

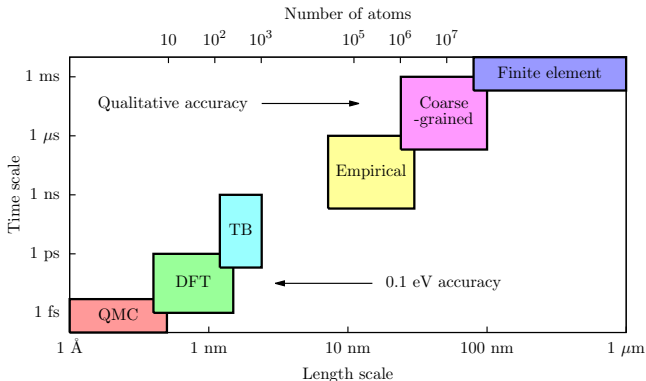
The gap-tungsten-1 interatomic potential.

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Computational Modelling of Materials



- Significant cost savings can be realized in materials design and in process optimization by using science-based computational modelling
- Calculations from first principles lead to predictive capabilities that allow discovering novel materials with desired properties

Creating Empirical Potentials

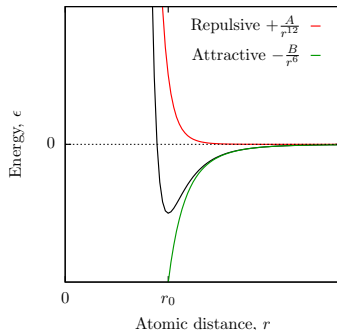
- Typical interatomic potential
 - fixed functional form with adjustable parameters (i.e. empirical, analytical formula)
 - fit fixed number of free parameters to reproduce target properties

$$E = \sum_i^N V_1(\mathbf{x}^{(i)}) + \underbrace{\sum_i^N \sum_{\substack{j \\ j < i}}^N V_2(\mathbf{x}^{(i)}, \mathbf{x}^{(j)})}_{\text{bonds}} + \underbrace{\sum_i^N \sum_{\substack{j \\ j < i}}^N \sum_{\substack{k \\ k < j}}^N V_3(\mathbf{x}^{(i)}, \mathbf{x}^{(j)}, \mathbf{x}^{(k)})}_{\text{angles}} + \dots$$

Lennard-Jones (LJ) Potential

$$E = \sum_i^N \epsilon_i$$

$$\epsilon_i = \sum_j^N \left(\frac{A}{r^{12}} - \frac{B}{r^6} \right)$$



- choose target properties
- fit parameters A and B to reproduce target properties

Gaussian Process Regression

- Start with prior distribution over functions
- Set of values is observed
- Apply **Bayesian probability** / **machine learning** to infer underlying function

Bayes' theorem

$$\text{posterior} = \frac{\text{likelihood} \times \text{prior}}{\text{marginal likelihood}}$$

- Combine Gaussian prior with Gaussian likelihood function for each observed value to calculate posterior distribution for any new location

Gaussian Process Regression

- Optimal way of interpolating many-dimensional functions
- No fixed functional form
- No fixed number of free parameters

$$\epsilon_i(\mathbf{q}_i) = \sum_j \alpha_j \overbrace{k(\mathbf{q}_j, \mathbf{q}_i)}^{\text{covariance function}}$$
$$\sigma_{\epsilon_i}^2(\mathbf{q}_i) = k(\mathbf{q}_i, \mathbf{q}_i) - \sum_j \beta_j k(\mathbf{q}_j, \mathbf{q}_i)$$

Covariance function $k(\mathbf{q}_j, \mathbf{q}_i)$

Prior distribution over functions is determined by choice of the covariance function.

