

# Towards sustainable electronic structure predictions

Lessons from embedding and machine learning

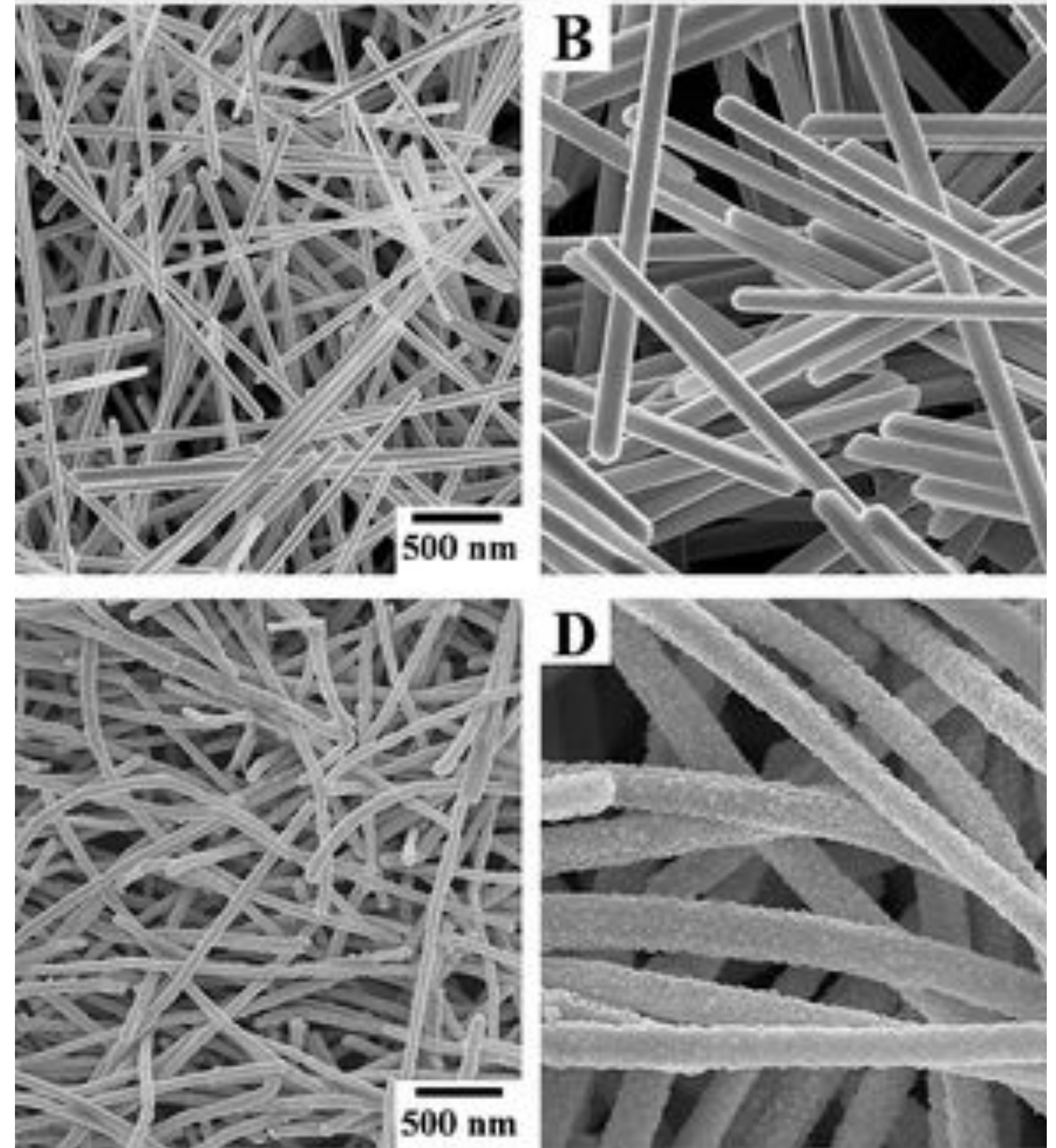
<b>Part 1</b>	<b>Part 2</b>
Embedding and ML Developments and some applications	<b><i>The code</i></b>



