

Accelerated Materials Discovery & Characterization with Quantum and Machine learning approaches

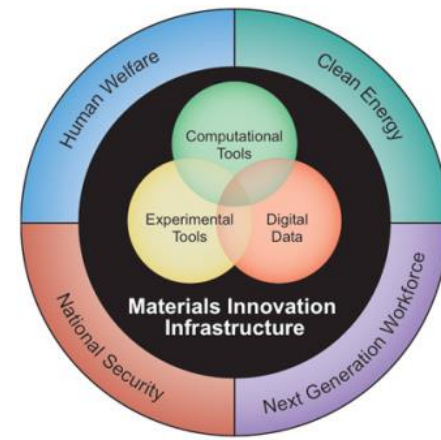
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PARADIM, Johns Hopkins University

November 14, 2018



Web: <https://jarvis.nist.gov>



Acknowledgement and Collaboration



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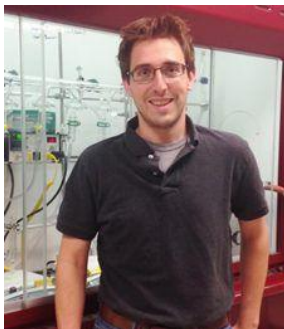
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Outline

- Motivation
- Basics: DFT
- Discovery & characterization:
 - low-dimensional materials (2D, 1D, 0D)
 - Topological materials
 - Efficient solar-cell materials
 - Thermoelectric materials
 - Flexible and negative Poisson ratio materials
- ML training
- Website/github demo

Navigate to:

<https://jarvis.nist.gov>

Motivation

Materials Genome Initiative



**Combine different approaches (computation, experiments etc.)
Making materials data publicly available**

Density Functional Theory

- Classical Newton's laws not applicable for electrons (**very fast, very tiny**);
- Schrödinger equation: mathematical equation that describes the evolution over time of a physical system in which quantum effects, such as **wave-particle duality**, are significant (such as electrons)
- Schrödinger equation of a **fictitious system** (the "Kohn-Sham system") of **non-interacting particles** (typically electrons) that generate the **same density** as any given system of interacting particles
- Uses density vs wavefunction quantity

Second derivative wrt X Schrodinger Wave-function

$$\frac{\partial^2 \psi}{\partial x^2} + \frac{8\pi^2 m}{h^2} (E - V) \psi = 0$$

Position Energy Potential Energy

$$H\psi = E\psi \quad \left[-\frac{\hbar^2}{2m} \nabla^2 + V_{\text{Eff}}(r) \right] \psi_i(r) = E_i(r) \psi_i(r) \quad V_{\text{Eff}} = T + V_{Ne} + V_{ee} + V_{XC}$$

Exchange-correlation



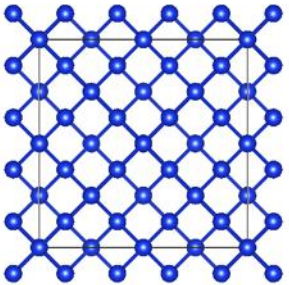
- **Different functionals: LDA, GGA (PBE, PW91), HSE06 etc.**
- **LDA:** developed for homogenous systems (Thomas-Fermi model), such as metals
- **GGA:** uses density gradient information on top of GGA
- **vdW-DF:** uses exchange from GGA, correlation from LDA, quantum-Monte-Carlo based non-local corrections, **optB88vdW** used here mainly



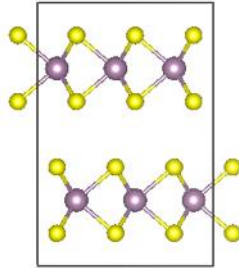
Walter Kohn

Discovery of 2D (low-D) materials

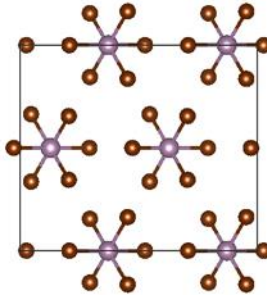
(a) 3D-bulk (Si)



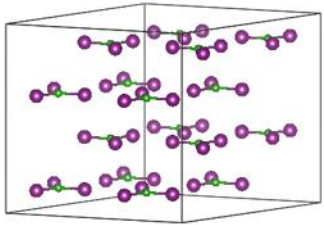
(b) 2D-bulk (MoS_2)



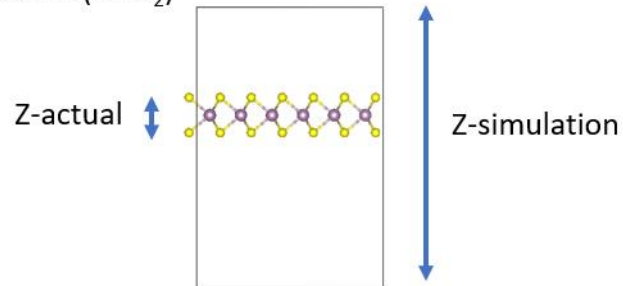
(c) 1D-bulk (MoBr_3)



(d) 0D-bulk (BiI_3)



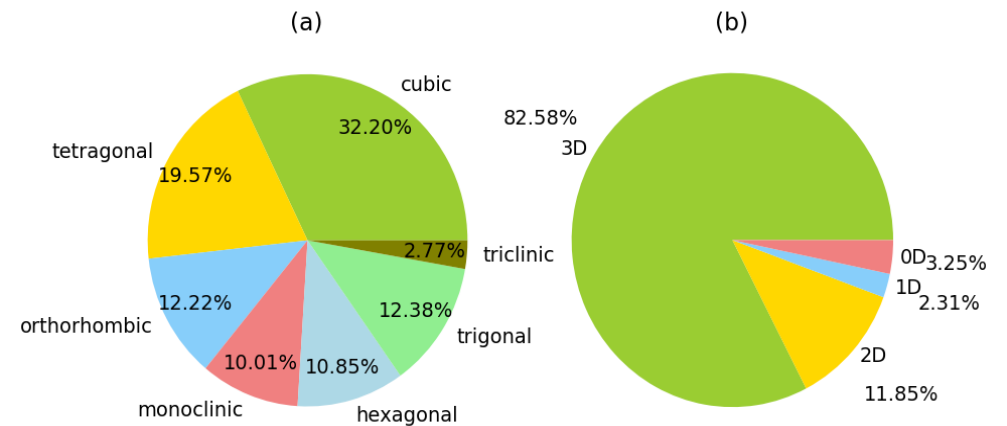
(e) 2D-1L (MoS_2)



$$\delta = \frac{|c_{PBE} - c_{ICSD}|}{c_{ICSD}}$$

Using lattice-constant
error to discover low-D
materials

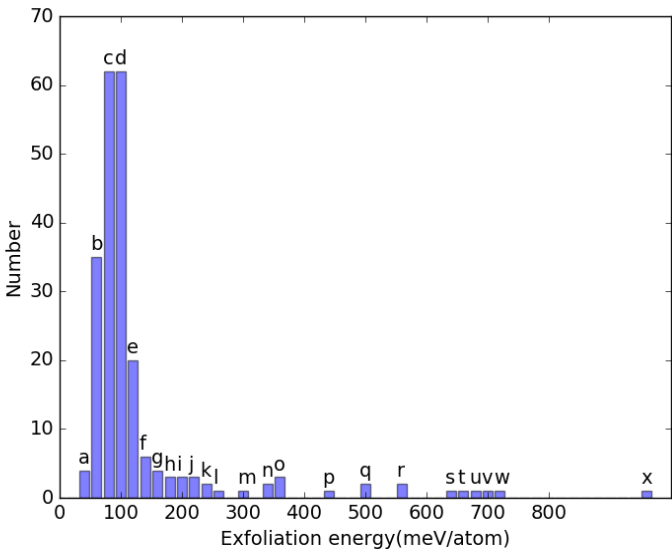
If the error is more than 5% > 1500 materials



Scientific Reports 7, 5179 (2017)
Physical Review B 98 (1), 014107 (2018)