Gaussian Process Regression

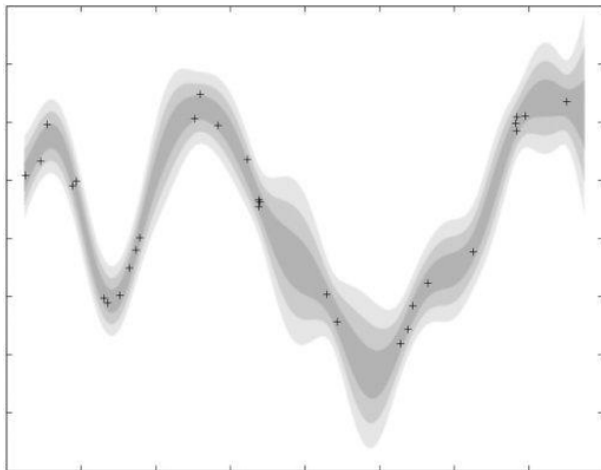
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Training data $\{\epsilon_j, \mathbf{q}_j\}_j$

Fit quality determined by both training data and choice of the covariance function.

Gaussian Process Regression



Gaussian Approximation Potential

- Compute many-body atomic energy function

$$\epsilon_i = \epsilon(\{\mathbf{x}_j - \mathbf{x}_i\}_j^N) = \epsilon(\mathbf{q}_i)$$

- Fit to arbitrary precision QM data
- **Need rotationally and permutationally invariant description of atomic environment!**

Descriptor vs. covariance function symmetries

$$\begin{array}{ccc} k(\mathbf{q}_j, \mathbf{q}_i) & & \\ + & \longleftrightarrow & k^*(\{\mathbf{x}_{k''} - \mathbf{x}_j\}_{k''}, \\ \{\mathbf{x}_{k'} - \mathbf{x}_i\}_{k'} \rightarrow \mathbf{q}_i & & \{\mathbf{x}_{k'} - \mathbf{x}_i\}_{k'}) \end{array}$$

Gaussian Approximation Potential

Bispectrum

expand atomic density
using 4d spherical
harmonics basis

atoms represented by
Dirac δ function

square exponential
covariance

Smooth Overlap of Atomic Positions

expand atomic density
using 3d spherical
harmonics and radial
basis

atoms represented by
Gaussian function

dot product
covariance

Gaussian Approximation Potential

- **Atomic energies cannot be directly computed from QM data!**

Training from total energies, forces and stresses

Inferring function $\epsilon(\mathbf{q}_i)$ from linear combination of its values / partial derivatives (and atomic positions) possible.

total energies:
$$E = \sum_i^N \epsilon_i$$

atomic forces:
$$\{\mathbf{f}^{(i)} = -\nabla^{(i)} \sum_j^N \epsilon_j\}_i^N$$

stress virials:
$$\tau_{\alpha\beta} = -\sum_i^N x_\alpha^{(i)} \frac{\partial}{\partial x_\beta^{(i)}} \sum_j^N \epsilon_j$$

- Pseudo training points to deal with large data sets efficiently (which optimally represent the underlying teaching data)

Tungsten

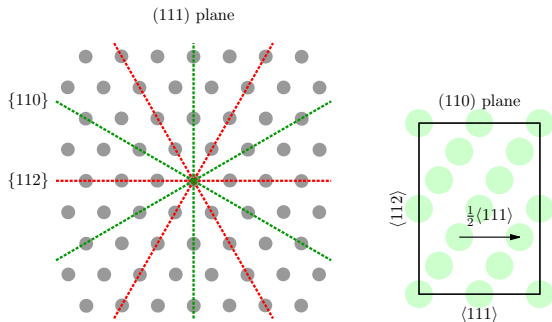
- Refractory transition metal with the highest melting temperature (3680 K)
- Crystallized in a body-centered-cubic (BCC) structure



- Applications include
 - light bulb filaments, electrical contacts, welding electrodes and high-temperature furnace elements
 - tungsten might be one of the structural materials for fusion reactor ITER project

Tungsten

- Slip can occur along nearest neighbour direction $\frac{1}{2}\langle 111 \rangle$ (also the shortest Burgers vector)
- The most densely packed planes of the $\langle 111 \rangle$ zone are the $\{110\}$ planes



