

Quantum Machine Learning

Parameters, Delta, Crystals

Anatole von Lilienfeld

"Machine Learning, Quantum Mechanics, and Chemical Compound Space"

By Ramakrishnan and von Lilienfeld

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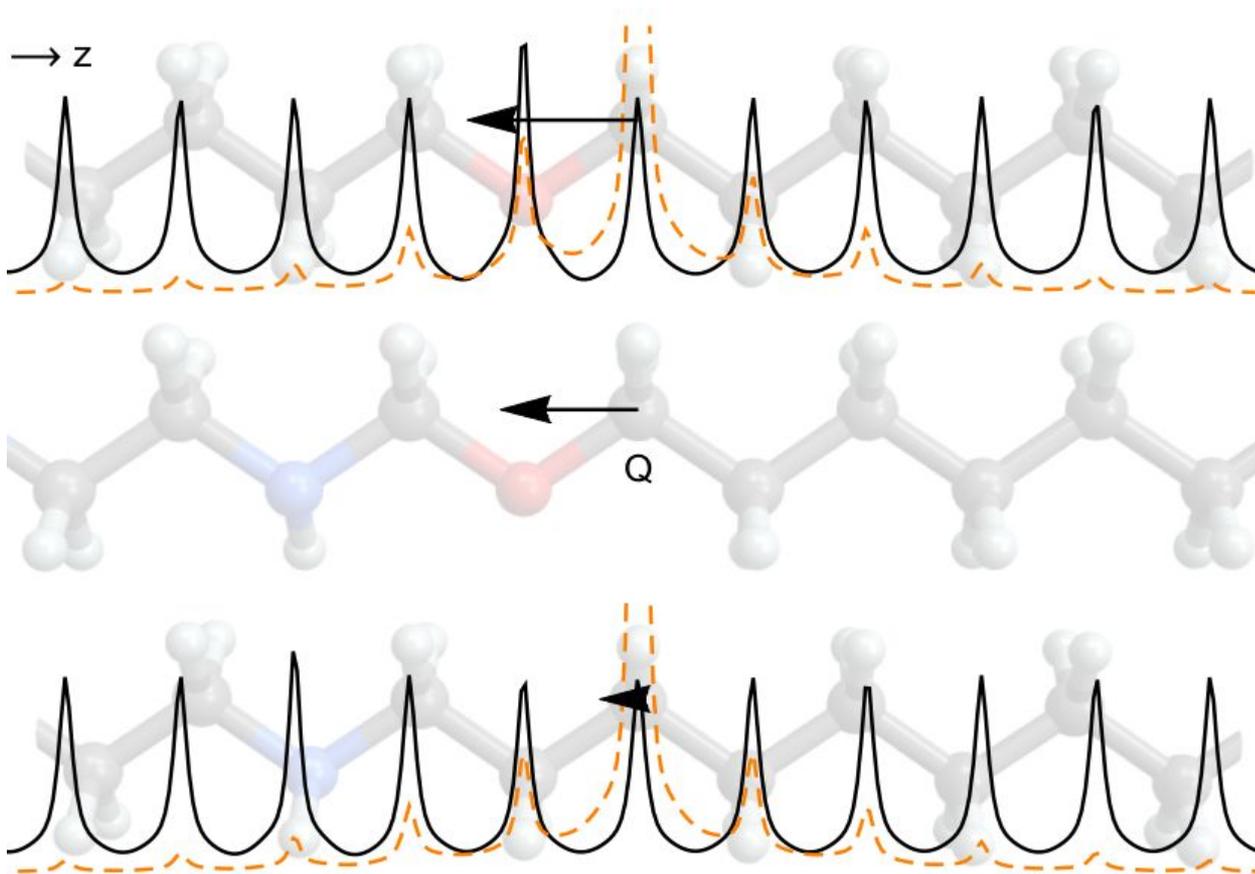


Conclusions

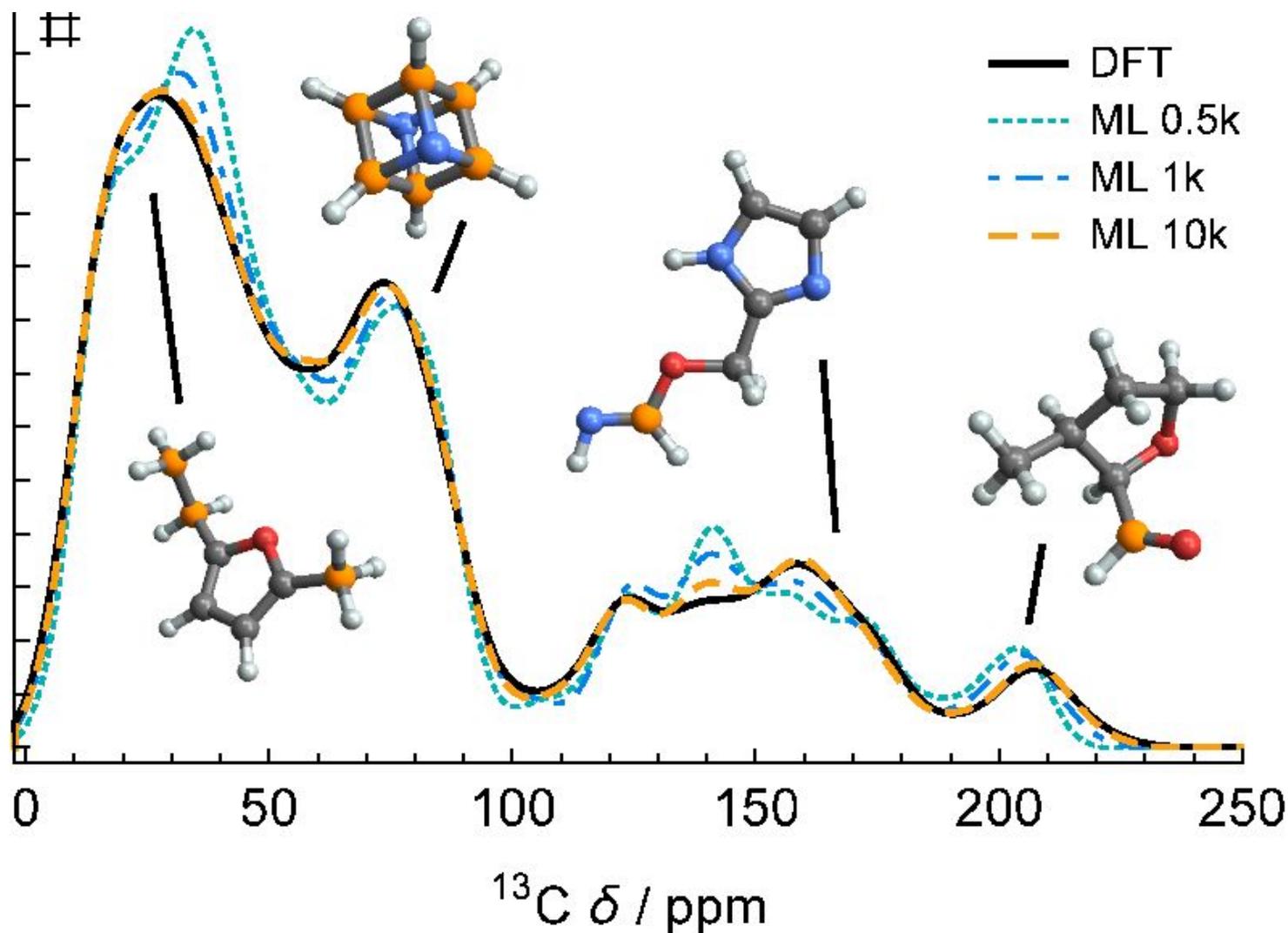
1. Parameter learning
2. Δ -ML (prior expert knowledge about property)
3. Crystals

An Atom in Many Molecules

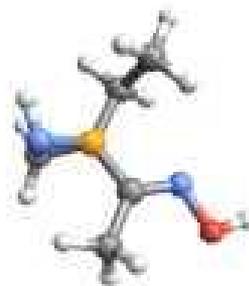
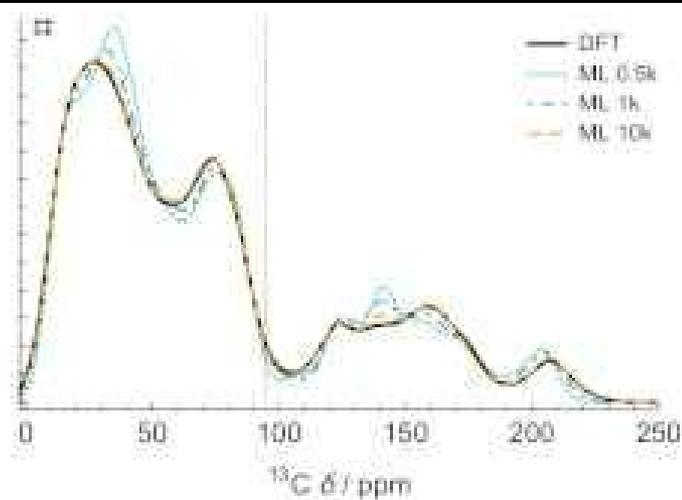
$$\langle \Psi | \partial_{\mathbf{R}_Q} \hat{H} | \Psi \rangle = \int d\mathbf{r} (\mathbf{r} - \mathbf{R}_Q) Z_Q n(\mathbf{r}) / \|\mathbf{r} - \mathbf{R}_Q\|^3$$



