Data-Driven Many-Body Models for Predictive Molecular Simulations Francesco Paesani **Department of Chemistry and Biochemistry** Materials Science and Engineering San Diego Supercomputer Center University of California, San Diego



@PaesaniLab

Graduates

Colin Egan Kartik Rallapalli Yaoguang Zhai Kelly Hunter **Teri Lambros Chanin Tangtartharakul Alessandro Caruso** Hanjun Kim

Postdocs

Ongun Ozcelik Marc Riera Raja Ghosh

Undergraduates

Eric Yeh Ethan Bull-Vulpe Xuanyu Zhu **Yuqing Shen** Kaushik Ganapathy **Alan Hirales Eric Kang** Perry Chu **Isaac Douglas**

High Schoolers Kimmy Fogliatti

Former Members

Greg Medders Wei Lin **Pushp Bajaj Debbie Zhuang Brandon Bizzarro Volodymyr Babin** Jordi Cirera Sandeep Reddy Huy Pham Dan Moberg Ayo Ajala Sandra Brown

Collaborations

S.M. Cohen (UCSD) A.F. Tezcan (UCSD) A.W. Götz (UCSD) V. Molinero (Utah)







N.C. Gianneschi (Northwestern)

F.M. Geiger (Northwestern)

G. Galli (Chicago)

T. Heine (TU Dresden)



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- M. Ceriotti (EPFL) G. Csányi (Cambridge) J. Behler (Göttingen) J.O. Richardson (ETH)





- **G.K. Schenter (PNNL)** J.L. Fulton (PNNL) **T. Carrington (Queen's)**
- A.C. Simmonett (NIH)
- NIH National Institutes of Health



M. Dinča (MIT) M. Bonn (MPI Mainz) Y. Nagata (MPI Mainz) E. Tyrode (KTH)







hydration of biomolecules



heterogeneous chemistry





water desalination



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Molecular simulations: Fiction or reality?



water desalination



Water: The Perfect Example!



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ge	Discussion		
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M MB-pol MCDHO MCCHO MCY MCYL Mercodes-Benz model mW	 refPOL RPOL RSL2 RWFF RWK S SAPT-5s SAPT-pp SCPDP SDFT-5s 	 TIP3P TIP3P/Fs TIP4F TIP4P TIP4P/2005 TIP4P/2005f TIP4P/ε TIP4P-Ew TIP4P/FQ
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MB-pol MCDHO MCHO MCY MCYL Mercedes-Benz model mW	 SAPT-5s SAPT-pp SCPDP SDFT-5s 	 TIP4P-Ew TIP4P/FQ
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MCHO MCY MCYL Mercedes-Benz model mW	SCPDP SDFT-5s	
MCYL Mercedes-Benz model mW	 SDFT-5s 	TIP4P-HB
MCYL Mercedes-Benz model mW		TIP4P-I
mW	Simple Point Charge models	TIP4P/Ice
	• SPC	TIP4P-pol
	• SPC/s	• TIP4PQ/2005
N	• SPC/A	• TIP4PO D20
NCC	• SPC/F	• TIP/PO T2O
NCCVID NCE	• SPC/E	
• NCF • NEMO	• SPC/F	TIP4P-QUP TIP4P-QUP
NSPCE	SPC/F2 SPC/FP	TIP4P-QDP-LJ
 NvdE 	• SPC/FP	• TIP4Q
	• SPC/FQ	TIP5P
0	SPC/Fw	 TIP5P-E
• OPC3	SPC/HW	TIPS
р	• SPC/L	TIPS2
	• SPCP	 TTM2-F
• PE • PMW	SPC-pol	 TTM2-R
• POL3	• SSD	• TTM2.1
POL4D	• ST2	• TTM2.1-F
• POL5	ST2RF	• TTM3-F
POLIR	SWFLEX	
PPC PTIPAP	SWM4-DP	V
PSRWK	SWM4-NDP	 VRT(MCY-5f)
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· q-SPC/FW q-TIP4P/F

http://www.sklogwiki.org/SklogWiki/index.php/Water_models

ntial models

Learning How to Survive in the "Water Community"





Learning How to Survive in the "Water Community"



hydration of biomolecules

heterogeneous chemistry

Molecular simulations: Fiction or reality?

water desalination

hydration of biomolecules

heterogeneous chemistry

Molecular simulations: Fiction or reality?

1) Accuracy of the reference data used to build the model

water desalination

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Molecular simulations: Fiction or reality?

- Accuracy of the reference data used to build the model
- 2) Ability to represent the reference data accurately

water desalination

ASSESSING THE RELIABILITY OF COMPLEX MODELS

THEMATICAL AND SENTSTICAL FOUNDATIONS VERHICATION, VAUDATION, AND REFININTY QUANTERATION

NATIONAL RESEARCH COUNCIL

Description

Advances in computing hardware and algorithms have dramatically improved the ability to simulate complex processes computationally. Today's simulation capabilities offer the prospect of addressing questions that in the past could be addressed only by resource-intensive experimentation, if at all.

Assessing the Reliability of Complex Models recognizes the ubiquity of uncertainty in computational estimates of reality and the necessity for its quantification.