Tungsten Slip Planes

**Slip plane
separation distance**

$$\langle 111 \rangle \{ 110 \} \rightarrow \frac{1}{\sqrt{2}} a$$

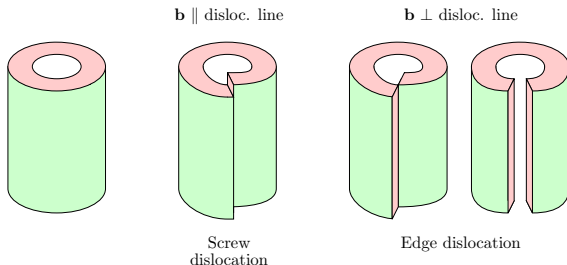
$$\langle 111 \rangle \{ 112 \} \rightarrow \frac{1}{\sqrt{6}} a$$

$$\langle 111 \rangle \{ 123 \} \rightarrow \frac{1}{\sqrt{14}} a$$

$$\langle 111 \rangle \{ 134 \} \rightarrow \frac{1}{\sqrt{26}} a$$

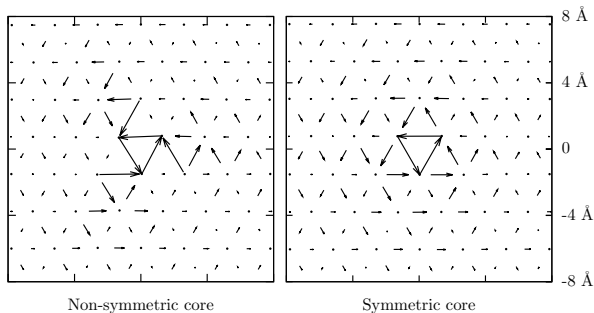
Tungsten Dislocations

- Plasticity behaviour largely attributed to lattice crystallography
- Dominant dislocation type in bcc metals is $\frac{1}{2}\langle 111 \rangle$ screw
- $\langle 110 \rangle$ dislocations observed, but believed to be product of the dominant $\frac{1}{2}\langle 111 \rangle$ screw dislocations

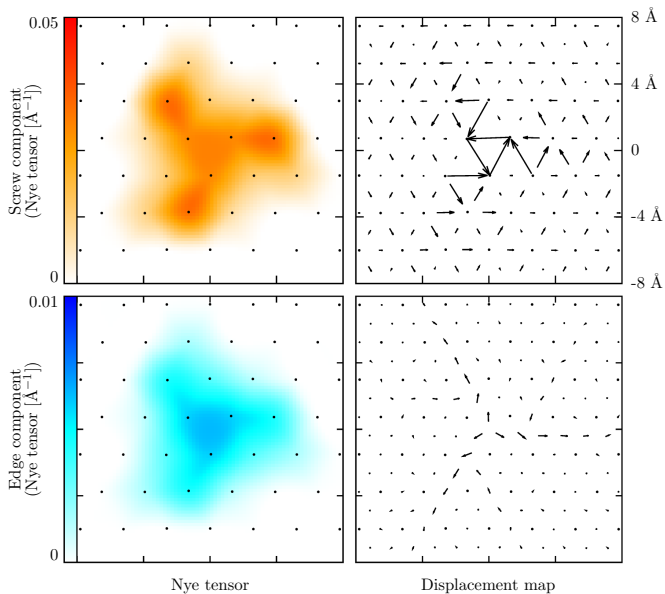


Dislocation Core

- At long range behaviour is determined by the linear elasticity theory
- Short range dislocation core structure

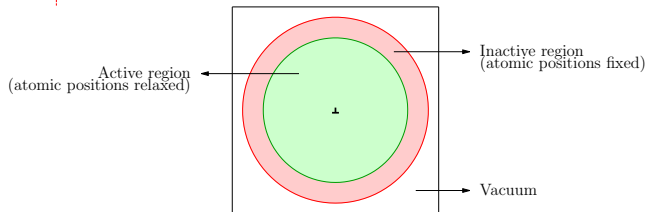
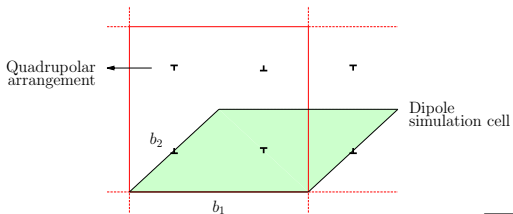


