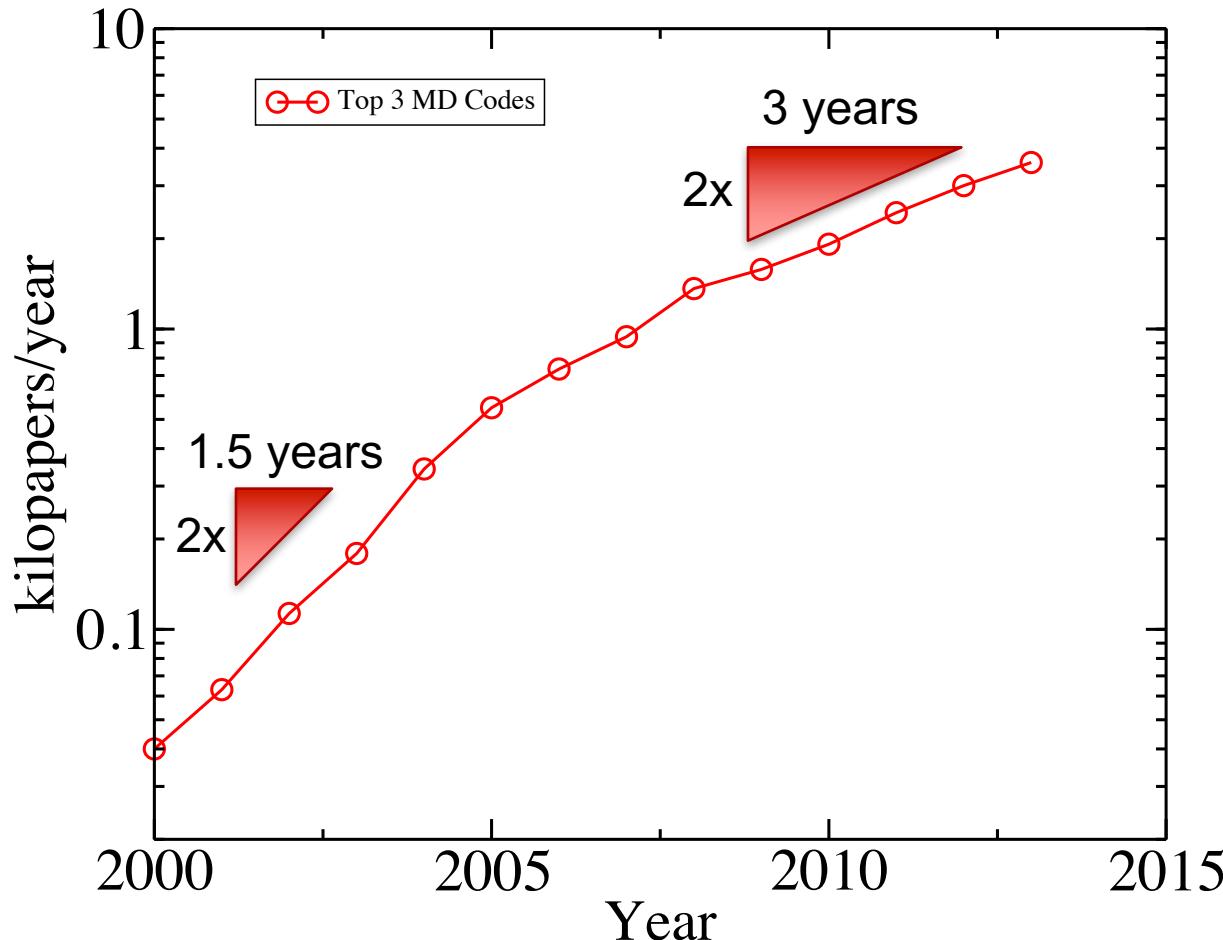


Growth in Use of MD

“Global scientific output doubles every nine years or 8-9% per year”

Nature, May 2014

Papers citing LAMMPS, NAMD, GROMACS
Measured using Web of Science citation reports



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Historical Development for Potentials

Twobody (B.C.)

Lennard-Jones

Hard Sphere

Coulomb

Bonded

Manybody (1980s)

Stillinger-Weber

Tersoff

Embedded Atom Method

Threebody Potentials for Covalent Solids

Diamond and other low symmetry crystals unstable for pure twobody potentials.

Solution: Add threebody angle terms

Tersoff

Stillinger-Weber

Manybody Potentials for Metals

Pure twobody potentials satisfy certain constraints:

$$C_{12} = C_{14}; E_v = E_{coh}$$

For FCC metals:

$$C_{12} / C_{14} \approx 2; E_v / E_{coh} \approx 0.35$$

Solution: Add manybody “embedding” energy
Embedded Atom Method
Finnis-Sinclair

Historical Development for Potentials

Twobody (B.C.)

Lennard-Jones

Hard Sphere

Coulomb

Bonded

Manybody (1980s)

Stillinger-Weber

Tersoff

Embedded Atom Method

Advanced (90s-2000s)

REBO

BOP

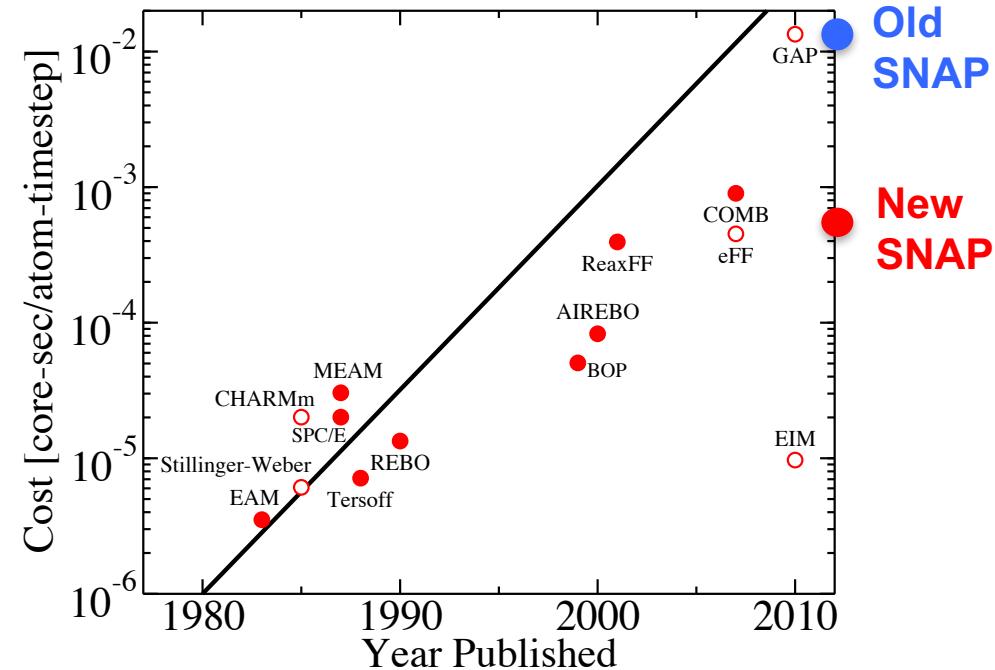
COMB

ReaxFF

Big/Deep/Machine Data/Learning (2010s)

GAP, SNAP, NN, ...

Moore's Law for Interatomic Potentials
Plimpton and Thompson, MRS Bulletin (2012).



Drivers

- Increased computer resources
- Application to Real Materials
- Quantum Methods

Two philosophical extremes in the development of interatomic potential models

The Force!

- Functional forms based on fundamental understanding of electronic origins of bonding
 - Bond Order Potentials (BOP)
 - Model Generalized Pseudopotential Theory (MGPT)
 - COMB
 - ReaxFF
 - ...
- Gives confidence that it will interpolate/extrapolate reasonably

Luke: *Is the dark side stronger?*

Yoda: *No, no no. Quicker, easier, more seductive.*



The Dark Side!

- Empirical fit of a flexible functional form
 - Gaussian Approximation Potentials (GAP)
 - Spectral Neighbor Analysis Potential (SNAP) - this work
 - ...
- Replaces the need for intuition/art with extensive computation
 - Automate the fitting process?
 - Apply across multiple materials classes?