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Molecular simulations

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$$A = -k_B T \ln Z \quad \left\langle \Box \right\rangle \quad Z = \frac{1}{N} \int e^{-\frac{1}{N}} e^{-\frac{1}{N}} e^{-$$

free energy

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$-\beta H(\mathbf{q}^n,\mathbf{p}^n) d\mathbf{q}^n d\mathbf{p}^n$

classical partition function

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Molecular simulations

$$A = -k_B T \ln Z \quad \left\langle \Box \right\rangle \quad Z = \frac{1}{N} \int \langle \mathbf{p} \rangle$$

free energy

http://paesanigroup.ucsd.edu

$\mathbf{p}^{n}, \mathbf{q}^{n} \mid e^{-\beta H(\mathbf{q}^{n}, \mathbf{p}^{n})} \mid \mathbf{p}^{n}, \mathbf{q}^{n} \rangle$

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Molecular properties & mechanisms

quantum partition function

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Molecular simulations

$$A = -k_B T \ln Z \quad \swarrow \quad Z = \frac{1}{N} \int \langle \mathbf{p}^n, \mathbf{q}^n | e^{-\mu (\mathbf{q}^n, \mathbf{p}^n)} | \mathbf{p}^n, \mathbf{q}^n \rangle \Box \rangle$$

free energy

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Molecular properties & mechanisms

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Molecular Hamiltonian: Molecular Interactions

Force fields

 $V(\vec{R}^N) = \sum_{bonds} \frac{k_b}{2} (r_b - r_{b,o})^2 + \sum_{angles} \frac{k_a}{2} (\theta_a - \theta_{a,o})^2 + \sum_{torsion} \left[\sum_n \frac{V_n}{2} (1 + \cos(n\omega - \gamma)) \right]$

$$+\sum_{i< j} \left\{ 4\epsilon_{ij} \left[\left(\frac{\sigma_{ij}}{r_{ij}} \right)^{12} - \left(\frac{\sigma_{ij}}{r_{ij}} \right)^6 \right] + \frac{q_i q_j}{4\pi\epsilon_0 R_{ij}} \right\}$$

1948: Hill, J. Chem. Phys. 14, 465 (1946) / Westheimer & Mayer, J. Chem. Phys. <u>14</u>, 733 (1946) 1968: Lifson & Warshel, J. Chem. Phys. <u>49</u>, 5116 (1968)

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Molecular Interactions: Quantum Mechanics

Electronic structure (ab initio) methods

 $\hat{H}\Psi = E\Psi$

$E[\rho] = T[\rho] + V_{ee}[\rho] + V_{xc}[\rho]$

1930: Hartree-Fock equations 1951: Hartree-Fock-Roothan equations 1965: Kohn & Sham equations 1966: Coupled-Cluster equations

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Molecular mechanics = Force fields: Not accurate, but cheap $V(\vec{R}^N) = \sum_{bonds} \frac{k_b}{2} (r_b - r_{b,o})^2 + \sum_{angles} \frac{k_a}{2} (\theta_a - \theta_{a,o})^2 + \sum_{torsion} \left[\sum_n \frac{V_n}{2} (1 + \cos\left(n\omega - \gamma\right)) \right]$

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Quantum mechanics = Ab initio: Accurate, but expensive $H\Psi = E\Psi$

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Molecular mechanics = Force fields: Not accurate, but cheap

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 $V_n(1 + \cos\left(n\omega - \gamma\right))$

Machine Learning

Machine Learning

Sumpter & Noid, Chem. Phys. Lett. <u>192</u>, 455 (1992) Lorenz, Gross & Scheffler, Chem. Phys. Lett. <u>395</u>, 210 (2004) 0.3 seconds on GPL ANI-1 Manzhos & Carrington, J. Chem. Phys. <u>125</u>, 194105 (2006) Behler & Parrinello, Phys. Rev. Lett. <u>98</u>, 146401 (2007) Bartók, Payne, Kondor, Csányi, Phys. Rev. Lett. <u>104</u>, 136403 (2010) Rupp, Tkatchenko, K.-R. Müller & von Lilienfeld, Phys. Rev. Lett. <u>108</u>, 058301 (2012) Hansen, Montavon, Biegler, Fazli, Rupp, Scheffler, von Lilienfeld, Tkatchenko & Müller, J. Chem. Theory Comput. 9, 3404 (2013) Smith, Isayev & Roitberg, Chem. Sci. <u>8</u>, 3192 (2017) Chmiela, Tkatchenko, Sauceda, Poltavsky, Schütt & Müller, Sci. Adv. <u>3</u>, e1603015 (2017) Yao, Herr & Parkhill, J. Chem. Phys. <u>146</u>, 014106 (2017) Schütt, Arbabzadah, Chmiela, Müller &. Tkatchenko, Nat. Commun. <u>8</u>, 13890 (2017) Chmiela, Sauceda, Müller &. Tkatchenko, Nat. Commun. <u>9</u>, 3887 (2018) Faber, Christensen, Huang & von Lilienfeld, J. Chem. Phys. <u>148</u>, 241717 (2018) Schütt, Sauceda, Kindermans, Tkatchenko & Müller, J. Chem. Phys. <u>148</u>, 241722 (2018) Grisafi, Wilkins, Csányi & Ceriotti, Phys. Rev. Lett. <u>120</u>, 036002 (2018) Zhang, Han, Wang, Car & E, Phys. Rev. Lett. <u>120</u>, 143001 (2018) Element-wise produc (∑)/(+) Element-wise sum Collins, Gordon, von Lilienfeld & D. J. Yaron, J. Chem. Phys. <u>148</u>, 241718 (2018) turh W^{*} $(W'_{W} : k^{h})$ Schütt, Kessel, Gastegger, Nicoli, Tkatchenko & Müller, J. Chem. Theory Comput. <u>15</u>, 448 (2019) Unke & Meuwly, J. Chem. Theory Comput. <u>15</u>, 3678 (2019)

2 molecules at a time







2 molecules at a time







2 molecules at a time





2 molecules at a time





2 molecules at a time





3 molecules at a time







3 molecules at a time







3 molecules at a time







3 molecules at a time







3 molecules at a time







4 molecules at a time







4 molecules at a time







5 molecules at a time







6 molecules at a time











$$E_N = \sum_{i}^{N} V^{1B}(i)$$

+
$$\sum_{i < j}^{N} V^{2B}(i, j)$$

+
$$\sum_{i < j < k}^{N} V^{3B}(i, j, k)$$

+
$$\dots$$

+
$$V^{NB}(1, \dots, N)$$

Hankins, Moskowitz & Stillinger, J. Chem. Phys. <u>53</u>, 4544 (1970) Popkie, Kistenmacher & Clementi, J. Chem. Phys. <u>59</u>, 1325 (1973)





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Hankins, Moskowitz & Stillinger, J. Chem. Phys. <u>53</u>, 4544 (1970)



FP, Acc. Chem. Res. <u>49</u>, 1844 (2016)

MB expansion converges quickly for non-metallic systems

see: Clementi, Stillinger, Xantheas, Gordon, Truhlar, Jordan, Szalewicz, Bowman, ...



