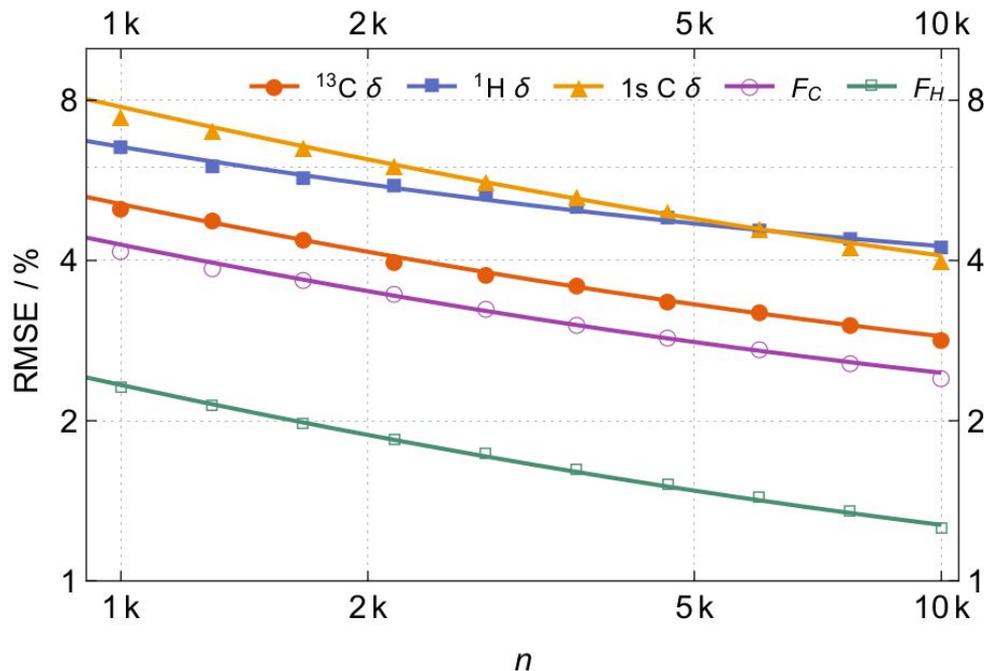
An Atom in Many Molecules



An Atom in Many Molecules



An Atom in Many Molecules

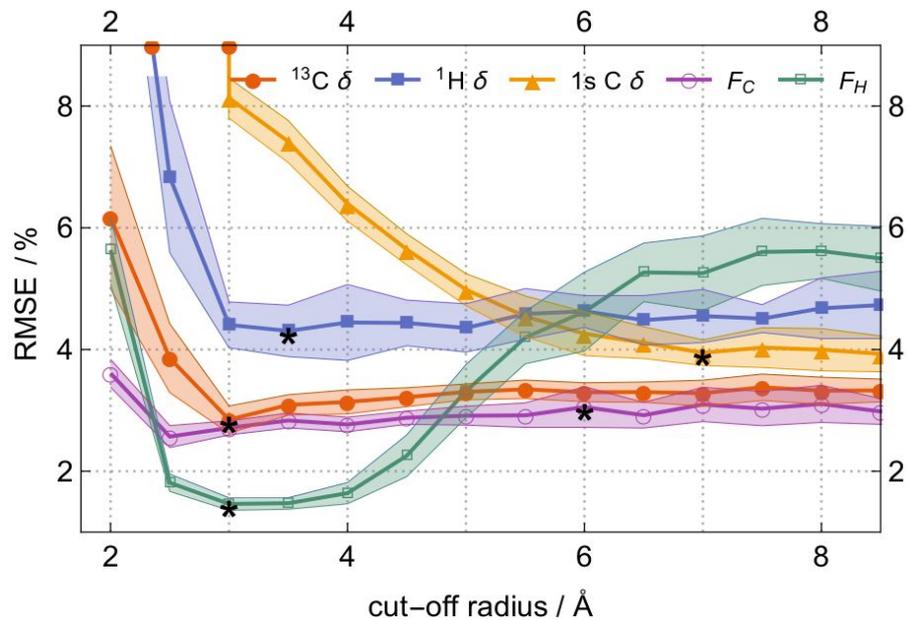


10k atoms from:

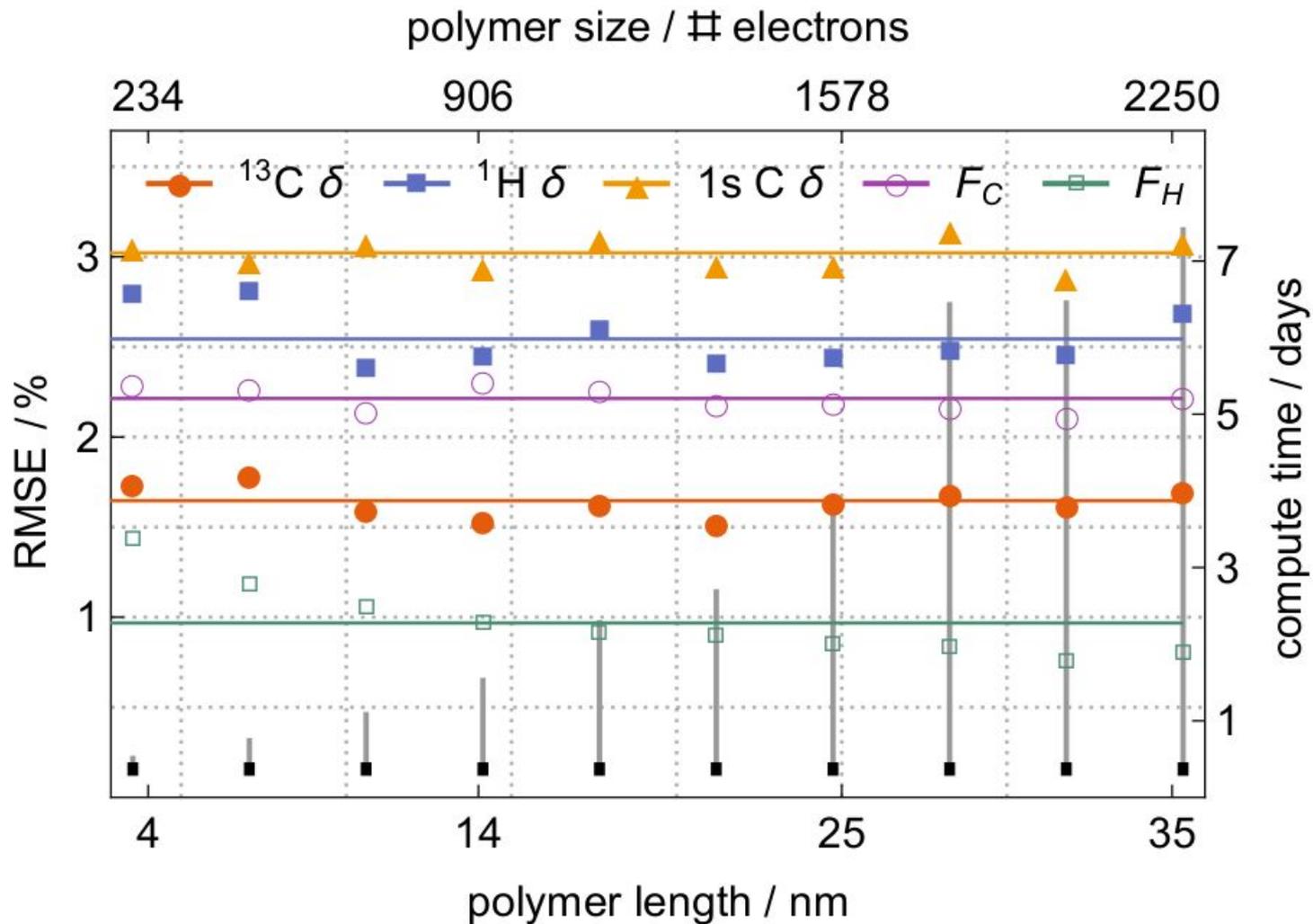
-16800 distortions from 168 $\text{C}_7\text{H}_{10}\text{O}_2$ isomers

