Materials Discovery Guided by Artificial Intelligence

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Crystal structure determines physical properties. Crystal structure determination was a major breakthrough.



The Nobel Prize in Physics 1914

"for his discovery of the diffraction of X-rays by crystals"



Max von Laue



The Nobel Prize in Physics 1915

"for their services in the analysis of crystal structure by means of Xravs"



Sir William Henry Bragg

(from http://nobelprize.org)





"for their outstanding achievements in the development of direct methods for the determination of crystal structures"



Herbert A. Hauptman



Jerome Karle







William Lawrence Bragg

Zincblende ZnS.

One of the first solved structures (1912-1913)



Briefly about big data

Big data have predictive power

We have:

~300,000 experimental (& >500,000 theoretical) inorganic crystal structures. For many of them, we have some physical properties (and for many, we don't).

Many studied syntheses of compounds.

Many studied industrial production processes.

Big data analysis gives:

Fast predictions

Predictions where the full calculation would be too complicated.

Input #1 Input #2 Output Input #3 Input #4





Predicting complex properties: hardness [Chen et al., 2011] and fracture toughness [Niu & Oganov, 2019]



Mendeleev number (Pettifor, 1984). Prediction of stability, structure, and properties of materials



Mendeleev numbers of the elements



Figure 5. The heat of solution of B in liquid metal A according to the semi-empirical model of Miedema *et al* (1977). The full-solid lines and the diagonal correspond to the contour $\Delta H_{\rm sol} = 0$. The dotted and full shaded regions correspond to $0 < \Delta H_{\rm sol} < 200$ and $\Delta H_{\rm sol} > 200$ kJ mol⁻¹ respectively. The light full and broken lines correspond to the contours $\Delta H_{\rm sol} = -200$ and $\Delta H_{\rm sol} = -400$ kJ mol⁻¹ respectively.

Enthalpies of formation of compounds

Example: search for new ternary nitrides (Sun, 2019)



916 systems

246 contain stable nitrides

In 127 of them nitrides were not experimentally known

Machine learning can be used for accelerating simulations without loss of accuracy



Phase diagram of uranium obtained with machine learning (Kruglov & Oganov, 2020)

Data mining gives quick-n-reasonable answers, but beware!



Davies & Oganov (2018): 4 interesting semiconductors, and for each data mining gave a wrong structure: -for $Sn_5S_4Cl_2$ by 24.7 meV/atom, -for Sn_4SF_6 by 5.1 meV/atom, -for Cd_4SF_6 by 0.2 meV/atom, -for $Cd_5S_4Cl_2$ by 33.3 meV/atom.

Briefly about crystal structure prediction

Faraday Discussions

Cite this: Faraday Discuss., 2018, 211, 643

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Crystal structure prediction: reflections on present status and challenges

Artem R. Oganov Dabc

Received 30th August 2018, Accepted 30th August 2018

Useful reviews and books

Faraday Discussions

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Crystal structure prediction: reflections on present status and challenges

Artem R. Oganov Dabc

Received 30th August 2018, Accepted 30th August 2018

Faraday Discussions (2018)



2011

REVIEWS

Structure prediction drives materials discovery

Artem R. Oganovo^{12,23}*, Chris J. Pickard^{6,63}*, Olang Zhu^a and Richard J. Needs⁷ Abstract.] Progress in the discovery of new materials has been accelerated by the development of reliable quantum mechanical approaches to crystal structure prediction. The properties of a material depend very sensitively on its structure; therefore, structure prediction is the key to computational materials discovery. Structure prediction was considered to be a formidable problem, but the development of new computational tools has allowed the structures of many new and increasingly complex materials to be anticipated. These widely applicable methods, based on global optimization and relying on little or no empirical Knowledge, have been used to structure prediction methods, examining their potential for the study of different materials systems, and present examples of computationally driven discoveries of new materials including superation materials. The materials – that will enable new technologies. Advances in first-principle structure predictions also lead to a better understanding of physical and chemical phronome in materials.

Nature Reviews Materials (2019)



Acc. Chem. Res. 1994, 27, 309-314

Are Crystal Structures Predictable?

Angelo Gavezzotti*



"No": by just writing down this concise statement, in what would be the first one-word paper in the chemical literature, one could safely summarize the present state of affairs





Crystal structure prediction – evolutionary or revolutionary crystallography?