Dislocation Displacement Maps vs. Nye Tensor



Dislocation Simulation Approaches

Dislocation Quadrupole



Isolated Dislocation

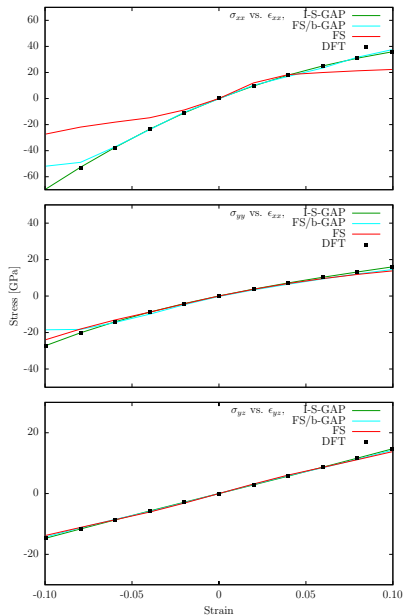
DFT parameters for converged energies, forces and stresses

plane-wave energy cutoff,	E_{cut}	\rightarrow	600	eV
k -point sampling density,	ρ	\rightarrow	0.015	\AA^{-1}
smearing width,	w	\rightarrow	0.1	eV

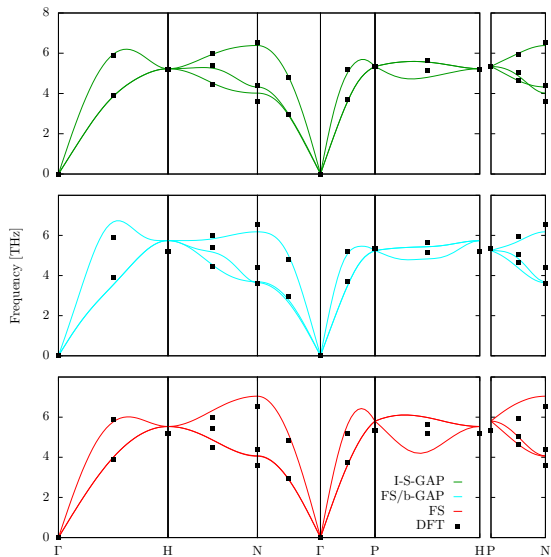
GAP Recipe

- | | | | |
|----|--|---|---|
| 1. | Elastic constants
2000 environments | → | MC sampling in the lattice space
temperature: 300 K <ul style="list-style-type: none">● slice sampling algorithm● primitive unit cell |
| 2. | Phonon spectrum
7680 environments | → | MD, no defects
temperature: 300, 1000 K
volumes: ground state, $\pm 1\%$ <ul style="list-style-type: none">● 128 at. simulation cell |
| 3. | Vacancy
23740 environments | → | MD, isolated monovacancy
temperature: 300, 1000 K
volumes: ground state, $\pm 1\%$ <ul style="list-style-type: none">● 53 and 127 at. simulation cell |
| 4. | Surfaces
2160 environments | → | MD, (100), (110), (111), (112)
temperature: 300 K
volumes: ground state <ul style="list-style-type: none">● 12 at. simulation cell |
| 5. | Gamma surfaces
74196 environments | → | MD, (110), (112)
temperature: 300 K
volumes: ground state, $\pm 1\%$ <ul style="list-style-type: none">● 12 at. simulation cell |