-9k GDB molecules with 7 to 9 atoms CONF/molecule

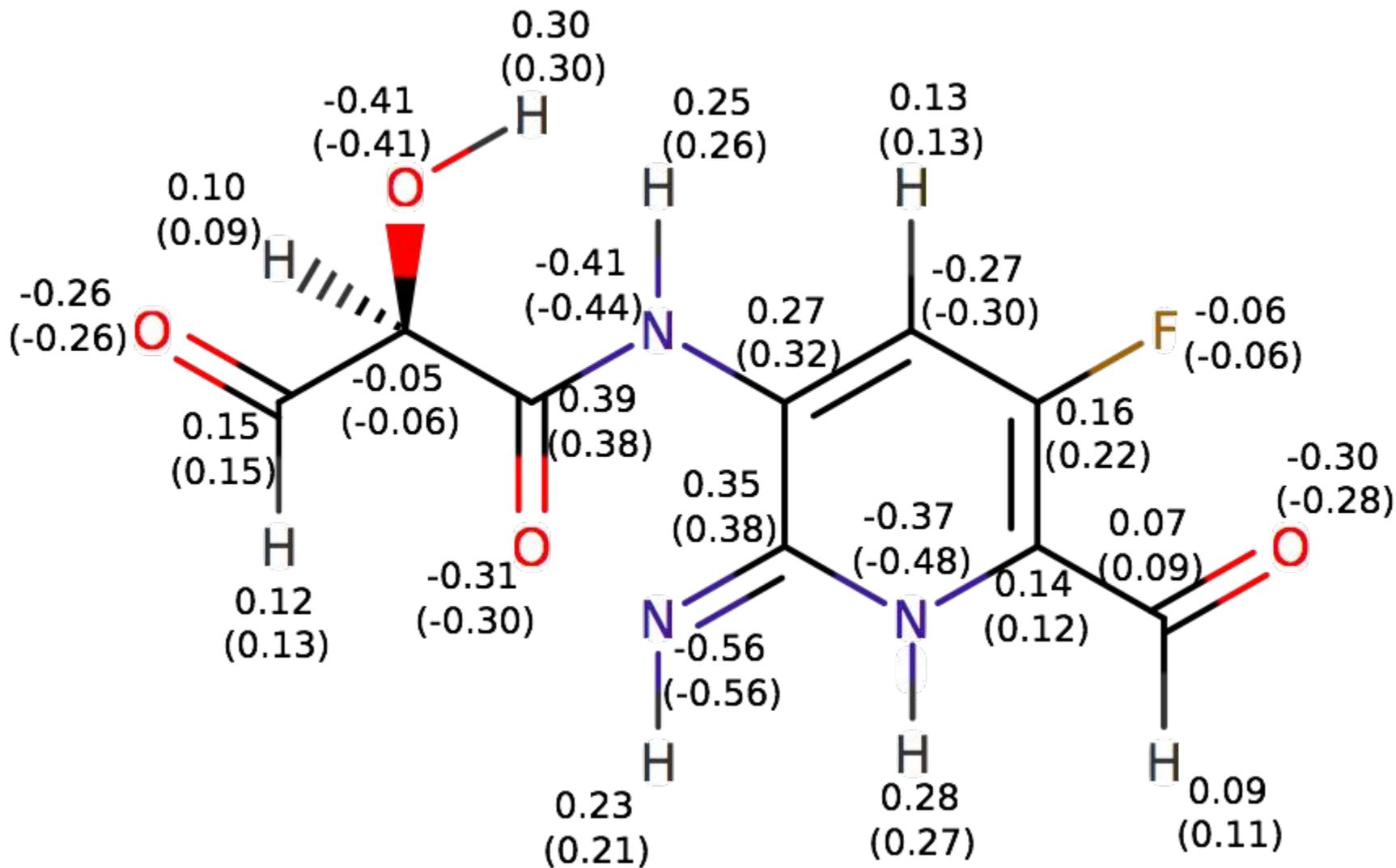
For 10k models



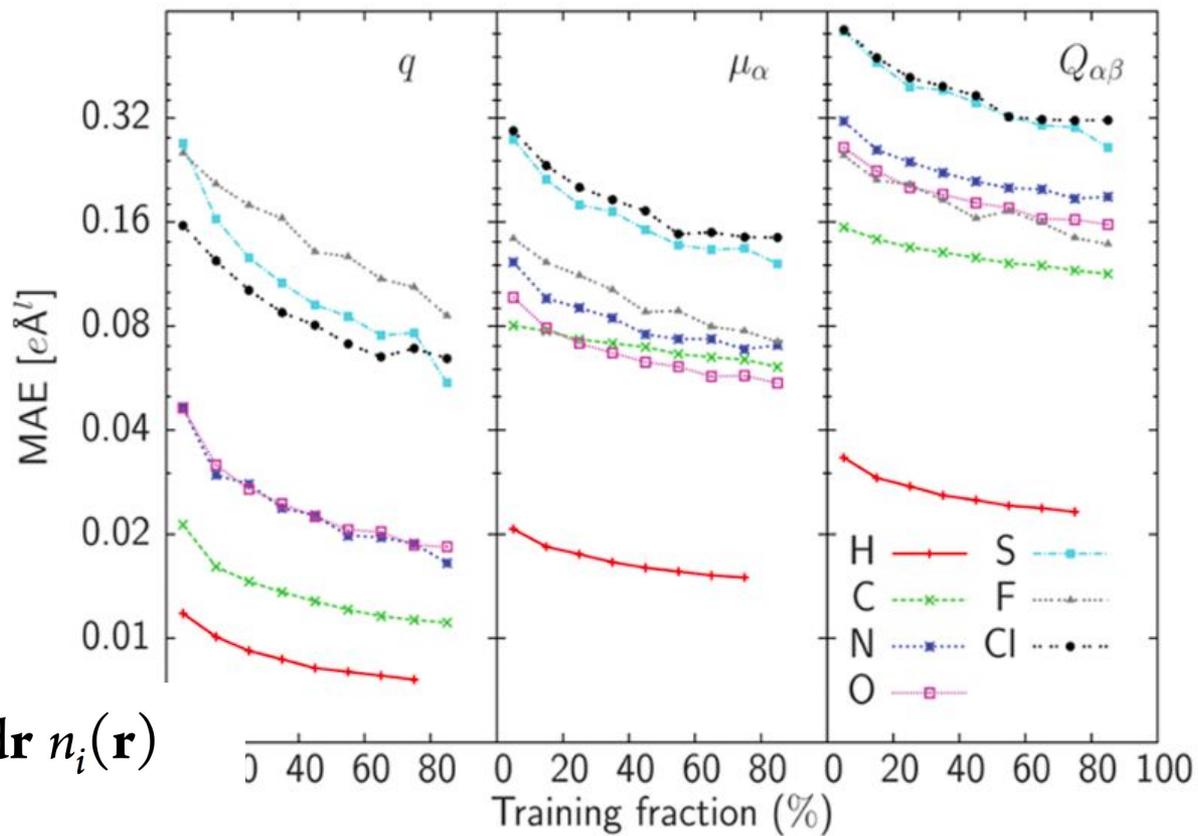
An Atom in Many Molecules



Atomic charges



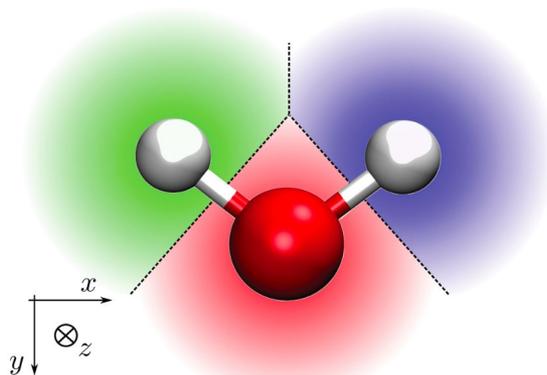
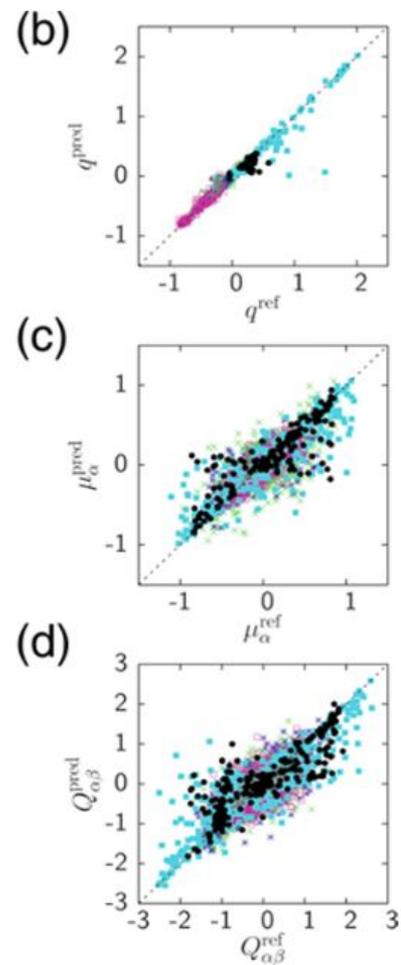
Atomic parameters for force-fields



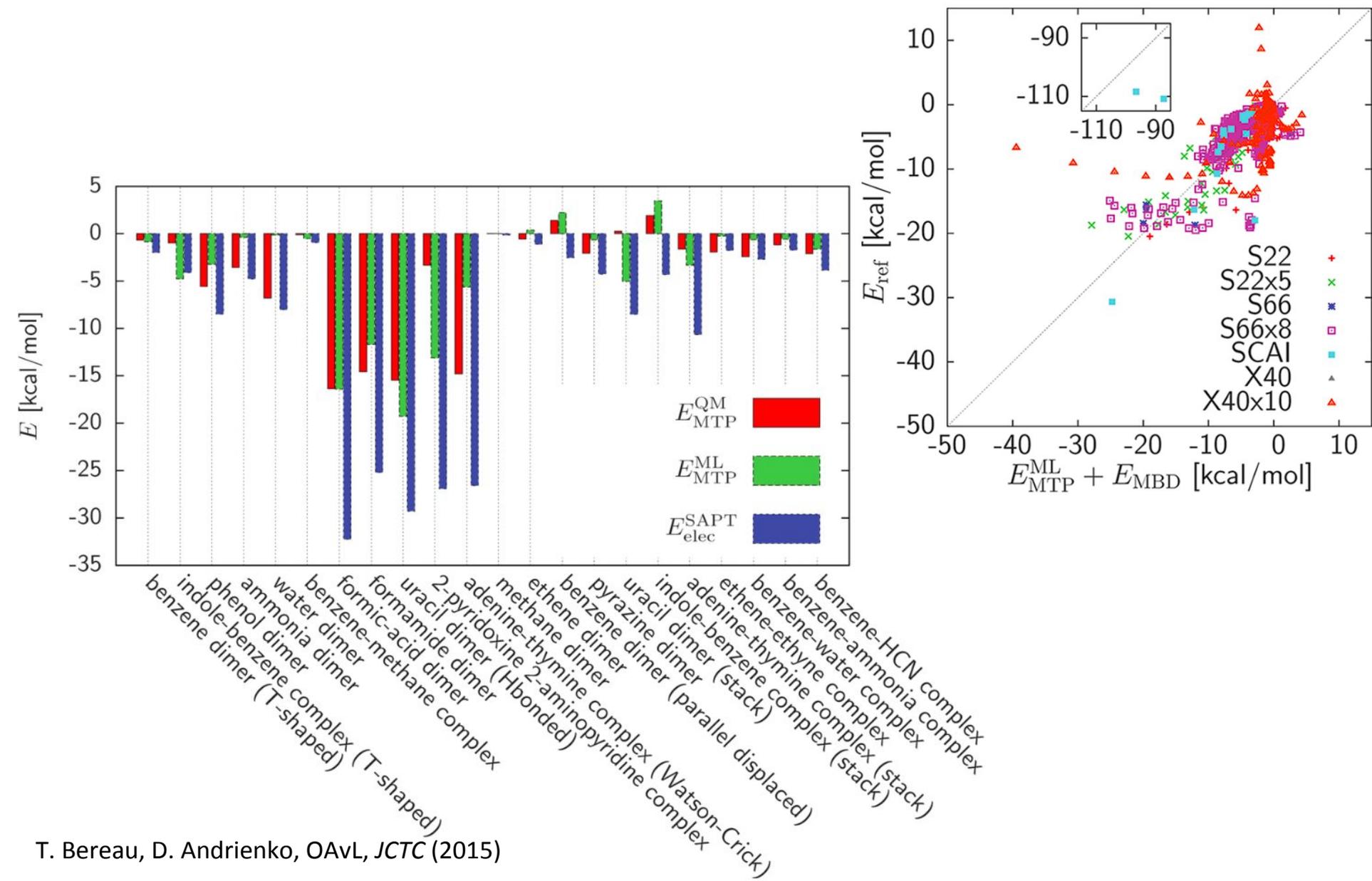
$$q^{(i)} = \int d\mathbf{r} n_i(\mathbf{r})$$

$$\mu_\alpha^{(i)} = \int d\mathbf{r} n_i(\mathbf{r}) r_\alpha$$

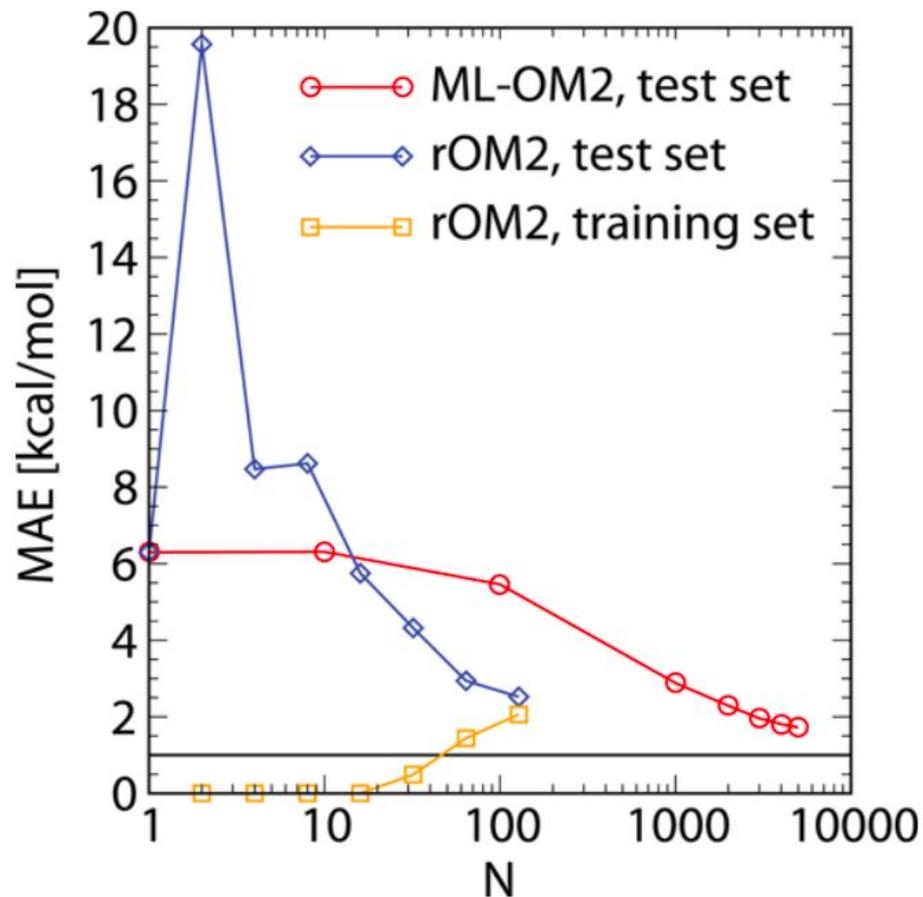
$$Q_{\alpha\beta}^{(i)} = \int d\mathbf{r} n_i(\mathbf{r}) r_\alpha r_\beta$$



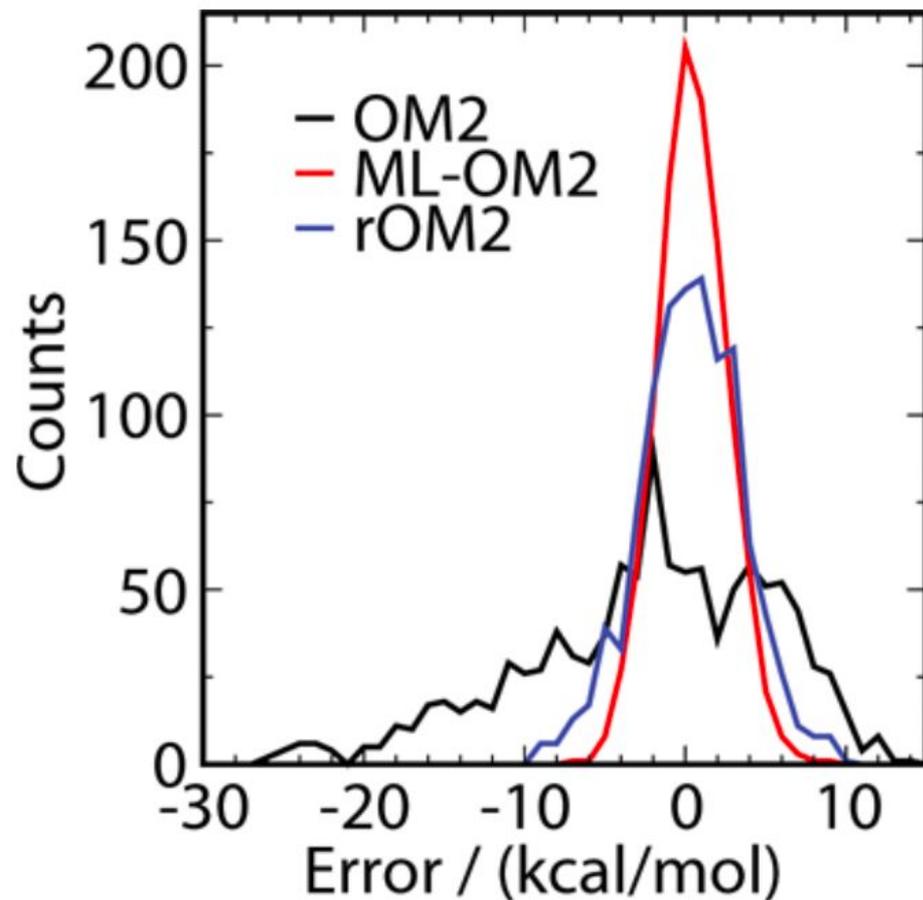
Atomic parameters for force-fields



Atomic parameters in OM2



$$\Delta P(M) = \sum_{i=1}^{N_{\text{train}}} \alpha_i e^{-\|M - M_i\|_1 / \sigma}$$



