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From First-Principles toward atomistic understanding of mechanical properties in High-Entropy Alloys

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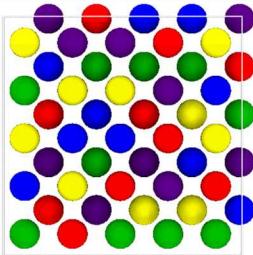
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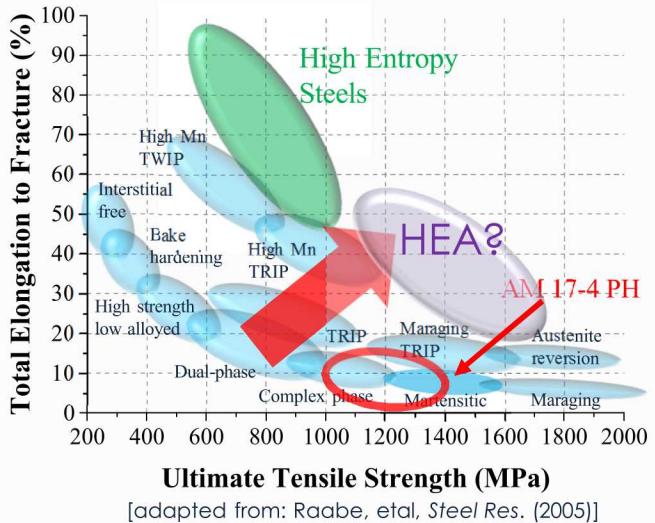
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Why High Entropy Alloys - HEA?

High entropy alloys



- ▶ Random composition crystalline alloys, four or more principal equiatomic constituents.
- ▶ Great potential for structural applications: strong, degradation-resistant.
- ▶ Amenable to additive manufacturing-AM?



Goal:

AM-friendly HEA alloy for high-temperature structural applications: high ductility and fracture resistant

Challenges:

High dimension composition space
Constraints of AM conditions

Need:

Physics-based framework to guide discovery/development of HEA

Focus: **systematic computational framework** for atomic-based structure-property relationships.

- What do you want? Structure-property relationships
 - structural stability → composition, phases, enthalpies
 - strength → ductility, shear properties (and at high temperature)
- Need:
 1. Accuracy of DFT (or better?) – too big/complex for DFT
 2. Dynamical properties with MD – *InterAtomic Potentials* not accurate/available
 3. Meso-scale microstructure evolution – lack effective models

DFT → IAP → MD → Meso

MULTISCALE in the face of LARGE COMBINATORIAL COMPLEXITY

Exemplar: refractory **Al-Nb-Ti** — “simple”, interesting, less studied

SNAP – Spectral Neighbor Analysis Potentials

- ▶ SNAP describes local environment as atomic (particle) density:

$$\rho_i(\mathbf{r}) = \delta(\mathbf{r}) + \sum_{r_{ij} < R_{cut}} f_c(r_{ij}) w_i \delta(\mathbf{r} - \mathbf{r}_{ij})$$