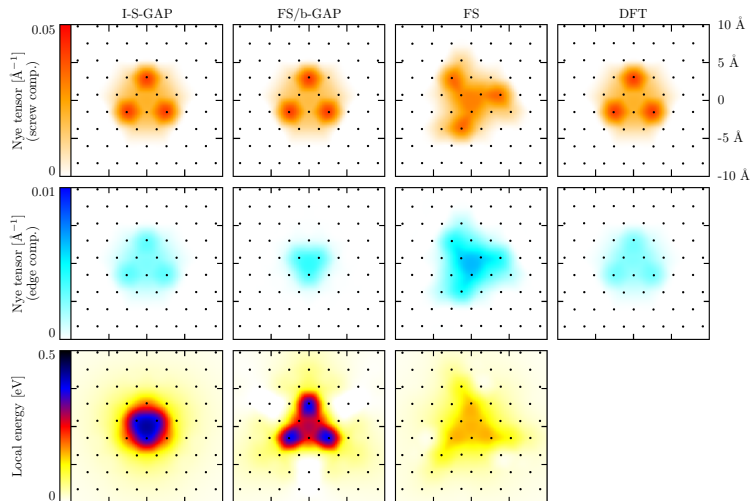
GAP Results



GAP Results

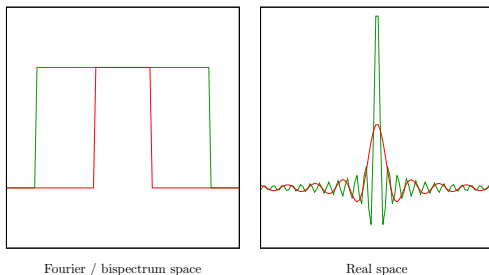


GAP Results



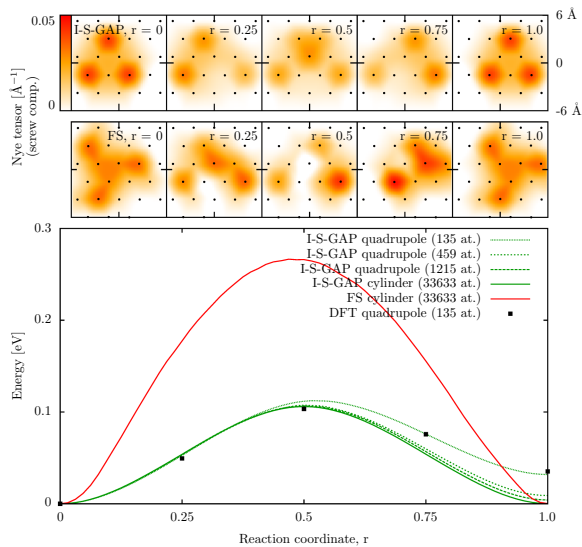
Bispectrum vs. SOAP

- Both bispectrum and SOAP are based on expansion in spherical harmonics that needs to be truncated

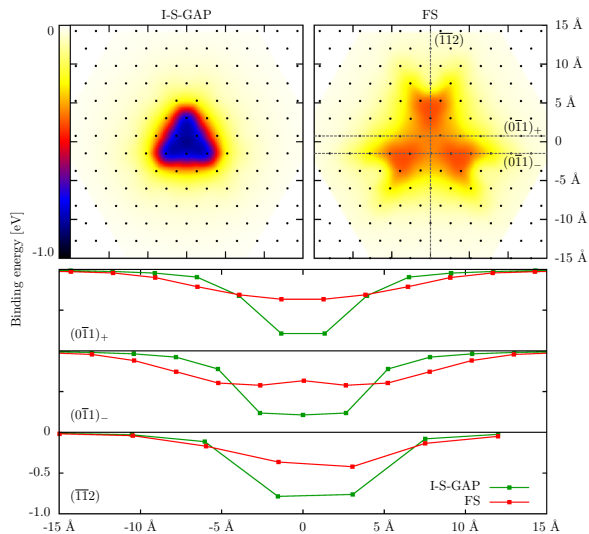


- **Failure of bispectrum based GAP is caused by the use of Dirac δ functions!**

GAP Results



GAP Results



Further Work

Tungsten Potential

- Crack propagation
- Dislocation jogs/kinks

Other Transition Metals

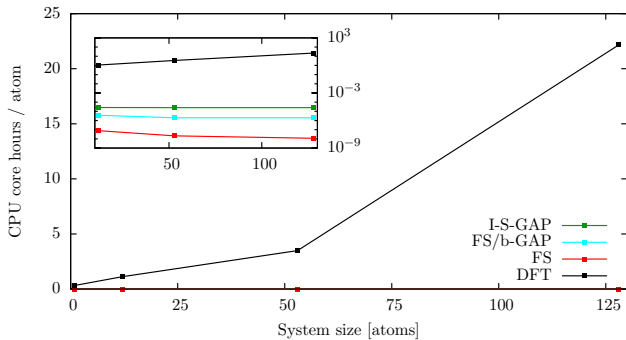
- Iron, iron + hydrogen
- Group 5 and 6 transition metals