Exfoliation energy calculations

$$E_f = \frac{E_{1L}}{N_{1L}} - \frac{E_{bulk}}{N_{bulk}}$$

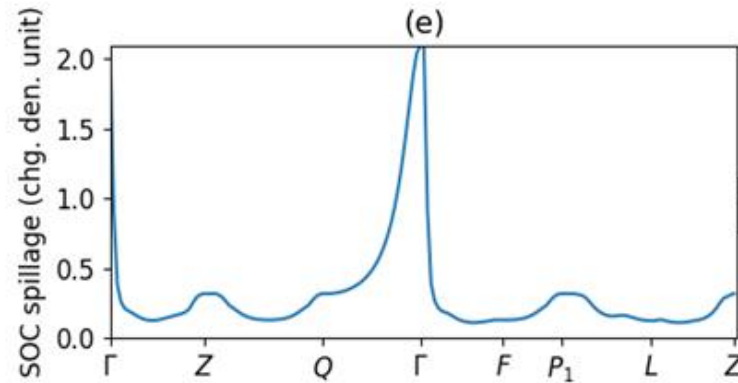
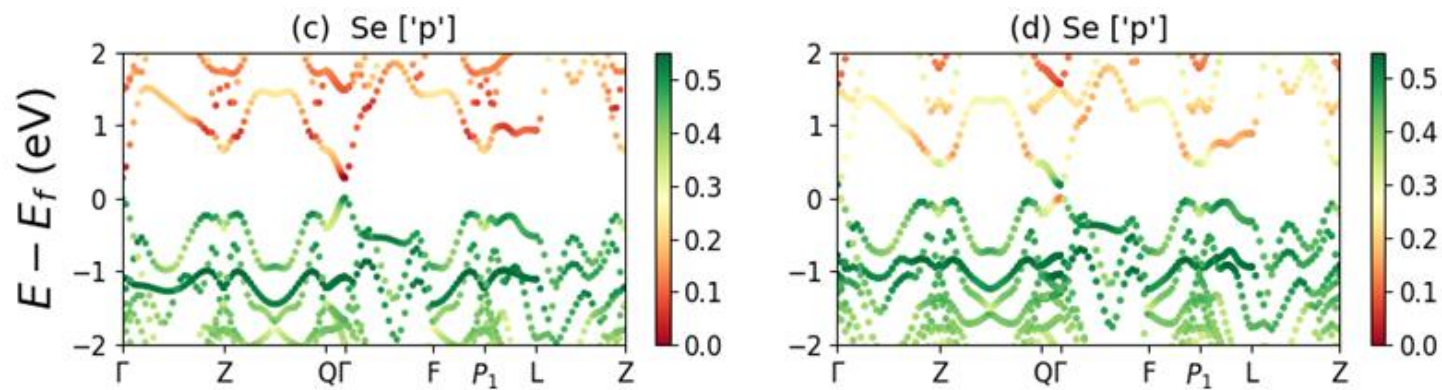


89% successful
Very simple criteria

Scientific Reports 7, 5179 (2017)

Energy range (meV)	Materials
a) 0-40	TiNCl, SiH4, HfBrN, Mg(AlSe2)2
b) 40-60	GaSe, CrS2, ZrS3, NiO2, GaS, ZrSe3, NdTe3, US3, TiS3, PrIO, DySI, Sc2CCl2, ThIN, TiBrN, InClO, LuSBr, SrHI, BiIO, BiBrO, KMnP, TiIN, Sc2NCl2, TlSbO3, ZrCl, SmTe3, PrTe3, As2O3, Nb2CS2, RbMnAs, SiH, Bi2TeI, ScCl, TbBr, Ge(BiTe2)2, GaS
c) 60-80	WSe2, WS2, MoS2, C, SnO2, PtO2, CdBr2, ReSe2, CrSe, MgCl2, CoBr2, ZrCl2, MgBr2, TcS2, FeCl2, MnCl2, MnBr2, InSe, CrBr3, VCl3, USE3, IrCl3, ScCl3, RhCl3, TaI2O, DySBr, ErSeI, ErSCL, BiClO, OsCl2O, CdCl2, BN, Nb(SCl)2, Bi2Te2S, ThBrN, HfCl4, Bi2Te2Se, MgPSe3, CdPS3, ScPS4, PPdS, TmAg(PSe3)2, ScAg(PSe3)2, ErAg(PSe3)2, ScAg(PS3)2, Nb3Cl8, Nb3TeCl7, InAg(PSe3)2, Hf3Te2, SNCl, Sr3Si2, TiCl2, HfFeCl6, GaTe, CS2, Nb(SeCl)2, CrCl3, BiI, TiBr2, GaAg(PSe3)2, CdPS3, TiS2
d) 80-100	NbS2, MoSe2, NbSe2, WTe2, MoTe2, VSe2, ZrS2, HfS2, HfSe2, MoS2, PtO2, PtS2, SnS2, SnSe2, TiO2, TiS2, TiSe2, ZrSe2, TaS2, SiTe2, TaSe2, VS2, TaSe2, MgI2, SbI3, PbI2, GeI2, SiS2, MnI2, CaI2, RhBr3, BiI3, MoBr3, RuBr3, PCl3, AuI, BPS4, IrBr3, Re(AgCl3)2, AlPS4, AlSiTe3, PPdSe, CrSiTe3, Nb3TeI7, NdI2, Al2Te3, S5N6, AlTeI7, AlSeBr7, CdI2, PSe, Ta3TeI7, TmI2, SbBr3, P4S5
e) 100-120	HfTe2, PtSe2, TiTe2, WO2, SnO, BCl3, Te2Br, Te2I, PBr3, TiI3, BiTeCl, BiTeI, TlPt2S3, AlBr3, BiSBr, CaN, Mn2Bi, HgI2, SrThBr6, P
f) 120-140	BBr3, AlI3, TlTe3Pt2, SbSBr, TlPd2Se3, P2Se5
g) 140-160	PdS2, Te2Pt, BI3, Ta(ICl)2
h) 160-180	PdSe2, NiTe2, NbI5
i) 180-200	ZrS, PI3, BaBrCl
j) 200-220	Te2Pd, Te2Ir, BiSe2
k) 220-240	SbSeI, BiSI
l) 240-260	Bi2Te3
m) 260-300	VS2
n) 300-340	CaSn, KAuSe
o) 340-360	KAuS, RbAuS, RbAuSe
p) 360-440	Sc2C
q) 440-500	GaN, TiSe2
r) 500-560	Sr2H3, Ca2H3
s) 560-640	AlN
t) 640-660	TiTe2
u) 660-680	CrSe2
v) 680-700	ZrTe2
w) 700-720	CoAs2
x) 720-960	Ti2O

Discovery of topological materials

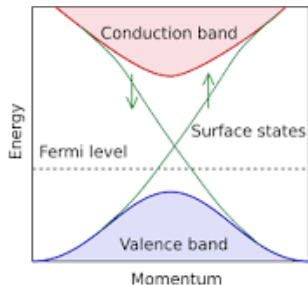
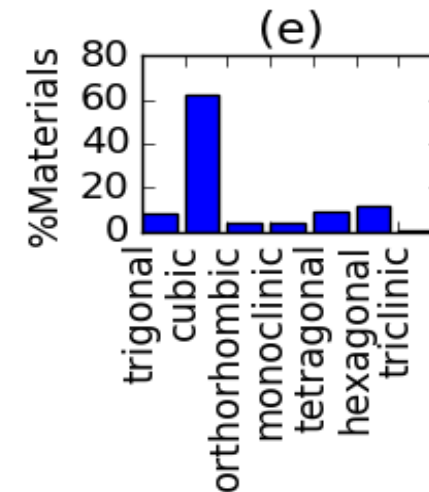
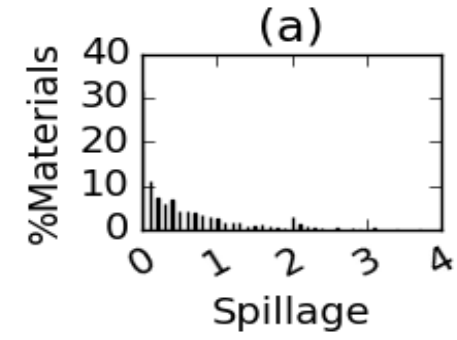


(f)

