

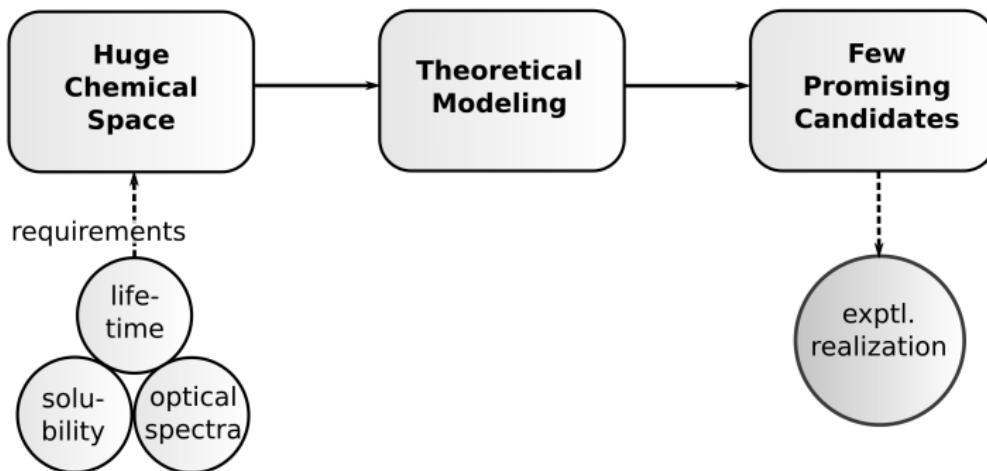


Towards the design of molecular materials

Gerit Brandenburg <j.g.brandenburg@gmx.de> | September 16, 2019

TALK AT THEORY OF CONDENSED MATTER SEMINAR, CAMBRIDGE UNIVERSITY, UK

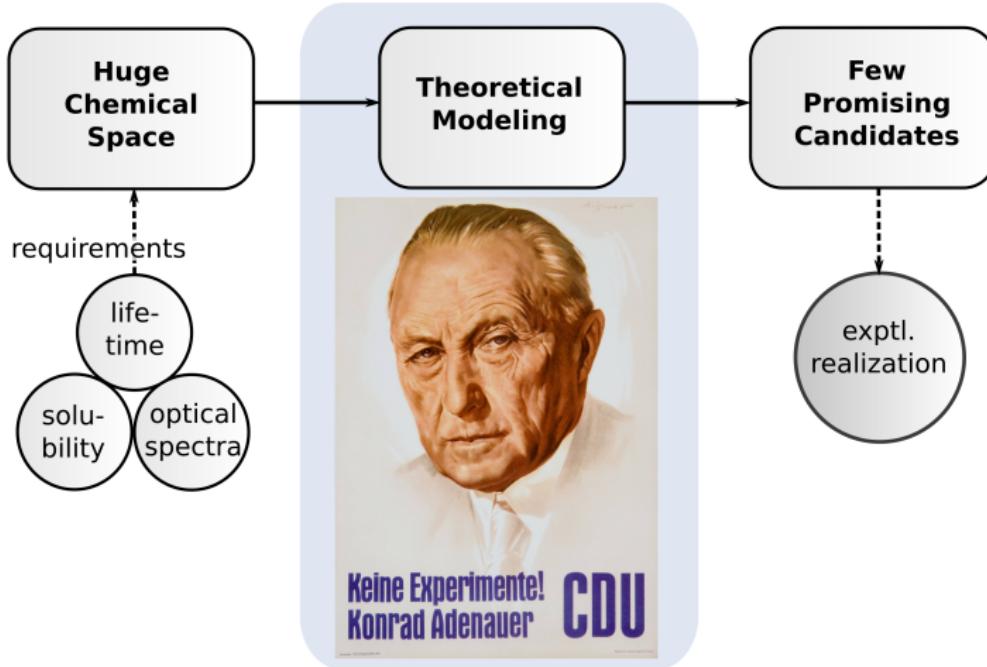
Material discovery can employ computational models



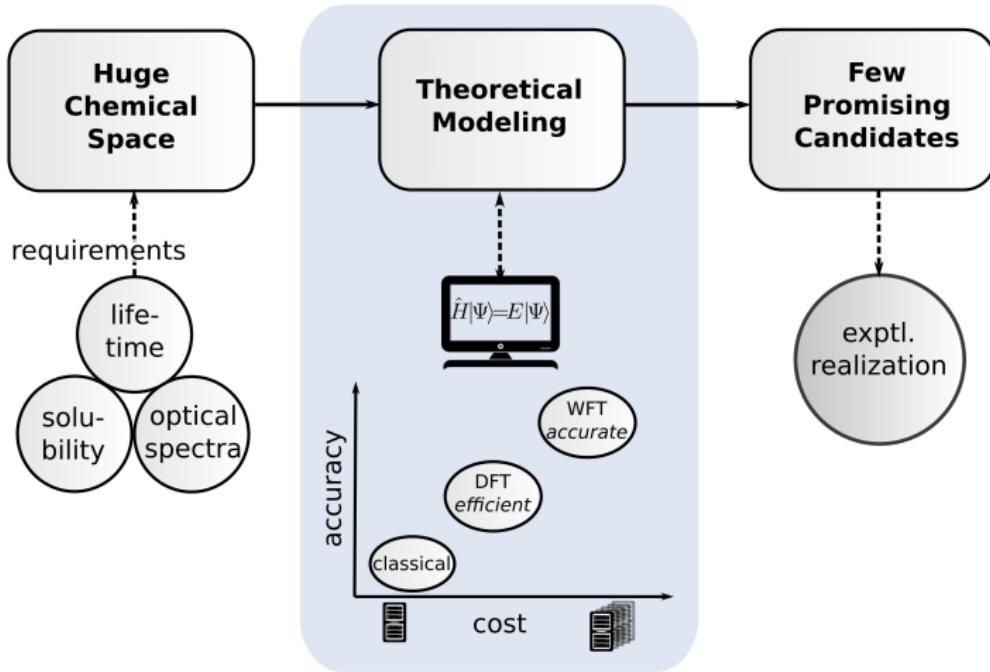
Material discovery can employ computational models