Darth Vader: *You underestimate the power of the dark side!*



Borrowed from
Stephen Foiles
and Lucasfilm

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ReaxFF Potential

van Duin, Dasgupta, Lorant, and Goddard, *J. Phys. Chem. A*, **105** 9396 (2001)

$$E^{ReaxFF} = E^{vdW} + E^{Coul} + E^{polar}$$

Twobody Repulsion and Charge

$$+ E^{over} + E^{under}$$

Manybody Atom Coordination

$$+ E^{bond} + E^{angle} + E^{torsion}$$

Standard 2-, 3-, 4-Body Bonding Terms



$$+ E^{lone-pair} + E^{angle,penalty}$$

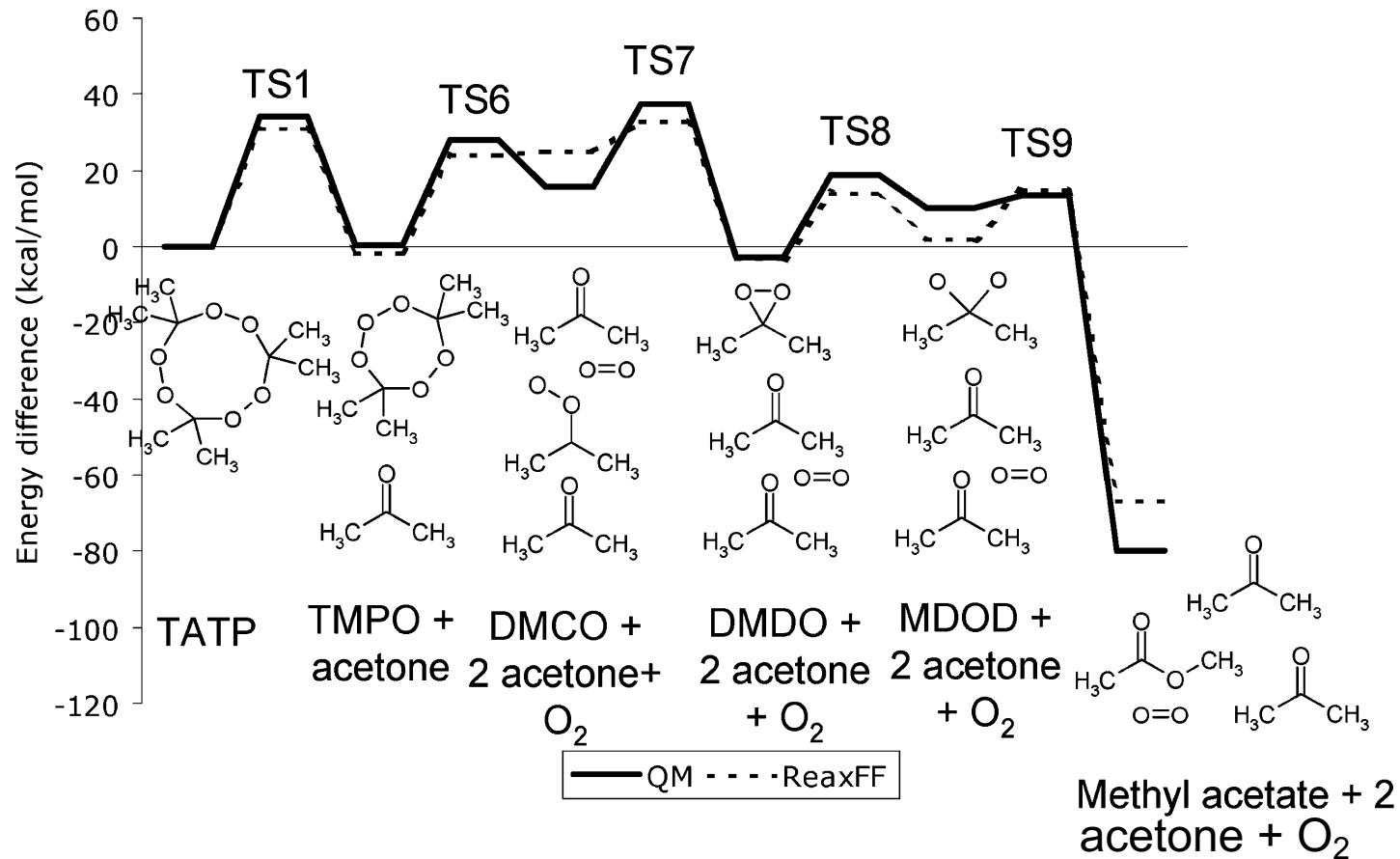
Special Chemical Bonding Terms

$$+ E^{conj} + E^{angle,conj} + E^{H-bond}$$

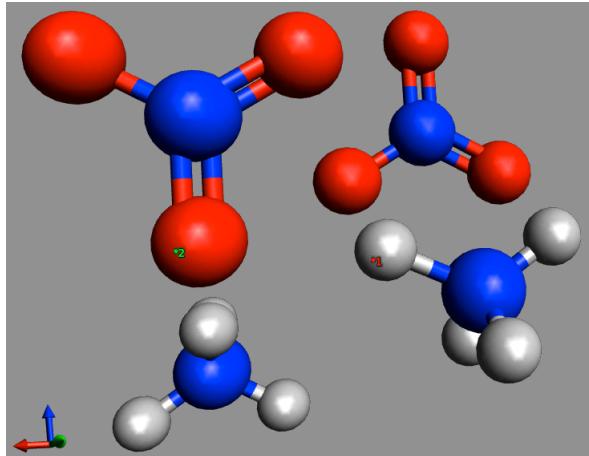
- Very powerful formulation
- About 100 citations/year
- Typical ReaxFF parameterization involves several hundred parameters
- Fit to large data sets of small gas phase QM calculations
- A lot of art involved in the fitting process

ReaxFF for Decomposition of TATP

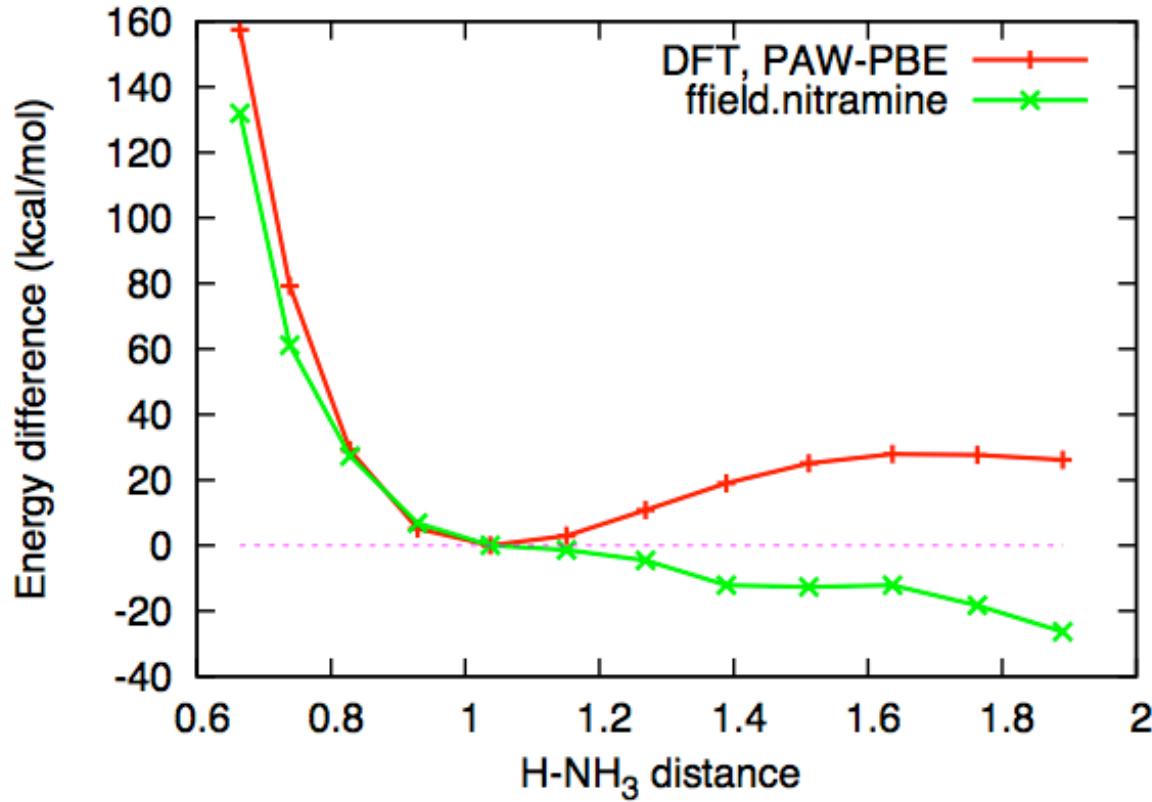
- QM and ReaxFF energies for a TATP unimolecular dissociation pathway