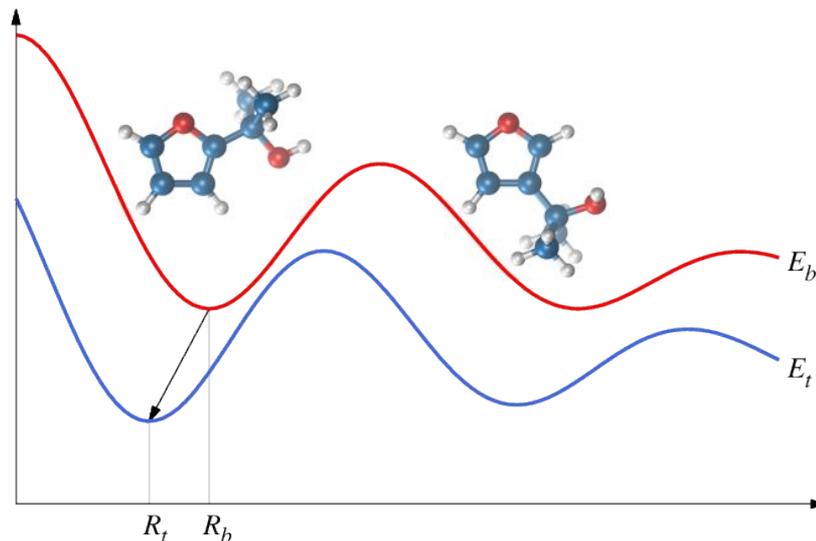
OM2 orbital exponent for Carbon (“screening”) selected due to high sensitivity

Conclusions

1. Parameter learning
2. Δ -ML (prior expert knowledge about property)
3. Crystals

Δ -ML

$$E_t(R_t) \approx E_b(R_b) + \Delta_b^t(R_b)$$



Big Data Meets Quantum Chemistry Approximations: The Δ -Machine Learning Approach

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[†]Institute of Physical Chemistry and National Center for Computational Design and Discovery of Novel Materials, Department of Chemistry, University of Basel, Klingelbergstraße 80, CH-4056 Basel, Switzerland

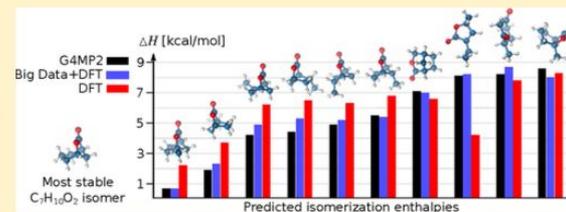
[¶]Max-Planck-Institut für Kohlenforschung, Kaiser-Wilhelm-Platz 1, 45470 Mülheim an der Ruhr, Germany

[‡]Computer-Chemie-Centrum and Interdisciplinary Center for Molecular Materials, Department Chemie und Pharmazie, Friedrich-Alexander-Universität Erlangen-Nürnberg, Nögelsbachstraße 25, 91052 Erlangen, Germany

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Supporting Information

ABSTRACT: Chemically accurate and comprehensive studies of the virtual space of all possible molecules are severely limited by the computational cost of quantum chemistry. We introduce a composite strategy that adds machine learning corrections to computationally inexpensive approximate legacy quantum methods. After training, highly accurate predictions of enthalpies, free energies, entropies, and electron correlation energies are possible, for significantly larger molecular sets than used for training. For thermochemical properties of up to

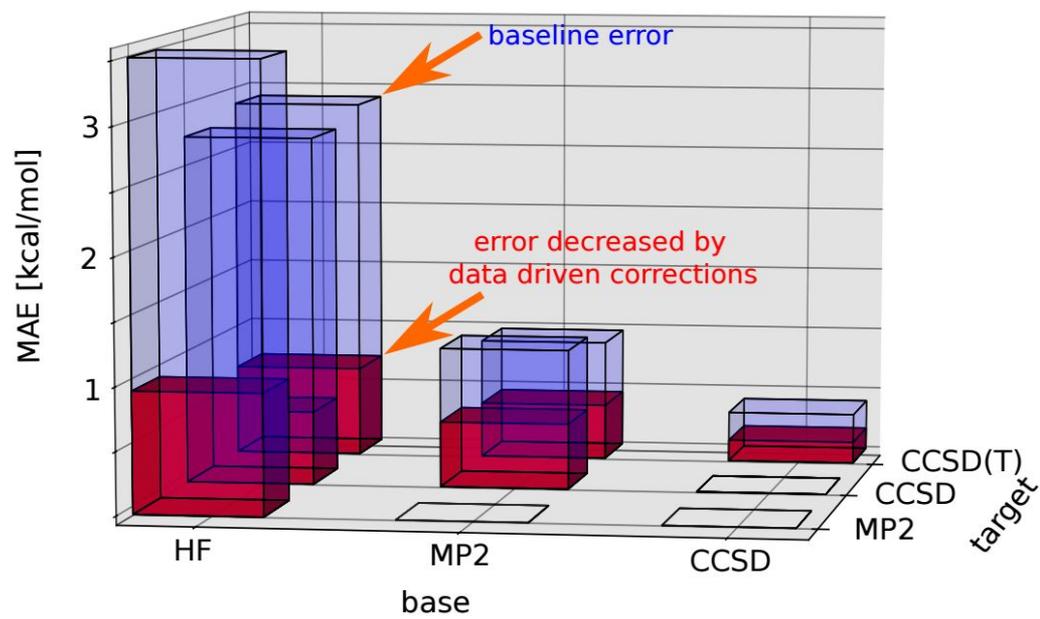
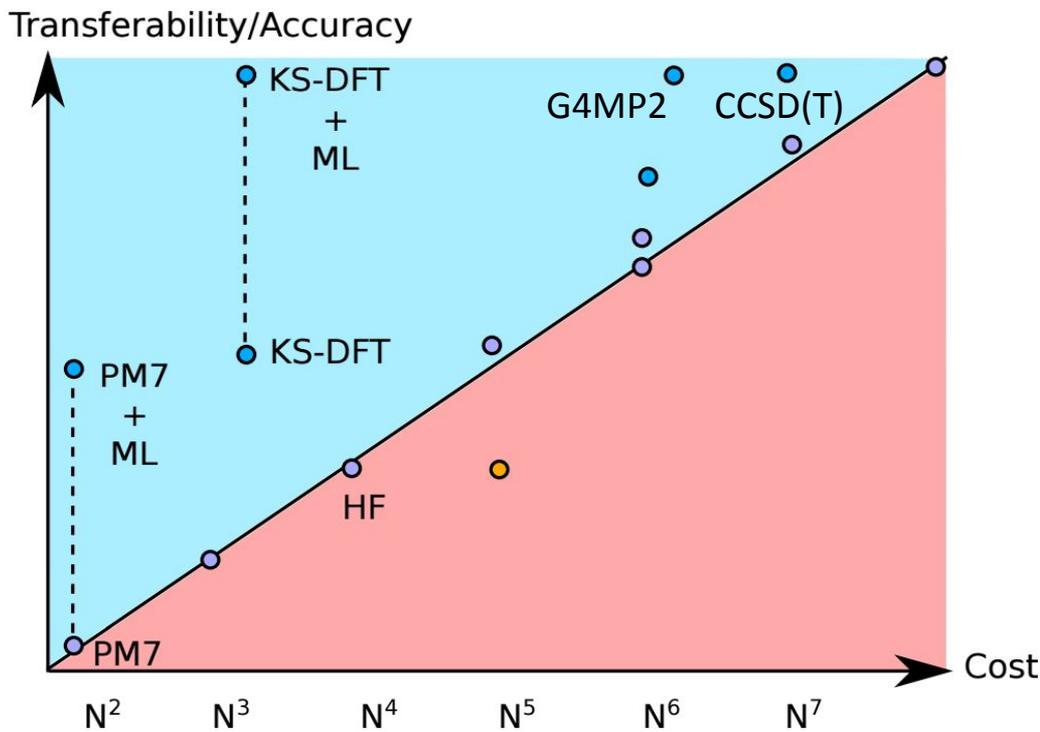
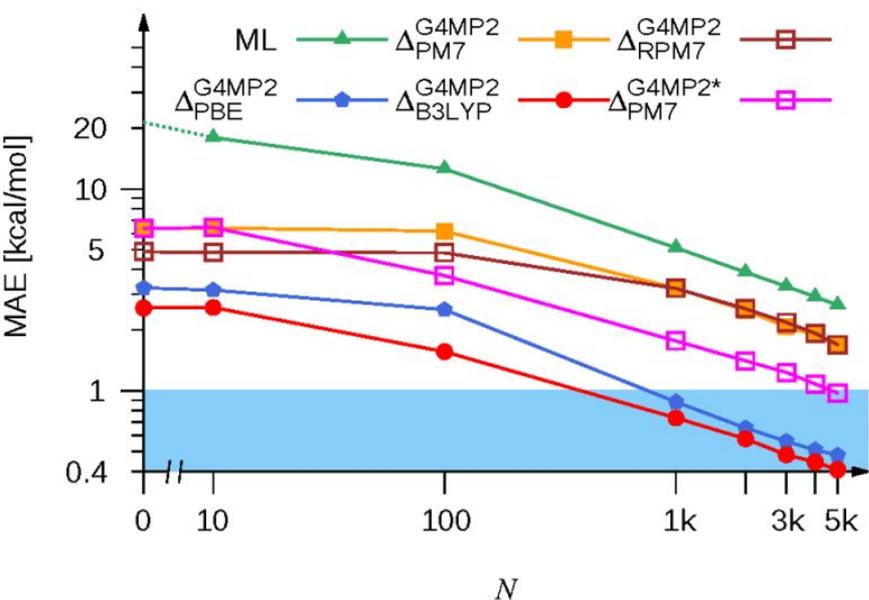


16k isomers of $C_7H_{10}O_2$ we present numerical evidence that chemical accuracy can be reached. We also predict electron correlation energy in post Hartree–Fock methods, at the computational cost of Hartree–Fock, and we establish a qualitative relationship between molecular entropy and electron correlation. The transferability of our approach is demonstrated, using