Method Improvements

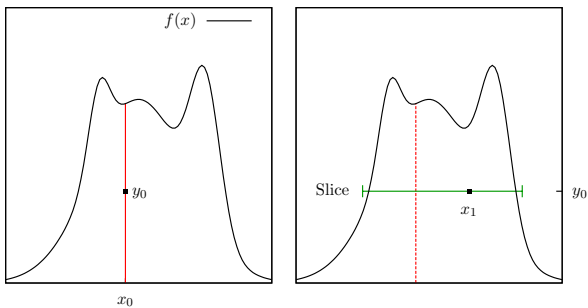
- Bond based smooth overlap of atomic positions
- Improvements to sparsification (dealing with large datasets)

Thank you for your attention.

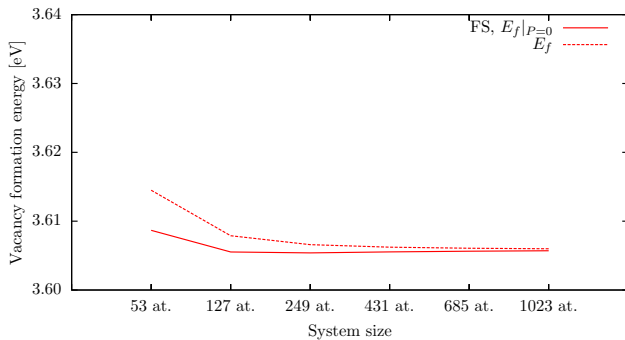
Appendix



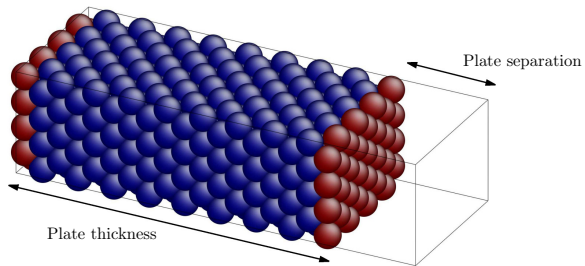
Appendix



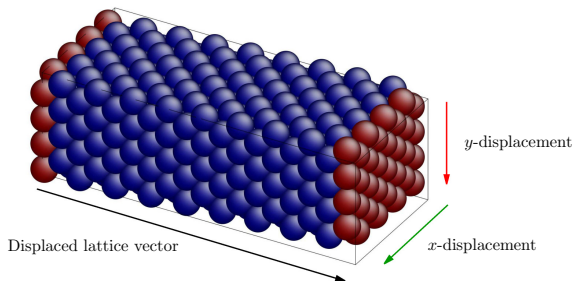
Appendix



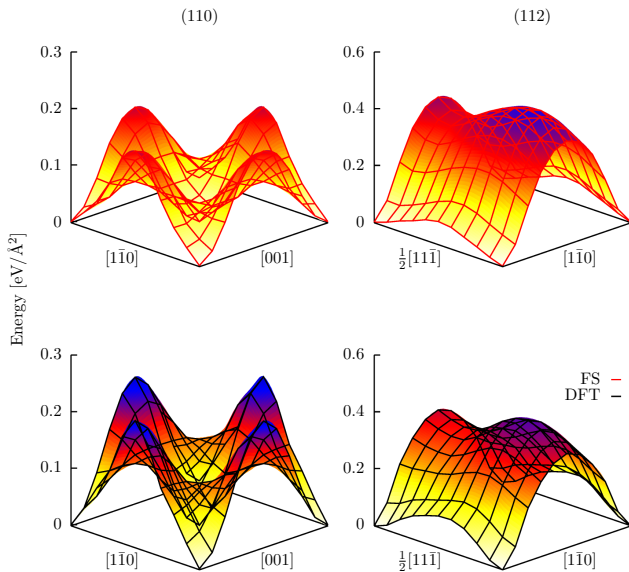
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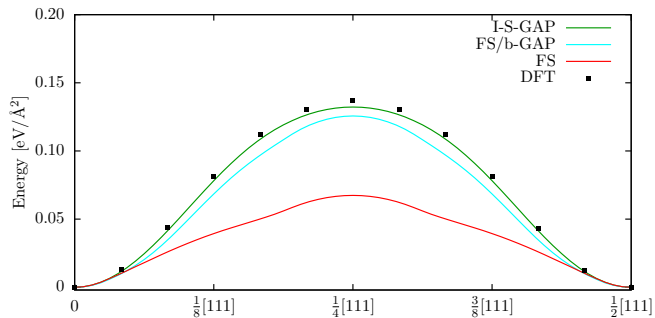