ReaxFF for ANFO

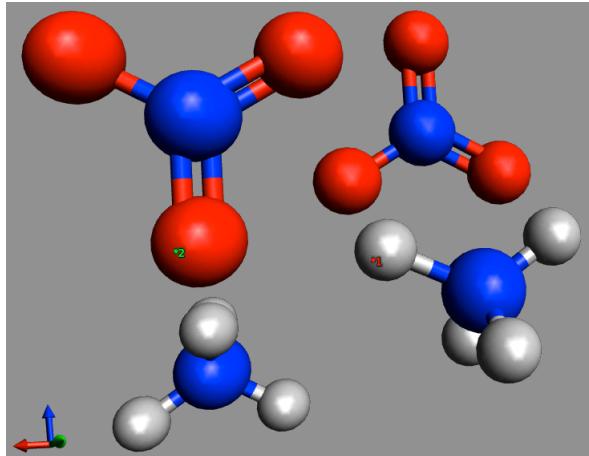


- One AN IV unitcell.
- Scanning one H moving from NH_4 to NO_3 with VASP
- Ions fixed, electrons relaxed

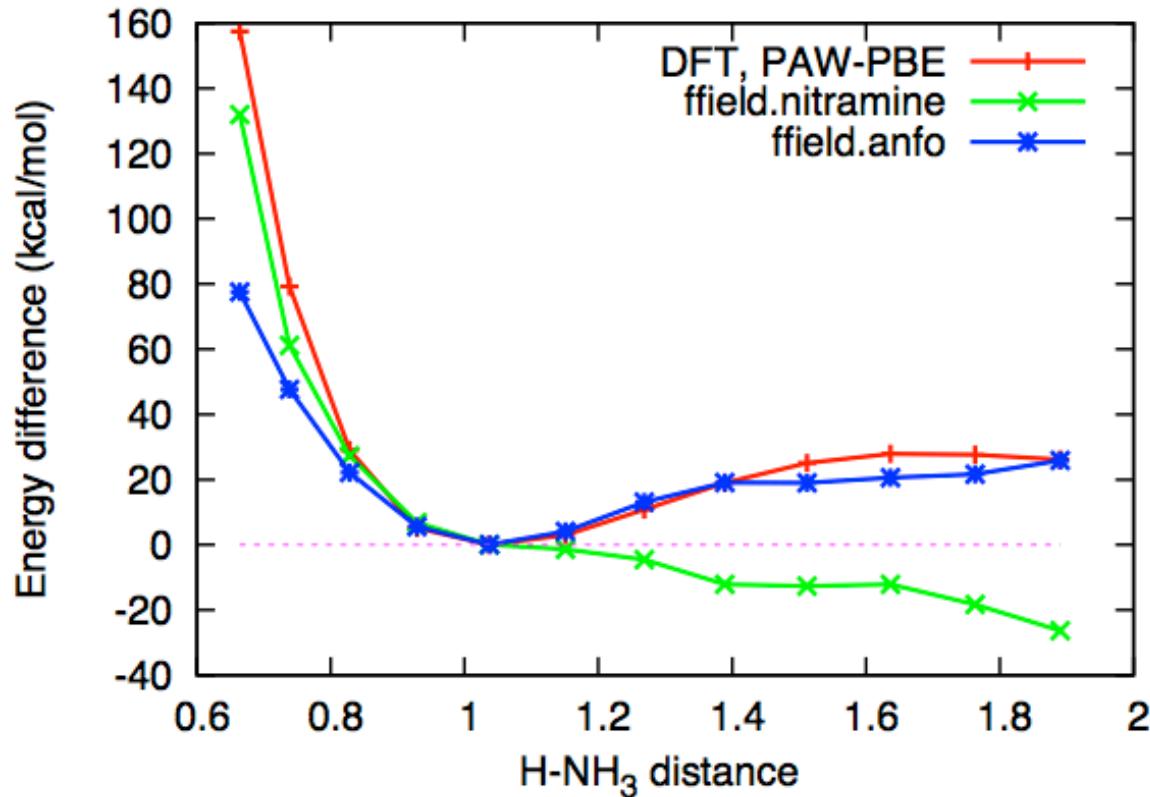


- VASP calculations indicate stable $\text{NH}_4\text{-NO}_3$
- However more stable to decompose to $\text{NH}_3 + \text{HNO}_3$ with the general nitramine force filed

ReaxFF for ANFO



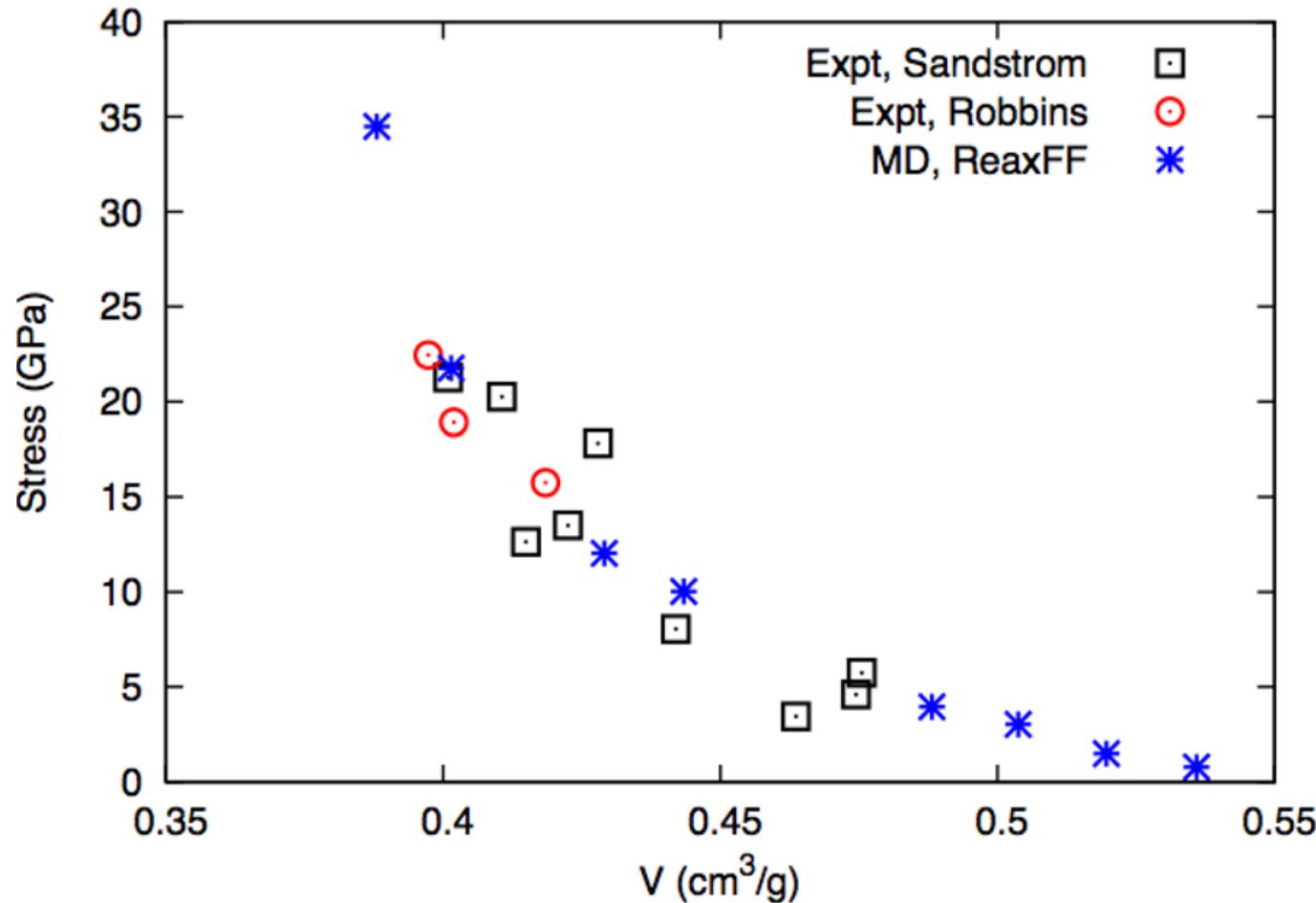
- One AN IV unitcell.
- Scanning one H moving from NH_4 to NO_3 with VASP
- Ions fixed, electrons relaxed