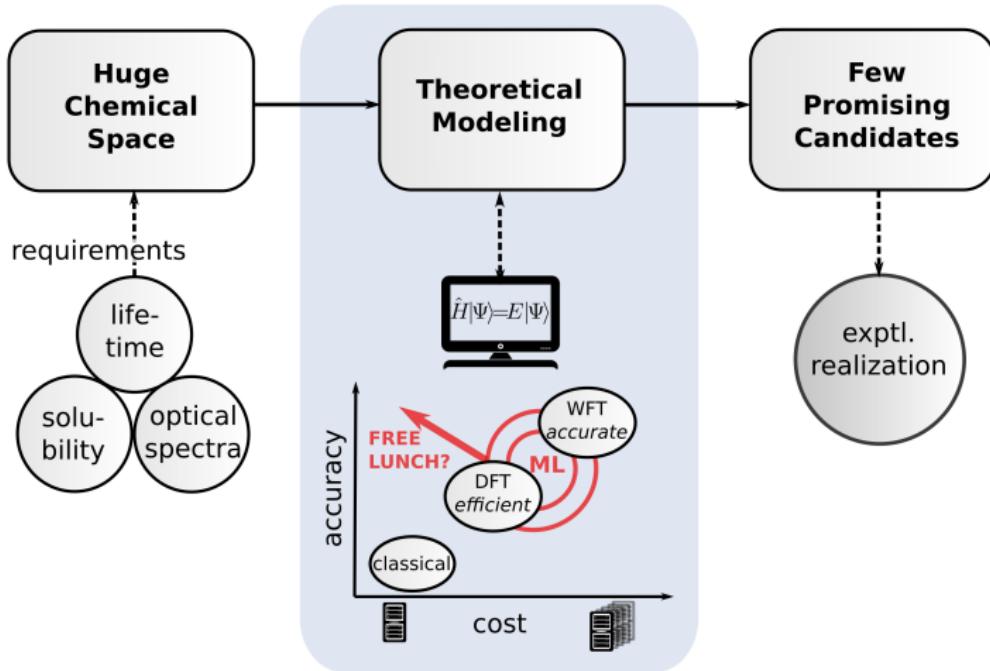
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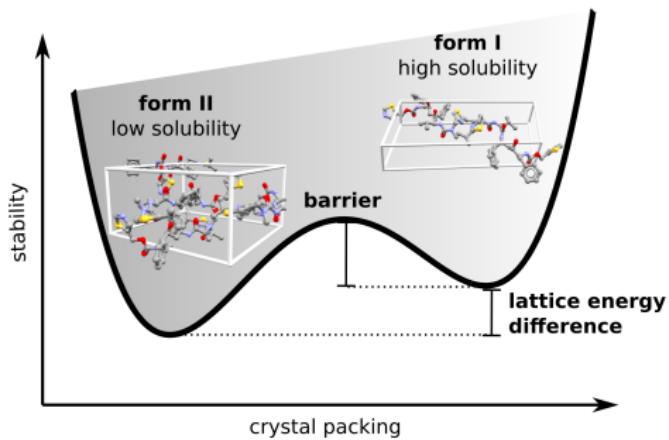
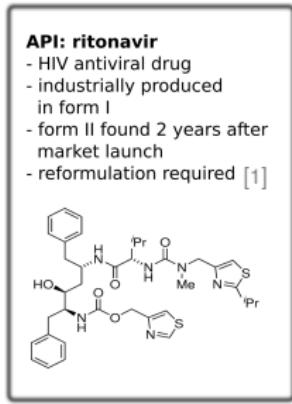
Material discovery can employ computational models



Material discovery can employ computational models



Many properties depend on the polymorphic form of a crystal



- tools to predict possible polymorphs would be valuable^[2]
→ Simulation methods aim at complementing experimental screening

[1] J. Bauer, et al., *J. Pharm. Res.* **18**, 859-866 (2001).

[2] S. L. Price, *JGB, Molecular Crystal Structure Prediction*; Elsevier Australia ISBN: 9780128098356 (2017).

Predict most stable crystal polymorphs based on the molecular diagram



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The inability to predict something as simple as how a molecule would crystallize is one of the continuing scandals in the physical sciences.^[3–5]

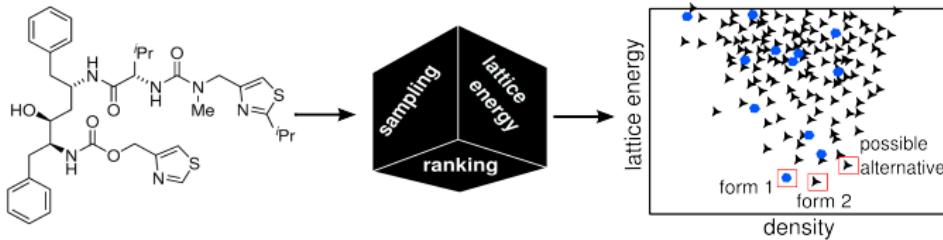
Task

- molecule is chosen due to its chemical/physical/biological properties
- based on the molecular diagram only, the most stable crystal structures should be predicted
- predict properties of interest for the most promising candidates

^[3] A. Gavezzotti, *Acc. Chem. Res.* **27**, 309-314 (1994). ^[4] J. Maddox, *Nature* **335**, 201-201 (1988).