# Mesososcopic

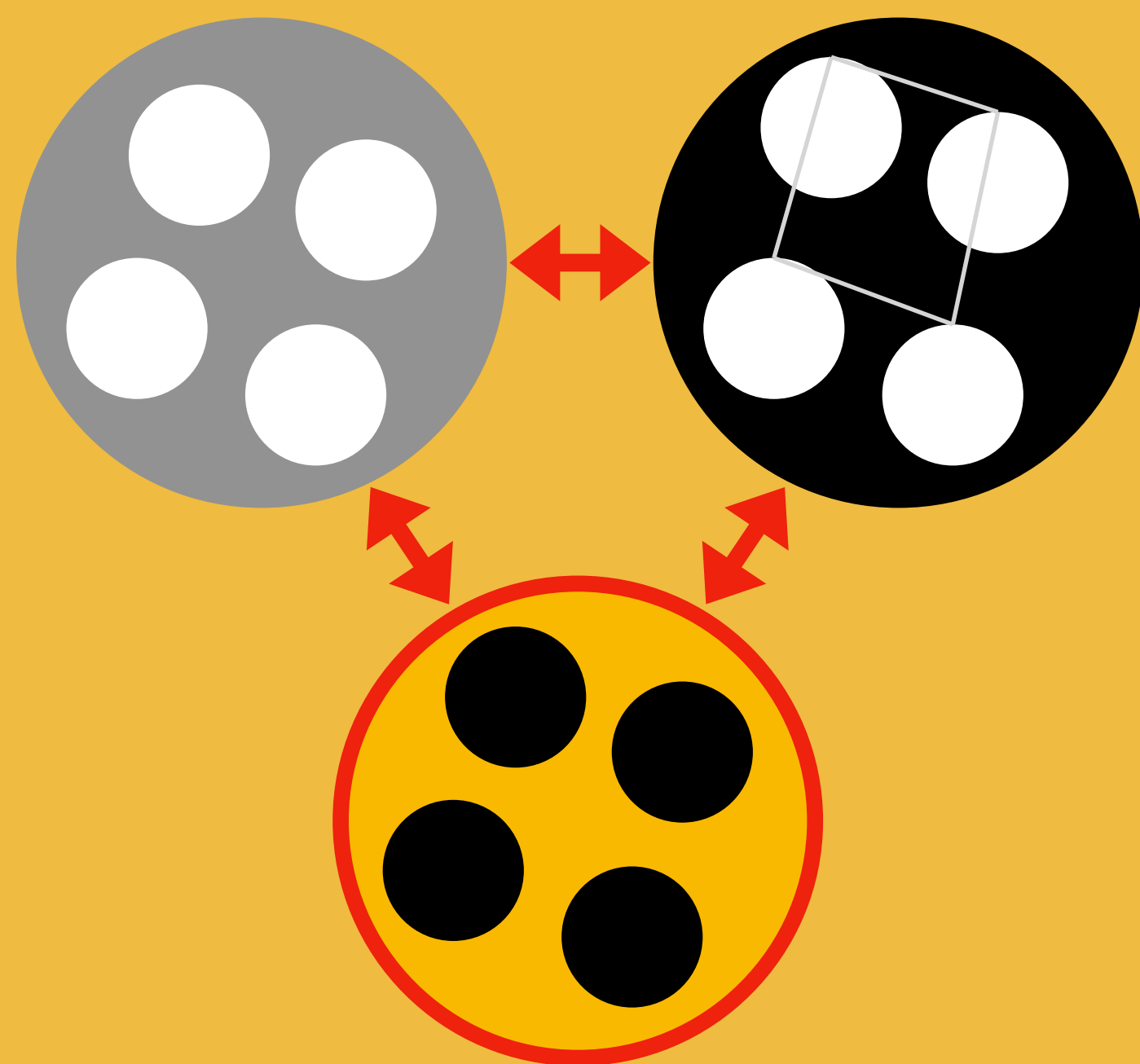
A synonym for reality

- ▶ Characteristic length scales of realistic chemical systems **> 100 nm**
- ▶ Electronic structure is #1 priority
- ▶ DFT scales like
- ▶ We focus on alternatives
  - Orbital-free DFT
  - Density Embedding / sDFT
  - Machine learning
- ▶ Other valid alternatives



# Alternatives to Kohn-Sham DFT

## Orbital-free DFT



○ Fermions      ● Bosons

## Density Embedding



## Machine learning



- ◆ Electronic energy?
- ◆ Dipole moment?
- ◆ Solvation energy?
- ◆ Electronic structure