- We developed a new ReaxFF parameterization for AN
 - Reproduces stable $\text{NH}_4\text{-NO}_3$ lattice
 - Trained against energy barrier, heats of formation, lattice constants

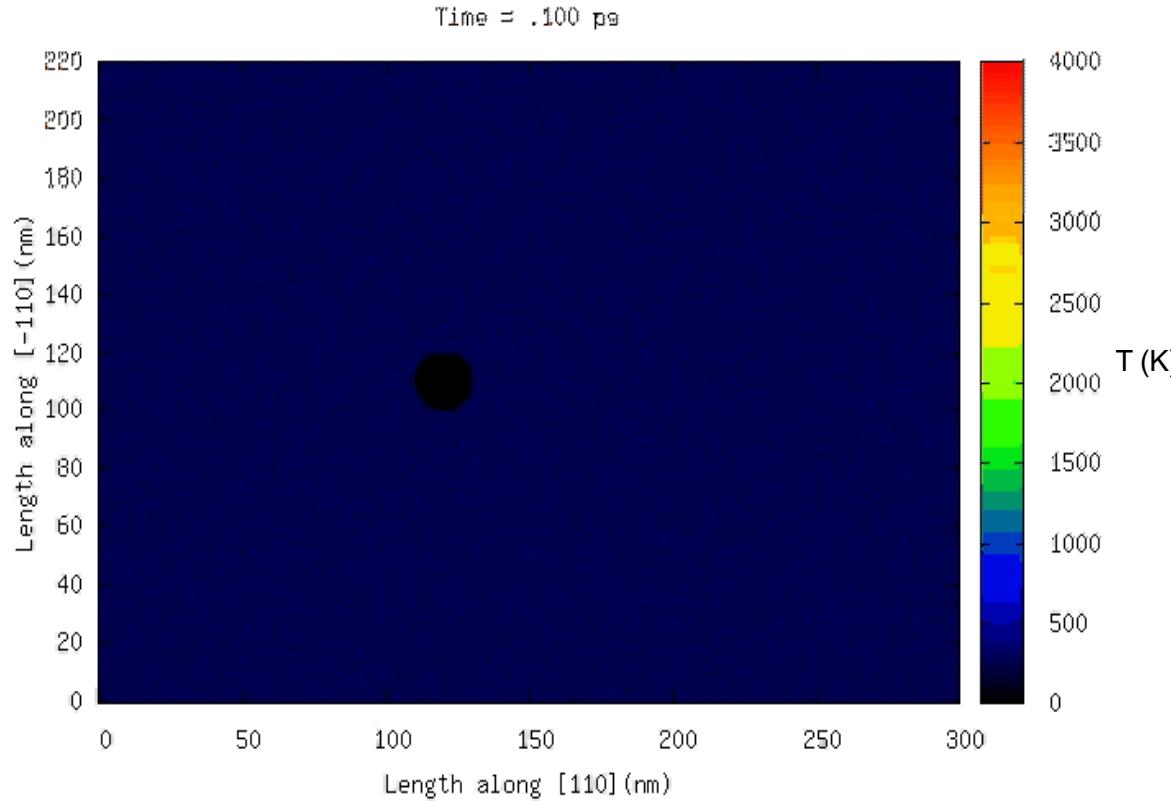
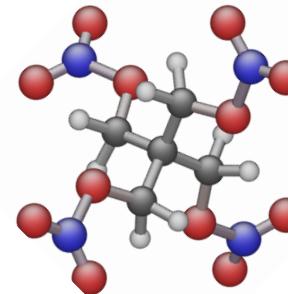
ReaxFF for ANFO

- Unreacted Hugoniot agrees well with experiments

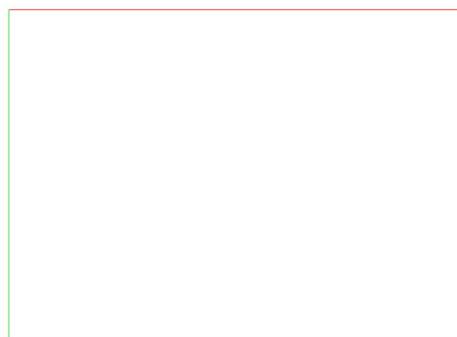


ReaxFF for PETN

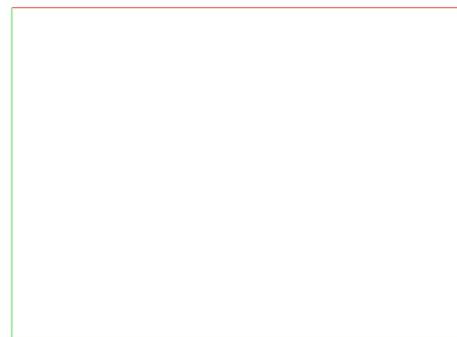
- Normal NEMD shock runs from 0 – 64 ps
 - Observed hotspot formation due to void collapse
- Shock-front ABC runs from 64 – 500 ps:
 - Observed hot spot growth due to coupling to exothermic chemical reactions



H_2O



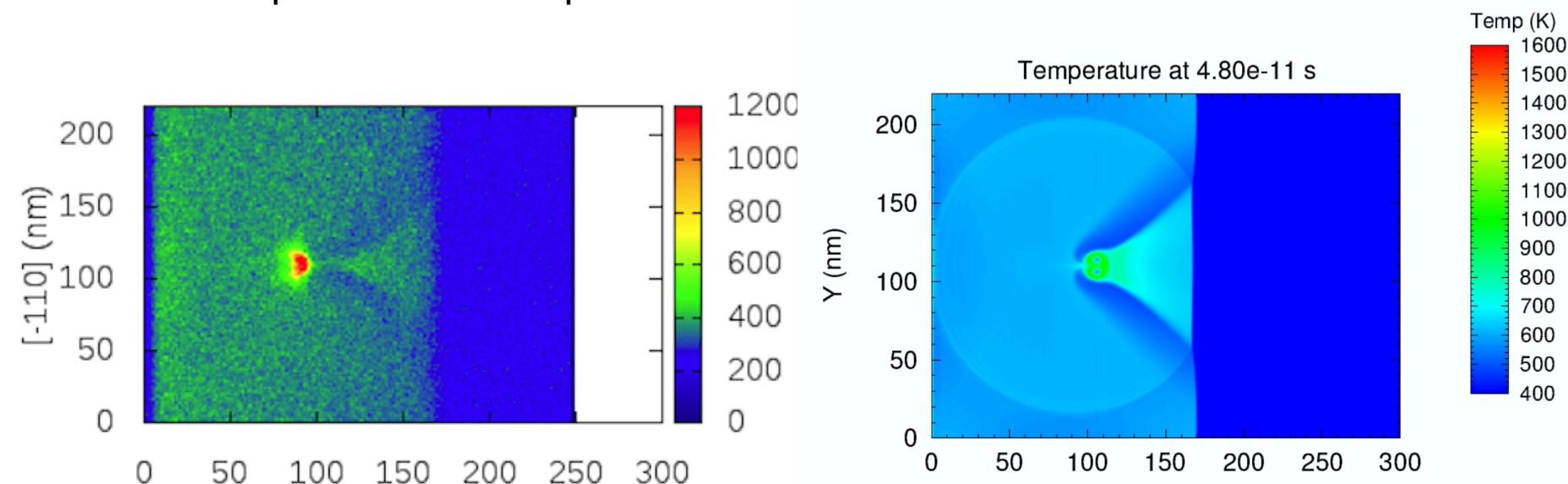
N_2



ReaxFF for PETN

- Effect of secondary shockwave

Temperature maps from (a) ReaxFF molecular dynamics simulation (LAMMPS) and (b) continuum hydrodynamics simulation (CTH) illustrating hot spot formation in the PETN crystal containing a 20 nm void 48 ps after initial impact.