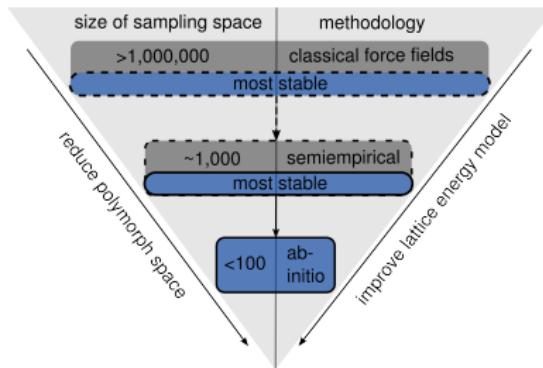
^[5] K. N. Houk, F. Liu, *Acc. Chem. Res.* **50**, 539 (2017).

Sampling and energetic ranking for crystal structure prediction



Layers of complexity:

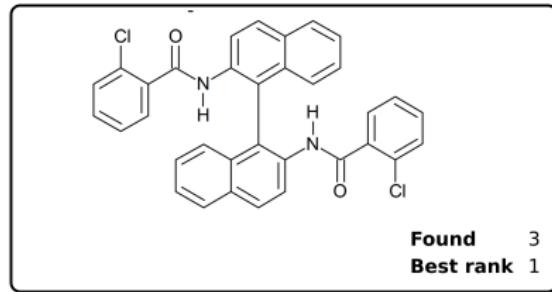
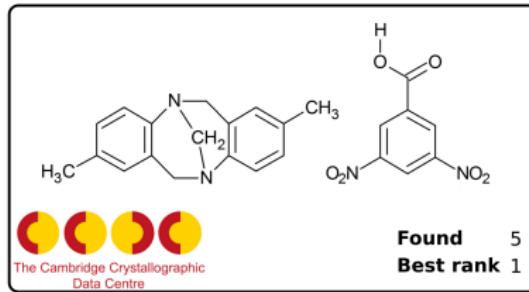
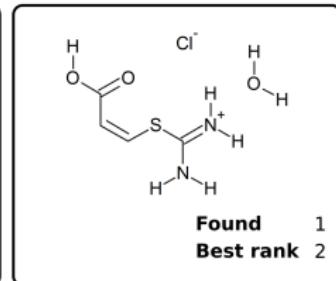
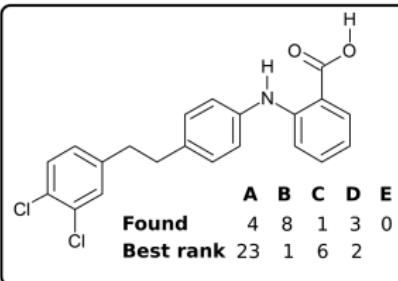
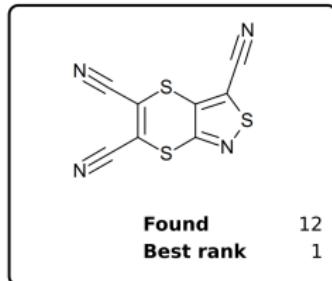
- molecular conformational space
- space groups (varying orientation, conformation, etc.)
- polymorph ranking according to free energy^[6,7]



^[6] S. Price, *Chem. Soc. Rev.* **43**, 2098 (2014)

^[7] S. L. Price, *JGB, Molecular Crystal Structure Prediction*; Elsevier Australia, 336-363 (2017).

Results of the 6th blind test for organic crystal structure prediction



- No group had a perfect sampling and ranking of structures^[8,9]

^[8] A. Reilly, et al. *Acta Cryst. B*, **72**, 439 (2016). ^[9] J. G. Brandenburg, S. Grimme, *Acta Cryst. B*, **72**, 502 (2016).

CSP bind test highlights two remaining challenges



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1. Ranking stage

Crystal polymorphs are often separated by just a few kJ/mol, exceeding the accuracy of standard density functional approximations (DFAs).

⇒ **Are many-body methods feasible?**

2. Sampling stage

Dealing with a vast search space, in particular for molecules with increased flexibility, one has to cover too many structures at DFT accuracy.

⇒ **Can we improve modern DFAs & employ ML techniques?**

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Methods with 'benchmark quality' for noncovalent interactions



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CCSD(T)

- + 'gold standard' of quantum chemistry
- + linear scaling variants
- pair-screening thresholds
- slow basis set convergence
- non-trivial to parallelize
(shared memory: 100 GB/core)

DMC

- + exact projection to ground state
- + N^3 scaling, [-] huge prefactor
- + fast basis set convergence
- + scaleable to HPCs
- stochastic error
- uncertainties from FN and non-local pseudopotentials

No benchmark quality: MP2, RPA, CCSD, CCSD(T)/cc-pVTZ, VMC

Quantum Monte-Carlo in a nutshell: A scalable high-level method



Fixed-node diffusion Monte-Carlo

1) Enforce nodal surface of Fermions

$$\Gamma = \{\mathbf{R}; |\Psi_T\rangle = 0\}$$

2) Walkers in configuration space

$$|\Psi_T(\mathbf{R}, \tau)\rangle = \text{hist} \left[\sum \delta(\mathbf{R} - \mathbf{R}_i(\tau)) \right]$$