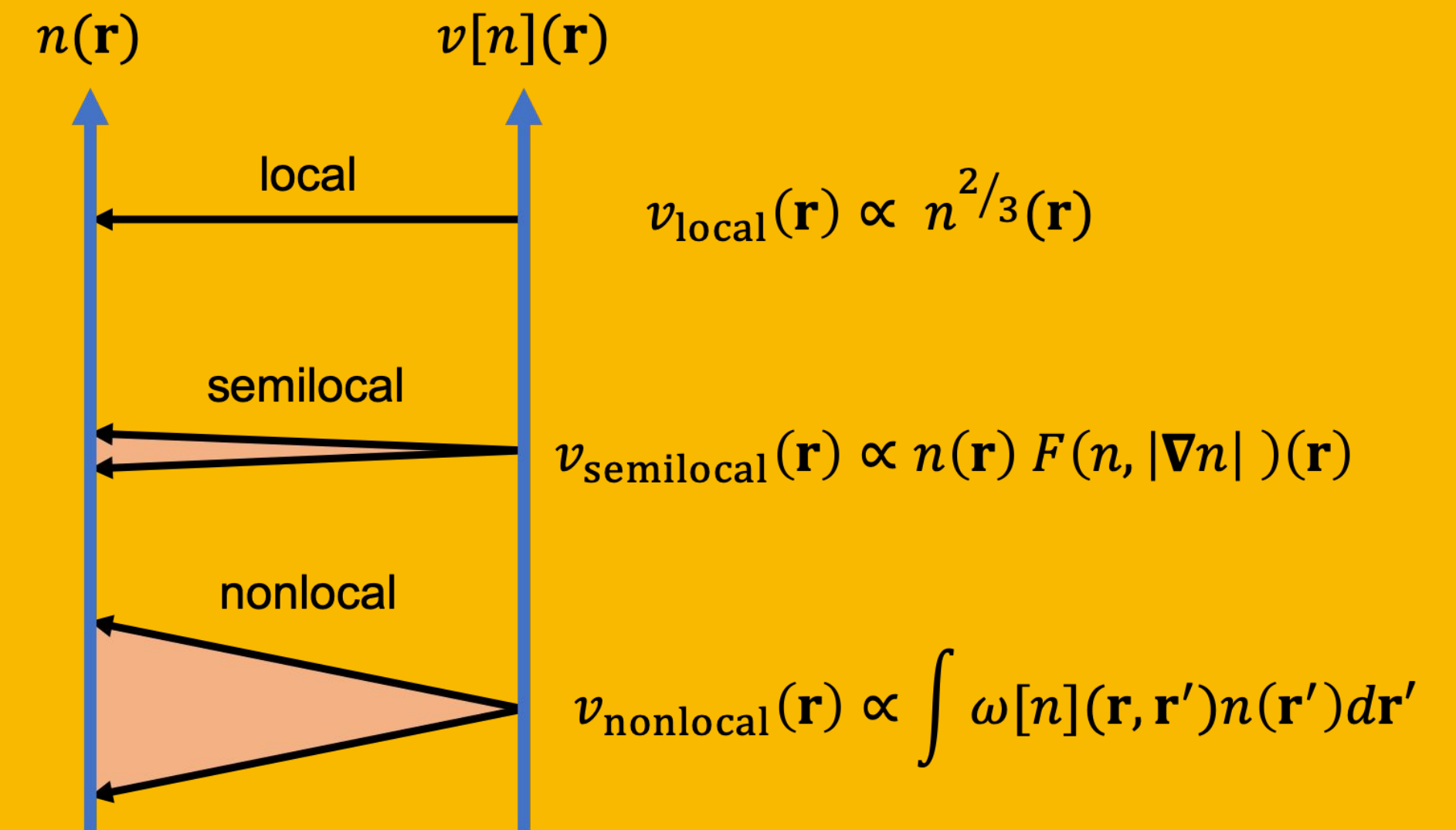
# Orbital-free DFT

## What can(t) be done

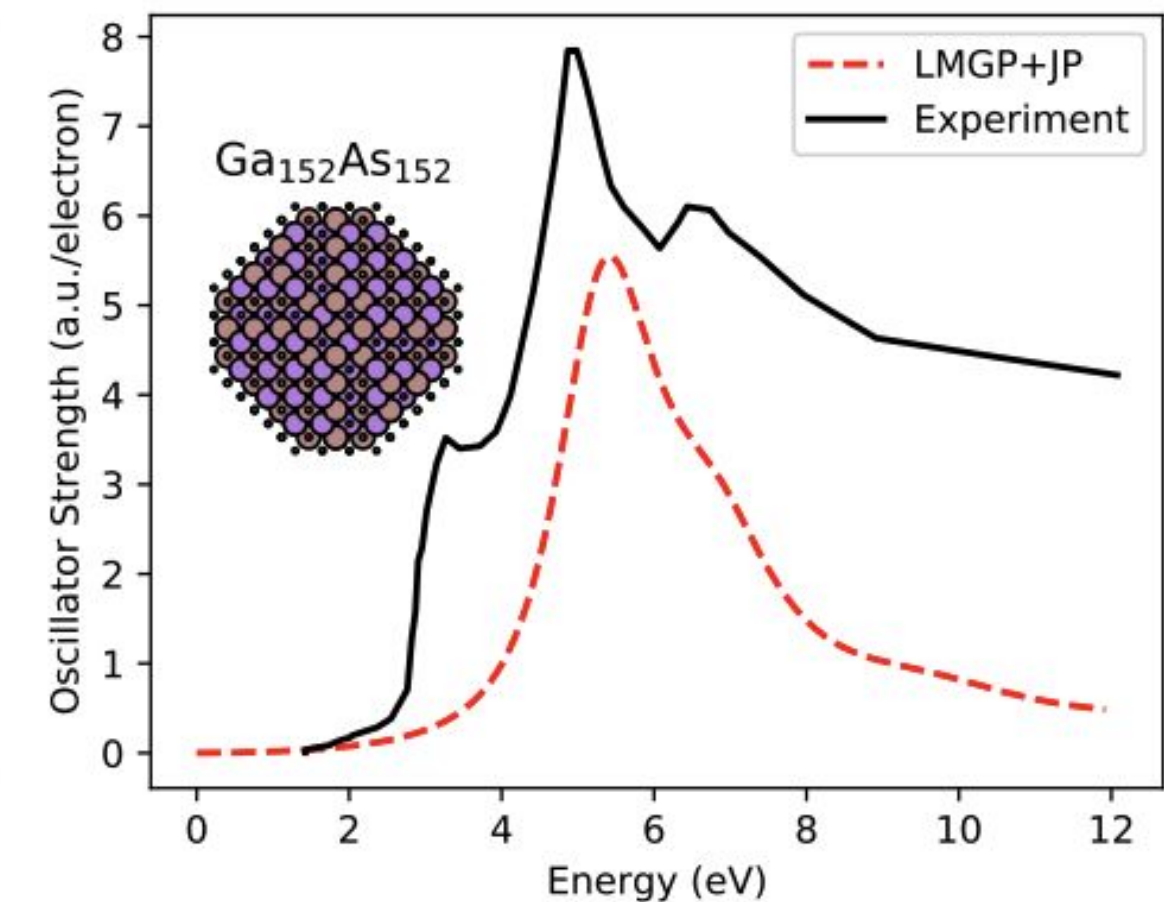
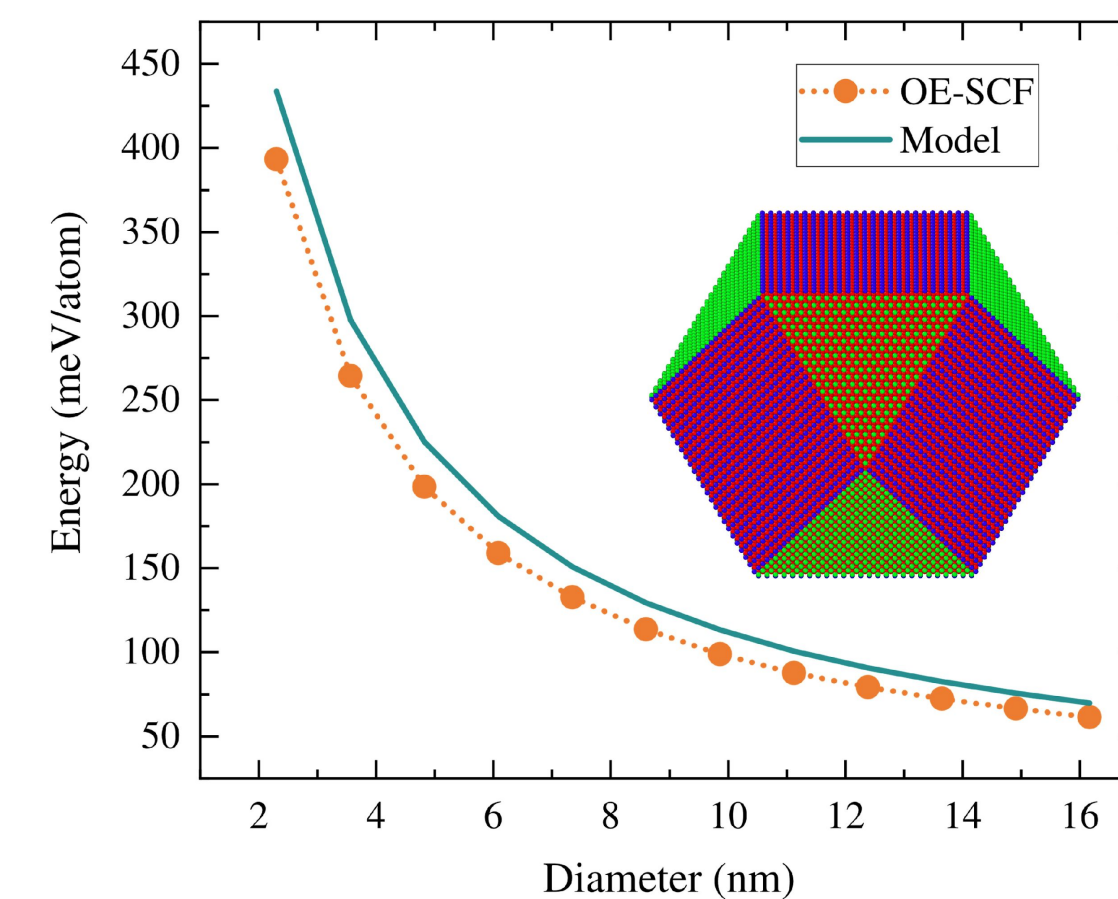
- ✓ Very large (mesoscopic) systems
  - ✓ Some semiconductors
  - ✓ TD-OFDFT for light-matter interaction
- 2<sup>nd</sup> row
  - It's approximate...