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$$\begin{split} E_N = & \sum_{i}^{N} V^{1B}(i) & 1\text{-body} \\ &+ \sum_{i < j}^{N} V^{2B}(i,j) & 2\text{-body} \\ &+ \sum_{i < j < k}^{N} V^{3B}(i,j,k) & 3\text{-body} \\ &+ \dots & 4\text{-body} \\ &+ \dots & \dots \\ &+ V^{NB}(1,\dots,N) & \text{N-body} \end{split}$$

Hankins, Moskowitz & Stillinger, J. Chem. Phys. <u>53</u>, 4544 (1970)



FP, Acc. Chem. Res. <u>49</u>, 1844 (2016)

quantum mechanics

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FP, Acc. Chem. Res. <u>49</u>, 1844 (2016)

quantum nechanics

MB expansion converges quickly for non-metallic systems

see: Clementi, Stillinger, Xantheas, Gordon, Truhlar, Jordan, Szalewicz, Bowman, ...

classical nechanics





$$\begin{split} E_N = & \sum_{i}^{N} V^{1B}(i) & \text{1-body} \\ &+ \sum_{i < j}^{N} V^{2B}(i,j) & \text{2-body} \\ &+ & \sum_{i < j < k}^{N} V^{3B}(i,j,k) & \text{3-body} \\ &+ & \dots & \dots \\ &+ & V^{NB}(1,\dots,N) & \text{N-body} \\ \end{split}$$



$E_N = \sum_{i}^{N} V^{1B}(i)$	1-body	c m
$+ \sum_{i < j}^{N} V^{2B}(i, j)$	2-body	fı
$+\sum_{i < j < k}^{N} V^{3B}(i,j,k)$	3-body	
$+$ $\cdot \cdot \cdot$	4-body	
$+ V^{NB}(1,\ldots,N)$	N-body	m


r c m	1-body	$E_N = \sum_{i}^{N} V^{1B}(i)$
f r	2-body	$+ \sum_{i < j}^{N} V^{2B}(i, j)$
,	3-body	$+\sum_{i < i < k}^{N} V^{3B}(i,j,k)$
/ Tro	4-body	$1 < j < \kappa$ +
y m	N-body	$+ V^{NB}(1,\ldots,N)$



$E_N = \sum_{i}^{N} V^{1B}(i)$	1-body	o m
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$+\sum_{i \in i}^{N} V^{3B}(i,j,k)$	3-body	
$1 < j < \kappa$ +	4-body	
$+ V^{NB}(1,\ldots,N)$	N-body	_ m

Hankins, Moskowitz & Stillinger, J. Chem. Phys. <u>53</u>, 4544 (1970) Popkie, Kistenmacher & Clementi, J. Chem. Phys. <u>59</u>, 1325 (1973)



FP, Acc. Chem. Res. <u>49</u>, 1844 (2016)

quantum echanics

learned rom data

$$\Delta^{nB} = V^{nB} - V^{nB}_{CM}$$

learned m physics

classical echanics









Babin, Leforestier & FP, J. Chem. Theory Comput. 9, 5395 (2013); Babin, Medders & FP, J. Chem. Theory Comput. 10, 1599 (2014)

$V^{2B} = s_2 V_{sr}^{2B} + V_{elec}^{2B} + V_{ind}^{2B} + V_{disp}^{2B}$













Babin, Leforestier & FP, J. Chem. Theory Comput. 9, 5395 (2013); Babin, Medders & FP, J. Chem. Theory Comput. 10, 1599 (2014)

permanent electrostatics













Babin, Leforestier & FP, J. Chem. Theory Comput. 9, 5395 (2013); Babin, Medders & FP, J. Chem. Theory Comput. 10, 1599 (2014)

permanent electrostatics

2B induction













Babin, Leforestier & FP, J. Chem. Theory Comput. 9, 5395 (2013); Babin, Medders & FP, J. Chem. Theory Comput. 10, 1599 (2014)















Babin, Leforestier & FP, J. Chem. Theory Comput. 9, 5395 (2013); Babin, Medders & FP, J. Chem. Theory Comput. 10, 1599 (2014)

from physics of isolated monomers









Babin, Leforestier & FP, J. Chem. Theory Comput. 9, 5395 (2013); Babin, Medders & FP, J. Chem. Theory Comput. 10, 1599 (2014)







Permutationally invariant polynomials

$$\begin{split} V^{2B}_{sr} &= V^{2B}_{PIP} = \sum_{l} A_{l} \eta_{l} = A_{1} \xi_{a} + A_{2} \xi_{b} + A_{3} \xi_{c} + A_{3$$

Babin, Leforestier & FP, J. Chem. Theory Comput. 9, 5395 (2013); Babin, Medders & FP, J. Chem. Theory Comput. 10, 1599 (2014)

Braams & Bowman, Int. Rev. Phys. Chem. <u>28</u>, 577 (2009)

 $+\ldots+A_i\xi_a\xi_b+A_i\xi_a\xi_c+A_k\xi_b\xi_c+\ldots+A_q\xi_a\xi_b\xi_c+\ldots+\ldots$





 $V^{2B} = s_{2}$

short-range interactions



Babin, Leforestier & FP, J. Chem. Theory Comput. 9, 5395 (2013); Babin, Medders & FP, J. Chem. Theory Comput. 10, 1599 (2014)









Permutationally invariant polynomials

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Many-Body Models: Do They Work?