JVASP-1067_Bi2Se3

	Dir gap (eV)	Indir gap (eV)
SOC	0.186	0.186
NSOC	0.279	0.279

Peaks = 2

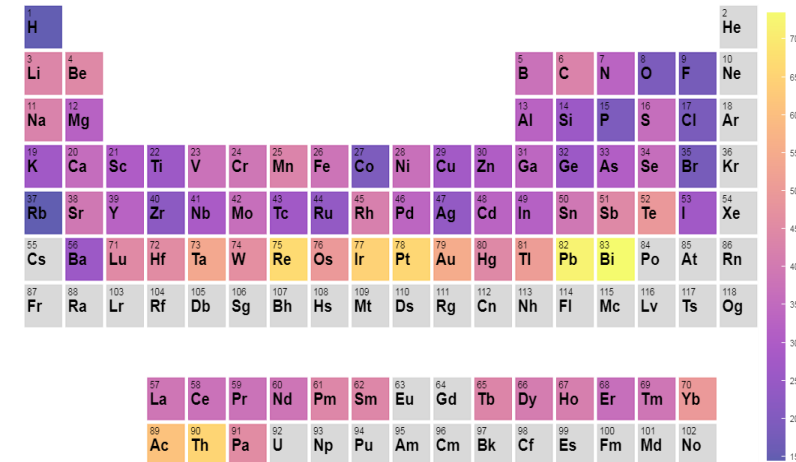
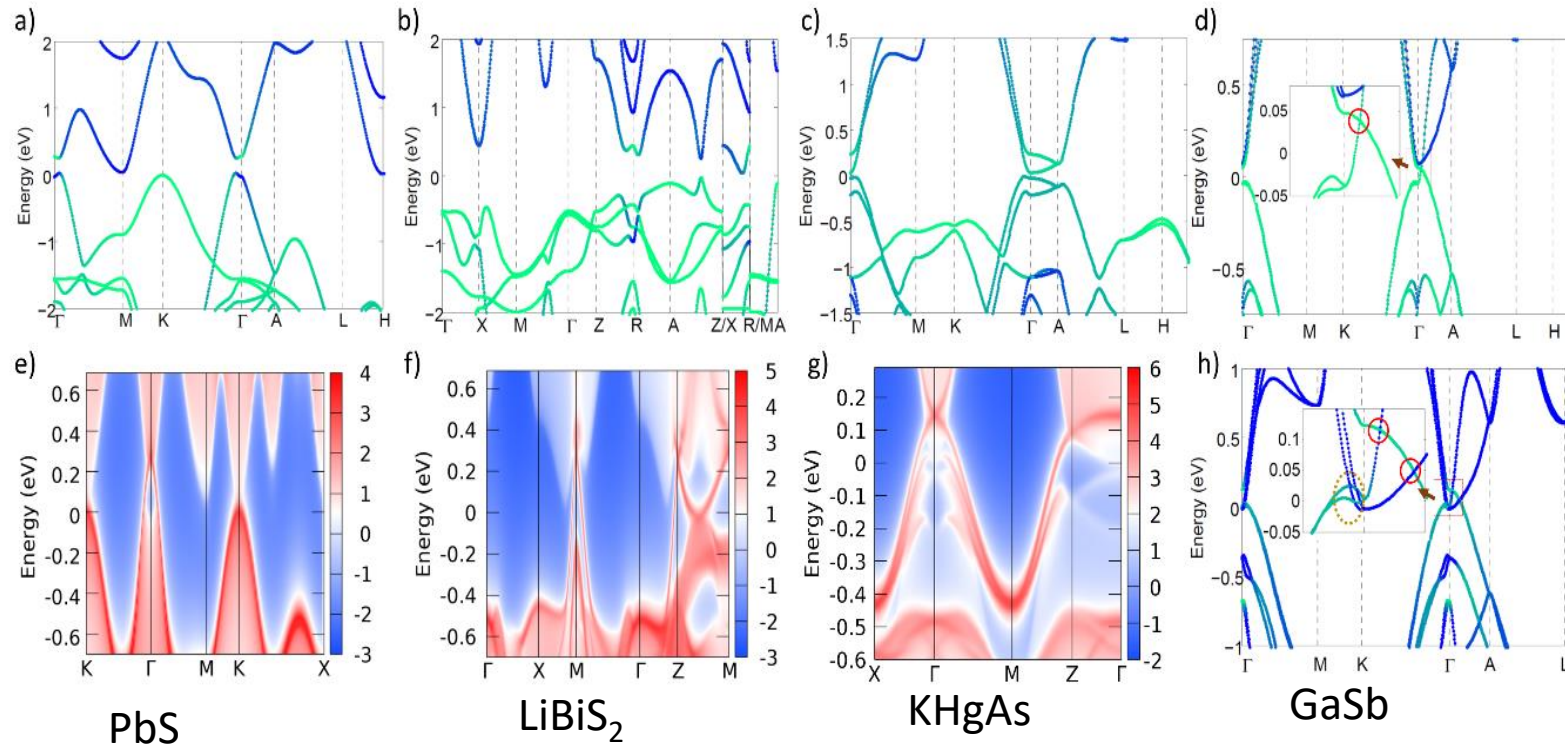


Surface states are topologically protected, aspect for Quantum computing

Using DFT wavefunctions w/o spin-orbit coupling to discover topological materials

<https://arxiv.org/abs/1810.10640>

Discovery of topological materials



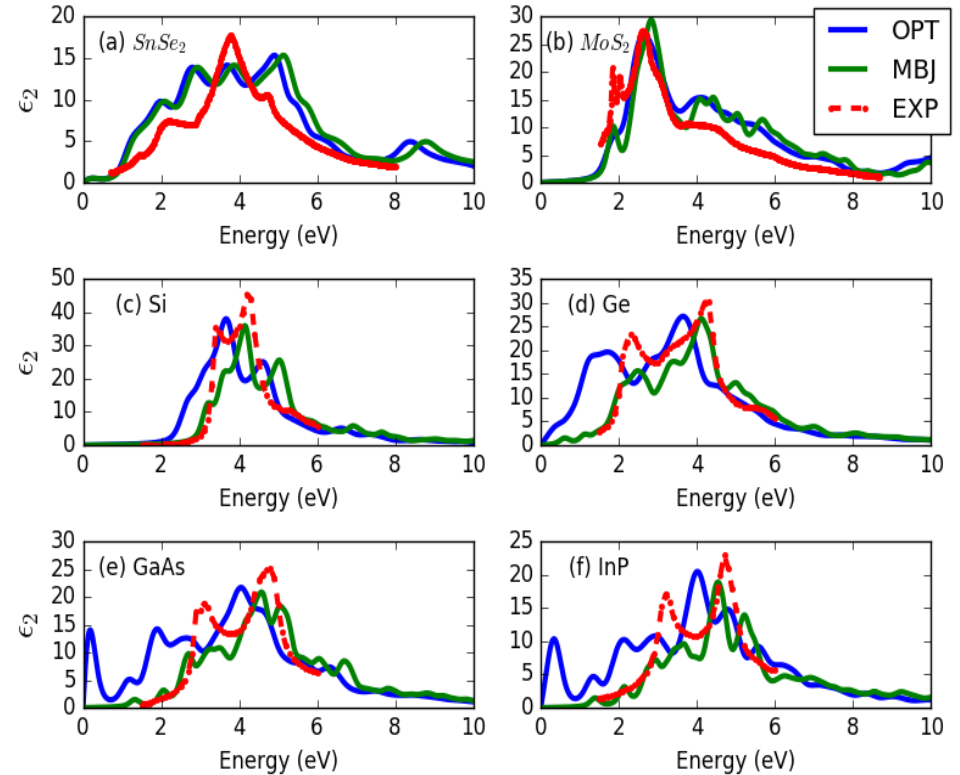
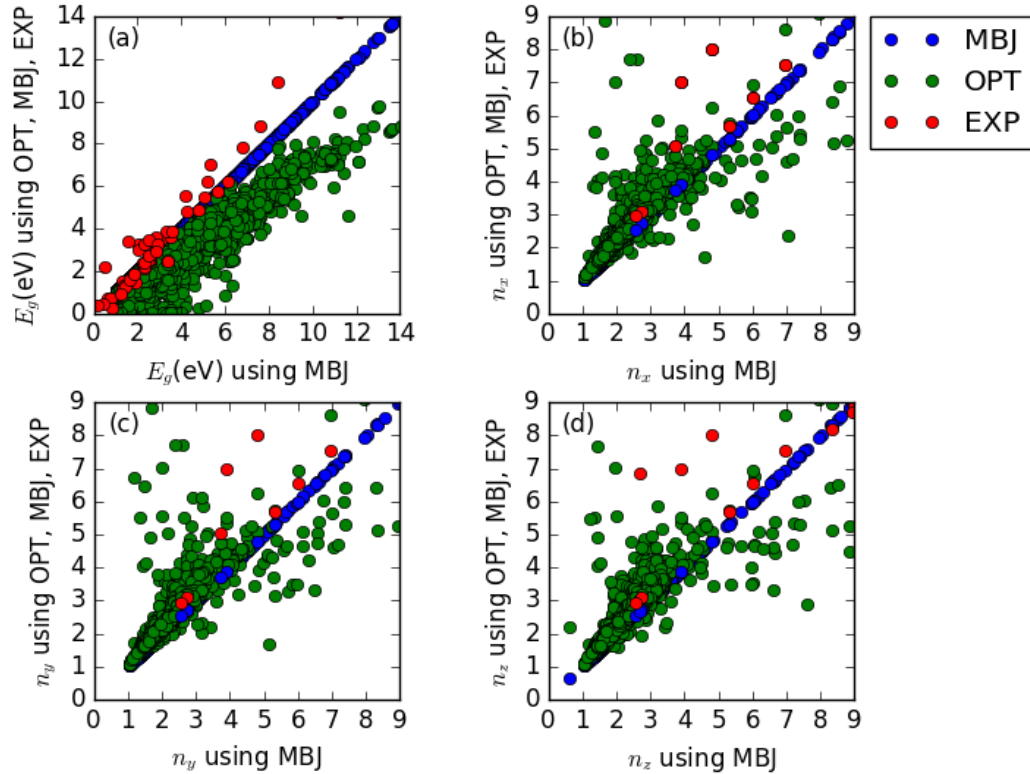
Wannier function, band-crossings, inversion, ARPES

