# Computational magnetic materials discovery

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Materials discovery

✓ Superconductor having highest *T*<sub>c</sub>?
 ✓ Harder material than diamond ?
 ✓ Strong magnet ?

- - -



Atomic species + Composition + Structure

## History of permanent magnet



- $\checkmark$  High saturation magnetization
- ✓ High coercivity  $\rightarrow$  High magnetocrystalline anisotropy
- ✓ High Curie temperature
- ✓ Phase stability

### Intrinsic properties

Sample dependent (microstructure, interfaces, ...)



## Nd-Fe-B magnet



### K. Hono (NIMS)

- ✓ Saturation magnetization
   ✓ Magneteon atomics
- ✓ Magnetocrystalline anisotropy
- ✓ Curie temperature

- ✓ Coercivity
- ✓ Microstructure

### Magnet compounds

### Magnetic properties

- Saturation magnetization
- Magnetocrystalline anisotropy
- Curie temperature

## Structural properties

• Phase stability

Fe, Co, Mn, ...

Nd, Sm, ...

B, C, N, ...

Other elements ???

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Slater-Pauling curve Calculation by H. Akai



### Hard-magnetic compounds



Hirayama, Miyake and Hono, JOM 67, 1344 (2015)

2:14:1 type  $Nd_2Fe_{14}B$ 

1:5 type (*m*=1, *n*=0) SmCo<sub>5</sub>, YCo<sub>5</sub>

2:17, 2:17:3 type (*m*=3, *n*=1) Sm<sub>2</sub>Co<sub>17</sub>, Sm<sub>2</sub>Fe<sub>17</sub>N<sub>3</sub>

1:12 type (*m*=2, *n*=1) SmFe<sub>11</sub>Ti, NdFe<sub>11</sub>TiN

 $R_{m-n}T_{5m+2n}$ 

# NdFe<sub>12</sub>N film



Y. Hirayama et al., Scripta Materialia **95**, 70 (2015)

## Chemical substitution



## High-throughput computational screening

### Direct screening of 1,280 compounds by first-principles calculation

System	(BH) <sup>£57</sup> <sub>mms</sub> [kJ/m <sup>3</sup> ]	""Мала [T]	K1454 [MJ/m3]	Hasa (T)	Kather [MJ/m3]	μ.M. 49 [T]	Hay (T)
NdFe <sub>12</sub>	636	1.99	3	3	-2.2*		
NdFe <sub>10</sub> B	611	1.95	45	58			
NdFe <sub>12</sub> C	617	1.96	47	60	8		
NdFe <sub>10</sub> N	686	2.06	47	57	9.91*	1.664	84
NdFe <sub>11</sub> Ti	438	1.65	4	7	-0.58' 1.70"	1.70*	2.0*
NdFe <sub>11</sub> TiB	432	1.64	48	72	-0.70/		
NdFenTiC	432	1.64	50	76	2.6/		
NdFe <sub>11</sub> TiN	487	1.74	49	71	11.3 10.6	1.484	≥7*,
CeFe <sub>12</sub>	586	1.91	4	5			
CeFegB/C/N	556/568/630	1.86/1.88/1.98	127/137/139	170/182/175			
CeFe <sub>11</sub> Ti	396	1.57	11	18		1.19' 1.55"	2.96 2.3*
CeFe <sub>11</sub> TtB/C/N	396/391/443	1.57/1.56/1.66	134/145/148	213/232/222			
SmFe <sub>12</sub>	538	1.83	-5	-6	2.4'		
SmFearTi	357	1.49	8	-13	-0.52"		
SmFe <sub>11</sub> TiN	401	1.58	-73	-115	-20.4*		
SmFe <sub>10</sub> N	580	1.90	-71	-93	-18.1*		
CeFe <sub>11</sub> Co <sub>1</sub> B/N	536/605	1.83/1.91	129/142	176/183			
CeFe <sub>g</sub> Co <sub>4</sub> B/C/N	464/464/521	1.70/1.70/1.80	116/141/146	168/208/203			
CeFe <sub>s</sub> Nt <sub>s</sub> N	417	1.61	167	260	1 C		
NdFe <sub>11</sub> Co <sub>1</sub> B/C/N	586/586/661	1.91/1.91/2.03	46/48/48	60/63/59			
NdFesCosB/C/N	520/505/574	1.80/1.77/1.89	41/49/50	57/69/67			

Körner, Krugel and Elsässer, Sci. Rep. 6, 24686 (2016)

### **Topological materials**

T. Zhang et al., arXiv: 1807.08756

c.f. F. Tang et al., arXiv:1807.09774 M.G. Vergniory et al., arXiv:1807.10271

Structure data from database 39,519 materials from ICSD Electronic structure 8,056 are topological by first-principles calc.

5,005 topological semimetals

1,814 topological insulators

1,237 topological crystalline insulators

### Exhaustive search ??



## Virtual screening



## Virtual screening



# ① Computational database

### OQMD:

Home Materials Analysis Documentation Download

The Open Quantum Materials Database

Newsflash: OQMD v1.1 is out! (Download it here.)

### Welcome to the Open Quantum Materials Database

The OQMD is a database of DFT-calculated thermodynamic and structural properties. This online interface is for convenient, small-scale access; for a more powerful utilization of the data, we recommend downloading the entire database and the API for interfacing with it, from the link below.

