Computational screening of solar energy materials



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Computational Atomic-scale Materials Design

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Computational materials screening



- What is the problem we want to solve? What are the properties of the "dream material"?
- What do we compute descriptors?
- How do we search in the materials space?

Light induced water splitting Tandem cells





Produce hydrogen as a fuel (and save the World)

Light absorbing materials – small/large band gaps Protection layers Catalysts p-n junctions



The challenge:

Small bandgap semiconductor: ~1.1 eV Silicon Large bandgap semiconductor: ~1.8 eV **????** = catalyst

Searching for light absorbing materials



- Mapping out a particular class of materials
 - Perovskites
- Known materials
 - Inorganic crystal structure database (ICSD)
- Searches guided by correlations in materials space
 - Machine learning

Sulfide perovskites Screening funnel





Candidates for experimental investigation



 $\cdot 4$

3

Identify semiconducting ABS₃ compounds

53 metal atoms

53 * 53 = 2809 compounds

Test for bandgap > 0 in distorted 5 atom unit cell



129 compounds identified



Perovskite sulfides





Most common ABS₃ structures in ICSD

Y.-Y. Sun et al., Nano Lett **15**, 581 (2015)



Stability





Band gaps (calculated with GLLB)





White circle: One structure significantly more stable Bold: All low-energy structures with interesting gaps

Crosses: AB->BA

Mobility – effective masses

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Mobility $\mu \propto 1/m$



Defect tolerance/sensitivity of ABS₃ compounds Electronic density-of-states



Interesting sulfides for photoabsorption (15 candidate materials)



	formula	$\mathrm{E}_{g}^{GLLB-SC}$	$\mathrm{E}_{g(direct)}^{GLLB-SC}$	E_{g}^{HSE06}	m_{h}^{*}	m_{e}^{*}	prototype
Ba-Hf	BaHfS ₃	1.31	1.31	1.60	-0.347	0.943	NH ₄ CdCl ₃ /Sn ₂ S ₃
Ba-Zr	BaZrS ₃	2.25	2.25	2.08	-0.749	0.426	GdFeO ₃
Bi-Tl	BiTlS ₃	1.36	1.98	1.30	-0.636	0.309	FePS ₃
Ca-Hf	CaHfS ₃	0.99	0.99	1.36	-0.336	0.759	NH ₄ CdCl ₃ /Sn ₂ S ₃
Ca-Sn	CaSnS ₃	1.58	1.93	1.45	-0.606	0.943	NH ₄ CdCl ₃ /Sn ₂ S ₃
Ca-Zr	CaZrS ₃	1.36	1.36	1.32	-0.765	0.884	NH ₄ CdCl ₃ /Sn ₂ S ₃
Hf-Sr	SrHfS ₃	1.12	1.12	1.45	-0.327	0.811	NH ₄ CdCl ₃ /Sn ₂ S ₃
Hf_Pb	HfPbS ₃	1.12	1.63	0.94	-0.275	0.235	BaNiO ₃
La-Y	LaYS ₃	1.79	1.79	1.47	-0.670	0.490	CeTmS ₃
Li-Ia	TaLiS ₃	1.98	2.00	2.06	-0.755	0.985	FePS ₃
Mg-Zr	MgZrS ₃	2.21	2.32	2.06	-0.718	0.779	distorted
Sb-Y	SbYS ₃	2.03	2.09	1.67	-0.372	0.484	NH ₄ CdCl ₃ /Sn ₂ S ₃
Sr-Zr	SrZrS ₃	1.46	1.46	1.37	-0.644	3.115	NH ₄ CdCl ₃ /Sn ₂ S ₃
Ta-Tl	TaTlS ₃	1.15	1.15	1.35	-0.297	0.241	distorted
Zn-Zr	ZrZnS ₃	1.91	1.97	1.87	-0.616	0.420	FePS ₃

Bold: all low-energy phases have relevant band gaps

BaZrS₃: W. Meng et al., *Chem Mater*, **28**, 821 (2016)

LaYS₃ Synthesis and characterization



Thin films produced by deposition of La and Y followed by sulfurization.



Theoretical spectrum calculated for random orientation. Blue curve with .2° smearing.

LaYS₃ Band gap



Spectroscopic ellipsometry – light absorption coefficient



Direct band gap determined from absorption coefficient and refractive index

LaYS₃ Photoluminescence





Defects not giving rise to non-radiative processes.

Performance in water-splitting device being investigated. (Andrea Crovetto).

Limitations



- Limited compositions (ABS₃)
- Limited number of structures (6)
- Absorption: band gap with GLLB (±0.4 eV)
- Mobility: effective mass
- Defects: only neutral vacancies

- But still useful:
 - 2809 -> 15 materials

Screening of known materials for photovoltaics or water splitting



Kuhar, Pandey, Thygesen, Jacobsen, ACS Energy Letters, doi:10.1021.acsenergylett.7b01312 (2018).

Abundance and Herfindahl–Hirschman index



Only abundant elements without a monopoly market.

Screening funnel



Toxicity, abundance, HHI

Binary or ternary

Materials in ICSD and OQMD

PBE band gap available in OQMD $0 < E_g < 2 \text{ eV}$



Screening funnel (cont.)