Overview of USPEX (Oganov & Glass, *J.Chem.Phys.* 2006)

S. L. Chaplot and K. R. Rao CURRENT SCIENCE, VOL. 91, NO. 11, 10 DECEMBER 2006

The USPEX project (Universal Structure Predictor: Evolutionary Xtallography) http://uspex-team.org

[Oganov A.R., Glass C.W., J.Chem.Phys. 124, 244704 (2006)]

Combination of evolutionary algorithm and quantum-mechanical calculations.
>6100 users.

•Solves «intractable» problem of structure prediction -3D, 2D, 1D, 0D –systems, -prediction of phase transition mechanisms.

• Interfaced with: VASP, Quantum Espresso, CASTEP, FHI-aims, ABINIT, Siesta, Gaussian, ORCA, ATK, DFTB, MOPAC, GULP, LAMMPS, Tinker, DMACRYS





W. Kohn

J. P. Perdew



Energy landscape of Au₈Pd

$$(-\frac{\nabla^2}{2} + v_{e-n}[\rho(\mathbf{r})] + v_H[\rho(\mathbf{r})] + v_{xc}[\rho(\mathbf{r})]\phi_i(\mathbf{r}) = \varepsilon_i\phi_i(\mathbf{r})$$
$$E_{GGA,xc} = \int d\mathbf{r} F_{xc}(\rho, \frac{|\nabla\rho|}{2k_F\rho(\mathbf{r})})\rho(\mathbf{r})e_x[\rho(\mathbf{r})]$$

Predicting new crystal structures without empirical information



New superhard structure of boron (Oganov et al., *Nature*, 2009)



High-pressure transparent allotrope of sodium (Ma, Eremets, Oganov, *Nature*, 2009)



α-boron $E^{\text{DFT}} = -6.706 \text{ eV/atom}$ Atoms: 12, Space group: R-3m, Core-hours: 10³ AL-MTP vs. $3 \cdot 10^3 \text{ DFT}$ $|E^{\text{DFT}} - E^{\text{MTP}}| = 28.6 \text{ meV/atom}$



β-boron approximant $E^{DFT} = -6.704 \text{ eV/atom},$ Atoms: 106, Space group: *P*1, Core-hours: 7·10³ AL-MTP vs. 6.6·10⁷ DFT $|E^{DFT} - E^{MTP}| = 10.1 \text{ meV/atom}$

Core-hours: 2.10³ AL-MTP vs. 2.5.10⁴ DFT

 $|E^{\text{DFT}} - E^{\text{MTP}}| = 58.1 \text{ meV/atom}$

 $|E^{\text{DFT}} - E^{\text{MTP}}| = 7.3 \text{ meV/atom}$

γ-boron

Atoms: 28,

Atoms: 54, Space group: Im-3,

 $E^{\text{DFT}} = -6.678 \text{ eV}/\text{atom}$

 $E^{\text{DFT}} = -6.667 \text{ eV/atom},$

Space group: Pnnm,









Core-hours: 3.103 AL-MTP vs. 3.5.105 DFT



 $E^{\text{DFT}} = -6.665 \text{ eV/atom},$ Atoms: 26, Space group: <u>Cccm</u>, Core-hours: 2·10³ AL-MTP vs. 2.1·10⁴ DFT $|E^{\text{DFT}} - E^{\text{MTP}}| = 13.6 \text{ meV/atom}$

Handling complexity with machine learning: boron allotropes

(E.Podryabinkin, E. Tikhonov, A. Shapeev, A.R. Oganov, PRB, 2019)

- ML potential with active learning (Shapeev, 2018). 800 parameters.
- MAE = 11 meV/atom.
- Reproduced α-, β-, γ-, T52 phases of boron.
- Predicted low-energy metastable cubic cl54 phase.
- Speedup by >100 times.

Structure of Li₁₅Si₄ with 152 atoms/cell: record complexity, promise for Li-batteries





Structural transformation of Li₁₅Si₄ at 7 GPa. New phase has more attractive properties for use in Li-batteries.

Evolutionary metadynamics is a hybrid of: -Metadynamics (Martonak, Laio, Parrinello, PRL 2003) -Evolutionary algorithm USPEX (Oganov & Glass, JCP 2006)

It includes q-vectors and allows system size to change spontaneously



XRD of *Fdd*2-Li₁₅Si₄ at 18 GPa [Zeng & Oganov, *Adv. Energy Mat.*, 2015] Prediction of stable structure for a given chemical composition is possible.