Periodic table trends

- >1699 high-spillage materials identified
- Further screened with close to zero indirect bandgap [ΔE_n] (to avoid trivial metallic cases)
- 278 Wannier calculations

<https://arxiv.org/abs/1810.10640>

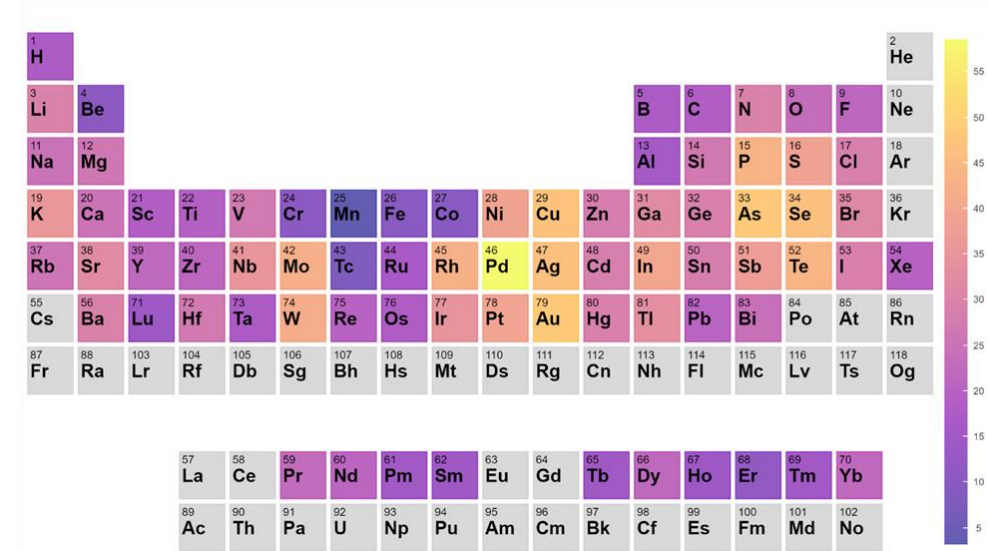
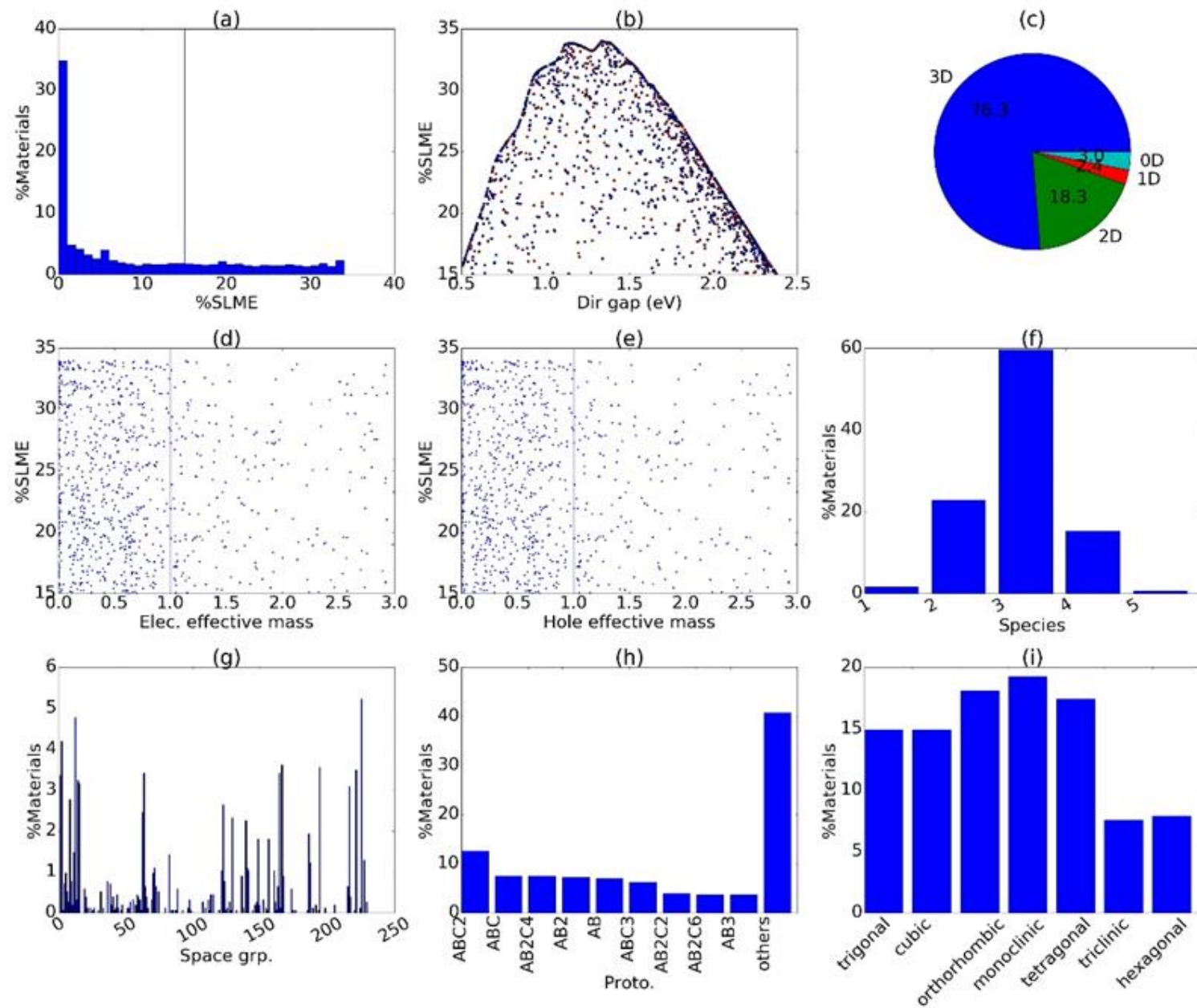
Discovery of solar cell materials



$$\epsilon_{\alpha\beta}^2(\omega) = \frac{4\pi^2 e^2}{\Omega} \lim_{q \rightarrow 0} \frac{1}{q^2} \sum_{c,v,k} 2w_{\vec{k}} \delta(\zeta_{c\vec{k}} - \zeta_{v\vec{k}} - \omega) \left\langle \psi_{c\vec{k}+\vec{e}_{\alpha}q} \left| \psi_{v\vec{k}} \right\rangle \left\langle \psi_{c\vec{k}+\vec{e}_{\beta}} \left| \psi_{v\vec{k}} \right\rangle^*\right.$$