3) Diffusion in imaginary time

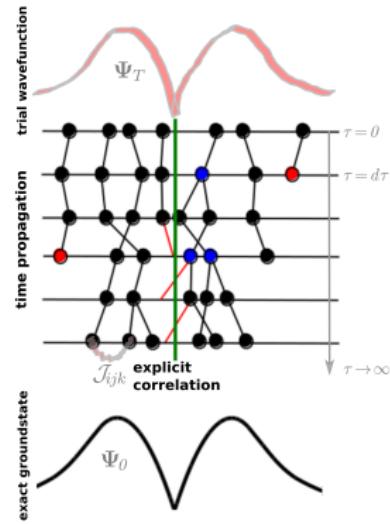
$$\partial_\tau |\Psi_T(\mathbf{R}, \tau)\rangle = \left[\frac{1}{2} \nabla_{\mathbf{R}}^2 - (V - E_T) \right] |\Psi_T(\mathbf{R}, \tau)\rangle$$

4) Projection to exact ground state

$$|\Psi_0(\mathbf{R})\rangle = \lim_{\tau \rightarrow \infty} \exp[-\tau(\hat{H} - E_T)] |\Psi_T(\mathbf{R}, \tau)\rangle$$

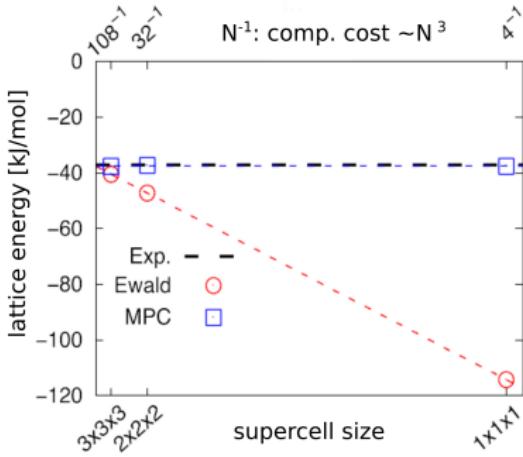
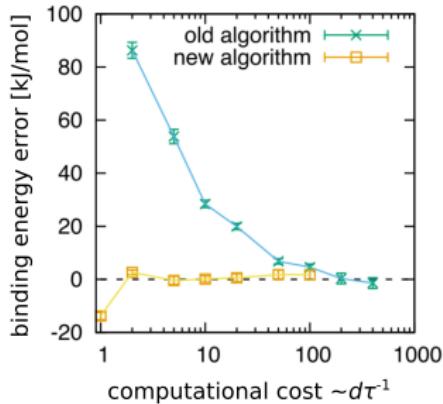
- exact within Γ and $d\tau \rightarrow 0$ and $\tau \rightarrow \infty$ ^[15]

- new DMC algorithms lead to substantial speed up^[16]



^[15] Chem. Rev. 116, 5188 (2016) ^[16] A. Zen, S. Sorella, M. J. Gillan, A. Michaelides, D. Alfé, Phys. Rev. B 93, 241118(R) (2016).

New DMC algorithm leads to substantial speed up



- new size-consistent implementation reduces $\Delta\tau$ error drastically^[13]
- Model periodic Coulomb for finite size correction^[14]

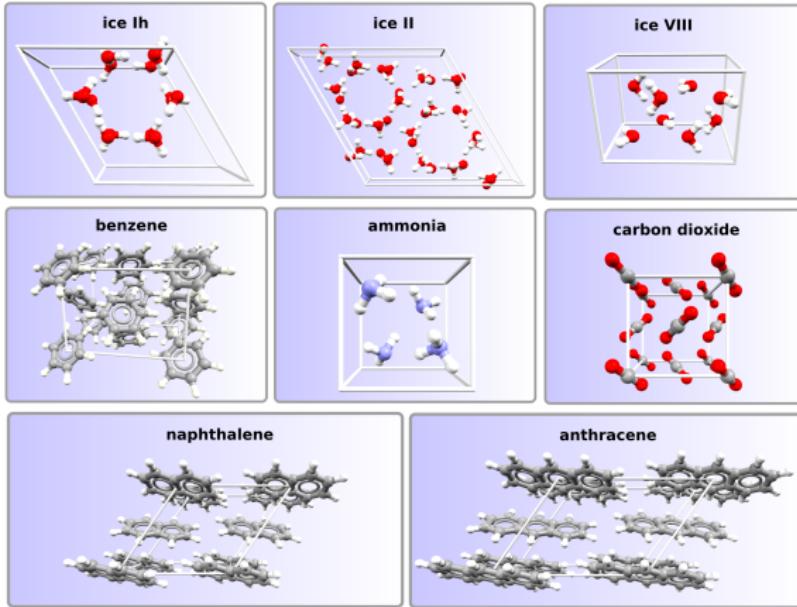
[16] A. Zen, S. Sorella, M. J. Gillan, A. Michaelides, D. Alf  , *Phys. Rev. B* **93**, 241118(R) (2016).

[17] L. M. Fraser, W. M. C. Foulkes, G. Rajagopal, R. J. Needs, S. D. Kenny, A. J. Williamson, *Phys. Rev. B* **53**, 1814 (1996).