## Functional development

Mi, Luo, Trickey & MP, **Chem Rev.** (2023)



## Applications



TD-OFDFT: Jiang & MP, **PRB** (2021) Jiang, Shao & MP, **PRB** (2021,2022)

# Density Embedding sDFT — Universally useful

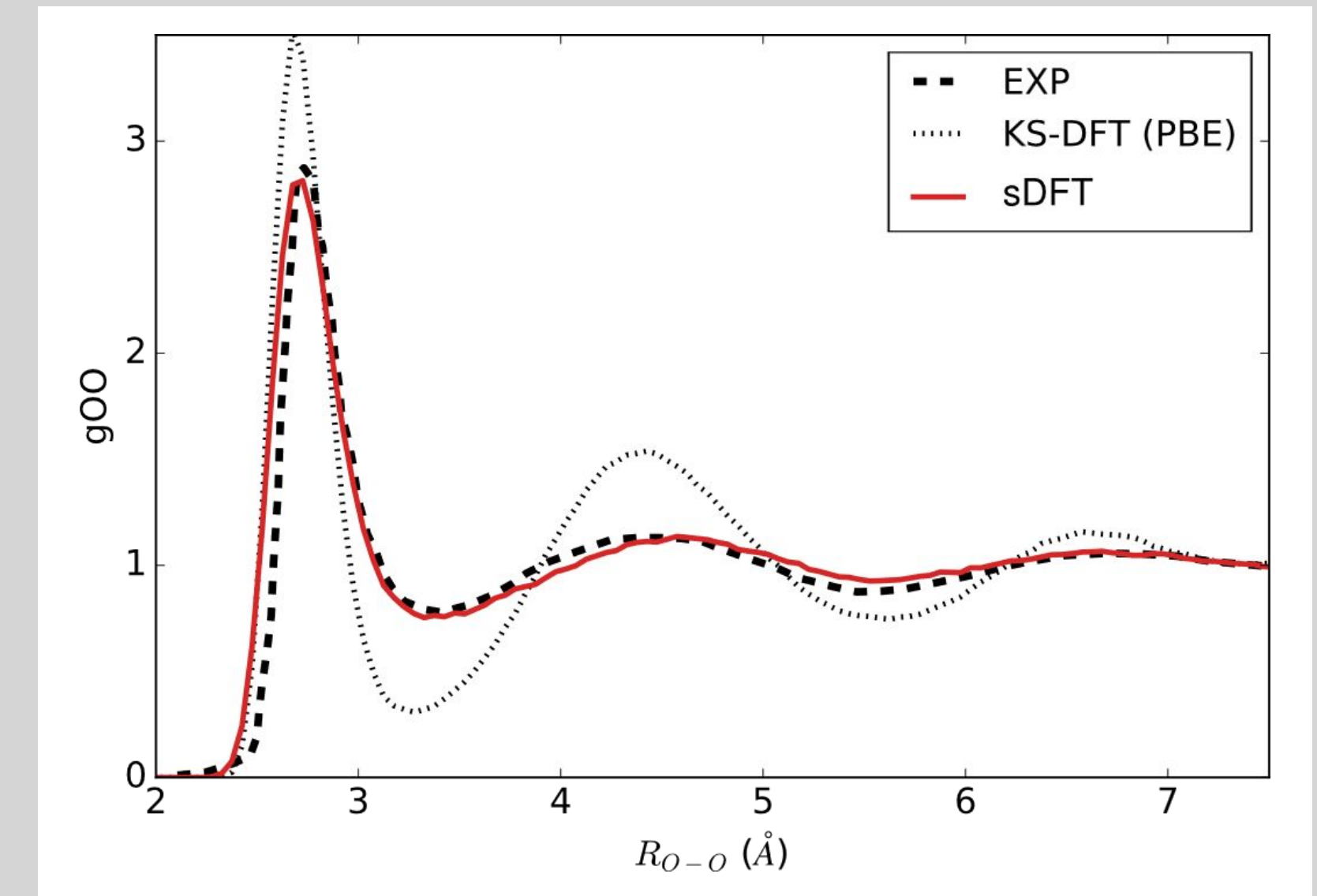


- ✓ Very large (mesoscopic) molecular condensed phases
- ✓ Liquids, solvated systems
  - Only weakly interacting subsystems