 $E_N = \sum_{i=1}^{N} V^{1B}(i) + \sum_{i < j}^{N} V^{2B}(i,j) + \sum_{i < j < k}^{N} V^{3B}(i,j,k) + \dots + V^{NB}(1,\dots,N)$



Many-Body Models: Do They Work?





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Braams & Bowman, Int. Rev. Phys. Chem. <u>28</u>, 577 (2009)

Nguyen, Székely, Imbalzano, Behler, Csányi, Ceriotti & FP, J. Chem. Phys. <u>148</u>, 241725 (2018)







Behler & Parrinello, Phys. Rev. Lett. <u>98</u>, 146401 (2007) radial functions angular functions $G_i^{rad} = \sum e^{-(R_{ij} - R_s)^2}$ $G_i^{ang} = 2^{1-\zeta} \sum$ $k \neq i, j$ Output many-body energy input, 3 hidden, and 1 output layers 2 networks: one for H and one for O activation functions: hyperbolic tangent / linear

Nguyen, Székely, Imbalzano, Behler, Csányi, Ceriotti & FP, J. Chem. Phys. <u>148</u>, 241725 (2018)

Neural Networks

$$(1 + \lambda \cos \theta_{ijk})^{\zeta} \times e^{-\eta (R_{ij} + R_{ik} + R_{jk})^2}$$







Gaussian Approximation Potentials

atomic energies kernel

$$\varepsilon(\mathbf{R}) = \sum_{k} b_{k} K(\mathbf{R}, \mathbf{R}_{k}),$$

$$K(\boldsymbol{R},\boldsymbol{R'}) = \left(\sum_{\alpha\beta n_1 n_2 l} p_{n_1 n_2 l}^{\alpha\beta}(\boldsymbol{R}) p_{n_1 n_2 l}^{\alpha\beta}(\boldsymbol{R'})\right)$$

Bartók, Payne, Kondor & Csányi, Phys. Rev. Lett. <u>104</u>, 136403 (2010)

local atomic neighbor densities

$$\rho_i^{\alpha}(\boldsymbol{r}) = \sum_{nlm} c_{nlm}^{\alpha} g_n(|\boldsymbol{r}|) Y_{lm}(\hat{\boldsymbol{r}}).$$

Nguyen, Székely, Imbalzano, Behler, Csányi, Ceriotti & FP, J. Chem. Phys. <u>148</u>, 241725 (2018)



$$E_N = \sum_{i}^{N} V^{1B}(i) + \sum_{i < j}^{N} V^{2B}(i,j) + \sum_{i < j < k}^{N} V^{3B}(i,j,k) + \dots + V^{NB}(1,\dots,N)$$

	2B (kcal/mol)			3B (kcal/mol)		
	Training	Validation	Test	Training	Validation	Test
PIP	0.0349	0.0449	0.0494	0.0262	0.0463	0.0465
BPNN	0.0493	0.0784	0.0792	0.0318	0.0658	0.0634
GAP	0.0176	0.0441	0.0539	0.0052	0.0514	0.0517

Nguyen, Székely, Imbalzano, Behler, Csányi, Ceriotti & FP, J. Chem. Phys. <u>148</u>, 241725 (2018)

Molecular Dynamics

MB-pol \iff **Born-Oppenheimer potential energy surface**

Nuclear quantum effects must be included explicitly in molecular simulations





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MB-pol \iff **Born-Oppenheimer potential energy surface**

Nuclear quantum effects must be included explicitly in molecular simulations



Methods based on:

• Basis set expansions

with Claude Leforestier (Montpellier), Ryan Steele (Utah) (clusters: anharmonic vibrational spectra)

• Path-integral molecular dynamics

(condensed phase: structure and thermodynamics)

Centroid molecular dynamics

(condensed phase: dynamics)

Ring polymer instanton

with Jeremy Richardson (ETH) (tunneling splittings)

Dimer	

Mode		Experiment (cm ⁻¹)	MB-pol (cm ⁻¹)
intermolecular	2	153.62	154.77
stretch	1		149.05
acceptor	1		129.49
twist	2	120.19	119.23
acceptor	2	108.89	109.14
wag	1	107.93	108.76
donor	1		113.18
torsion	2	64.52	61.24
ground	2	11.18	11.88
state	1	0	0

J. Chem. Theory Comput. <u>9</u>, 4844 (2013) J. Chem. Theory Comput. <u>10</u>, 1599 (2014)



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J. Chem. Theory Comput. <u>9</u>, 4844 (2013) J. Chem. Theory Comput. <u>10</u>, 1599 (2014)









FP, Acc. Chem. Res. <u>49</u>, 1844 (2016)

Electron affinity







Reference data from monomer, dimer, hexamer, and ice

Gillan, Alfé, Michaelides, "Perspective: How Good Is DFT for Water?", J. Chem. Phys. <u>144</u>, 130901 (2016)



Cisneros, Wikfeldt, Ojamäe, Lu, Xu, Torabifard, Bartók-Pártay, Csányi, Molinero & FP, Chem. Rev. <u>116</u>, 7501 (2016)

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Reference data from monomer, dimer, hexamer, and ice

Gillan, Alfé, Michaelides, "Perspective: How Good Is DFT for Water?", J. Chem. Phys. <u>144</u>, 130901 (2016)

10 "At present, MB-pol achieves unprecedented accuracy in describing water properties from the dimer to the condensed phase and is perhaps one of the all-around best MM water models..." "Advanced models for water simulations"

Demerdash, Wang & Head-Gordon, WIREs Wiley Interdiscip. Rev. Comput. Mol. Sci. <u>8</u>, e1355 (2018)



Cisneros, Wikfeldt, Ojamäe, Lu, Xu, Torabifard, Bartók-Pártay, Csányi, Molinero & FP, Chem. Rev. <u>116</u>, 7501 (2016)



9.6

Learning Physics from Many-Body Models

What makes water water?