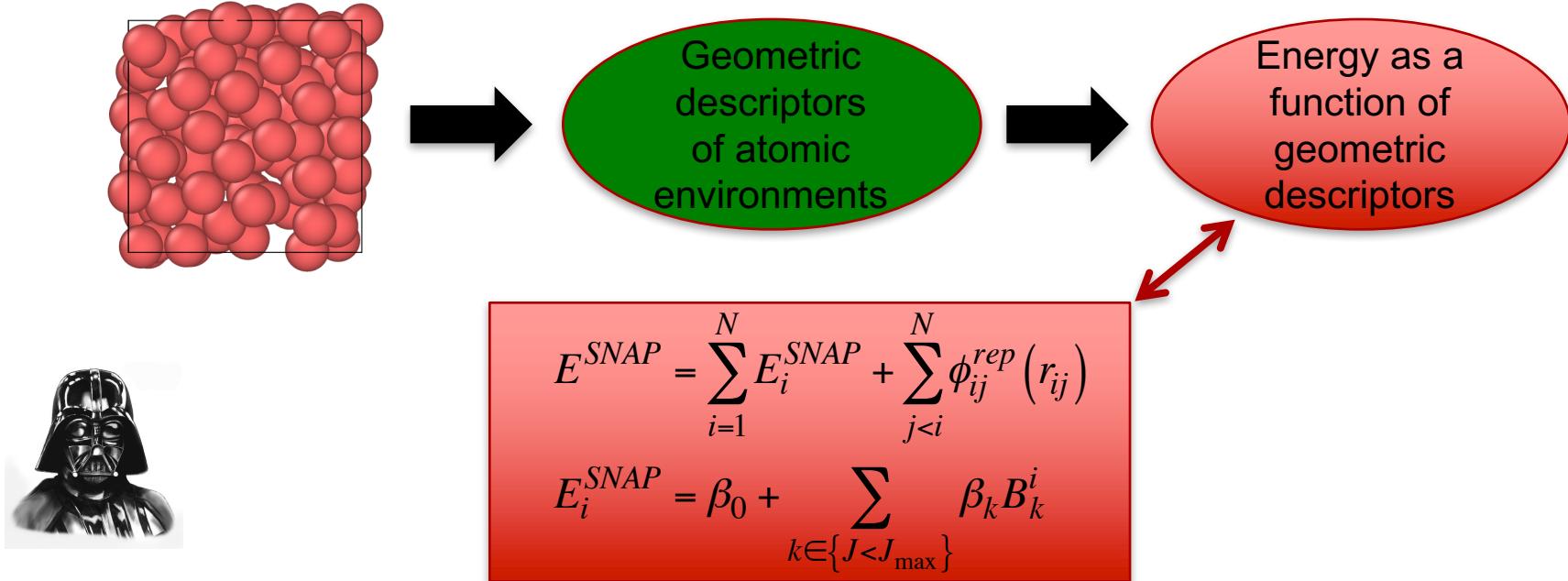


Shan, Wixom, Thompson, "Extended Asymmetric Hot Region Formation due to Shockwave Interactions Following Void Collapse in Shocked High Explosive", *Phys. Rev. B* **94** 054308 (2016)

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- Outlook

SNAP: Spectral Neighbor Analysis Potentials



- **GAP (Gaussian Approximation Potential):** Bartok, Csanyi et al., *Phys. Rev. Lett.* 2010. Uses 3D neighbor density bispectrum and **Gaussian process regression**.
- **SNAP (Spectral Neighbor Analysis Potential):** Our SNAP approach uses GAP's neighbor bispectrum, but replaces Gaussian process with **linear regression**.
 - More robust
 - Lower computational cost
 - Decouples MD speed from training set size
 - Enables large training data sets, more bispectrum coefficients
 - Straightforward sensitivity analysis

Bispectrum Components as Descriptor

- Neighbors of each atom are mapped onto unit sphere in 4D

$$(\theta_0, \theta, \phi) = \left(\theta_0^{\max} r/r_{cut}, \cos^{-1}(z/r), \tan^{-1}(y/x) \right)$$

- Expand density around each atom in a basis of **4D hyperspherical harmonics**,
- Bispectrum components of the 4D hyperspherical harmonic expansion are used as the geometric descriptors of the local environment
 - Preserves universal physical symmetries
 - Rotation, translation, permutation
 - Size-consistent

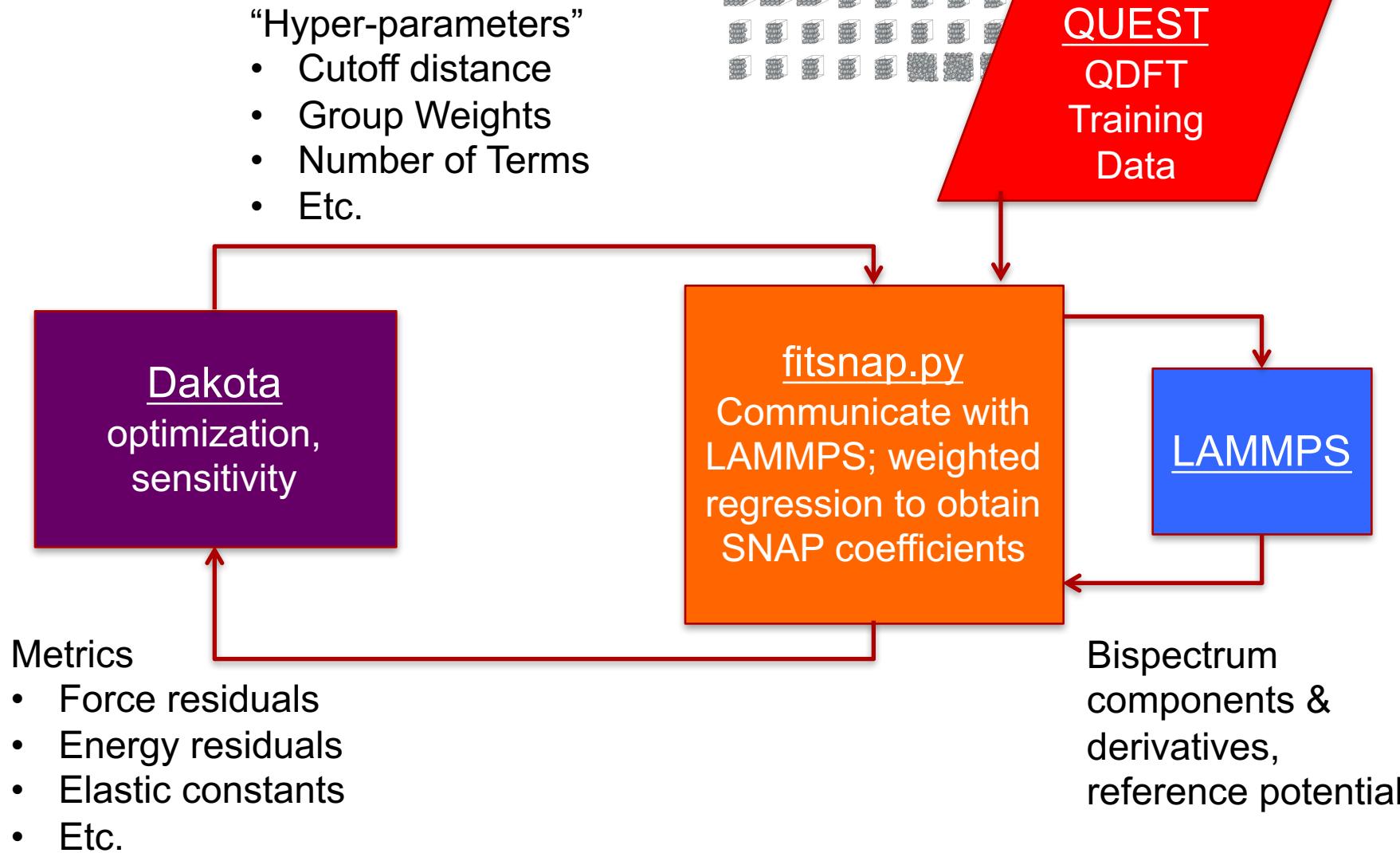
$$u_{m,m'}^j = U_{m,m'}^j(0,0,0) + \sum_{r_{ii'} < R_{cut}} f_c(r_{ii'}) w_i U_{m,m'}^j(\theta_0, \theta, \phi)$$

$$B_{j_1, j_2, j} = \sum_{m_1, m'_1 = -j_1}^{j_1} \sum_{m_2, m'_2 = -j_2}^{j_2} \sum_{m, m' = -j}^j (u_{m,m'}^j)^* H_{j_1 m_1 m'_1 \atop j_2 m_2 m'_2}^{j m m'} u_{m_1, m'_1}^{j_1} u_{m_2, m'_2}^{j_2}$$