#### You can...

Search for materials by composition,

- Create phase diagrams using the thermochemical data in OQMD,
- Determine ground state compounds at any composition,

Visualize crystal structures, or

Download the entire database (and the API) for your own use!

### **Current status**

OQMD v1.1 has been released! Download it here. The database now contains 471857 entries. In addition, calculations of new structures are constantly ongoing! Recently added compounds include: EuPaBe PrPaFe PaReHg AcLaPa KPaMo

✓ 9485 Fe compounds
✓ 9541 Co compounds
✓ 9932 Ni compounds

### **RTX materials**

T<sub>4d-5d</sub> = ["Y", "Zr", "Nb", "Mo", "Tc", "Ru", "Rh", "Pd", "Ag", "Cd", "Hf", "Ta", "W", "Re", "Os", "Ir", "Pt", "Au", "Hg"]

T<sub>3d</sub> = ["Ti", "V", "Cr", "Mn", "Fe", "Co", "Ni", "Cu", "Zn"]

R = ["La", "Ce", "Pr", "Nd", "Pm", "Sm", "Eu", "Gd", "Tb", "Dy", "Ho", "Er", "Tm", "Yb", "Lu"]

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X = ["B", "C", "N", "O"]
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Optimized structure Total energy Magnetic moment etc.

# 2 Machine-learning model

Kernel regression

$$f(\vec{x}) = \sum_{i=1}^{N} \alpha_i k(\vec{x}^{(i)}, \vec{x})$$

Gaussian kernel

$$k(\vec{x}, \vec{x'}) = C \exp(-\beta ||\vec{x} - \vec{x'}||^2)$$

Laplacian kernel

$$k(\vec{x}, \vec{x'}) = C \exp(-\beta ||\vec{x} - \vec{x'}||)$$



### **Orbital Field Matrix (OFM)**

### Pham et al., STAM 18, 756 (2017)





# 2 Orbital Field Matrix (OFM)



### Formation energy

### Pham et al., STAM **18**, 756 (2017)

- Data: 4,220 *R*-*T*-*X* compounds
- DFT: VASP+GGA
- Machine learning: KRR + OFM

RMSE = 0.190 eV/atomMAE = 0.112 eV/atom $R^2 = 0.98$ 





### Pham et al., STAM 18, 756 (2017)

- Data: 4,220 *R*-*T*-*X* compounds
- DFT: VASP+GGA
- Machine learning: KRR + OFM

RMSE = 0.190 eV/atom MAE = 0.112 eV/atom  $R^2 = 0.98$ 

OFM1 + Manhattan distance + Laplace kernel regressor

RMSE = 0.110 eV/atom

MAE = 0.067 eV/atom

Pham et al., JCP 148, 204106 (2018)

 $R^2 = 0.994$ 





https://materialsproject.org/wiki/images/6/6f/Convexhull.png



Collect experimental  $T_{\rm C}$ 's of 101 *R*-*T* alloys from database (AtomWork)

H. Kino (NIMS)

- ✓ Represent a compound by a vector x
- ✓ 27 primary descriptors characterizing crystal constituent elements and structure

Category	Descriptors
Atomic properties of	$Z_T, r_T, r_T^{cv}, IP_T, \chi_T, S_{3d}, L_{3d}, J_{3d}$
transition metals (T)	
Atomic properties of	$Z_R, r_R, r_R^{cv}, IP_R, \chi_R, S_{4f}, L_{4f}, J_{4f}, g_J, J_{4f}g_J,$
rare-earth metals (R)	$J_{4f}(1-g_J)$
Structural information	$C_T, C_R, d_{T-T}, d_{T-R}, d_{R-R}, N_{T-R}, N_{R-R},$
(S)	$N_{R-T}$



# Machine learning

- ✓ Select a subset of 27 primary descriptors that maximizes prediction accuracy (Exhaustive search for 2<sup>27</sup>-1 combinations)
- ✓ Gaussian kernel-ridge regression
- ✓ 10-fold cross validation



Dam et al., J. Phys. Soc. Jpn. (accepted)

 $T_{\rm C}$  of *R*-*T* bimetals

### Prediction

### Understanding?



## Subgroup relevance analysis

Dam et al., J. Phys. Soc. Jpn. (accepted)



 $\operatorname{cov}(X,Y) = \langle X - \langle X \rangle \rangle \langle Y - \langle Y \rangle \rangle$ 

covariance

## Subgroup relevance analysis

Dam et al., J. Phys. Soc. Jpn. (accepted)



n	score	descriptor(s)
2	0.870153	C <sub>R</sub> ,Z <sub>T</sub>
3	0.942222	$(C_R, Z_R, Z_T)$
4	0.953386	$J_{3d}, C_R, Z_R, Z_T$
5	0.954294	$L_{3d}, J_{3d}, C_R, Z_R, Z_T$
6	0.954391	$L_{3d}, J_{3d}, \chi_T, C_R, Z_R, Z_T$
7	0.954452	$L_{3d}, J_{3d}, \chi_T, C_R, Z_R, Z_T, r_T^{cv}$
8	0.954448	$L_{3d}, J_{3d}, \chi_T, IP_T, C_R, Z_R, Z_T, r_T^{cv}$

Result by exhaustive search

## Summary

- High-throughput screening by a combined computational and machine-learning techniques
- Virtual screening of Nd-Fe-B compounds using kernel-ridge regression and orbital-field-matrix
- Kernel-ridge regression of Curie temperature: important descriptors and descriptor groups by subgroup relevance analysis