How good are simulations of hydration?

Data-driven many-body models: Quo vadis?







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Why MB-pol Works

MB-pol vs. CCSD(T): Interaction energies for water clusters



Why MB-pol Works

MB-pol vs. CCSD(T): Interaction energies for water clusters



FP, Acc. Chem. Res. <u>49</u>, 1844 (2016)
Why MB-pol Works

MB-pol vs. CCSD(T): Interaction energies for water clusters



FP, Acc. Chem. Res. <u>49</u>, 1844 (2016)

Why MB-pol Works

MB-pol vs. CCSD(T): Many-body energy decomposition for water clusters



FP, Acc. Chem. Res. <u>49</u>, 1844 (2016)

Why MB-pol Works

MB-pol vs. CCSD(T): Many-body energy decomposition for water clusters



FP, Acc. Chem. Res. <u>49</u>, 1844 (2016)

MB-pol vs. DFT: Interaction energies for water clusters



MB-pol vs. DFT: Interaction energies for water clusters



MB-pol vs. DFT: Interaction energies for water clusters



MB-pol vs. DFT: Interaction energies for water clusters



MB-pol vs. DFT: Interaction energies for water clusters



MB-pol vs. DFT: Interaction energies for water clusters



MB-pol vs. DFT: Interaction energies for water clusters



MB-pol vs. DFT: Interaction energies for water clusters



MB-pol vs. DFT-D3: Interaction energies for water clusters



MB-pol vs. DFT-D3: Many-body energy decomposition for water clusters



MB-pol vs. DFT-D3: Many-body energy decomposition for water clusters



MB-pol vs. DFT-D3: Many-body energy decomposition for water clusters



MB-pol vs. DFT-D3: Many-body energy decomposition for water clusters



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MB-pol vs. DFT-D3: Many-body energy decomposition for water clusters

REPORT

THEORETICAL CHEMISTRY

Density functional theory is straying from the path toward the exact functional

Michael G. Medvedev,^{1,2,3}*+ Ivan S. Bushmarinov,¹*+ Jianwei Sun,⁴‡ John P. Perdew,^{4,5}⁺ Konstantin A. Lyssenko¹⁺

The theorems at the core of density functional theory (DFT) state that the energy of a many-electron system in its ground state is fully defined by its electron density distribution. This connection is made via the exact functional for the energy, which minimizes at the exact density. For years, DFT development focused on energies, implicitly assuming that functionals producing better energies become better approximations of the exact functional. We examined the other side of the coin: the energy-minimizing electron densities for atomic species, as produced by 128 historical and modern DFT functionals. We found that these densities became closer to the exact ones, reflecting theoretical advances, until the early 2000s, when this trend was reversed by unconstrained functionals sacrificing physical rigor for the flexibility of empirical fitting.

Science <u>355</u>, 49 (2017)



MB-pol vs. DFT-D3: Many-body energy decomposition for water clusters



Climbing Jacob's ladder of DFT approximations

2B and 3B energies

Riera, Lambros, Nguyen, Götz & FP, Chem. Sci. <u>10</u>, 8211 (2019)

Climbing Jacob's ladder of DFT approximations

2B and 3B energies



Riera, Lambros, Nguyen, Götz & FP, Chem. Sci. <u>10</u>, 8211 (2019)

Climbing Jacob's ladder of DFT approximations

2B and 3B energies



Riera, Lambros, Nguyen, Götz & FP, Chem. Sci. <u>10</u>, 8211 (2019)



Climbing Jacob's ladder of DFT approximations





Riera, Lambros, Nguyen, Götz & FP, Chem. Sci. <u>10</u>, 8211 (2019)

GGA: revPBE-D3

Climbing Jacob's ladder of DFT approximations

Meta-GGA: B97M-rV



Riera, Lambros, Nguyen, Götz & FP, Chem. Sci. <u>10</u>, 8211 (2019)

Climbing Jacob's ladder of DFT approximations



Lambros, Hu & FP, in progress

Meta-GGA: SCAN

Climbing Jacob's ladder of DFT approximations

Hybrid: revPBE0-D3



Riera, Lambros, Nguyen, Götz & FP, Chem. Sci. <u>10</u>, 8211 (2019)

water hexamer

Climbing Jacob's ladder of DFT approximations

Range-separated, hybrid: ωB97M-V



Riera, Lambros, Nguyen, Götz & FP, Chem. Sci. <u>10</u>, 8211 (2019)

water hexamer

Climbing Jacob's ladder of molecular models

MB-pol



Riera, Lambros, Nguyen, Götz & FP, Chem. Sci. <u>10</u>, 8211 (2019)

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MB-pol: CCSD(T) Accuracy at the Cost of a Force Field

$$\begin{split} E_N = & \sum_{i}^{N} V^{1B}(i) & \text{1-body} \\ & + \sum_{i < j}^{N} V^{2B}(i,j) & \text{2-body} \\ & + \sum_{i < j < k}^{N} V^{3B}(i,j,k) & \text{3-body} \\ & + \dots & \text{4-body} \\ & + \dots & \dots \\ & + V^{NB}(1,\dots,N) & \text{N-body} \end{split}$$

Hankins, Moskowitz & Stillinger, J. Chem. Phys. <u>53</u>, 4544 (1970) Popkie, Kistenmacher & Clementi, J. Chem. Phys. <u>59</u>, 1325 (1973)



FP, Acc. Chem. Res. <u>49</u>, 1844 (2016)

flexible monomers

N-body polarization

Explicit 2B and 3B corrections from CCSD(T)/CBS

- J. Phys. Chem. Lett. <u>3</u>, 3765 (2012)
- J. Chem. Theory Comput. <u>9</u>, 1103 (2013)
- J. Chem. Theory Comput. <u>9</u>, 5395 (2013)
- J. Chem. Theory Comput. <u>10</u>, 1599 (2014)
- J. Chem. Theory Comput. <u>10</u>, 2906 (2014)