Frequency dependent dielectric function with TBmBJ

Scientific Data 5, 180082 (2018)



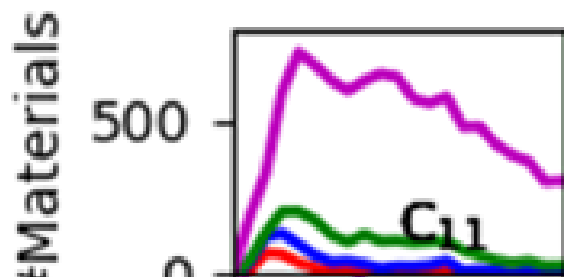
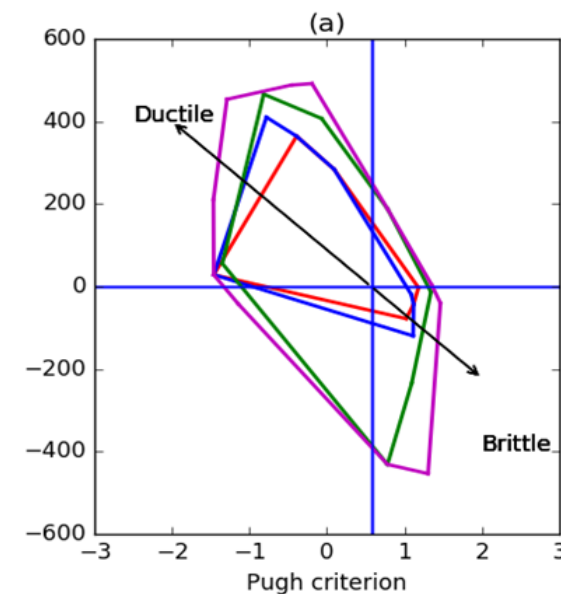
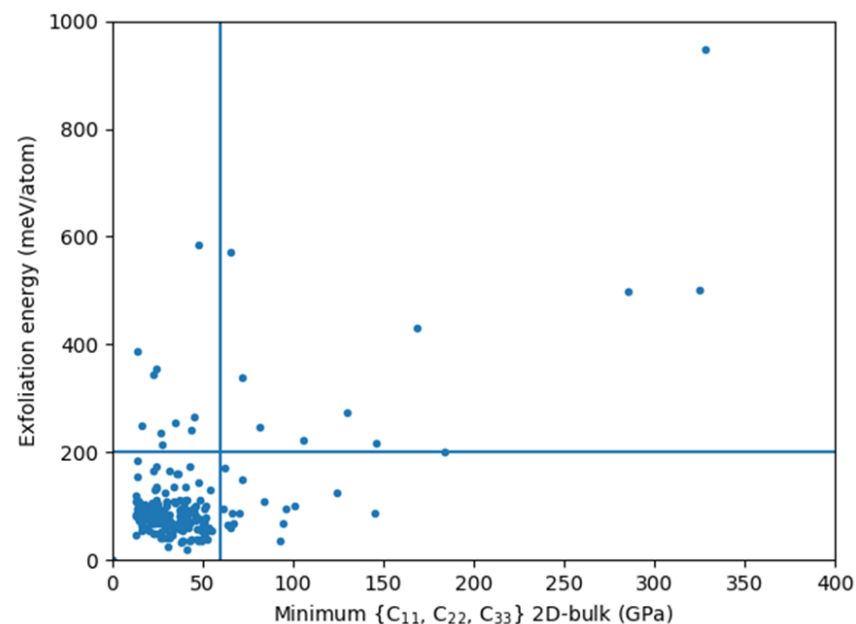
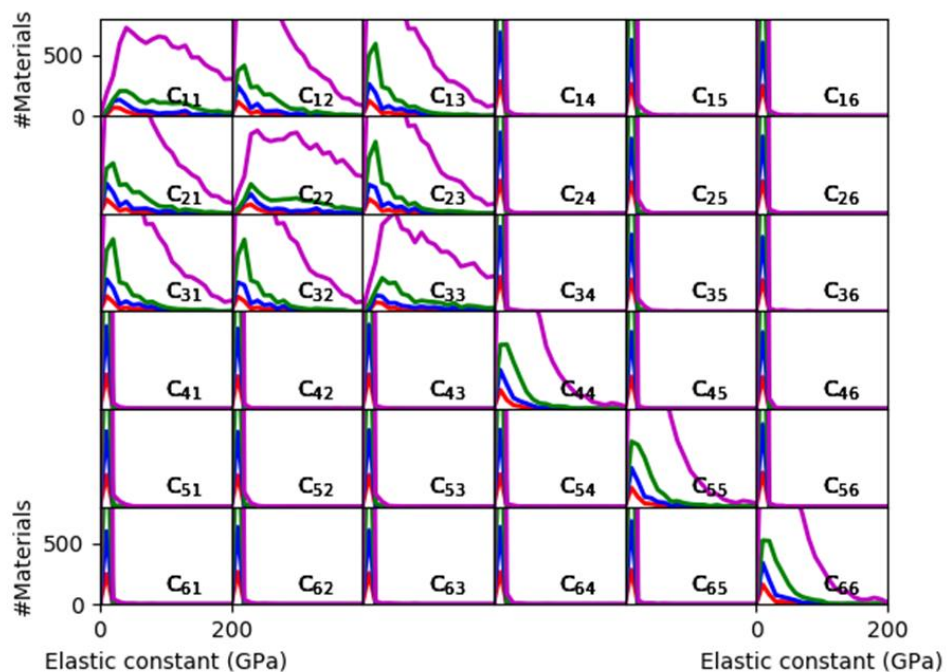
Spectroscopic Limited Maximum Efficiency (SLME)

$$\eta = \frac{P_{mat}}{P_{inc}} = \frac{\left(J_{sc} - J_0 \left(e^{\frac{eV}{kT}} - 1 \right) \right) V}{1000}$$

>1500 screened materials

Paper in preparation

Discovery of negative Poisson and flexible materials



PbS (-0.5, Cmc, JVASP-28369), Al (-6.2, Im-3m, JVASP-25408), CSi₂ (-0.13, P6/mmm, JVASP-16869), YbF₃ (-0.06, Pnma, JVASP-14313), SiO₂ (-0.03, Pna21, JVASP-22571)

Physical Review B 98 (1), 014107 (2018)