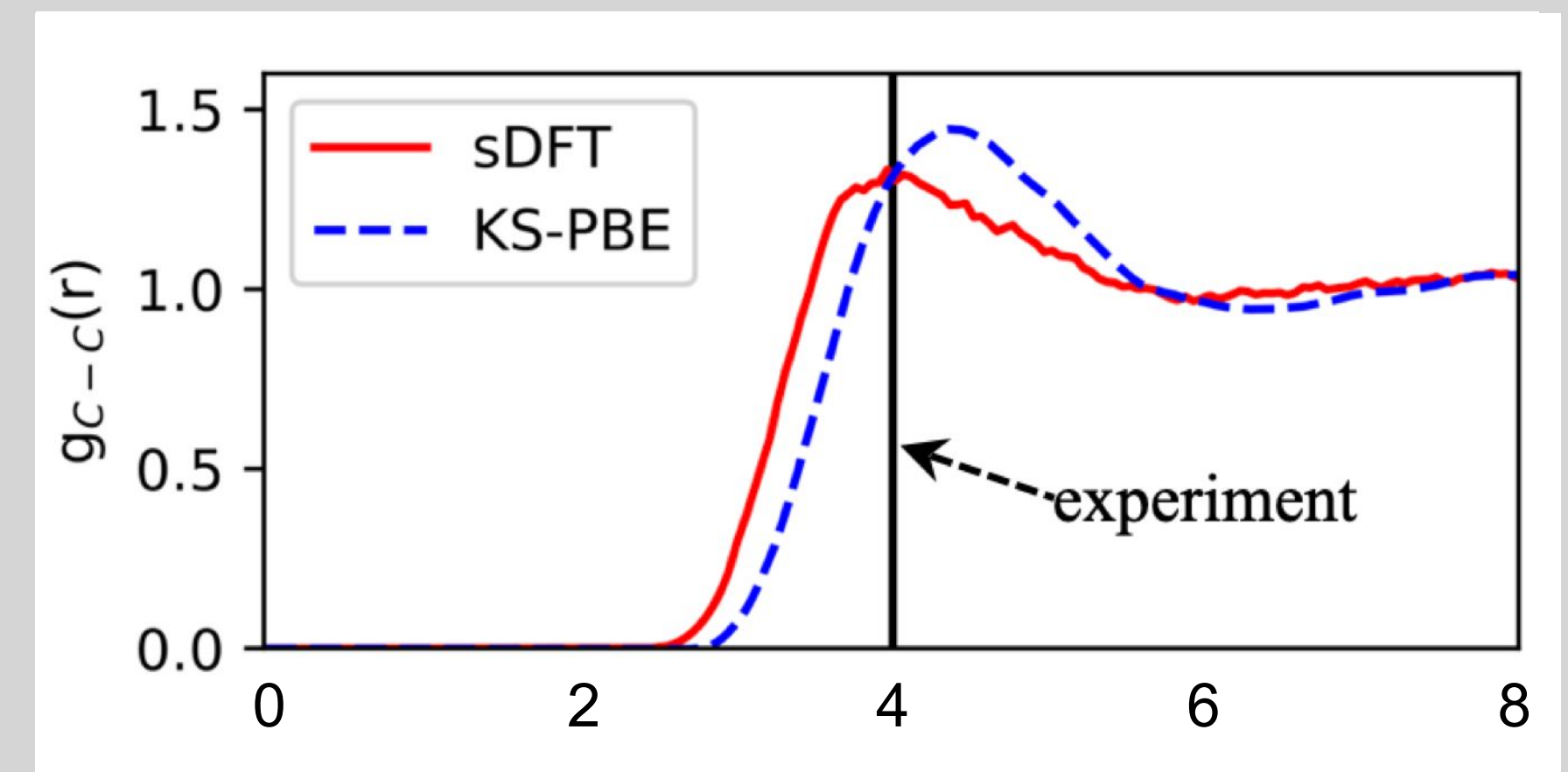
- ➔ **Liquid water:** Genova, Ceresoli and MP, **J. Chem. Phys.** (2016)
- ➔ **Liquid CO<sub>2</sub>:** Mi, Ramos, Maranhao and MP, **J. Phys. Chem. Lett.** (2019)
- ➔ **Optical spectrum of water:** Kumar, Genova and MP, **J. Phys. Chem. Lett.** (2017)
- ➔ Neugebauer, Jacob **WIREs Comput. Mol. Sci.** (2014 and 2024)

## Early success stories

➔ **Liquid water:** Genova, Ceresoli and MP, **J. Chem. Phys.** (2016)



➔ **Liquid CO<sub>2</sub>:** Mi, Ramos, Maranhao and MP, **J. Phys. Chem. Lett.** (2019)



## Functional development:

- ✓ Non-additive kinetic energy borrowed from OF-DFT
- ✓ Special-purpose “non-decomposable” non-additive functionals
  - Strong inter-subsystem interactions

➔ Mi and MP, **J. Phys. Chem. Lett.** (2019)

➔ Shao, Mi and MP **J. Chem. Theory Comput.** (2022)

## Method development: subsystem TD-DFT

- ✓ Real-time subsystem TD-DFT for complex systems
- ✓ Van der Waals interactions between subsystems from first principles

➔ Kevorkyants, Eshuis and MP, **J. Chem. Phys.** (2014)

➔ Sinha and MP, **J. Chem. Phys.** (2015)

➔ Krishtal and MP, **J. Chem. Phys.** (2015, 2016)

➔ Umerbekova and MP, **Eur. J. Phys. B** (2018)