MB-DFT: Probing Many-Body Effects in Water

$$\begin{split} E_N = & \sum_{i}^{N} V^{1B}(i) & \text{1-body} \\ + & \sum_{i < j}^{N} V^{2B}(i,j) & \text{2-body} \\ + & \sum_{i < j < k}^{N} V^{3B}(i,j,k) & \text{3-body} \\ + & \dots & & \\ + & \dots & & \\ + & V^{NB}(1,\dots,N) & \text{N-body} \end{split}$$



Riera, Lambros, Nguyen, Götz & FP, Chem. Sci. <u>10</u>, 8211 (2019)

flexible monomers

N-body polarization

Explicit 2B and 3B corrections from DFT



MB-DFT a.k.a. "DFT à la Carte": MB Models with DFT Accuracy

MB-DFT vs. DFT

256 molecules vs. 64 molecules



* PIMD DFT: Marsalek & Markland, J. Phys. Chem. Lett. <u>8</u>, 1545 (2017) Pestana, Marsalek, Markland & Head-Gordon, J. Phys. Chem. Lett. <u>9</u>, 5009 (2018)

Riera, Lambros, Nguyen, Götz & FP, Chem. Sci. <u>10</u>, 8211 (2019)





Climbing Jacob's ladder of DFT approximations





Riera, Lambros, Nguyen, Götz & FP, Chem. Sci. <u>10</u>, 8211 (2019)

many-body contributions

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Climbing Jacob's ladder of DFT approximations



many-body contributions

Riera, Lambros, Nguyen, Götz & FP, Chem. Sci. <u>10</u>, 8211 (2019)

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or 7	
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6B	
$$\begin{split} E_N = & \sum_{i}^{N} V^{1B}(i) & \text{1-body} \\ + & \sum_{i < j}^{N} V^{2B}(i,j) & \text{2-body} \\ + & \sum_{i < j < k}^{N} V^{3B}(i,j,k) & \text{3-body} \\ + & \dots & & \\ + & \dots & & \\ + & V^{NB}(1,\dots,N) & \text{N-body} \end{split}$$



Riera, Lambros, Nguyen, Götz & FP, Chem. Sci. <u>10</u>, 8211 (2019)

flexible monomers

N-body polarization

Explicit 2B and 3B corrections from DFT



$$\begin{split} E_N = & \sum_{i}^{N} V^{1B}(i) & \text{1-body} \\ + & \sum_{i < j}^{N} V^{2B}(i,j) & \text{2-body} \\ + & \sum_{i < j < k}^{N} V^{3B}(i,j,k) & \text{3-body} \\ + & \dots & & \\ + & \dots & & \\ + & V^{NB}(1,\dots,N) & \text{N-body} \end{split}$$

Hankins, Moskowitz & Stillinger, J. Chem. Phys. <u>53</u>, 4544 (1970) Popkie, Kistenmacher & Clementi, J. Chem. Phys. <u>59</u>, 1325 (1973)



Riera, Lambros, Nguyen, Götz & FP, Chem. Sci. <u>10</u>, 8211 (2019)

flexible monomers

N-body polarization

Explicit 2B corrections from DFT

Explicit 3B corrections from CCSD(T)/CBS

3 MB PEFs for each XC functional

- (2B+3B)-XC \bullet
- (2B)-XC



$$\begin{split} E_N = & \sum_{i}^{N} V^{1B}(i) & \text{1-body} \\ + & \sum_{i < j}^{N} V^{2B}(i,j) & \text{2-body} \\ + & \sum_{i < j < k}^{N} V^{3B}(i,j,k) & \text{3-body} \\ + & \dots & & \\ + & \dots & & \\ + & V^{NB}(1,\dots,N) & \text{N-body} \end{split}$$

Hankins, Moskowitz & Stillinger, J. Chem. Phys. <u>53</u>, 4544 (1970) Popkie, Kistenmacher & Clementi, J. Chem. Phys. <u>59</u>, 1325 (1973)



Riera, Lambros, Nguyen, Götz & FP, Chem. Sci. <u>10</u>, 8211 (2019)

flexible monomers

N-body polarization

Explicit 2B corrections from CCSD(T)/CBS

Explicit 3B corrections from DFT



- (2B+3B)-XC
- (2B)-XC
- (3B)-XC



Climbing Jacob's ladder of DFT approximations

2B DFT + 3B DFT + NB MB-pol



Riera, Lambros, Nguyen, Götz & FP, Chem. Sci. <u>10</u>, 8211 (2019)

water structure: O-O RDF

Climbing Jacob's ladder of DFT approximations

2B DFT + 3B DFT + NB MB-pol

water structure: O-O RDF





Climbing Jacob's ladder of DFT approximations

2B DFT + 3B CCSD(T) + NB MB-pol

water structure: O-O RDF





Climbing Jacob's ladder of DFT approximations

2B CCSD(T) + 3B DFT + NB MB-pol

water structure: O-O RDF





Climbing Jacob's ladder of DFT approximations water structure: O-O RDF



Climbing Jacob's ladder of DFT approximations: SCAN water structure: O-O RDF



Lambros, Hu & FP, in progress

Learning Physics from Many-Body Models

What makes water water?

- Low-order many-body interactions determine the local structure of water
- Delocalization errors make current DFT models unreliable for water

How good are simulations of hydration?

Data-driven many-body models: Quo vadis?