Δ -ML

$$E_t(R_t) \approx E_b(R_b) + \Delta_b^t(R_b)$$

6k constitutional isomers of $C_7O_2H_{10}$

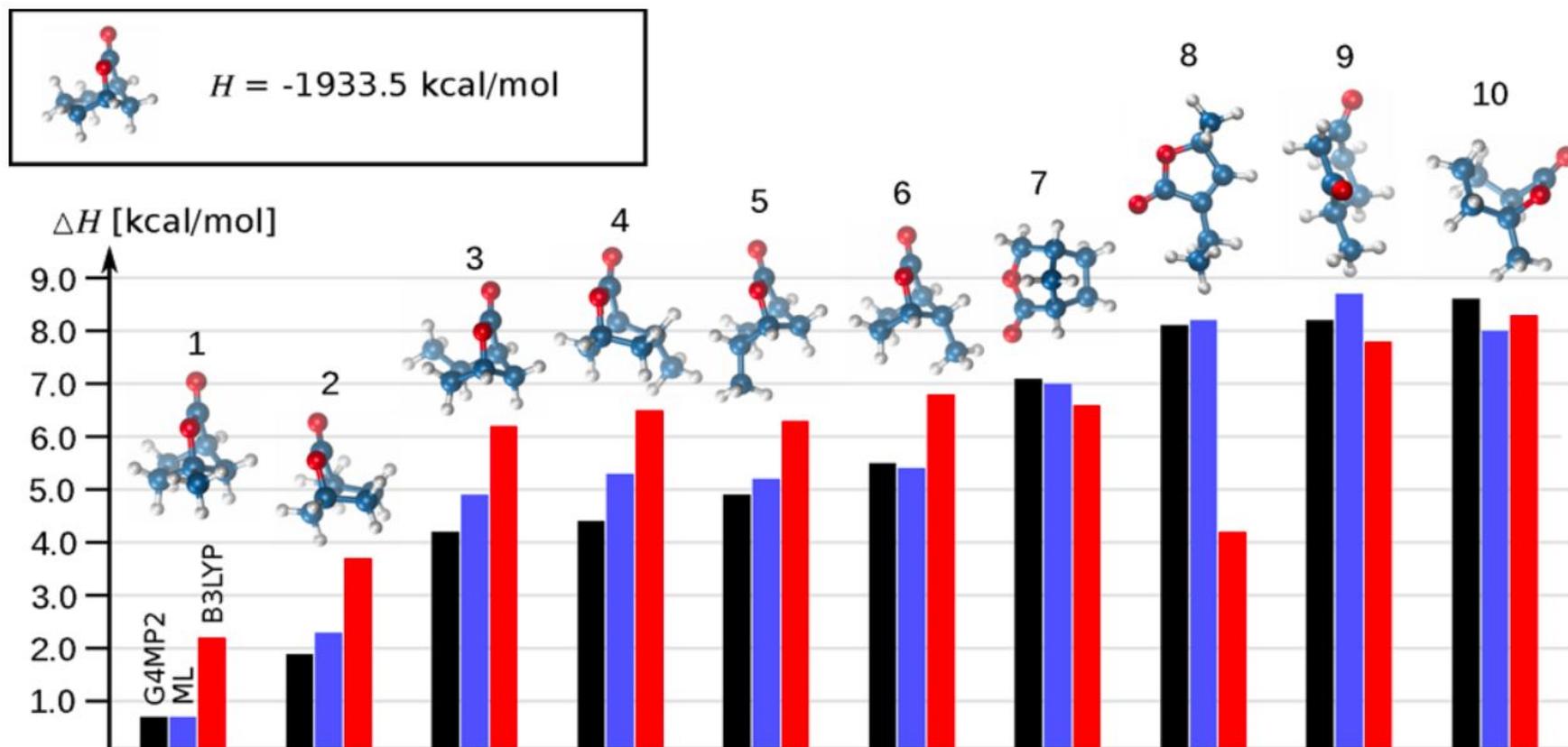


Δ -ML

$$E_t(R_t) \approx E_b(R_b) + \Delta_b^t(R_b)$$

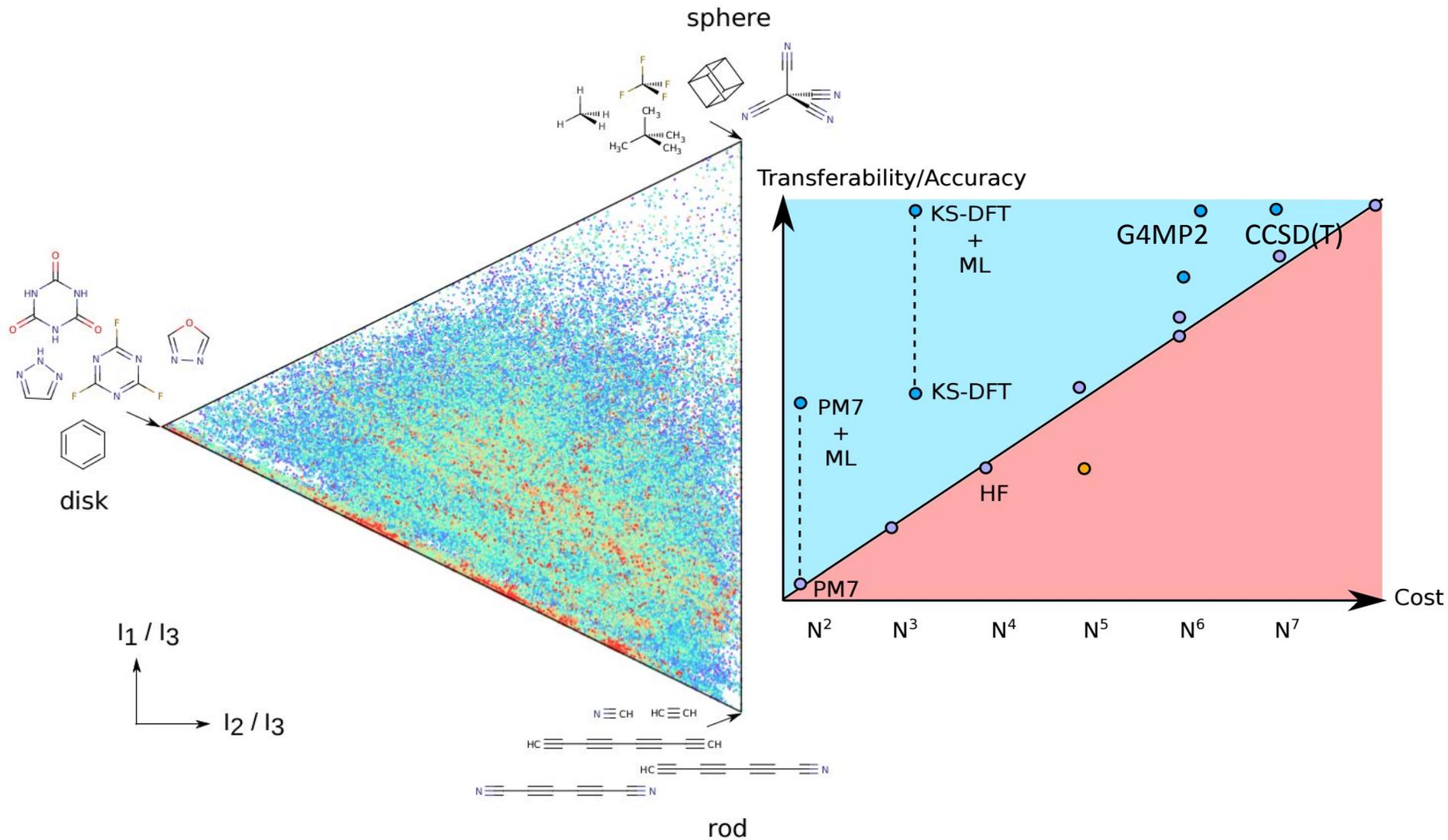
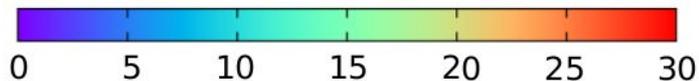
Ranking 10k diastereomers derived from 6k constitutional isomers of $C_7O_2H_{10}$

→ Global minimum, and its 10 closest isomers ...

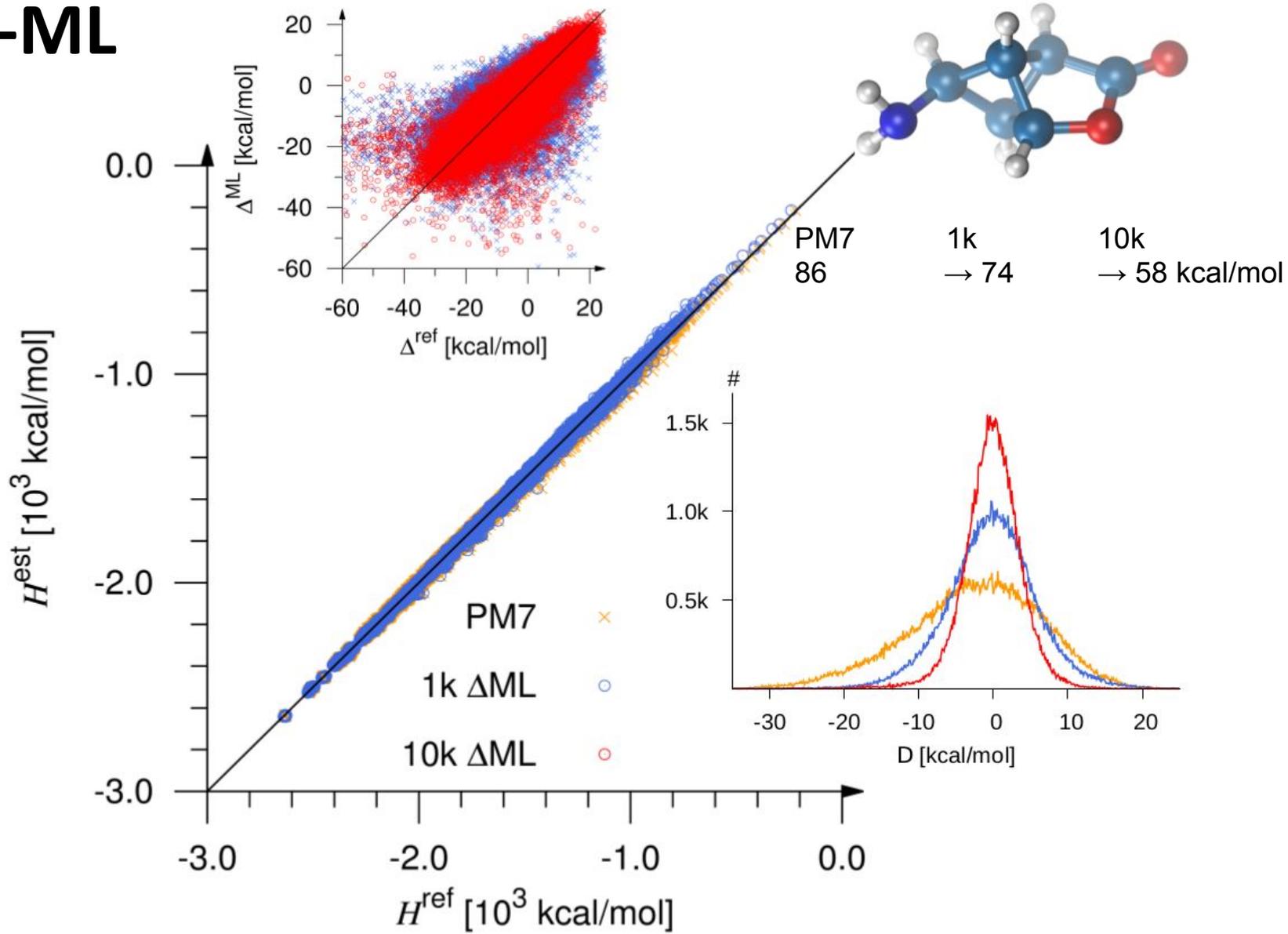


Δ -ML

absolute error [kcal/mol]