w_i = weights defining atomic species
 f_c = radial switching functions

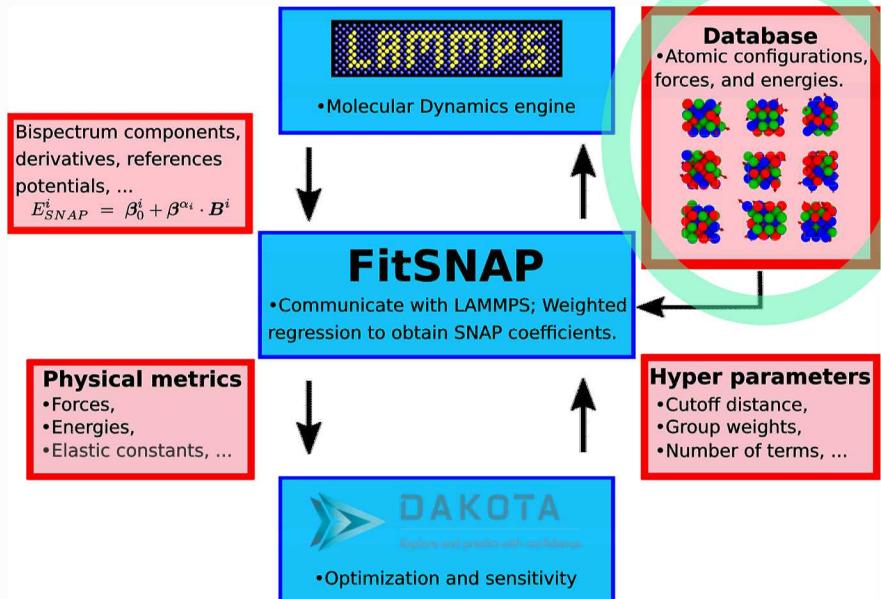
- ▶ Density expressed in terms of bispectrum components. Those bispectrum components express energy and forces on each atom:

$$\left\{ \begin{array}{l} E_{SNAP}^i = \beta_0^i + \beta^{\alpha_i} \cdot \mathbf{B}^i \\ \mathbf{F}_{SNAP}^j = -\beta \cdot \sum_{i=1}^N \frac{\partial \mathbf{B}_i}{\partial \mathbf{r}_j} \end{array} \right.$$

- ▶ Fit bispectrum components and weights to reproduce potential energy surface of DFT.

Data/ML-driven interatomic potential

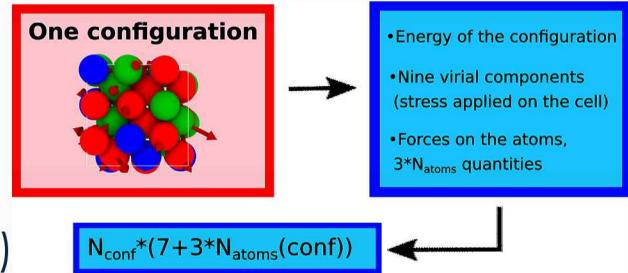
Thompson, A. P., et al.. (2015). J. Comp. Phys., 285, 316-330.



... Only as good as its data

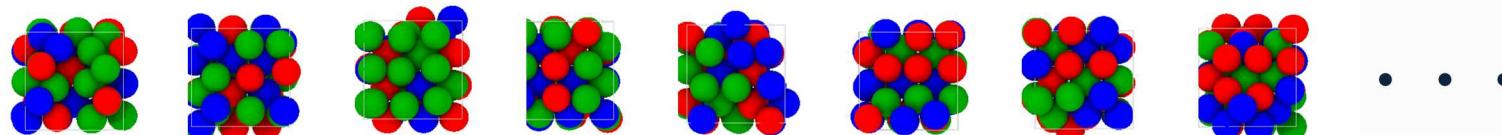
Goals with DFT:

- accurate structure/composition energies
- accurate elastic properties
- discern crucial materials physics of HEA
- computationally practical (combinatorial complexity)



Representative "SQS" model **impractical** and **insufficient** for HEA alloys

Strategic sampling of random 54-atom cubic (3x3x3) cells:



- atoms isolated (near-sightedness), “cheap”, equi-composition (18-18-18)

- General purpose DFT code **SeqQuest** (<http://dft.sandia.gov/Quest>)
 - well-converged (Gaussian-based) local orbital basis
 - both LDA and PBE functionals
 - converged norm-conserving pseudopotentials
 - full force-relaxed atoms
 - stress-relaxed cells (accurate stress-strain)
 - carefully verified against converged FP-LAPW results
- **HEA supercells**
 - 54-atom cubic supercells (3x3x3 conventional 2-atom bcc cubic cell)
 - real-space grids: 96^3
 - offset k-grids
 - Constrained to cubic
- **And then also Quantum Espresso**

			a_0 (Å)	c_0 (Å)	c/a	B(GPa)	Energy
Al	expt.	fcc	4.04			72.2	
	PBE	fcc	4.053			75	0
		bcc	3.246			67	+0.093 eV/Al
Nb	expt.	bcc	3.30			170.2	
	PBE	bcc	3.316			171	0
Ti	expt.	hcp	2.95	4.68	1.586	105.1	
	PBE	hcp	2.931	4.662	1.590	114	
		bcc	3.352			108	+0.104/Ti