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From Water to Complex Solutions



http://paesanigroup.ucsd.edu

From Water to Complex Solutions



http://paesanigroup.ucsd.edu

F-(H₂O): Errors in interaction energies relative to CCSD(T)/CBS



Bizzarro, Egan & FP, J. Chem. Theory Comput. <u>15</u>, 2983 (2019)



F-(H₂O): Errors in interaction energies relative to CCSD(T)/CBS



Bizzarro, Egan & FP, J. Chem. Theory Comput. <u>15</u>, 2983 (2019)



Cl-(H₂O): Errors in interaction energies relative to CCSD(T)/CBS



Bizzarro, Egan & FP, J. Chem. Theory Comput. 15, 2983 (2019)



Cl-(H₂O): Errors in interaction energies relative to CCSD(T)/CBS



Bizzarro, Egan & FP, J. Chem. Theory Comput. 15, 2983 (2019)



Br-(H₂O): Errors in interaction energies relative to CCSD(T)/CBS



Bizzarro, Egan & FP, J. Chem. Theory Comput. <u>15</u>, 2983 (2019)



Br-(H₂O): Errors in interaction energies relative to CCSD(T)/CBS



Bizzarro, Egan & FP, J. Chem. Theory Comput. <u>15</u>, 2983 (2019)



I-(H₂O): Errors in interaction energies relative to CCSD(T)/CBS



Bizzarro, Egan & FP, J. Chem. Theory Comput. 15, 2983 (2019)



I-(H₂O): Errors in interaction energies relative to CCSD(T)/CBS



Bizzarro, Egan & FP, J. Chem. Theory Comput. 15, 2983 (2019)



M+(H₂O): Errors in interaction energies relative to CCSD(T)/CBS



Riera, Mardirossian, Bajaj, Götz & FP, J. Chem. Phys. <u>147</u>, 161715 (2017)



M+(H₂O): Errors in interaction energies relative to CCSD(T)/CBS



Riera, Mardirossian, Bajaj, Götz & FP, J. Chem. Phys. <u>147</u>, 161715 (2017)



Comparison between different water-Cs+ models



Comparison between different water-Cs+ models



Comparison between different water-Cs+ models



Comparison between different water-Cs+ models



Comparison between different water-Cs+ models





Comparison between different water-Cs+ models





Comparison between different water-Cs+ models





Cs+ hydration: Experiment vs. Simulation



point charge model

Cs+ hydration: Experiment vs. Simulation

point charge model



Cs+ hydration: Experiment vs. Simulation

point charge model



Cs+ hydration: Experiment vs. Simulation

polarizable model



Cs+ hydration: Experiment vs. Simulation

many-body model with explicit 2B term



Cs+ hydration: Experiment vs. Simulation

many-body model with explicit 2B & 3B terms



Cs+ hydration: Experiment vs. Simulation

many-body model with explicit 2B & 3B terms and nuclear quantum effects


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From Water to Ice...

Homogeneous ice nucleation



Moberg, Becker, Dierking, Zurheide, Bandow, Buck, Hudait, Molinero, FP & Zeuch, Proc. Natl. Acad. Sci. U.S.A., in press https://doi.org/10.26434/chemrxiv.8856053.v1

From Water to Ice...

3800

Homogeneous ice nucleation



Moberg, Becker, Dierking, Zurheide, Bandow, Buck, Hudait, Molinero, FP & Zeuch, Proc. Natl. Acad. Sci. U.S.A., in press https://doi.org/10.26434/chemrxiv.8856053.v1

Heterogeneous ice nucleation



Hudait, Moberg, Qiu, Odendahl, FP & Molinero Proc. Natl. Acad. Sci. U.S.A. <u>115</u>, 8266 (2018) ongoing collaboration with Peter Frazier (Cornell University)



... to Aqueous Solutions in Confinement and Fluid Mixtures

Water harvesting and desalination in MOFs



Rieth, Hunter, Dinča & FP, Nat. Commun. <u>10</u>, 4771 (2019) ongoing collaboration with Sicun Gao (UC San Diego)

... to Aqueous Solutions in Confinement and Fluid Mixtures

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Rieth, Hunter, Dinča & FP, Nat. Commun. <u>10</u>, 4771 (2019) ongoing collaboration with Sicun Gao (UC San Diego)

http://paesanigroup.ucsd.edu

Complex fluid mixtures



Riera, Hirales, Ghosh & FP, in progress

Many-Body Models as a Reference for ML DFT Models

THE JOURNAL OF CHEMICAL PHYSICS 144, 224101 (2016)



Optimization of an exchange-correlation density functional for water

Michelle Fritz,¹ Marivi Fernández-Serra,^{2,3} and José M. Soler⁴ ¹Departamento de Física de la Materia Condensada, Universidad Autónoma de Madrid, E-28049 Madrid, Spain ²Department of Physics and Astronomy, Stony Brook University, Stony Brook, New York 11794-3800, USA ³Institute for Advanced Computational Science, Stony Brook University, Stony Brook, New York 11794-3800, USA ⁴Departamento e Instituto de Física de la Materia Condensada, Universidad Autónoma de Madrid, E-28049 Madrid, Spain

(Received 23 March 2016; accepted 18 May 2016; published online 9 June 2016)

We describe a method, that we call data projection onto parameter space (DPPS), to optimize an energy functional of the electron density, so that it reproduces a dataset of experimental magnitudes. Our scheme, based on Bayes theorem, constrains the optimized functional not to depart unphysically from existing *ab initio* functionals. The resulting functional maximizes the probability of being the "correct" parameterization of a given functional form, in the sense of Bayes theory. The application of DPPS to water sheds new light on why density functional theory has performed rather poorly for liquid water, on what improvements are needed, and on the intrinsic limitations of the generalized gradient approximation to electron exchange and correlation. Finally, we present tests of our wateroptimized functional, that we call vdW-DF-w, showing that it performs very well for a variety of condensed water systems. *Published by AIP Publishing*. [http://dx.doi.org/10.1063/1.4953081]

"As prior information for the Bayesian optimization, we have used the 15 enhancement factors shown in Fig. 1. For the reference energies, we use the MB-pol force field, a sophisticated fit to highly accurate quantum chemical calculations of water monomers and clusters."