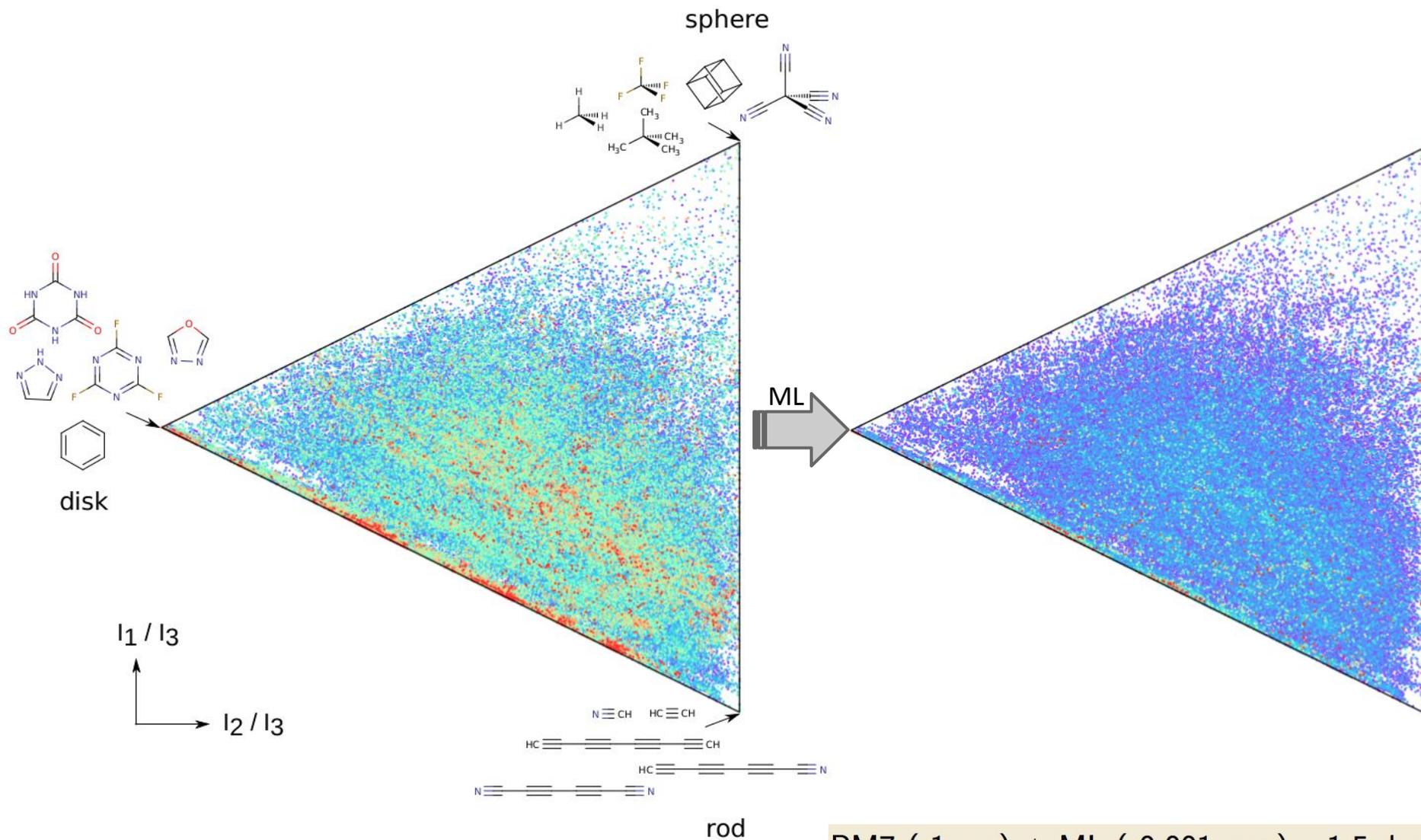
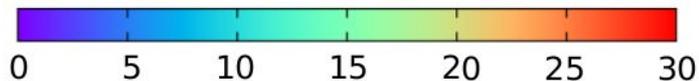


Δ -ML



Δ -ML

absolute error [kcal/mol]



PM7 (1 sec) + ML (0.001 sec) – 1.5 days
DFT (30 min) – 8 yrs !

Conclusions

1. Parameter learning
2. Δ -ML (prior expert knowledge about property)
3. Crystals

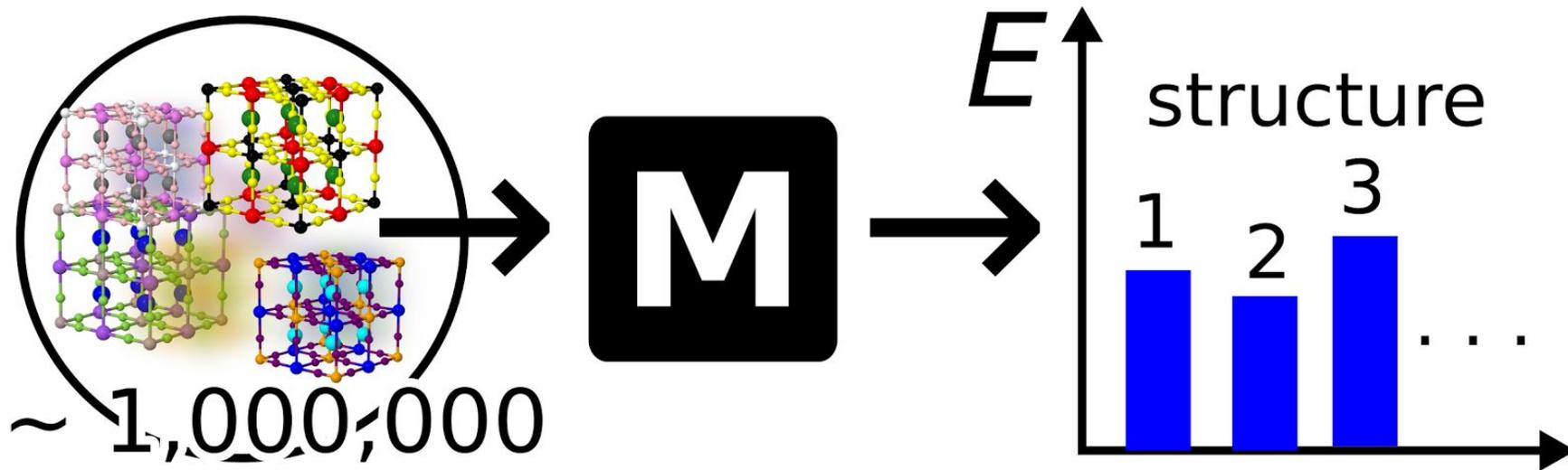
Machine Learning Energies of 2 Million Elpasolite (ABC_2D_6) Crystals

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²*Department of Physics, Chemistry and Biology, Linköping University, SE-581 83 Linköping, Sweden*

³*General Chemistry, Free University of Brussels, Pleinlaan 2, 1050 Brussels, Belgium*



Crystals

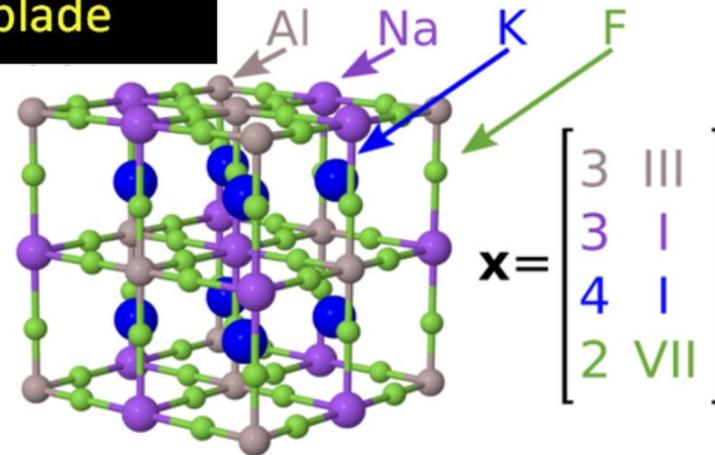
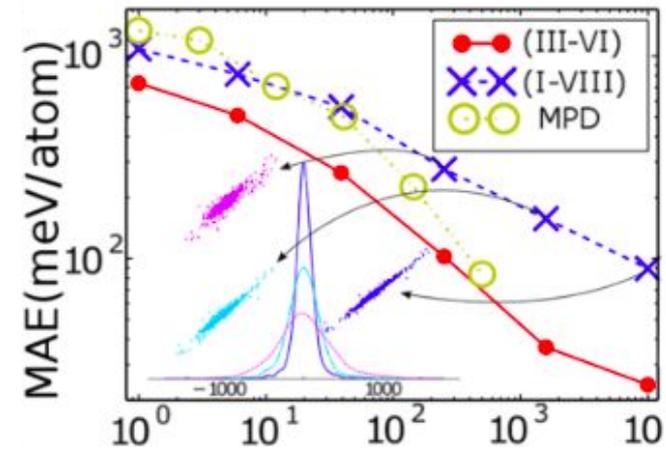


- most abundant quaternary crystal structure in Inorganic Crystal Structure Database
- can emit light when exposed to ionic radiation (→ Scintillator candidates)
- transparent, glossy, colorless and soft crystal in Fm3m space group
- $\text{AlNa}_2\text{K}_2\text{F}_6$ found in Rocky Mountains, Virginia, or the Apennines