Now, let's predict the chemical composition!

USPEX can automatically find all stable compounds in a multicomponent system.

Thermodynamic stability in variable-composition systems



Stable structure must be below all the possible decomposition lines !!



Predictive power of modern methods:

Na₃Cl, Na₂Cl, Na₃Cl₂, NaCl, NaCl₃, NaCl₇ are stable under pressure [Zhang, Oganov, et al. *Science*, 2013].



Chemical anomalies:

- -Divalent CI in Na₂CI!
- -Coexistence of metallic and ionic blocks in Na₃Cl!
- -Positively charged CI in NaCl₇!



NaCl₃: atomic and electronic structure, and experimental XRD pattern

[Zhang, Oganov, et al., Science (2013)] [Saleh & Oganov, PCCP (2015)]

Helium chemistry? Yes! [Dong, Oganov, Goncharov, *Nature Chemistry* 2017]



- Helium is the 2nd most abundant element in the Universe (24 wt.%).
- No stable compounds are known at normal conditions. Under pressure: van der Waals compound NeHe₂ (Loubeyre et al., 1993).



- 1. Na₂He is stable at >113 GPa, at least up to 1000 GPa.
- 2. New stable helium compounds: Na₂HeO (Dong & Oganov, 2017); CaF₂He, MgF₂He (Liu, 2018).

Highest-Tc superconductivity: new record, 203 Kelvin (Duan et al., *Sci. Rep.* 4, 6968 (2014))





OPEN Pressure-induced metallization of dense $(H_2S)_2H_2$ with high- T_c superconductivity

THEORY AND COMPUTATION COMPUTATION CONDENSEDMATTER PHYSCS

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The high pressure structures, metallization, and superconductivity of recently synthesized H_2 -containing compounds $(H_2S)_2H_2$ are elucidated by *ab initio* calculations. The ordered crystal structure with P1 symmetry is determined, supported by the good agreement between theoretical and experimental X-ray diffraction data, equation of states, and Raman spectra. The *Cccm* structure is favorable with partial hydrogen bond symmetrization above 37 GPa. Upon further compression, H_2 molecules dis appear and two intriguing metallic structures with R3m and *Im-3m* symmetries are reconstructive above 111 and 180 GPa, respectively. The predicted metallization pressure of bulk molecular hydrogen. Application of the currently suggested metallization pressure of bulk molecular hydrogen. Application of the Allen-Dynes-modified McMillan equation for the *Im-3m* symmetrize tries thigh *T*, values of 191 K to 204 K at 200 GPa, which is among the highest values reported for H_2 -rich van der Waals compounds and MH₃ type hydride thus far.

SCIENTIFIC REPORTS | 4:6968 | DOI: 10.1038/srep06968

Conventional superconductivity at 203 kelvin at high pressures in the sulfur hydride system

A. P. Drozdov, M. I. Eremets, I. A. Troyan, V. Ksenofontov & S. I. Shylin

Nature (2015) | doi:10.1038/nature14964 Received 25 June 2015 | Accepted 22 July 2015 | Published online 17 August 2015

A superconductor is a material that can conduct electricity without resistance below a superconducting transition temperature, T_c . The highest T_c that has been achieved to date is in the copper oxide system¹: 133 kelvin at ambient pressure² and 164 kelvin at high pressures³. As the nature of superconductivity in these materials is still not fully understood (they are not conventional superconductors), the prospects for achieving still higher transition temperatures by this route are not clear. In contrast, the Bardeen-Cooper-Schrieffer theory of conventional superconductivity gives a guide for achieving high T_c with no theoretical upper bound—all that is needed is a favourable combination of high-frequency phonons, strong electron-phonon coupling. and a high density of states⁴. These conditions can in principle be fulfilled for metallic hydrogen and covalent compounds dominated by hydrogen^{5, 6}, as hydrogen atoms provide the necessary highfrequency phonon modes as well as the strong electron-phonon coupling. Numerous calculations support this idea and have predicted transition temperatures in the range 50-235 kelvin for many hydrides⁷, but only a moderate T_c of 17 kelvin has been observed experimentally⁸. Here we investigate sulfur hydride9, where a T c of 80 kelvin has been predicted 10. We find that this system transforms to a metal at a pressure of approximately 90 gigapascals. On cooling, we see signatures of superconductivity: a sharp drop of the resistivity to zero and a decrease of the transition temperature with magnetic field, with magnetic susceptibility measurements confirming a T_c of 203 kelvin. Moreover, a pronounced isotope shift of T_c in sulfur deuteride is suggestive of an electron– phonon mechanism of superconductivity that is consistent with the Bardeen-Cooper-Schrieffer scenario. We argue that the phase responsible for high- T_c superconductivity in this system is likely to be H₃S, formed from H₂S by decomposition under pressure. These findings raise hope for the prospects for achieving room-temperature superconductivity in other hydrogen-based materials.