Symmetry relation: $\frac{B_{j_1, j_2, j}}{2j + 1} = \frac{B_{j, j_2, j_1}}{2j_1 + 1} = \frac{B_{j_1, j, j_2}}{2j_2 + 1}$

SNAP Fitting Process

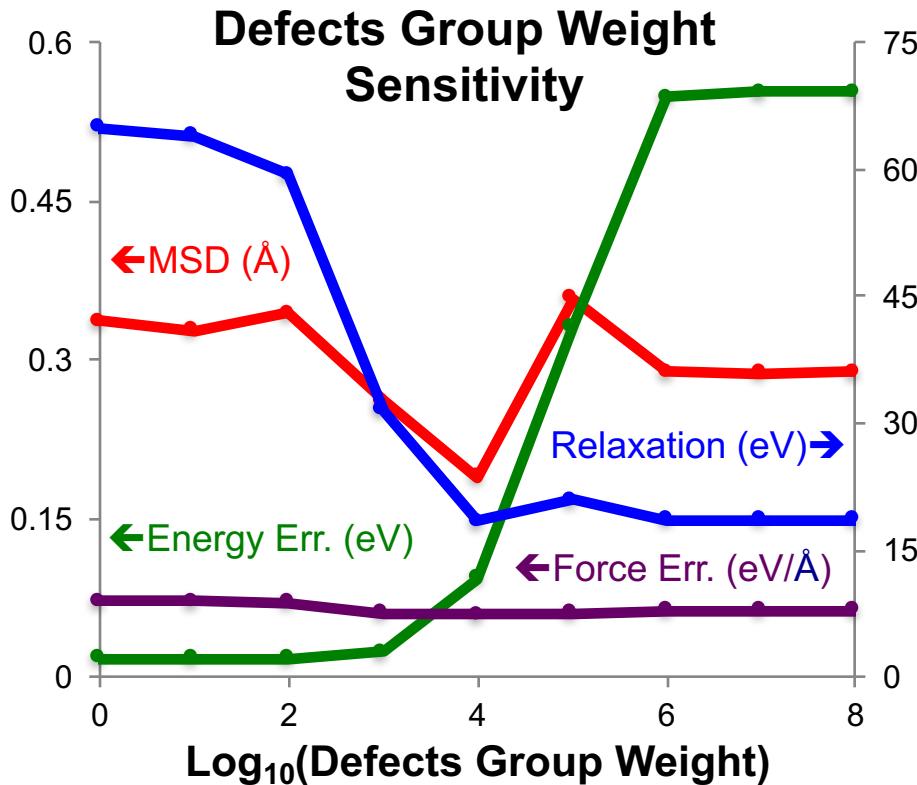
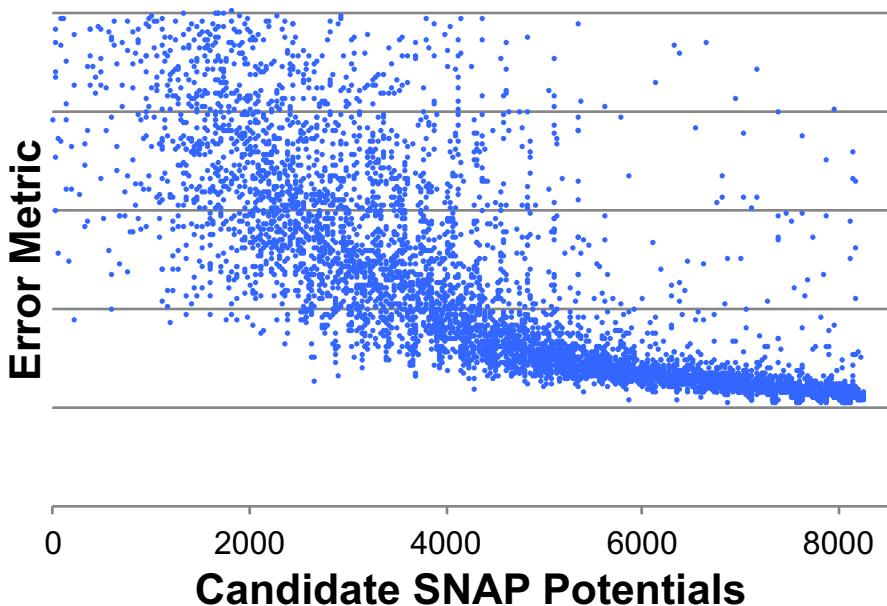
FitSnap.py



FitSnap.py: Robust Software Framework

- Fitting previously based on a fragile collection of shell scripts, Python scripts, and C++ code.
- All scripts and codes were brought under version control and systematically combined and re-written into a unified tool: fitsnap.py.

Hyper-parameter Optimization



Key advantages of fitsnap.py

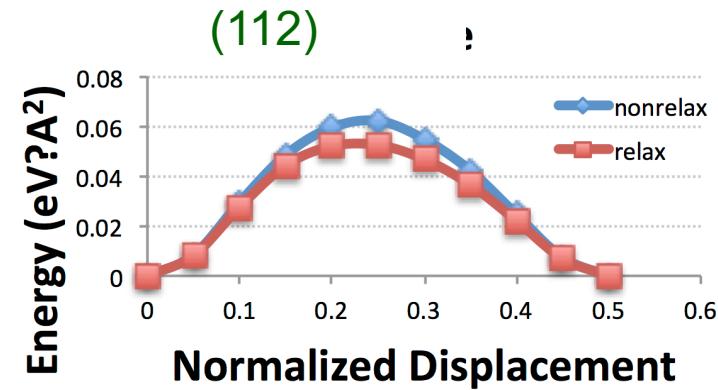
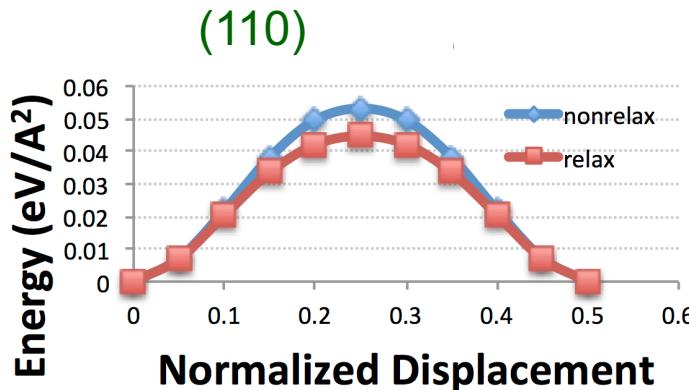
- Minimal file I/O
- Use of NumPy/SciPy
- Caching and reuse of data
- File-based input
- Supports parallel LAMMPS

Ta SNAP potential was fit to a DFT-based training set containing ‘usual suspects’

For each configuration in training set, fit total energy, atomic forces, stress

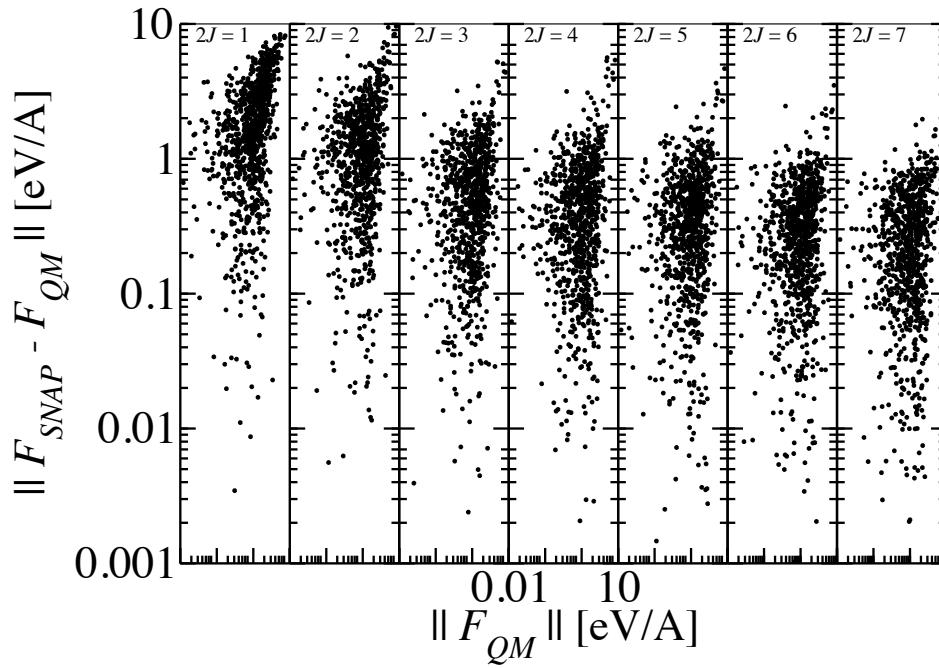
- Equilibrium lattice parameter
- Elastic constants (C_{11} , C_{12} , and C_{44}) and bulk modulus (B)
- Free surface energies: (100), (110), (111), and (112)
- Generalized planar stacking fault curves: {112} and {110}
- Energy-Volume (Contraction and Dilation) - BCC, FCC, HCP, and A15
- Lattices with random atomic displacements
- Liquid structure