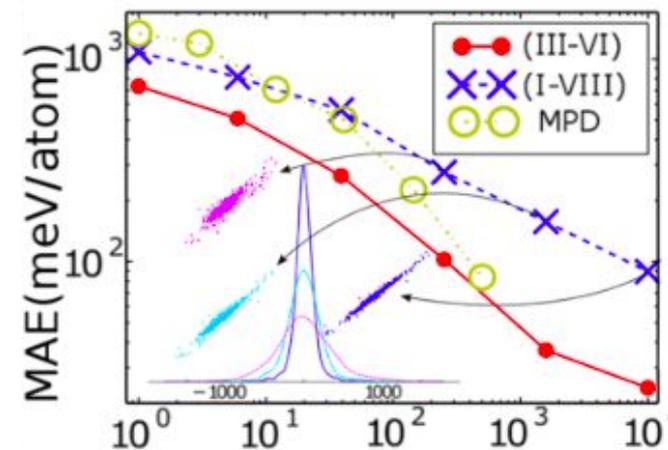


$$P^{\text{est}}(\mathbf{M}) = \sum_i \alpha_i k(\mathbf{M}, \mathbf{M}_i)$$

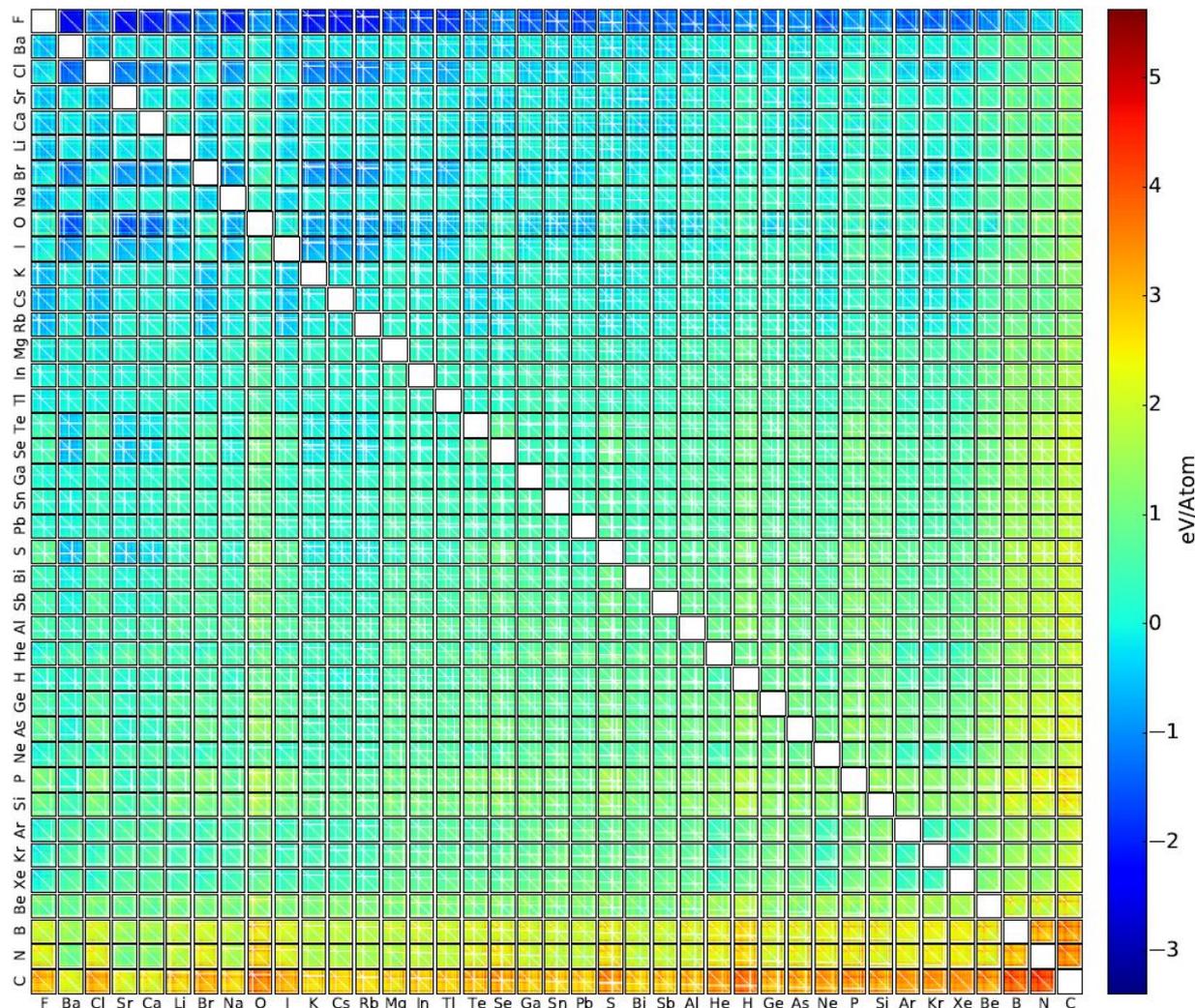
$$\vec{\alpha} = \mathbf{K}^{-1} \vec{P}^{\text{ref}}$$



Crystals



Reduction in cost:
 DFT: ~20 M CPU hours (optimized)
 ML: ~20 CPU hours (not optimized)



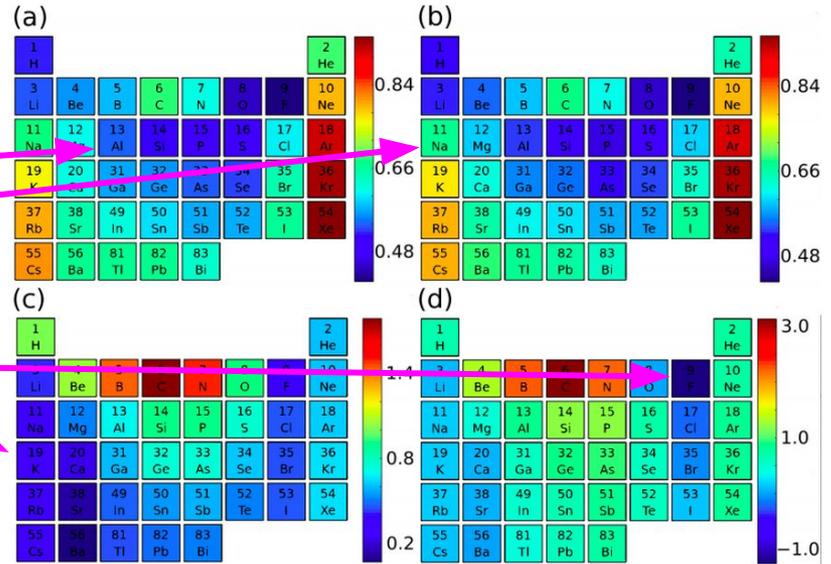
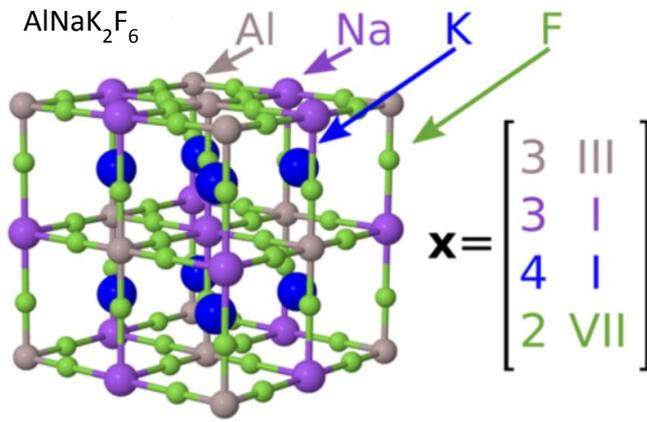
Crystals

TABLE VI – Continued from previous page

#	Elpasolite				ΔE (eV/atom)	Type	$\Delta \epsilon$ (eV)	MP ID	Competing mixed phase in MP
	x_1	x_2	x_3	x_4					
50	Cl	N	Tl	Ba	-0.0312	C	0.00	mp-989542	0.5 Ba ₆ N ₂ + 0.5 Ba ₁ Cl ₂ + 0.5 Ba ₂ Tl ₄ + 1.5 Ba ₁
51	Tl	K	Cs	F	-0.0329	I	3.82	mp-989526	0.6667 Cs ₃ Tl ₁ F ₆ + 0.0417 K ₂₄ Tl ₈ F ₄₈
52	N	O	Sn	Sr	-0.0333	C	0.00	mp-989540	Sr ₂ N ₁ + Sr ₃ Sn ₁ O ₁ + 0.5 Sr ₂ Sn ₂
53	S	F	Cs	Cl	-0.0336	C	0.00	mp-989521	0.1458 Cl ₁₆ + 0.1667 S ₁ F ₆ + 0.1042 S ₈ Cl ₁₆ + 2 Cs ₁ Cl ₁
54	Se	Cl	Cs	F	-0.0349	C	0.03	mp-989544	0.5 Cs ₁ Cl ₁ + 0.125 Cl ₄ F ₄ + 1.5 Cs ₁ F ₁ + 0.25 Se ₄ F ₁₆
55	Ga	K	Cs	F	-0.0359	I	6.04	mp-989531	0.5 Cs ₁ F ₁ + 0.0833 Cs ₁₈ Ga ₁₂ F ₅₄ + K ₁ F ₁
56	Pb	Rb	Cs	F	-0.0370	C	0.00	mp-989525	2 Cs ₁ F ₁ + 0.25 Pb ₄ F ₁₂ + Rb ₁ F ₁
57	F	Br	Rb	Cl	-0.0382	S	0.92	mp-989573	0.5 Cl ₄ + 0.5 Br ₂ Cl ₂ + 2 Rb ₁ Cl ₁ + 0.25 Cl ₄ F ₄
58	N	Rb	Cs	F	-0.0384	S	2.96	mp-989519	0.5 Rb ₂ F ₆ + 0.125 N ₈ + 2 Cs ₁ F ₁ + 0.25 F ₄
59	N	Li	Na	F	-0.0396	S	2.72	mp-989504	0.375 F ₈ + 0.5 N ₂ + Li ₁ F ₁ + 2 Na ₁ F ₁
60	Bi	Na	Rb	Cl	-0.0416	I	3.73	mp-989520	0.25 Bi ₄ Cl ₁₂ + 2 Rb ₁ Cl ₁ + Na ₁ Cl ₁
61	Na	Mg	Cs	F	-0.0449	C	0.00	mp-989568	0.25 F ₄ + 0.6667 Cs ₁ F ₁ + 0.1667 Cs ₈ Mg ₆ F ₂₀ + Na ₁ F ₁
62	Tl	Al	Rb	H	-0.0451	S	0.72	mp-989539	H ₁ + 0.5 Al ₂ H ₆ + Tl ₁ + 2 Rb ₁ H ₁
63	S	Br	Rb	Cl	-0.0452	C	0.00	mp-989518	0.25 Cl ₄ + 0.5 Br ₂ Cl ₂ + 2 Rb ₁ Cl ₁ + 0.125 S ₈ Cl ₁₆
64	N	F	Sn	Sr	-0.0454	C	0.00	mp-989592	0.5 Sr ₈ Sn ₄ + 0.0625 Sr ₃₂ N ₁₆ F ₁₆
65	As	Na	Rb	F	-0.0467	I	4.55	mp-989523	2 Rb ₁ F ₁ + 0.25 As ₄ F ₁₂ + Na ₁ F ₁
66	Pb	K	Cs	F	-0.0486	C	0.00	mp-989585	2 Cs ₁ F ₁ + 0.25 Pb ₄ F ₁₂ + K ₁ F ₁
67	In	Al	Cs	H	-0.0488	S	0.61	mp-989535	0.5 Al ₂ H ₆ + 0.1111 Cs ₃ In ₉ + 1.6667 Cs ₁ H ₁ + 1.3333 H ₁
68	Pb	Na	Cs	F	-0.0513	C	0.00	mp-989556	2 Cs ₁ F ₁ + 0.25 Pb ₄ F ₁₂ + Na ₁ F ₁
69	Ga	Na	Tl	F	-0.0514	I	4.39	mp-989561	0.2 Ga ₂ F ₆ + 0.5 Tl ₄ F ₄ + 0.1 Na ₁₀ Ga ₆ F ₂₈
70	In	Tl	Rb	Cl	-0.0528	S	2.40	mp-989550	0.5 In ₂ Cl ₆ + Tl ₁ Cl ₁ + 2 Rb ₁ Cl ₁
71	In	Na	Rb	Cl	-0.0538	I	3.05	mp-989547	0.3333 In ₂ Cl ₆ + 0.1667 Na ₆ In ₂ Cl ₁₂ + 2 Rb ₁ Cl ₁
72	Li	Na	Cs	H	-0.0565	S	1.26	mp-989610	3.3333 H ₁ + 0.1111 Cs ₃ In ₉ + 1.6667 Cs ₁ H ₁ + Na ₁ H ₁
73	Li	In	Rb	Cl	-0.0603	S	2.83	mp-989583	0.0556 Li ₁₈ In ₆ Cl ₃₆ + 2 Rb ₁ Cl ₁ + 0.3333 In ₂ Cl ₆
74	In	Na	Tl	F	-0.0604	I	4.27	mp-989533	Na ₁ F ₁ + 0.5 Tl ₄ F ₄ + 0.5 In ₂ F ₆
75	Br	F	Cs	Cl	-0.0610	S	0.95	mp-989543	0.5 Cl ₄ + 2 Cs ₁ Cl ₁ + 0.5 Br ₂ Cl ₂ + 0.25 Cl ₄ F ₄
76	In	Ga	Rb	F	-0.0616	I	3.27	mp-989566	0.1667 Ga ₄ + 0.0833 Rb ₈ In ₁₂ F ₄₄ + 0.1667 Ga ₂ F ₆ + 1.3333 Rb ₁ F ₁
77	N	K	Cs	F	-0.0618	I	-	mp-989580	0.25 F ₄ + 0.125 K ₈ F ₂₄ + 0.0625 N ₁₆ + 2 Cs ₁ F ₁
78	Li	Na	Cs	F	-0.0634	C	0.00	mp-989559	0.5 F ₄ + Cs ₁ F ₁ + 0.25 Cs ₄ Li ₄ F ₈ + Na ₁ F ₁
79	Na	In	Rb	F	-0.0672	I	5.34	mp-989578	0.0833 Rb ₈ In ₁₂ F ₄₄ + Na ₁ F ₁ + 1.3333 Rb ₁ F ₁
80	O	N	Sn	Ca	-0.0686	C	0.00	mp-989584	0.0625 Ca ₂₄ N ₁₆ + Ca ₃ Sn ₁ O ₁ + 0.0227 Ca ₆₂ Sn ₄₀ + 0.0455 Ca ₂ Sn ₂
81	N	F	Sn	Ca	-0.0738	S	0.14	mp-989590	0.5 Ca ₄ N ₂ F ₂ + 0.5 Ca ₈ Sn ₄
82	In	Rb	Cs	F	-0.0776	I	5.37	mp-989605	0.0833 Rb ₈ In ₁₂ F ₄₄ + 0.3333 Rb ₁ F ₁ + 2 Cs ₁ F ₁
83	S	Br	Cs	Cl	-0.0848	C	0.00	mp-989517	2 Cs ₁ Cl ₁ + 0.5 Br ₂ Cl ₂ + 0.25 Cl ₄ + 0.125 S ₈ Cl ₁₆
84	In	K	Cs	F	-0.0875	I	5.46	mp-989639	0.025 K ₂₄ In ₈ F ₄₈ + 0.1 K ₄ In ₈ F ₂₈ + 2 Cs ₁ F ₁
85	Tl	Al	Cs	H	-0.0884	S	1.14	mp-989575	2 Cs ₁ H ₁ + 0.5 Al ₂ H ₆ + Tl ₁ + H ₁
86	Tl	Ga	Rb	F	-0.0945	I	4.40	mp-989565	2 Rb ₁ F ₁ + 0.5 Ga ₂ F ₆ + 0.25 Tl ₄ F ₄
87	Ga	Na	Rb	F	-0.1008	I	5.90	mp-989400	2 Rb ₁ F ₁ + 0.1 Na ₁₀ Ga ₆ F ₂₈ + 0.2 Ga ₂ F ₆
88	Al	Na	Cs	H	-0.1019	S	2.14	mp-989642	2 Cs ₁ H ₁ + 0.5 Na ₂ Al ₂ H ₈
89	N	Na	Cs	F	-0.1064	S	2.80	mp-989527	0.75 F ₄ + 0.5 N ₂ + Na ₁ F ₁ + 2 Cs ₁ F ₁