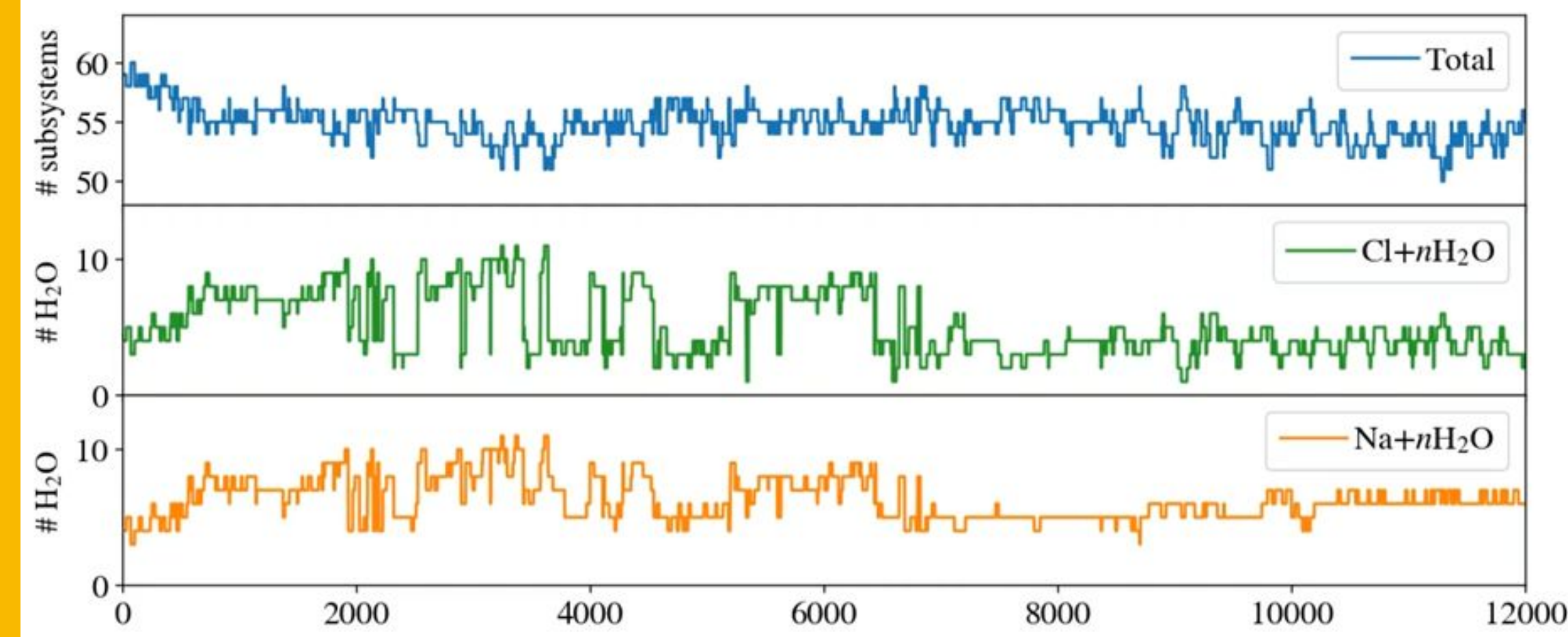
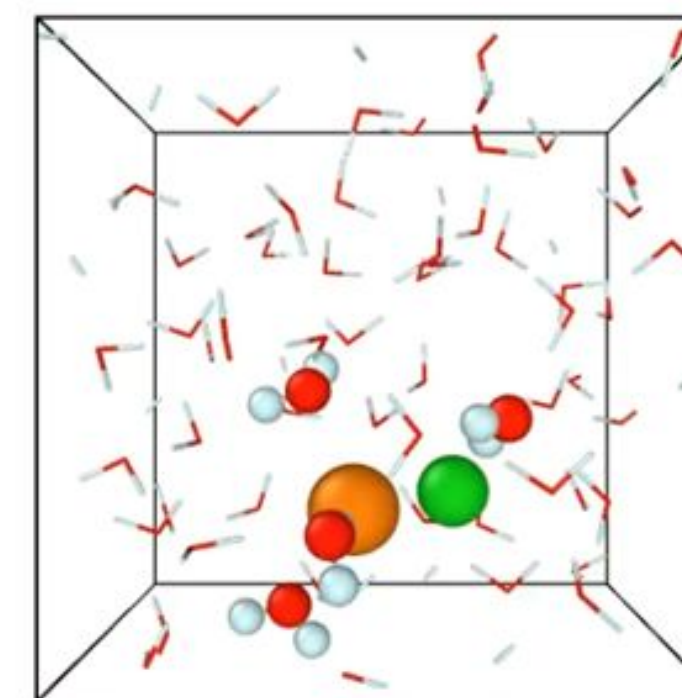
➔ SKP, Genova and MP, **J. Phys. Chem. Lett.** (2019)

➔ Umerbekova and MP, **Int. J. Quantum Chem.** (2020)

➔ Shao, Umerbekova and MP, **Electronic Structure** (2022)

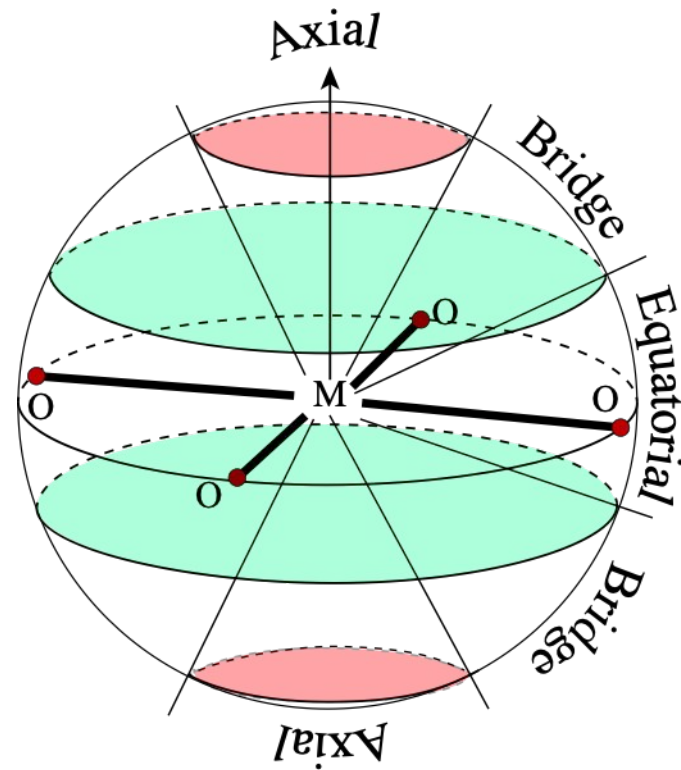
## Workflow development

- ✓ Strong inter-subsystem interaction: adaptive sDFT dynamics



Shao, Cifuentes, Nouri Musa and MP, **J. Chem. Theory Comput.** (2022)