Molecular crystals as challenging test

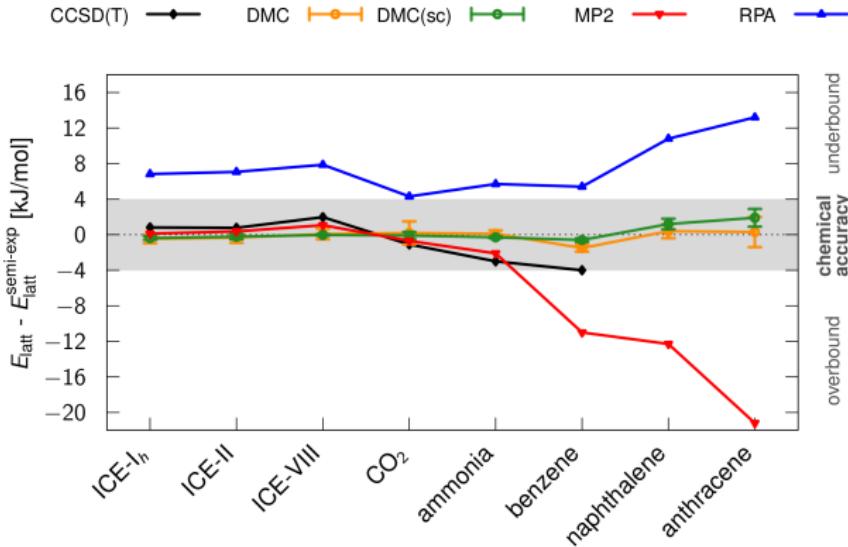


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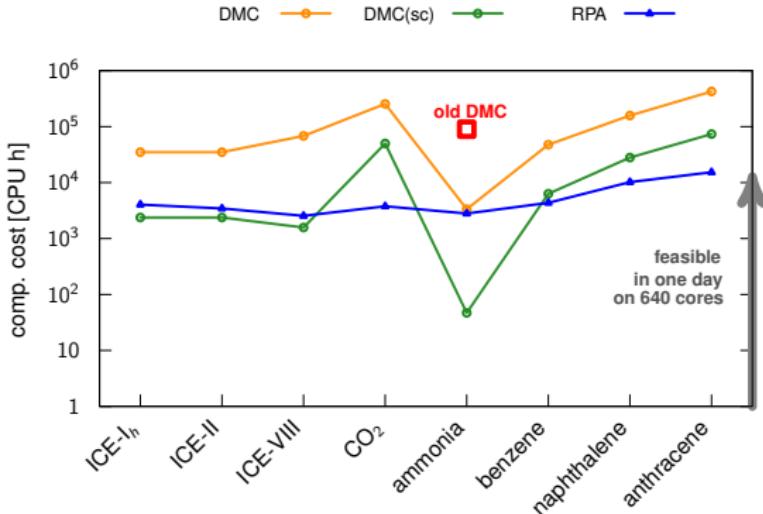
- strong H-bonds, vdW of saturated and unsaturated molecules
- problematic for all readily applicable methods (DFA-DISP, MP2)

QMC delivers (sub-) chemical accuracy for all tested systems



- excellent agreement with experiment and CCSD(T)
- uncertainty in $H_{\text{sub}}^{\text{exp}}$ probably larger than DMC errors

QMC is feasible within one day on standard computer cluster



- up to three orders of magnitude speed-up compared to best DMC practice two years ago
- significance will extend to all classes of systems^[18]

[18] A. Zen, JGB, J. Klimeš, A. Tkatchenko, D. Alfè, A. Michaelides, Proc. Natl. Acad. Sci. U.S.A., 115, 1724 (2018).

Outline of talk



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Multilevel methodologies: Finding the right compromise



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	task/property	example method
accurate QM	single-point energy	many-body WFT (DMC ^[18])
cheap QM	optimization	DFT ^[19–20] (HSE-3c ^[21])
very cheap QM	optimization/Hessians conformations	semi-empirical ^[22,23]
force field	dynamics conformational sampling	transferable or molecule specific (QM derived) FF

[19] [JGB](#), J. E. Bates, J. Sun, J. P. Perdew *Phys. Rev. B*, **94**, 115144 (2016).

[20] [JGB](#), C. Bannwarth, A. Hansen, S. Grimme, *JCP*, **148**, 064104 (2018). [21] [JGB](#), E. Caldeweyher, S. Grimme, *Phys. Chem. Chem. Phys.* **18**, 15519 (2016).

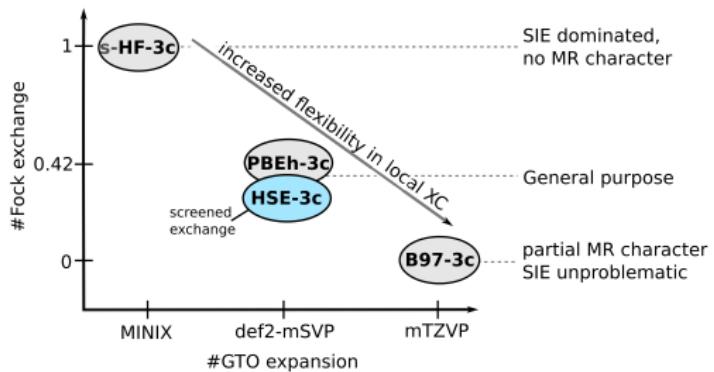
[22] [JGB](#), S. Grimme, *JPCL*, **5**, 1785 (2014). [23] M. Mortazavi, [JGB](#), R. J. Maurer, A. Tkatchenko, *JPCL*, **9**, 399 (2018).