Example: DFT-based Generalized Stacking Fault Energies



Effect of Higher-order Bispectrum Components

- Liquid force errors decrease with increasing J
- Diminishing returns beyond $J = 7/2$



$2J$	N	Ferr
1	2	2.09
2	5	1.39
3	8	0.66
4	14	0.53
5	20	0.44
6	30	0.35
7	40	0.30

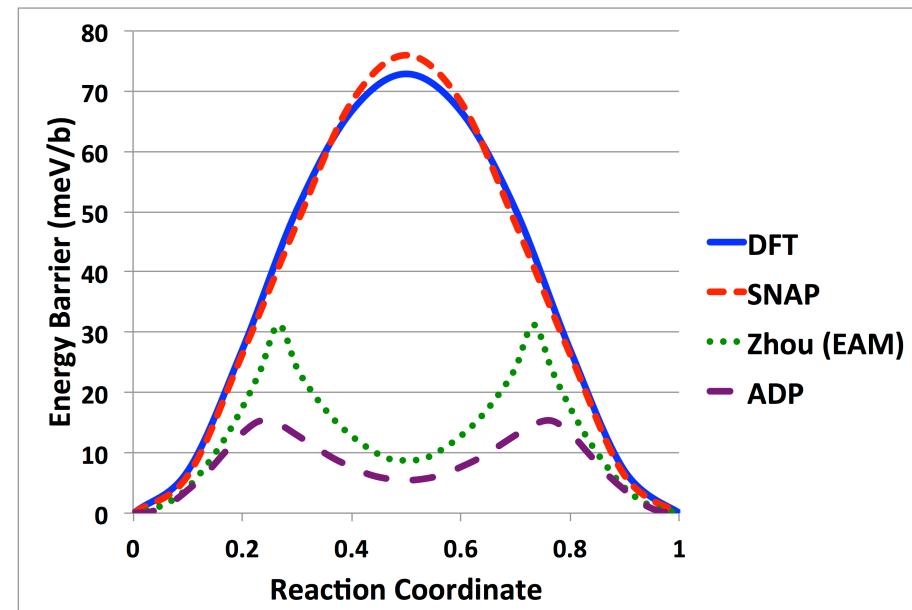
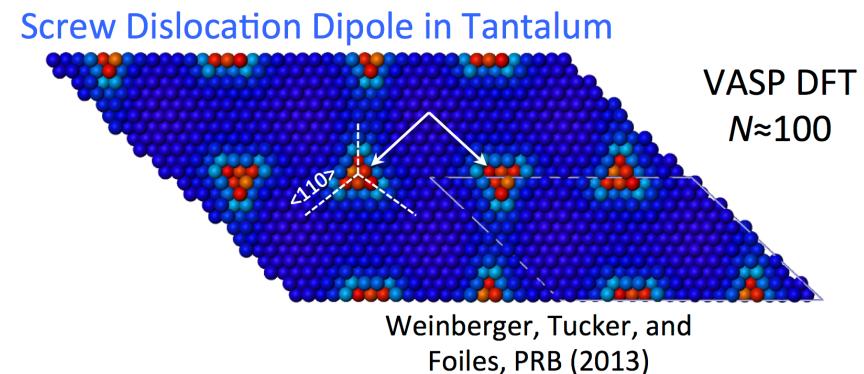
SNAP potential yields good agreement with DFT results for some standard properties

	DFT	SNAP	Zhou (EAM)	ADP
Lattice Constant (Å)	3.320	3.316	3.303	3.305
B (Mbar)	1.954	1.908	1.928	1.971
$C' = (1/2)(C_{11} - C_{12})$ (Mbar)	50.7	59.6	53.3	51.0
C_{44} (Mbar)	75.3	73.4	81.4	84.6
Vacancy Formation Energy (eV)	2.89	2.74	2.97	2.92
(100) Surface Energy (J/m ²)	2.40	2.68	2.34	2.24
(110) Surface Energy (J/m ²)	2.25	2.34	1.98	2.13
(111) Surface Energy (J/m ²)	2.58	2.66	2.56	2.57
(112) Surface Energy (J/m ²)	2.49	2.60	2.36	2.46
(110) Relaxed Unstable SFE (J/m ²)	0.72	1.14	0.75	0.58
(112) Relaxed Unstable SFE (J/m ²)	0.84	1.25	0.87	0.74

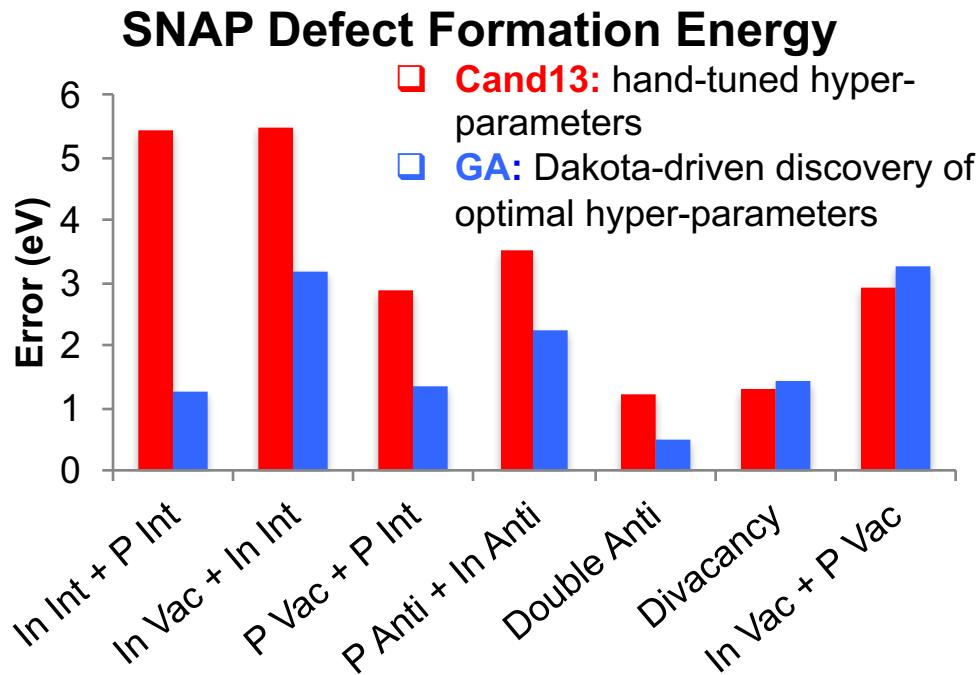
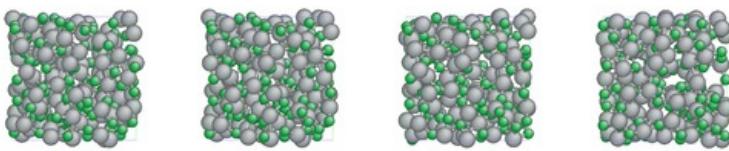
SNAP potentials predict correct Peierls barrier for Ta screw dislocations