# Hydration of aqua ions

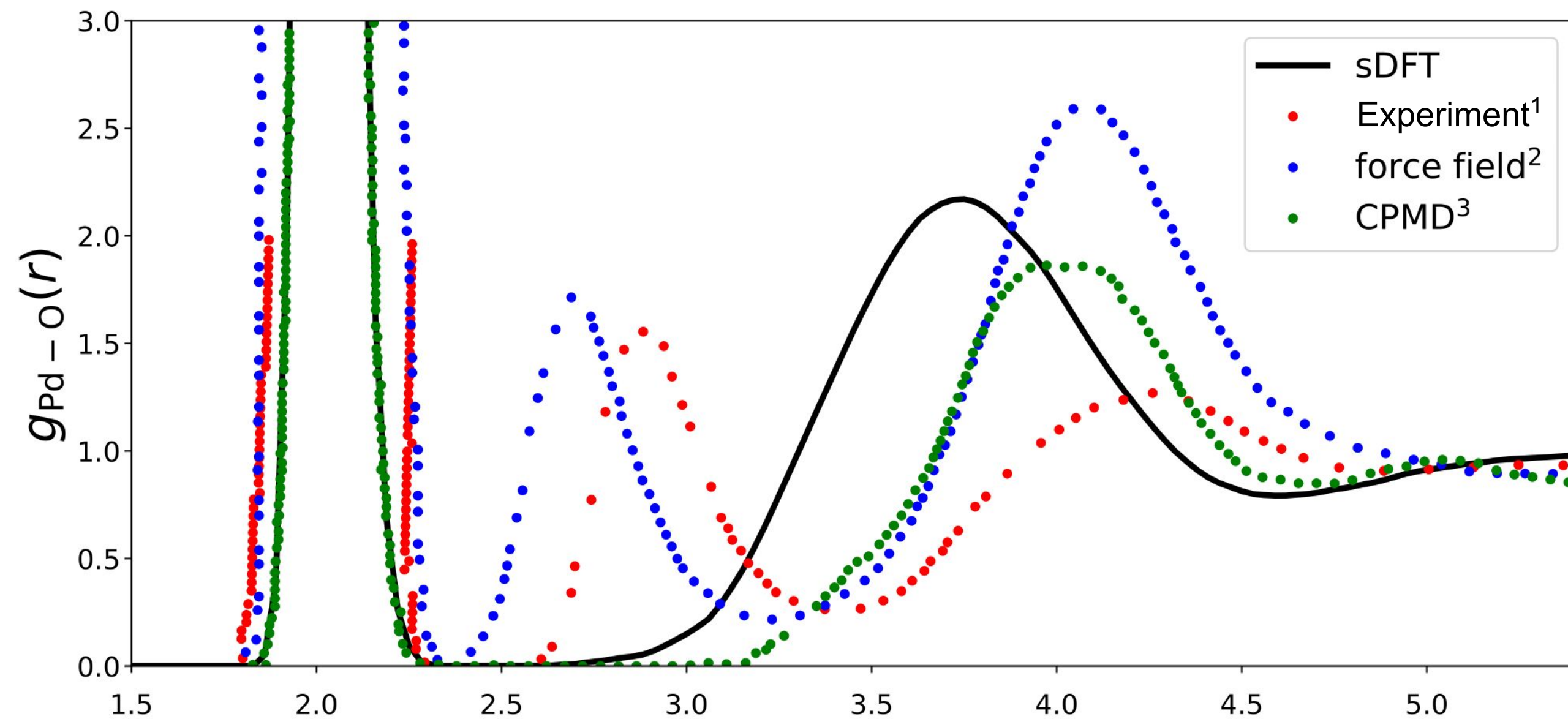


- ✓ 4 water molecules in the first solvation shell
- ✓ Axial hydration is crucial for chemistry

<sup>1</sup>Bowron et al. **JACS** 134, 962 (2012)