Dimensionality dependent elastic properties

2D-Heterostructure design with elastic constant and work-function data

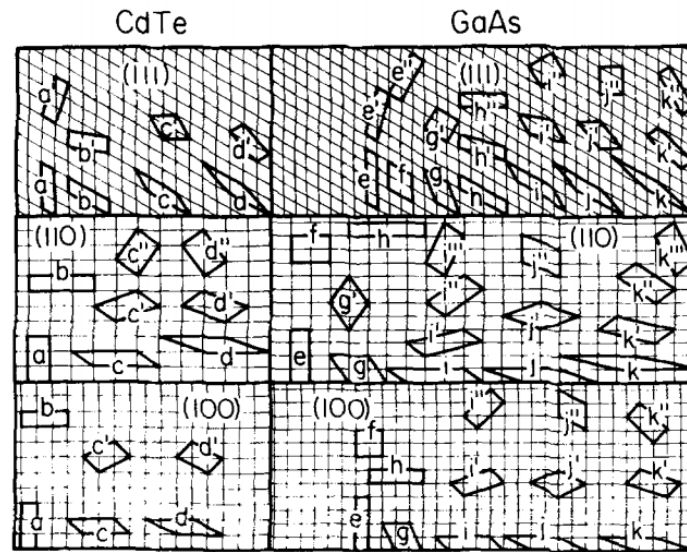
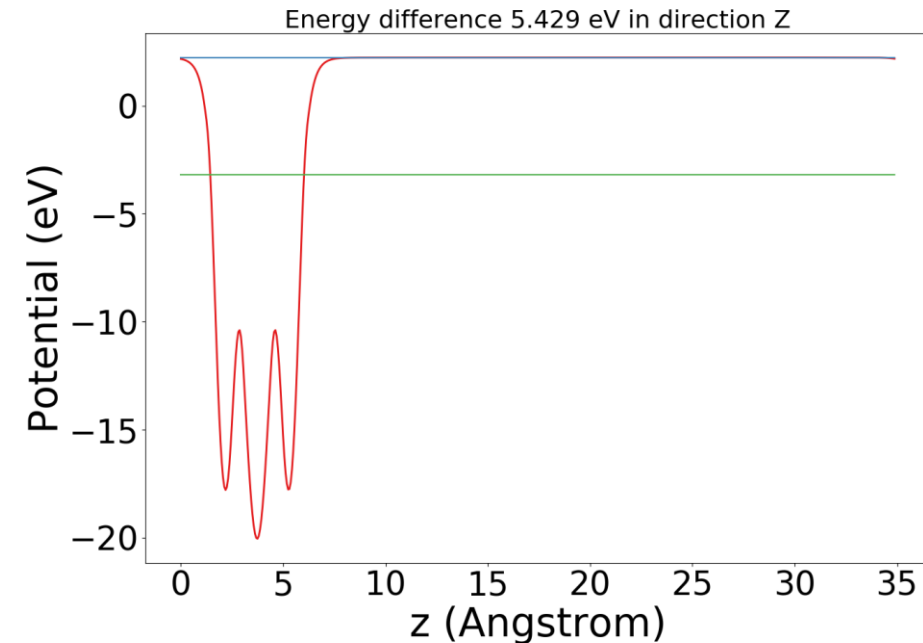


FIG. 3. Lattice translations parallel to the (100), (110), and (111) faces of CdTe and GaAs. Nonequivalent unit cells of order 3 for CdTe and 4 for GaAs are shown as parallelograms bounded by thick lines and denoted by unprimed letters. Various stages of the reduction procedure are denoted by primed letters.

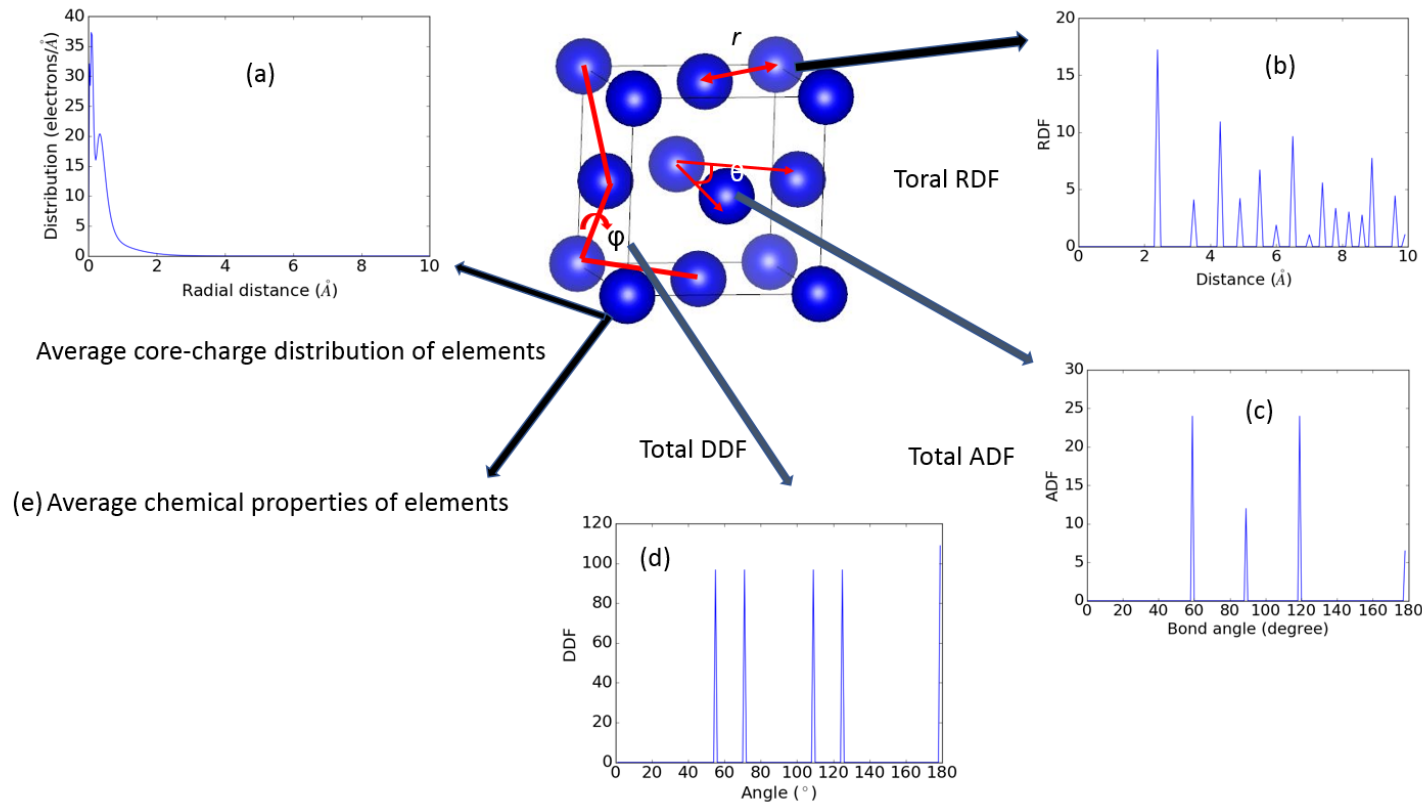
Zur, Journal of Applied Physics **55**, 378 (1984)



- Lattice mismatch and elastic tensor to predict elastic energy of the interface
- Work-function/band-alignment match