**SeqQuest/PBE: lattice constants within < 1%
bulk moduli within 8%**

DFT– two-component B2/bcc alloys



a_0 (Å)	Al	Nb	Ti
Al	3.246		
Nb	3.236	3.316	
Ti	3.188	3.270	3.352

Expect $a_0 \sim 3.2\text{-}3.3$ Å for HEA

B (GPa)	Al	Nb	Ti
Al	67		
Nb	141	171	
Ti	113	135	108

Expect $B \sim 110\text{-}140$ GPa for HEA

H_f (eV/fu)	Al	Nb	Ti
Al	+0.186		
Nb	-0.050	0	
Ti	-0.537	+0.136	+0.206

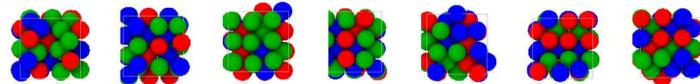
Ti – Al very happy
Nb – Ti less happy

H_f^{bcc} (eV/fu)	Al	Nb	Ti
Al	0		
Nb	-0.143	0	
Ti	-0.733	+0.035	0

Binding dominated by Ti – Al?

Need to be concerned about intermetallics?

DFT Equation-of-State for HEA



7 random colorings X 6 element mappings
42 $\text{Al}_{18}\text{-Nb}_{18}\text{-Ti}_{18}$ cells

	a_0 (Å)	B (GPa)	H_f (meV/at)
18-18-18	3.246 (2)	125 (2)	176 (14)
Al-Nb-Ti			
20-19-15	3.245	125	190
19-21-14	3.249	129	175
17-15-22	3.242	124	170
21-14-19	3.240	114	186
20-16-18	3.242	122	184

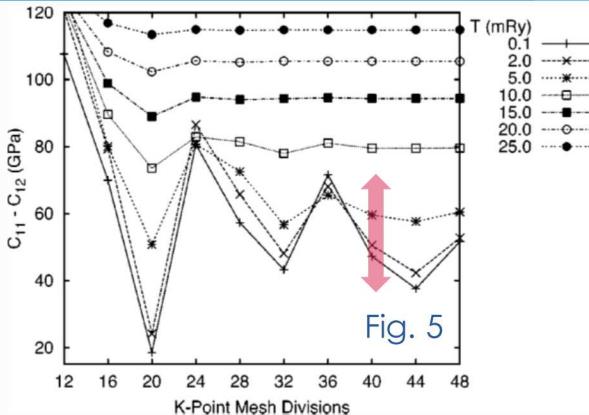
Consistent between 42 random cells:
Random-54 cell ~ "SQS"

Deviation from equi-atomic:
Not sensitive



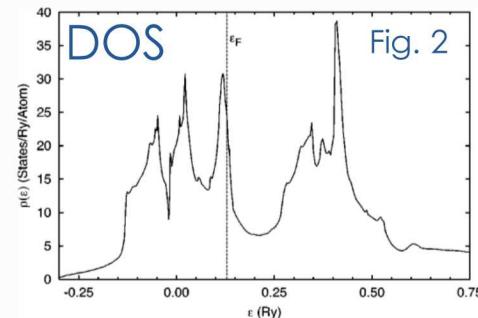
Vindicates sufficiency of 54-site cells.

Shear – k-point catastrophe?