Full hierarchy of 'low-cost' methods



HSE-3c construction principles

- fast for optimizations and frequencies → compact orbital expansion
- avoid most self-interaction error → use Fock exchange
- numerically robust → screening of Fock exchange
- combine with semi-classical correction potentials (3c)

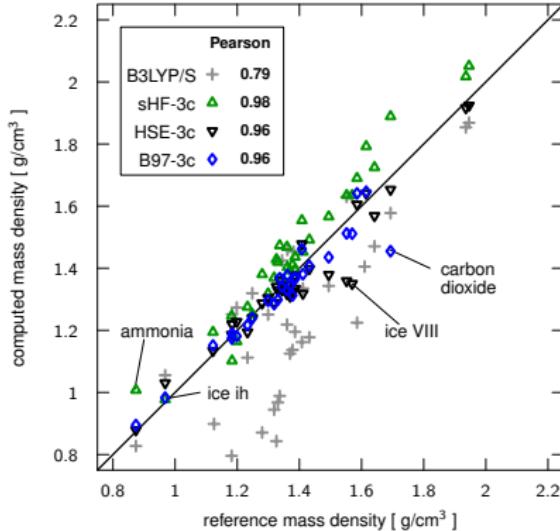
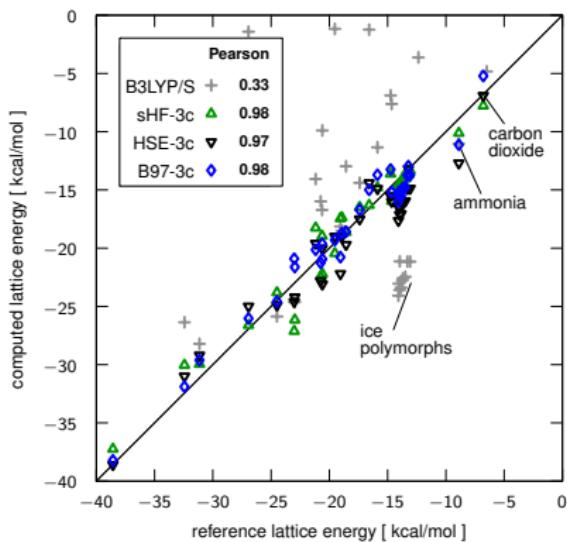


[24] E. Caldeweyher, *JGB, J. Phys.: Condens. Matter* **30**, 213001 (2018) [Psi-k Highlight Jan. 2019]

Good results on molecular crystals



X23^[25,26] and ICE10^[27] benchmark sets:

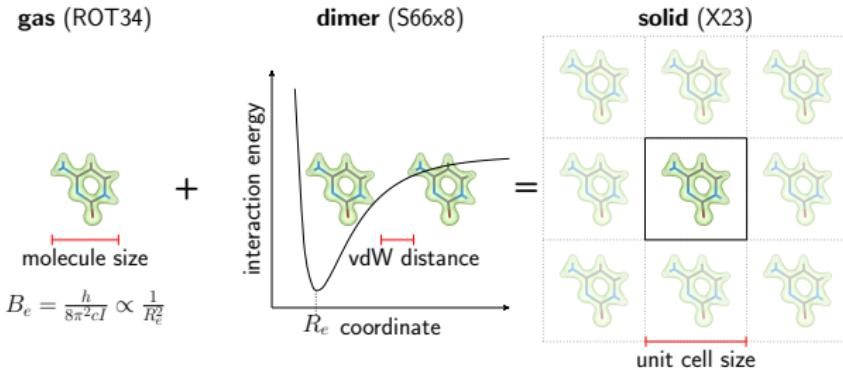


- consistent structures and interaction energies by HSE-3c

[25] E. Johnson, A. Otero-de-la-Roza, *J. Chem. Phys.* **137**, 054103 (2012), [26] A. Reilly, A. Tkatchenko, *JCP* **139**, 024705 (2013)

[27] JGB, T. Maas, S. Grimme, *J. Chem. Phys.* **142**, 124104 (2015)

Consistency for structures achieved



	ROT34 org. mol.	S66x8 non-covalent	X23 molecular crystal
TPSS/large basis	1.9	14.6	27.9
TPSS-D3/large basis	1.3	1.3	1.0
HF-3c (very cheap QM)	1.5	-1.2	-5.7
DFTB3-D3 (very cheap QM)	1.2	-2.9	-12.6
HSE-3c (cheap QM)	0.2	1.3	0.7

mean of relative deviation in %

Fast electronic structure with ab-initio accuracy

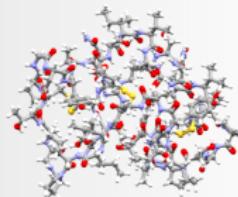


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gas phase protein

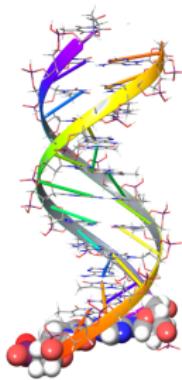
dim:
#atoms/unit:
wall time:
(HSE-3c on 16 cores)