In preparation

Finding the right features/descriptors: ML

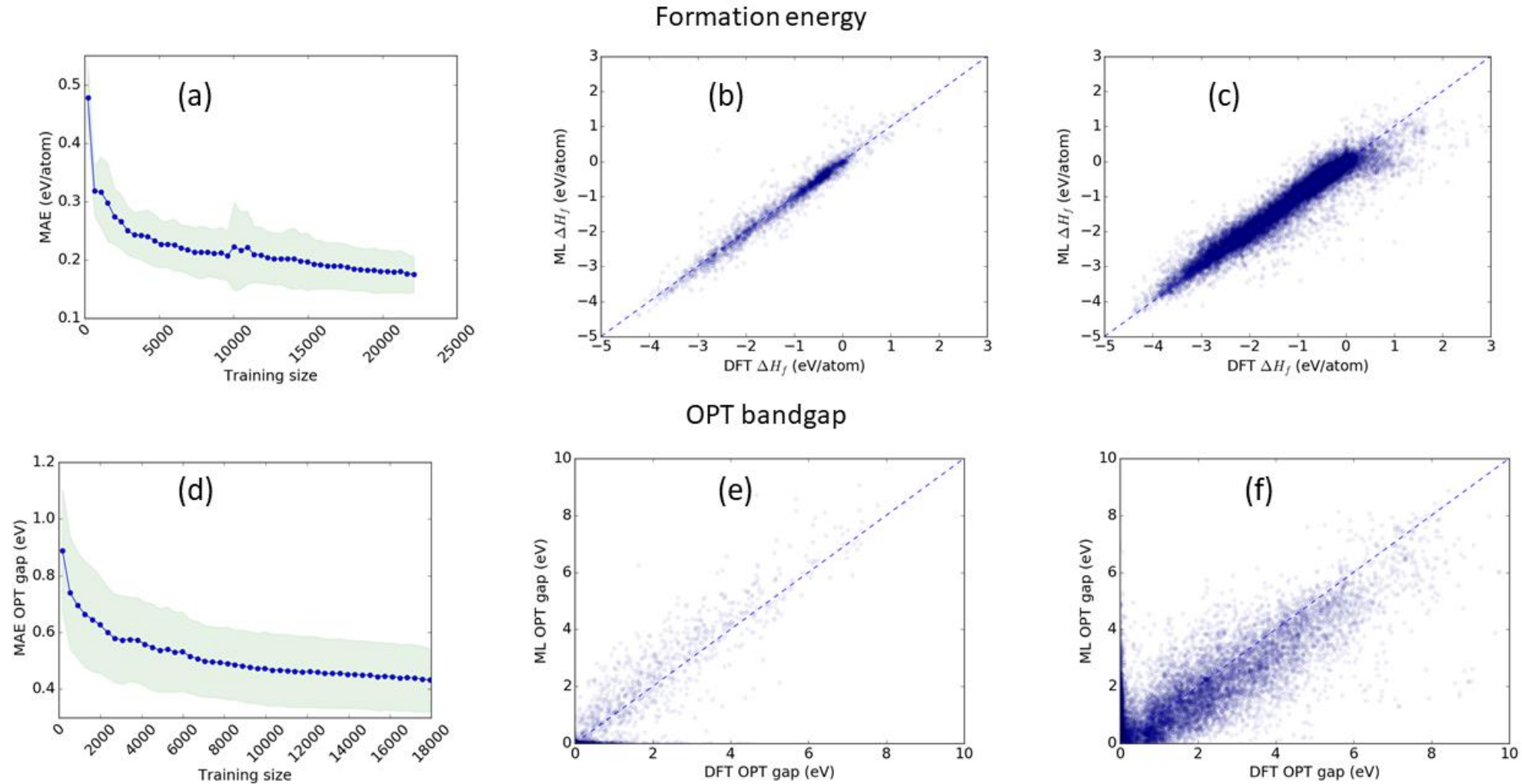


- Arithmetic operations (mean, sum, std. deviation...) of **electronegativity, atomic radii, heat of fusion,....** of atoms at each site
(example: Electronegativity of Mo+Mo+S+S+S+S)/6 = 0.15
- Atomic bond distance based descriptors
- Angle based descriptors

**1557 descriptors/features for one material
GBDT algorithm**

Physical Review Materials 2, 083801 (2018)

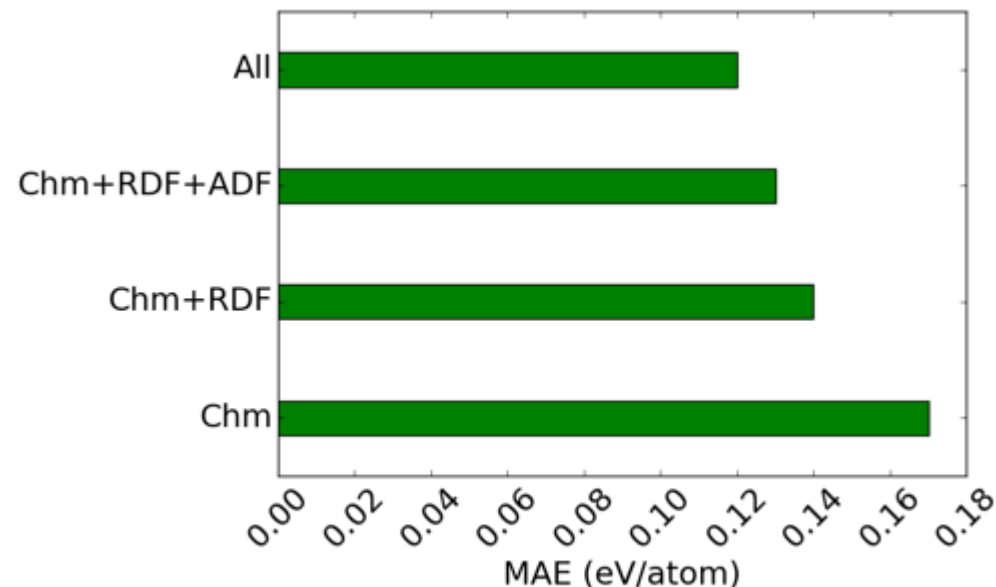
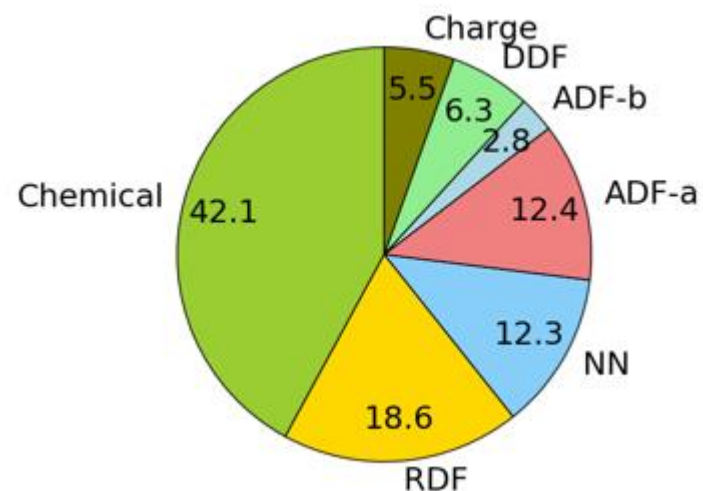
Regression models: formation energy and bandgap model



Learning curve, 1 and 5-fold CV plots

Physical Review Materials 2, 083801 (2018)

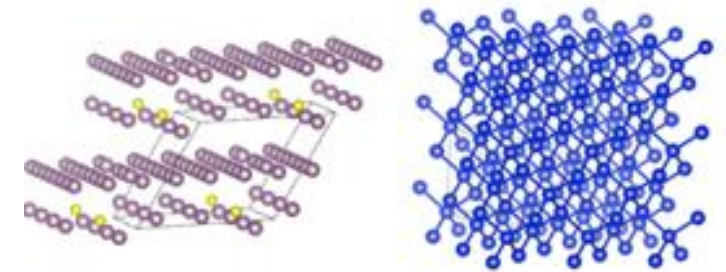
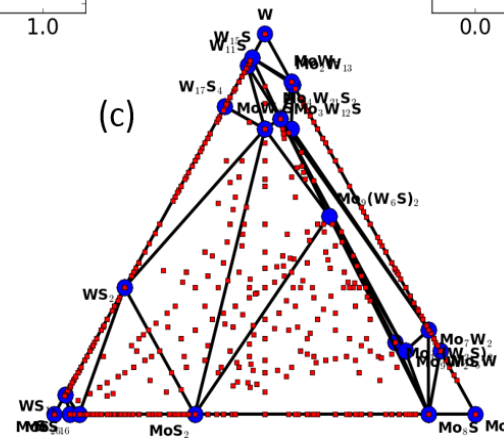
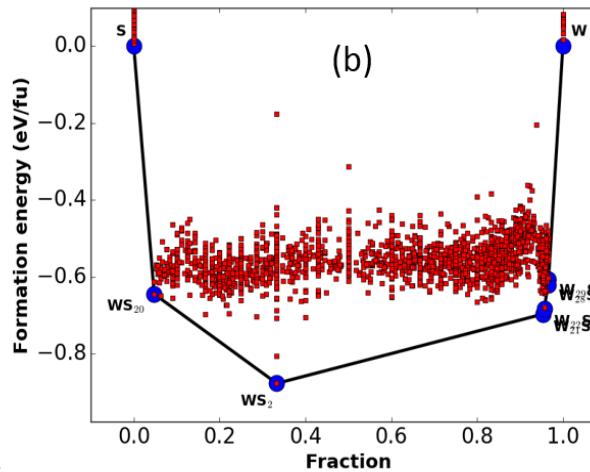
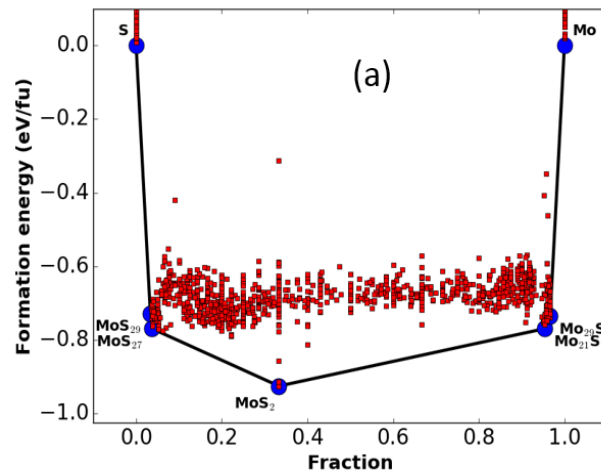
Explainability: feature importance