ACS Energy Letters, doi:10.1021.acsenergylett.7b01312 (2018).

Screening results (74 materials)



	formula	$E_{\rm g}^{ m GLLB-SC}$ (eV)	$E_{g(direct)}^{GLLB-SC}$ (eV)	$m_{\rm h}^{*}~(m_{\rm e})$	$m_{\rm e}^{*}$ $(m_{\rm e})$
	Al ₂ MgSe ₄ *	2.47	2.47	0.38	0.21
	$(B_{12}S)^*$	0.58	0.75	0.40	0.29
	Ba_3P_4	1.07	1.07	0.95	0.97
Antinerovskite —	→ Ba ₃ SbN	2.05	2.05	0.18	0.25
Antiperovskite	Ba_5Sb_4	0.94	1.27	0.66	0.36
	Ba_4SnP_4	1.78	1.79	0.32	0.47
	BaCaSn	0.88	0.88	0.34	0.73
	BaLiP	1.98	1.98	0.16	0.16
	$BaZrN_2$	2.45	2.45	0.38	0.28
	π BaZrS ₃	2.34	2.34	0.35	0.43
Known nerovskites	Ca ₃ NP	2.46	2.46	0.21	0.29
Known perovskites	CaLiSb	1.36	1.36	0.13	0.40
	$Cs_2SnI_6^*$	0.77	0.77	0.84	0.26
	Cs ₃ Sb	2.45	2.75	0.76	0.23
Some interesting	Cs ₆ AlSb ₃	2.11	2.21	0.91	0.28
candidates for water	Cs_6GaSb_3	1.84	1.94	0.99	0.29
snlitting:	CsCuSe ₄	1.94	2.01	0.48	0.26
uf N Nbi CrC 7r N	CsGe Cl ₃	2.31	2.31	0.27	0.29
$\Pi_{3}\Pi_{4}, \Pi_{0}\Pi_{5}, 3\Pi_{3}, 2\Pi_{3}\Pi_{4}$	CsNaGe ₂	2.48	2.51	0.35	0.51
Ba_3SDN , $BaZrN_2$,	CsSnBr ₃	0.99	0.99	0.09	0.08
Cs ₆ GaSb ₃ , CsGeCl ₃ ,	•	•	•	•	•
Rb_2SnBr_6 , Sr_3GaN_3 , and	•	•	•	•	•
Sr ₃ SbN	Danday Thurson	n Jacobson ACC From	raulattara dai:10.1(+ 7601212 (2010)

Kuhar, Pandey, Thygesen, Jacobsen, ACS Energy Letters, doi:10.1021.acsenergylett.7b01312 (2018).

Machine learning new materials



- Many different techniques
 - Representation of materials (fingerprints, ···)
 - Kernel regression, neural networks, …
- Two challenges:
 - Can we predict material properties without knowing where the atoms are?
 - Can we avoid evaluation of properties of many (irrelevant) materials? Can we directly identify relevant materials?

Organic solar cell (PCBM-based blended polymer solar cell)



PCBM = Phenyl-C'61-Butyric-Acid-Methyl-Ester



Donor-acceptor molecules (polymer units)





What is the position of the LUMO and the optical gap for these molecules?

In principle 10¹⁴ molecules!

Training set with ~4000 molecules (Gaussian, B3LYP)

Jørgensen, Mesta, Shil, García Lastra, Jacobsen, Thygesen, and Schmidt, (2018).

Data representation



String representation of molecules.

Grammatical production rules.

No specification of atomic coordinates.



FIG. 2: String representation of one of the molecules of the solar cell dataset: "Acceptor backbone"-"X groups"-"Y groups"+"Donor backbone"-"X groups"-"Y groups". Whenever no side groups are present "*" character is used instead.

Earlier work uses SMILES to represent molecules:

Gómez-Bombarelli et al. (2016), arXiv:1610.02415 [cs.LG]. Kusner et al. (2017), arXiv:1703.01925 [stat.ML].

Grammar Variational AutoEncoder



Jørgensen, Mesta, Shil, García Lastra, Jacobsen, Thygesen, and Schmidt, (2018).

Latent space



First two principal components.

Bright points are within target range for LUMO energy and optical band gap.

New materials can be predicted by optimization or interpolation in the latent vector space.

Decoder: Latent space -> strings -> molecules



Prediction of new molecules

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Computational screening and exa-scale: Some naïve considerations



- Opportunities
 - Screening more different materials
 - More accurate calculations
 - Light absorption, PBE -> GLLB -> GW -> BSE
 - New properties
 - Carrier lifetimes
- Challenges
 - Better and more descriptors
 - 1% of 1000 materials -> 10 candidates
 - 1% of 10⁶ materials -> 10000 candidates

Acknowledgements



CAMD/DTU:

Mohnish Pandey Korina Kuhar Ivano E. Castelli Suranjan Shil Thomas Olsen Kristian S. Thygesen

DTU ENERGY:

Murat Mesta Juan Maria Garcia-Lastra

DTU COMPUTE:

Peter Bjørn Jørgensen Mikkel N. Schmidt

SURFCAT/DTU:

Andrea Crovetto Brian Seger Søren Dahl Peter Vesborg Ole Hansen Ib Chorkendorff



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