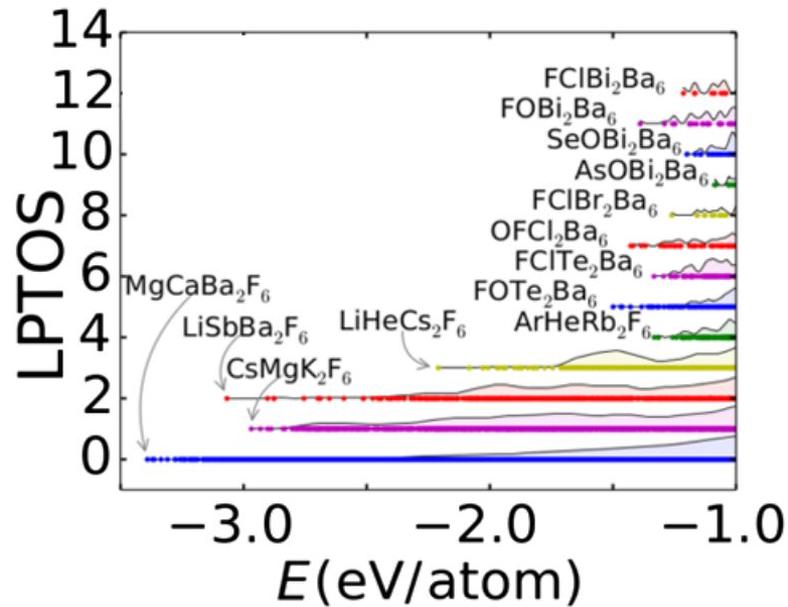
Discovery of
~90 new crystals!!!

Crystals



Crystals

Element	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	Element	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8
H					✓		✓							Ga	✓	✓		✓	✓	✓								
He						✓								Ge		✓	✓	✓	✓	✓								
Li							✓							As			✓		✓	✓	✓							
Be								✓						Se				✓	✓	✓								
B	✓						✓	✓	✓					Br					✓	✓			✓					
C		✓					✓	✓	✓	✓				Kr						✓	✓							
N	✓	✓					✓	✓	✓	✓	✓			Rb					✓	✓	✓							
O							✓	✓						Sr							✓	✓						
F							✓							In	✓						✓	✓						
Ne								✓						Sn							✓	✓						
Na							✓		✓					Sb							✓	✓		✓				
Mg								✓	✓					Te							✓	✓		✓				
Al								✓	✓	✓				I								✓	✓		✓			
Si		✓						✓	✓	✓	✓			Xe								✓	✓		✓			
P			✓					✓	✓	✓	✓	✓		Cs								✓	✓					
S				✓				✓	✓	✓	✓	✓		Ba								✓	✓					
Cl					✓			✓		✓	✓	✓	✓	Ti	✓							✓	✓					
Ar														Pb								✓	✓					
K							✓							Bi								✓	✓					
Ca								✓														✓	✓					



Lowest Possible Total Oxidation State (LPTOS)

Formula	LPTOS	E_{ML}	E_{DFT}	q_1	q_2	q_3	q_4
MgSbBa ₂ F ₆	1	-2.88	-2.70	1.66	0.42	1.63	-0.89
CaTeBa ₂ F ₆	1	-2.90	-2.68	1.58	0.31	1.67	-0.87
TeCaBa ₂ F ₆	1	-2.83	-2.68	0.31	1.59	1.67	-0.87
LiSbBa ₂ F ₆	2	-3.06	-2.62	0.89	1.06	1.62	-0.86
CsMgRb ₂ F ₆	1	-2.93	-2.61	0.98	1.67	0.92	-0.75
BeSbBa ₂ F ₆	2	-2.88	-2.60	1.68	0.35	1.62	-0.88
CsMgK ₂ F ₆	1	-2.97	-2.58	1.01	1.68	0.92	-0.75
SrSbBa ₂ F ₆	2	-2.90	-2.56	1.48	0.60	1.59	-0.88
SrTeBa ₂ F ₆	2	-2.89	-2.55	1.70	0.40	1.66	-0.90

Crystals

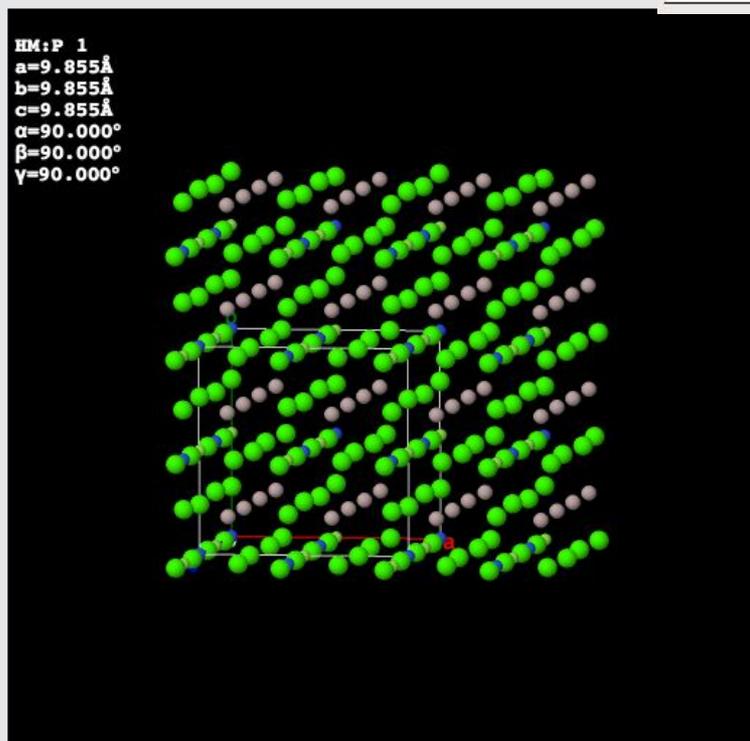
Calculated atomic charges in NFAI_2Ca_6 elpasolite using different methods (obtained using SIESTA[43]).

https://materialsproject.org/materials/mp-989399/

Home

MATERIAL ID: **Ca₆Al₂NF** mp-989399

Method	N	F	Al	Ca
Bader	-2.00	-0.98	-2.13	1.20
Hirshfeld	-0.63	-0.36	-1.05	0.52
Voronoi deformation density	-0.81	-0.29	-1.13	0.56



Material Details

Final Magnetic Moment

0.882 μ_B

Magnetic Ordering

Non-magnetic

Formation Energy/Atom

-1.007 eV

Energy Above Hull

0.000 eV/atom

Density

2.27 g/cm³

Decomposes To

Stable

Band Gap

0.000 eV

Space Group

Lattice Parameters

a 6.969 Å α 60.000°
 b 6.969 Å β 60.000°
 c 6.969 Å γ 60.000°

Volume 239.311 Å³

Final Structure

Fractional Coordinates



Ca

a	b	c
0.2407	0.7593	0.7593
0.2407	0.7593	0.2407
0.2407	0.2407	0.7593
0.7593	0.2407	0.7593
0.7593	0.7593	0.2407

Al

Structure Type: Conventional Standard Primitive Refined

Space Filling Polyhedra

Quantum Machine: Elpasolite Crystal Energy Predictions

Input panel

Single Prediction

Group Prediction

Crystal Design

Elements in first position:

Elements in second position:

Elements in third position:

Elements in fourth position:

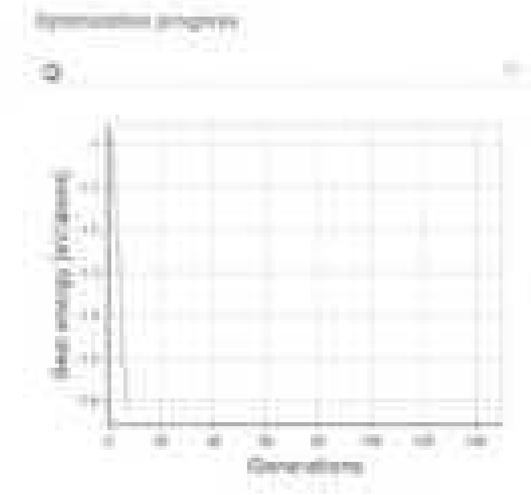
Target formation energy:

Search steps:

Population size:

Output panel

Optimizing crystal with
target value: -5.00
after generations: 100
evolution size: 20



Conclusions II

Scientific method - proper way to gain knowledge

Inductive (Data)

1. Assume a law
2. Metric
3. Examples
4. Infer
5. New combination

Fast (ms)

Arbitrary reference

Automatic improvement

Transferable?

Minimally condensed

Deductive (Laws)

1. Assume a law
2. Approximate
3. Solve
4. Predict
5. New regimes

Slow (depending on approx.)

Approximation dependent

Human improvement

Transferable?

Maximally condensed