 Old record Tc=135 K (Schilling, 1993) is broken: theorists (T. Cui, 2014) predicted new compound H₃S with Tc~200 K.

1

Confirmed by A. Drozdov et al. (*Nature* 525, 73 (2015)).

Superconductivity is linked with Mendeleev's Table [Semenok & Oganov, JPCL, 2018; Curr. Opinion Solid St. Mater. Sci., 2020]



Distribution of Tc for hydrides





 CaH_{6} ($T_{c} = 220 - 235 \text{ K}$)

LaH₁₀ ($T_c = 274 - 286 \text{ K}$) AcH₁₀ ($T_c = 226 - 251 \text{ K}$) YH₁₀ ($T_c = 305 - 326 \text{ K}$) ThH₁₀ ($T_c = 220 - 241 \text{ K}$)

 AcH_{16} ($T_c = 221 - 241 \text{ K}$) We can simultaneously optimize composition, structure, stability and other properties for a given chemical system.

Now, let's predict the best material(s) among all possible chemical systems!

Mendelevian Search – breakthrough method for discovering best materials among all possible compounds [Allahyari & Oganov, NPJ Comp. Mat., 2020]





- 118 elements
- 7021 binary systems
- 273937 ternaries
- In each system ∞ possible structures

Mendeleev Number – a way to arrange elements and compounds by properties [Pettifor, 1984; Allahyari & Oganov, *NPJ Comp. Mat.*, 2020]

Mendeleev	Atom	Mendeleev	Atom	Mendeleev	Atom
Number		Number		Number	
1	Fr	32	п	62	Po
2	Cs	33	U	63	Fe
3	Rb	34	Pa	64	Cu
4	к	35	Zr	65	Co
5	Ra	36	Pu	66	As
6	Ba	37	Np	67	Ni
7	Sm	38	Nb	68	Kr
8	Gd	39	Та	69	Mo
9	Eu	40	In	70	1
10	Sr	41	Pb	71	Pd
11	Tm	42	Cd	72	Ir
12	Pm	43	Xe	73	Os
13	Ca	44	п	74	Р
14	Na	45	AI	75	Ru
15	Ac	46	Bi	76	Pt
16	La	47	Sn	77	At
17	УЪ	48	Hg	78	Rh
18	ть	49	Zn	79	w
19	Y	50	Ga	80	Rn
20	Dy	51	v	81	Se
21	Но	52	Mn	82	в
22	Ce	53	Sb	83	Au
23	Er	54	Te	84	s
24	u	55	Cr	85	Br
25	Th	56	Ag	86	н
26	Lu	57	Be	87	c
27	Pr	58	Go	88	СІ
28	Nd	59	Re	89	N
29	Mg	60	Si	90	0
30	Sc	61	Тс	91	F
31	Hf				



Grouping of hardness by (a) sequential number, (b) Pettifor's Mendeleev number, (c) our Mendeleev number

Mendelevian search for the hardest possible material: diamond and lonsdaleite are found!



"Treasure" map of superhard materials [Kvashnin, Allahyari, Oganov, *J. Appl. Phys.*, 2019]



WB_{5-x}: hard & tough material [Kvashnin & Oganov, J. Phys. Chem. Lett., 2018; Advanced Science, 2020]



Advanced algorithms predict new supermaterials and help us understand nature



Unusual chemistry at extreme conditions



New record of high-Tc superconductivity



New superhard materials

Our team. Where great minds do NOT think alike

Haiyang Niu

Artem R. Oganov





Vladimir Baturin

Pavel Bushlanov









Michele Galasso







Eugene Tikhonov

Alexander Kvashnin







Q. Zhu



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