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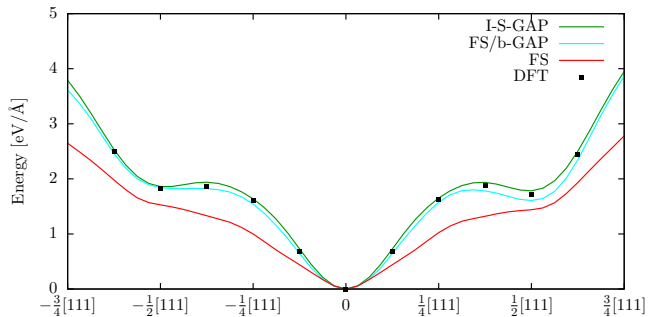
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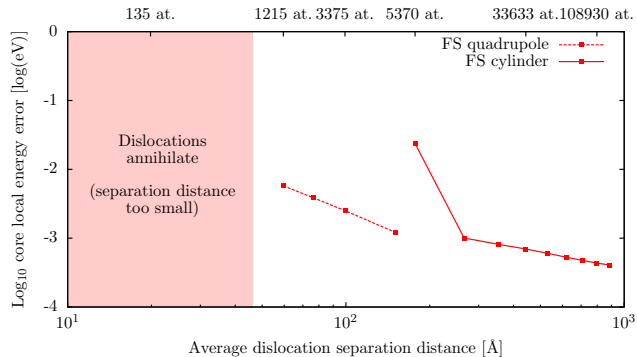
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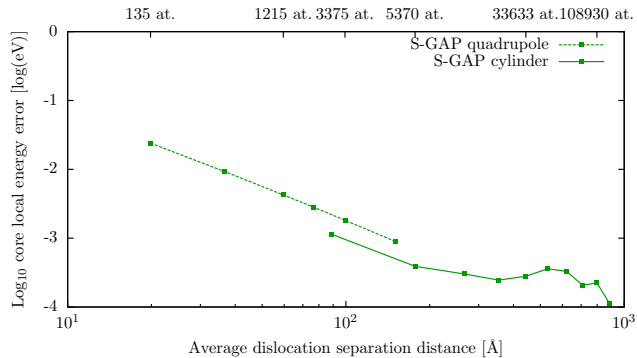
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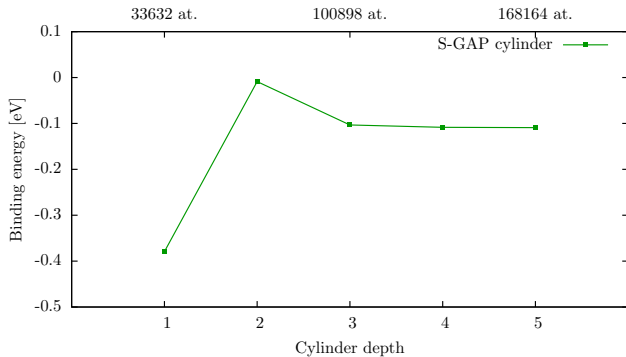
Appendix



Appendix



Appendix



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