"It is important to emphasize that, although fitted only to monomers, dimers, and trimers, the MB-pol force field has been shown to reproduce accurately the structural and thermodynamic properties of condensed phases of water."

Machine learning a highly accurate exchange and correlation functional of the electronic density

Sebastian Dick and Marivi Fernandez-Serra

Physics and Astronomy Department, Stony Brook University, Stony Brook, New York 11794-3800, United States and Institute for Advanced Computational Science, Stony Brook University, Stony Brook, New York 11794-3800, United States

Density Functional Theory (DFT) is the standard formalism to study the electronic structure of matter at the atomic scale. The balance between accuracy and computational cost that DFT-based simulations provide allows researchers to understand the structural and dynamical properties of increasingly large and complex systems at the quantum mechanical level. In Kohn-Sham DFT, this balance depends on the choice of exchange and correlation functional, which only exists in approximate form. Increasing the non-locality of this functional and climbing the figurative Jacob's ladder of DFT, one can systematically reduce the amount of approximation involved and thus approach the exact functional. Doing this, however, comes at the price of increased computational cost, and so, for extensive systems, the predominant methods of choice can still be found within the lower-rung approximations. Here we propose a framework to create highly accurate density functionals by using supervised machine learning, termed NeuralXC. These machine-learned functionals are designed to lift the accuracy of local and semilocal functionals to that provided by more accurate methods while maintaining their efficiency. We show that the functionals learn a meaningful representation of the physical information contained in the training data, making them transferable across systems. We further demonstrate how a functional optimized on water can reproduce experimental results when used in molecular dynamics simulations. Finally, we discuss the effects that our method has on self-consistent electron densities by comparing these densities to benchmark coupled-cluster results.





Representability of Low-Order Many-Body Interactions

2B interaction energies



Nguyen, Székely, Imbalzano, Behler, Csányi, Ceriotti & FP, J. Chem. Phys. <u>148</u>, 241725 (2018)

training point density

distribution of 2B energies in the training set

Representability of Low-Order Many-Body Interactions

3B interaction energies



Nguyen, Székely, Imbalzano, Behler, Csányi, Ceriotti & FP, J. Chem. Phys. <u>148</u>, 241725 (2018)

training point density

distribution of 2B energies in the training set

Active Learning of Low-Order Many-Body Interactions





Active Learning of Low-Order Many-Body Interactions





Generating "Optimal" Many-Body Training Sets

Actively learning water-Cs+ many-body interactions







Generating "Optimal" Many-Body Training Sets

Actively learning water-Cs+ many-body interactions







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- Common force fields are unable to correctly predict the hydration structure of monovalent ions

Data-driven many-body models: Quo vadis?

- Materials discovery for: anti-icing, water harvesting and desalination, separation
- **Reference for more accurate DFT models**
- Improved approaches for many-body training sets







MBX: C++ Library for Data-Driven Many-Body Models

if (do_grads) {
 // POLYNOMIALS
 std::vector<double> grad1(coord1.size(), 0.0);
 std::vector<double> grad2(coord2.size(), 0.0);
 std::vector<double> grad3(coord3.size(), 0.0);
 // POLYNOMIALS
 e3b_pool[rank] += e3b::get_3b_energy(m1, m2, m3, nt, xyz1, xyz2, xyz3, grad1, grad2,

MBX is a standalone C++ library that provides an interface to MD drivers, such as i-PI, and enables classical and pathintegral molecular dynamics simulations using MB-pol and MB-nrg potential energy functions

for (size_t) = 0;) < 3 * nat_[trimers[10 + 3 * K + 1]];]++) {
 grad_pool[rank][3 * first_index_[trimers[i0 + 3 * k + 1]] + j];
 grad2[k * 3 * nat_[trimers[i0 + 3 * k + 1]] + j];
}
// Monomer 3
for (size_t j = 0; j < 3 * nat_[trimers[i0 + 3 * k + 2]]; j++) {
 grad_pool[rank][3 * first_index_[trimers[i0 + 3 * k + 2]] + j] +=
 grad3[k * 3 * nat_[trimers[i0 + 3 * k + 2]] + j];
}</pre>

Riera, Smith, Simmonett & FP, http://paesanigroup.ucsd.edu/software/mbx.html



On the Quality of the Reference Data





On the Quality of the Reference Data





Greetings from Las Vegas!

Learning Physics from Many-Body Models

What makes water water?

Acc. Chem. Res. <u>49</u>, 1844 (2016) J. Am. Chem. Soc. <u>138</u>, 3912 (2016) J. Am. Chem. Soc. <u>139</u>, 7082 (2017) Nat. Commun. <u>9</u>, 247 (2018) *Phys. Rev. Lett.* <u>121</u>, 137401 (2018) Chem. Sci. <u>10</u>, 8211 (2019)

How good are simulations of hydration?

J. Chem. Theory Comput. <u>12</u>, 2698 (2016) J. Chem. Phys. <u>147</u>, 161715 (2017) J. Chem. Theory Comput. <u>15</u>, 2983 (2019) J. Phys. Chem. Lett. <u>10</u>, 406 (2019) J. Phys. Chem. Lett. <u>10</u>, 2823 (2019) Nat. Chem. <u>11</u>, 367 (2019)

Data-driven many-body models: Quo vadis?

Proc. Natl. Acad. Sci. U.S.A. <u>115</u>, 8266 (2018) Nat. Commun. 10, 4771 (2019) Proc. Natl. Acad. Sci. U.S.A., in press. https://doi.org/10.26434/chemrxiv.8856053.v1 J. Chem. Phys. <u>144</u>, 224101 (2016) J. Chem. Phys. <u>148</u>, 241725 (2018)