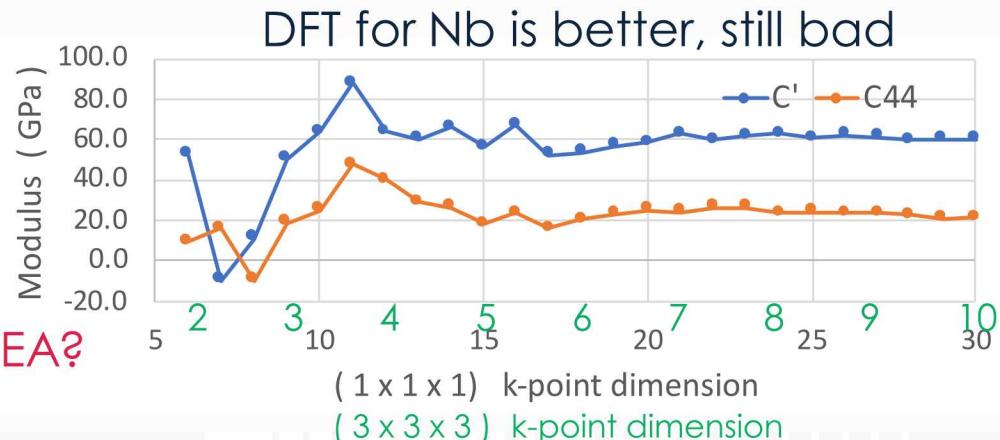
Mike Mehl, PRB **61**, 1654 (2000)
Nb – Tight Binding

- Shear moduli do not converge
- Structure interacts with DOS at ϵ_f

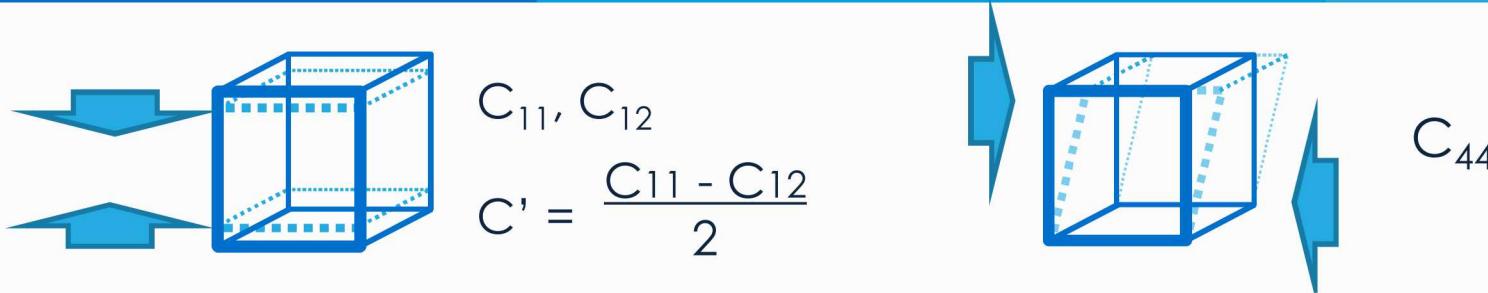


General issue for metals –
Ta is worse (MSMSE 13, R1 2009)
Al is worse
NbTi (B2) is worse

Need expensive $>5^3$ k-points for HEA?