A. P. Thompson, L.P. Swiler, C.R. Trott, S.M. Foiles, and G.J. Tucker, *J. Comp. Phys.*, **285** 316 (2015).

- Peierls barrier is the activation energy to move a screw dislocation
- Many simple interatomic potentials incorrectly predict a metastable state
 - Leads to erroneous dynamics
- SNAP potential agrees well with DFT calculations
 - Future work will explore dislocation dynamics based on this potential



SNAP Indium Phosphide



Additional Challenges

- Two elements
- Different atom sizes
- Diverse structures
- Defect formation energies
- Sensitive to curvature

Innovations

- Differentiate elements by: density weight, linear coefficients, neighbor cutoff
- Trained against relaxed defect structures
- Trained against deformed defect structures

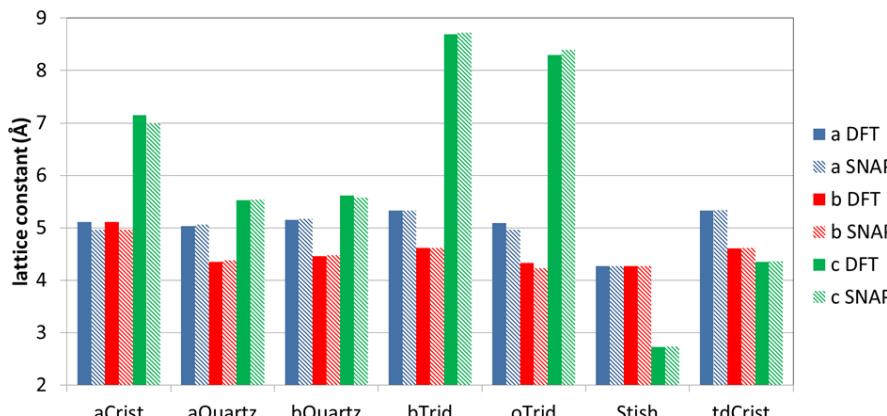
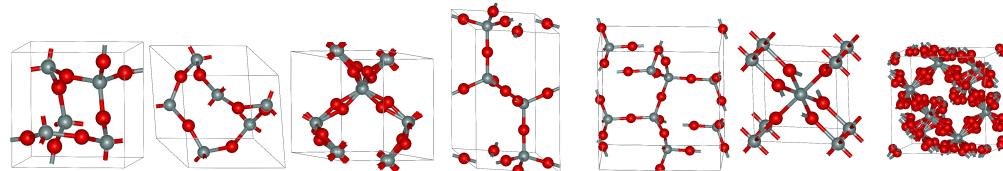
Result

- Good overall fit
- Defect energy error > 1 eV

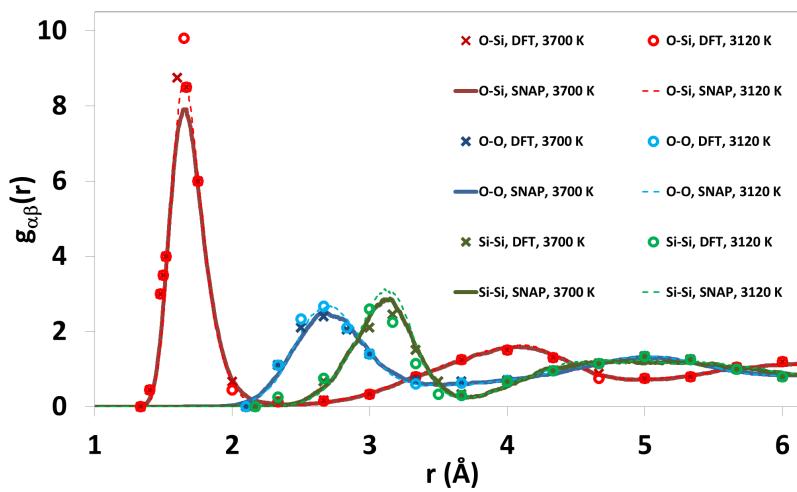
SNAP Silica: Promising Start

(Stan Moore, Paul Crozier, Peter Schultz)

Less than 3% error in predicted lattice parameters of 7 crystal polymorphs



Good agreement with QM liquid structure for SiO₂



Additional Challenges

- Electrostatics
- Started with no training data
- Goal: quantum-accurate prediction of Si/SiO₂ interface

Innovations

- Generated training data adaptively, on-the-fly
- Added fixed point charges, long-range electrostatics

Result (so far)

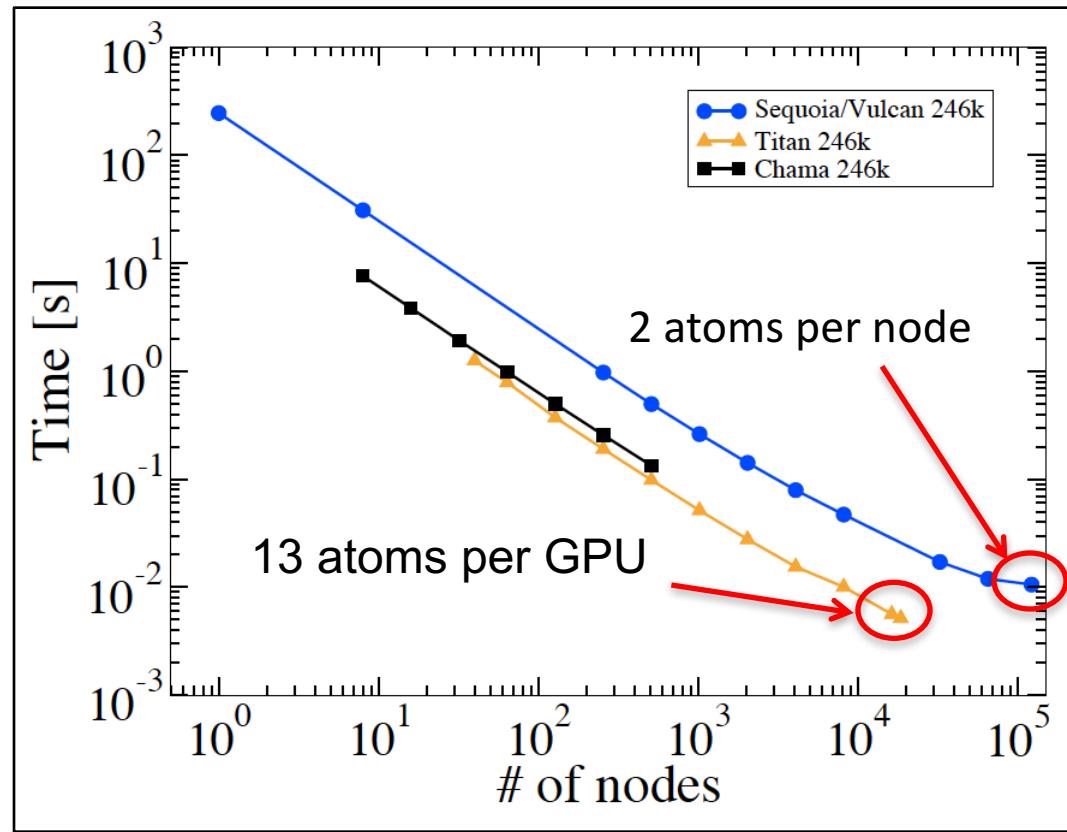
- Good agreement with QM for SiO₂ crystal polymorphs
- Good agreement with QM liquid structure for SiO₂

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- SNAP
- **Outlook**

Bigger Computers \leftrightarrow More Expensive Potentials

**Strong-scaling LAMMPS MD Benchmark
with SNAP Tantalum Potential**



Bigger Computers Better Potentials

Quantum-Accurate MD Simulations Leveraging Exascale Computing Resources

1. Generation of large QM training datasets
2. UQ analysis via simulations with ensembles of potentials
3. On-the-fly potential development combining quantum-accurate MD with on-demand generation of QM training data
4. Database-driven MD simulations with forces interpolated directly on dynamic database of quantum calculations

Conclusions

- Ever-increasing demand for interatomic potentials that can quantitatively match quantum methods and other data sources
- Driving continued development of both traditional potentials and automated machine learning potentials 
- This work is inherently multidisciplinary, requiring expertise in computational materials science, electronic structure methods, scientific computing, and statistical analysis.

Collaborators

Ray Shan

Steve Plimpton

Reese Jones

Laura Swiler

Stephen Foiles

Garrett Tucker

Christian Trott

Peter Schultz

Mitch Wood

Paul Crozier

Stan Moore

Adam Stephens