- Chemical features most important followed by RDF and NN
- Incrementally adding structural features decreases MAE

Physical Review Materials 2, 083801 (2018)

Search for new materials: Genetic algorithm with ML



- **New way** of validating ML model for materials
- MoS₂, WS₂ indeed stable as in DFT and experiments
- Need further verification for low-lying energy structures with DFT

Exploring the github and webpages

https://github.com/usnistgov/jarvis

usnistgov / jarvis

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Code Issues 8 Pull requests 0 Projects 0 Wiki Insights Settings

Joint Automated Repository for Various Integrated Simulations (JARVIS) is an integrated framework for computational science using density functional theory, classical force-field/molecular dynamics and machine-learning. <https://jarvis.nist.gov>

dft md vasp lammps scikit-learn Manage topics

245 commits 1 branch 9 releases 2 contributors View license

Branch: master New pull request Create new file Upload files Find file Clone or download

knc6 vasp update Latest commit 916a22 17 hours ago

.circleci	ci path	6 days ago
docs	new docs	22 days ago
jarvis	vasp update	17 hours ago
nix	Fix typo	12 days ago
.gitignore	Implement Nix recipe	13 days ago
.travis.yml	tra	7 days ago
LICENSE	re-upload	25 days ago
README.rst	Update README	6 days ago
default.nix	Implement Nix recipe	13 days ago
requirements.txt	numpy requirement for phonopy	a day ago
setup.py	update setup	a day ago

README.rst

circleci passing docs passing code quality A

JARVIS

Joint Automated Repository for Various Integrated Simulations (JARVIS) is an integrated framework for computational science using density functional theory, classical force-field/molecular dynamics and machine-learning. Official website: <https://jarvis.nist.gov>

JARVIS for DFT

Search Refresh

Periodic table with highlighted elements: H, He, Li, Be, Na, Mg, K, Ca, Sc, Ti, V, Cr, Mn, Fe, Rb, Sr, Y, Zr, Nb, Mo, Tc, Ru, Cs, Ba, Hf, Ta, W, Re, Os, Fr, Ra, Rf, Db, Sg, Bh, Hs, La, Ce, Pr, Nd, Pm, Ac, Th, Pa, U, Np.

https://www.ctcms.nist.gov/~knc6/jsmol/JVASP-1067.html

HOME JARVIS-DFT JARVIF-FF JARVIF-ML MDCS Github Publications News Workshops DOCUMENTATION OTHER LINKS CONTACT

Convergence	Structure	Electronic	Potential	Optics	Elastic	Thermoelectric	Magnetic	Exfoliation energy	Spillage	See also
JARVIS-ID:JVASP-1067	Functional:optB88-vdW	Primitive cell	Primitive cell	Conventional cell	Conventional cell					
Structural formula:Bi2 Se3	Formation energy/atom (eV):-0.404	a 10.025 Å	α:24.149 °	a 4.194 Å	α:90.0 °					
Space group :R-3m (166)	Relaxed energy/atom (eV):-1.9949	b 10.025 Å	β:24.149 °	b 4.194 Å	β:90.0 °					
Calculation type:Bulk	SCF bandgap (eV):0.058	c 10.025 Å	γ:24.149 °	c 29.185 Å	γ:120.0 °					

Download input files

100: P 1
a=20.050Å
b=20.050Å
c=17.917Å
α=24.149°
β=24.149°
γ=24.149°

JSmol

Example: <https://www.ctcms.nist.gov/~knc6/jsmol/JVASP-1067.html>

Github:
<https://github.com/usnistgov/jarvis>

Continuous integration, various modules, notebooks etc.

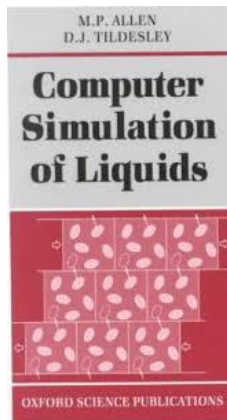
Exploring material properties

JARVIS-FF

Force-field (classical)



$$F = ma = -\nabla V(r)$$



- Solve Newton's equation for atomic positions
- Approximations for V (force-fields):
EAM, EIM, MEAM, AIREBO, REAXFF, COMB, COMB3, Tersoff, SW *etc.*
- Contains:
Automated LAMMPS based force-field calculations on DFT geometries. Some of the properties included in JARVIS-FF are energetics, elastic constants, surface energies, defect formation energies and phonon frequencies of materials
- Time: Takes years to fit FFs, relatively quick calculations
- Website: <https://www.ctcms.nist.gov/~knc6/periodic.html>
- Publications:
 - Nature:Scientific Data 4, 160125 (2017)
 - arXiv:1804.01024 (2018)

Email: knc6@nist.gov or
kamal.choudhary@nist.gov

JARVIS-DFT

Density-functional theory (quantum)

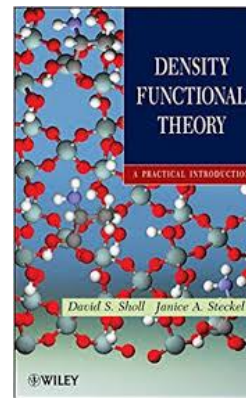
Schrödinger's cat

$$\frac{1}{\sqrt{2}}|\uparrow\rangle + \frac{1}{\sqrt{2}}|\downarrow\rangle$$

$$H\psi = E\psi$$

$$\left[-\frac{\hbar^2}{2m} \nabla^2 + V_{\text{eff}}(r) \right] \psi_i(r) = E_i(r) \psi_i(r)$$

$$V_{\text{eff}} = T + V_{\text{Ne}} + V_{\text{ee}} + V_{\text{XC}}$$

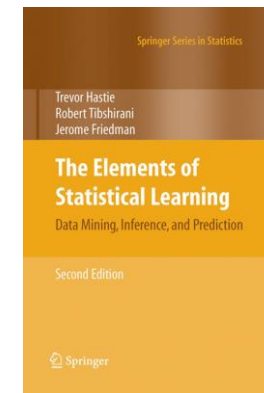
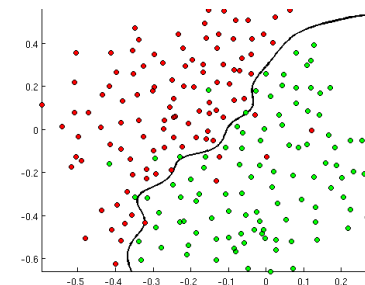


- Solve Schrödinger equation for electrons
- >30,000 materials data (3D, 2D, 1D, 0D)
- Contains:
Formation energy, exfoliation energy, diffraction pattern, radial distribution function, band-structure (SOC/Non-SOC), density of states, carrier effective mass, temperature and carrier concentration dependent thermoelectric properties, elastic constants and gamma-point phonons
- Time: 5000 cores for last 4 years
- Website: <https://www.ctcms.nist.gov/~knc6/JVASP.html>
- Publications:
 - Nature:Scientific Reports 7, 5179 (2017)
 - Nature:Scientific Data 5, 180082 (2018)
 - Phys. Rev. B 98, 014107 (2018)

Web: <https://jarvis.nist.gov>

JARVIS-ML

Machine learning (data-driven)



- Drawing the line, dimensionality reduction, curve-fitting?
- Neural nets, decision trees, fuzzy-logic *etc.*
- Uses gradient boosting decision tree
- Contains:
Machine learning prediction tools, trained on JARVIS-DFT data.
Some of the ML-predictions focus on energetics, heat of formation, GGA/METAGGA bandgaps, bulk and shear modulus, exfoliation energy, refractive index, magnetic moment, carrier effective masses
- Time: Much easier and faster to train
- Website: <https://www.ctcms.nist.gov/jarvisml/>
- Publication:
 - Phys. Rev. Materials 2, 08380 (2018)

Github:
<https://github.com/usnistgov/jarvis>