0D
647 (647)
5h



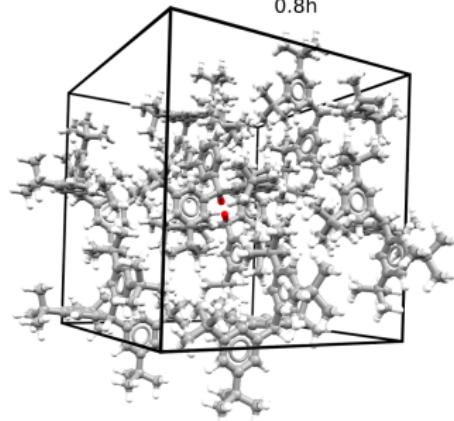
DNA helix

1D
726 (66)
0.5h



molecular crystal

3D
856 (37)
0.8h



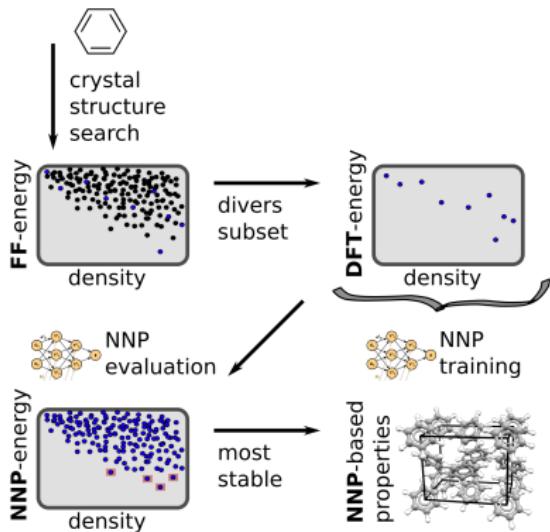
- fast computer code CRYSTAL17^[28] with cost-efficient methods
- enabling routine electronic structure calculation of large systems

^[28] R. Dovesi, A. Erba, R. Orlando, C. Zicovich-Wilson, B. Civalleri, L. Maschio, et al., *WIREs Comput. Mol. Sci.* 8, 1360 (2018).

Employing ML to enhance CSP workflow



1. Generate putative structures with crude FF stability
2. Construct a diverse subset of structures
3. Compute DFT stability on subset
4. Train a high-dimensional NNP on DFT references
5. Recompute stability of all structures employing the NNP



[29] V. L. Deringer, D. M. Proserpio, G. Csányi, and C. J. Pickard, *Faraday Discuss.* **211**, 45 (2018).

[30] E. V. Podryabinkin, E. V. Tikhonov, A. V. Shapeev, and A. R. Oganov, *Phys. Rev. B* **99**, 064114 (2019).

[31] JGB and J. Behler, in preparation.

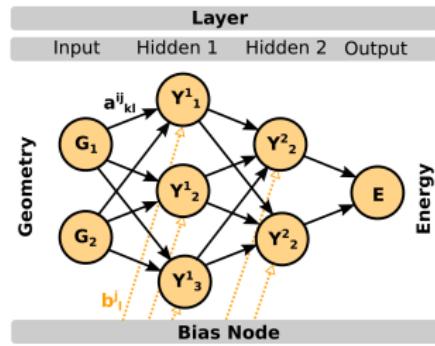
High-dimensional neural network for benzene crystal landscape



Energy decomposed to atomic contributions

$$E_{\text{tot}} = \sum_i^{\text{atoms}} E_i [Z_i, G(\{R_j\})]$$

- symmetry functions as local geometry descriptors $G^{[32-34]}$
- element specific feed-forward neural network (2 hidden layers, 25 nodes each)
- training based on electronic energies and nuclear forces



[32] J. Behler and M. Parrinello, *Phys. Rev. Lett.* **98**, 146401 (2007).

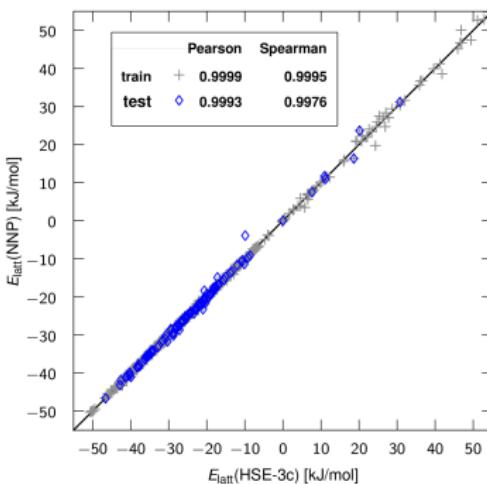
[33] J. Behler, *J. Chem. Phys.* **134**, 074106 (2011).

[34] J. Behler, *Angew. Chem. Int. Ed.* **56**, 12828 (2017).

Stable training on 10% of generated putative polymorphs



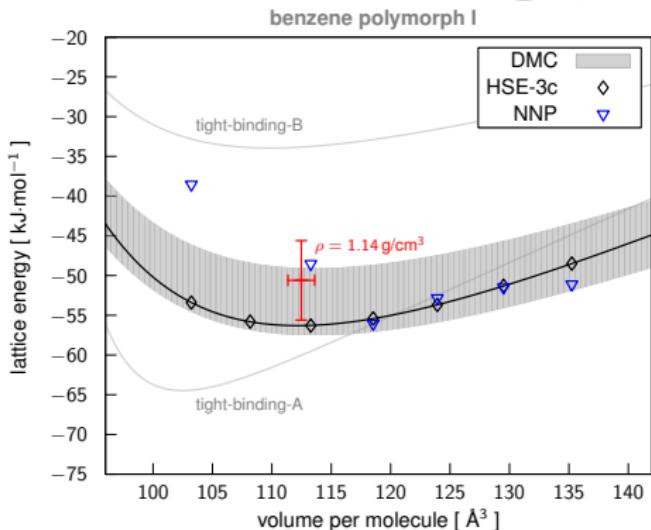
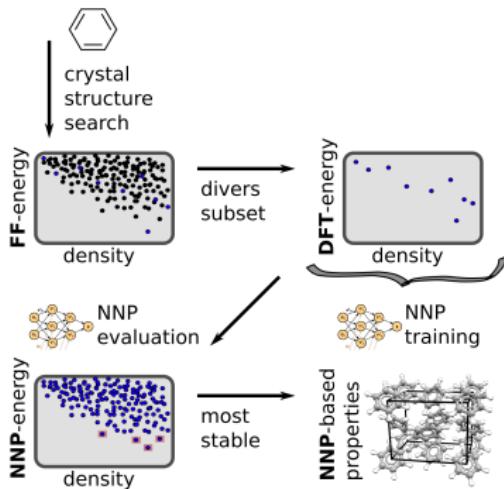
	training	testing
#structures	1 077	127
#data points	39 849	4 699
range E [kJ/mol]	[-50:147]	[-55:120]
range ρ [g/cm ³]	[0.1:1.1]	[0.1:1.1]
RMSD(E) [kJ/mol]	0.53	0.93
RMSD(F) [a.u.]	0.001	0.001