HEA elastic constants – strain-stress Hooke's Law



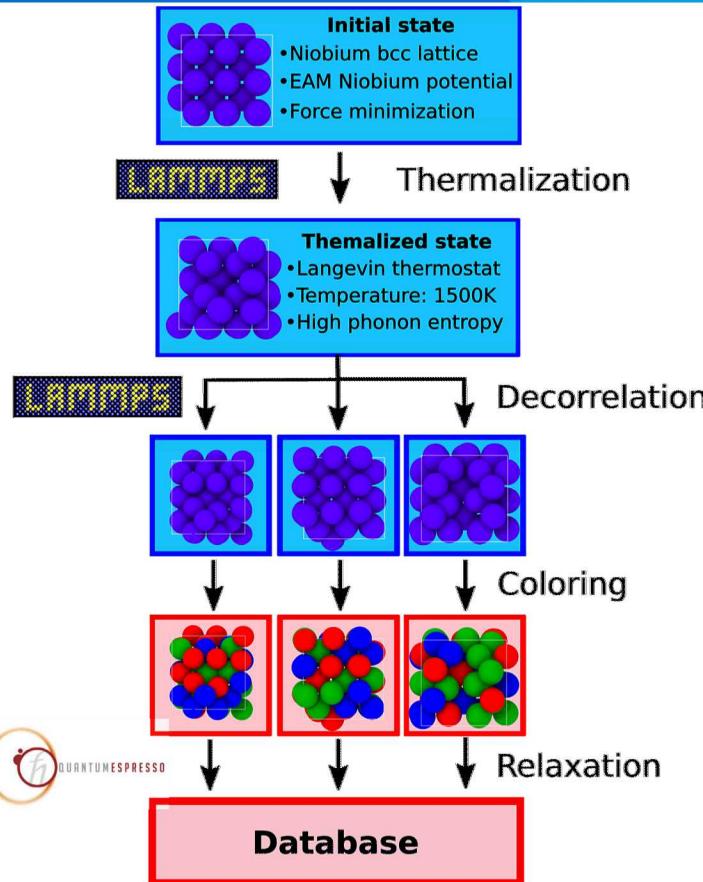
$k(1 \times 1 \times 1)$	$k(54\text{-cell})$	$C' \text{ (GPa)}$	$C_{44} \text{ (GPa)}$	$B \text{ (GPa)}$
$6 \times 6 \times 6$	$2 \times 2 \times 2$	15	69	125
$9 \times 9 \times 9$	$3 \times 3 \times 3$	17	70	125
$12 \times 12 \times 12$	$4 \times 4 \times 4$	18	71	126

Very fast convergence

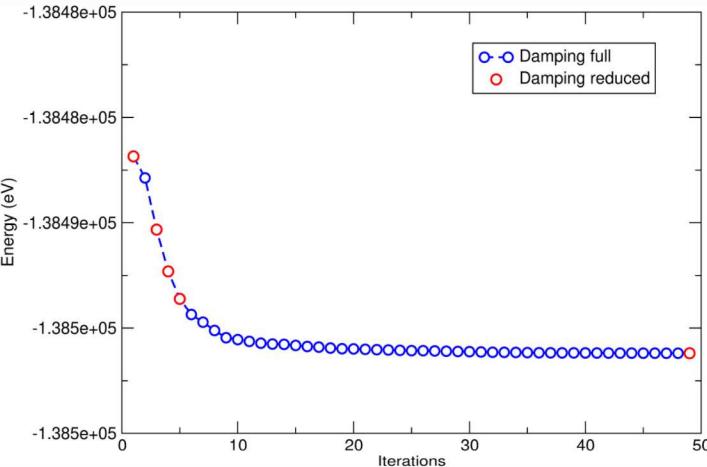
Compositional randomness → localizes electrons, damps electronic effects

DFT → IAP: sampling of small (54-atom), fast ($2 \times 2 \times 2$ k-pts) cells suffices

Framework for generating (decorrelated) DFT data



- ▶ 600 decorrelated MD configurations sampled
- ▶ DFT relaxation ~40 steps → ~24000 configurations
- ▶ Use 5 energy-distinct points → 3000 configurations



- ▶ Future:
 - Use ML to filter this copious data set.
 - Use ML to identify and augment deficiencies

- Developed physics-based protocol for DFT training data
 - Sampling small 54-site cells, random-composition sufficient
 - Small k-points suffice – atomic structure \leftrightarrow electronic structure
 - Huge training data possible \rightarrow ideal for ML
- Path to combinatorial 4-5-6-7 component HEA
 - Insensitivity to most variations in local environment
 - SNAP-ML potentials & training data protocols accommodate large data
- Future challenges:
 - Will these potentials really work? - see you next year
 - Can DFT and MD-SNAP give good enough data to inform meso?