- neural network delivers sub-chemical accuracy
- CSP cost reduced by one order of magnitude ^[32]

[32] JGB and J. Behler, *in preparation*.

Employing ML to enhance CSP workflow



- EOS within 1 kJ/mol for $\rho < 1.1 \text{ g/cm}^3$, large errors for $\rho > 1.2 \text{ g/cm}^3$
- too few data points to generate globally smooth EOS

[32] JGB and J. Behler, *in preparation*.

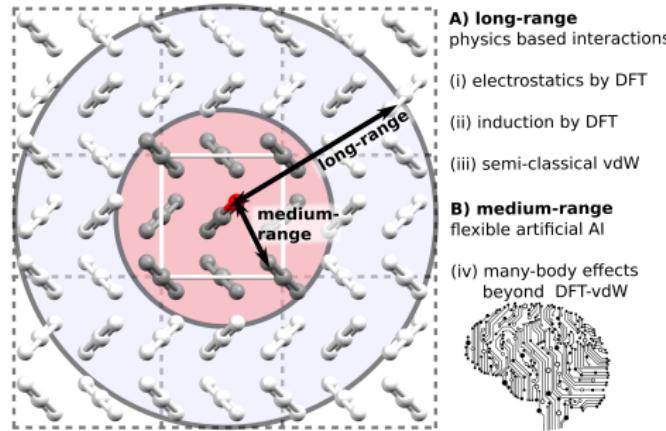
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Learn many-body exchange-correlation to improve DFAs



- DFT-vdW is capable to describe long-range interactions very accurately
- ML with local descriptor to learn medium-range many-body effects

Remaining challenges in crystal structure prediction



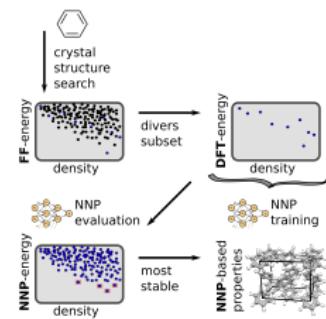
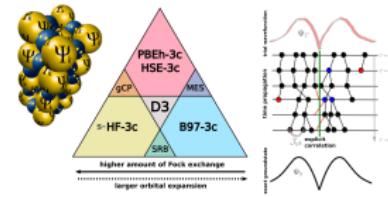
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- Thermodynamics of crystals, i.e. full PT phase diagram
- Kinetics of crystallization
- Reducing the human and CPU time for prediction

Summary



- DMC delivers (sub-) chemical accuracy with three orders of magnitude speed up
- hierarchy of simplified DFAs has been developed
- enhancing CSP by combining simplified DFA & ML



Acknowledgements



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(Luxembourg)



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Benjamin
Ramberger



Theodoros
Tsatsoulis



Grimme (Bonn)



Perdew (Temple)



Kresse (Vienna)



Behler (Göttingen)



Rebecca Sure (BASF)



Eike Caldeweyher



Luca Iuzzolino



Price (UCL)



Grüneis (Vienna)



Civalleri (Turin)



Maschio (Turin)



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(NovaMechanics)



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PhD / Postdocs



Andrea Zen



Martin Fitzner



Michaelides (UCL)

Principal investigator



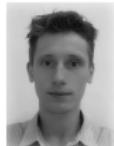
Alfè (UCL)



Tkatchenko
(Luxembourg)



Klimes (Prague)



Benjamin
Ramberger



Theodoros
Tsatsoulis



Grimme (Bonn)



Perdew (Temple)



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Eike Caldeweyher



Luca Iuzzolino



Price (UCL)



Grüneis (Vienna)



Civalleri (Turin)



Maschio (Turin)



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LEADERSHIP COMPUTING



Key references



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■ Crystal structure prediction:

S. L. Price, JGB, *Molecular Crystal Structure Prediction*, G. DiLabio, A. Otero-de-la-Roza, Eds., Elsevier Australia, 336-363 (2017).

L. Iuzzolino, P. McCabeb, S. L. Price, JGB, *Faraday Discuss.* **211**, 275 (2018).

■ QMC for molecular crystals:

A. Zen, JGB, J. Klimeš, A. Tkatchenko, D. Alfè, A. Michaelides, *Proc. Natl. Acad. Sci. U.S.A.* **115**, 1724 (2018).

■ DFT development

S. Grimme, A. Hansen, JGB, C. Bannwarth, *Chem. Rev.* **116**, 5105 (2016).

E. Caldeweyher, JGB, *J. Phys.: Condens. Matter* **30**, 213001 (2018).

■ website: gerit-brandenburg.de