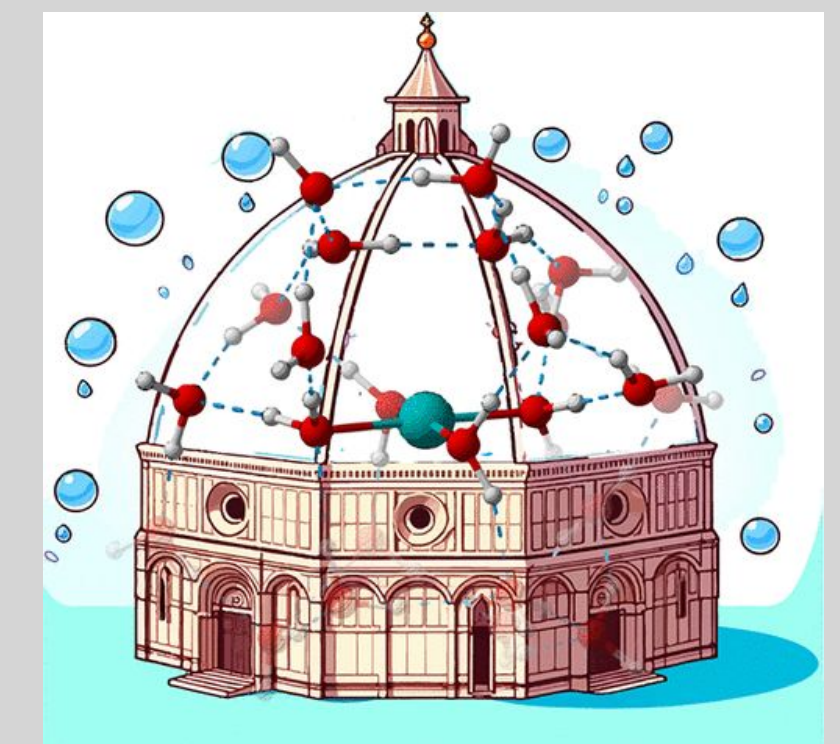
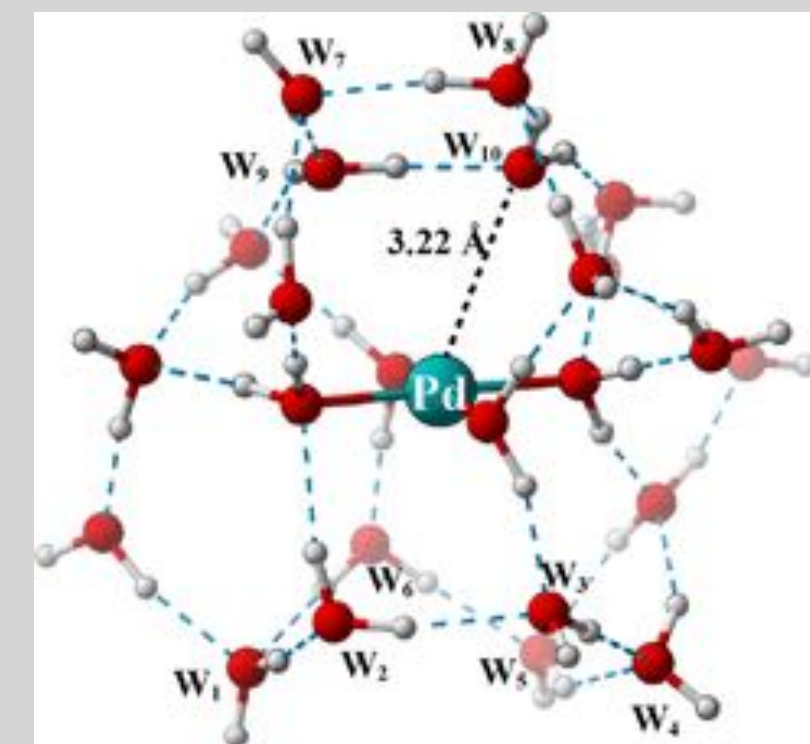
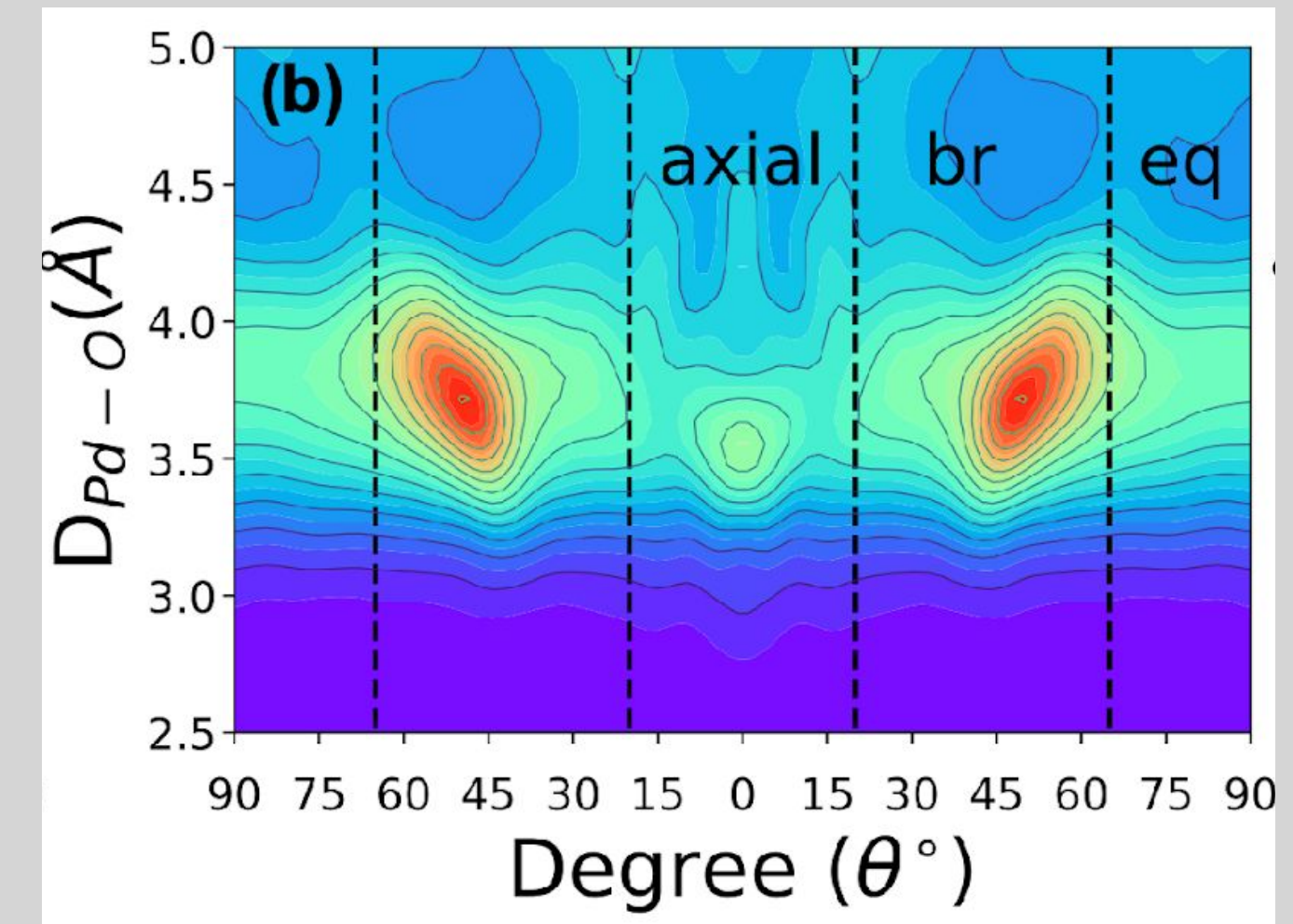
<sup>2</sup>Martinez et al. **J. Phys. Chem. B** 108, 15851 (2004)

<sup>3</sup>Beret et al. **J. Chem. Theory Comput.** 4, 2108 (2008)



## Pd aqua ion $\text{Pd}^{2+}(\text{H}_2\text{O})_?$

- Experiments do not give direct access to partial structure factors
- Calculations are either too approximate or only reproduce a selected set of experiments
- We don't have definitive information on the axial hydration structure and dynamics



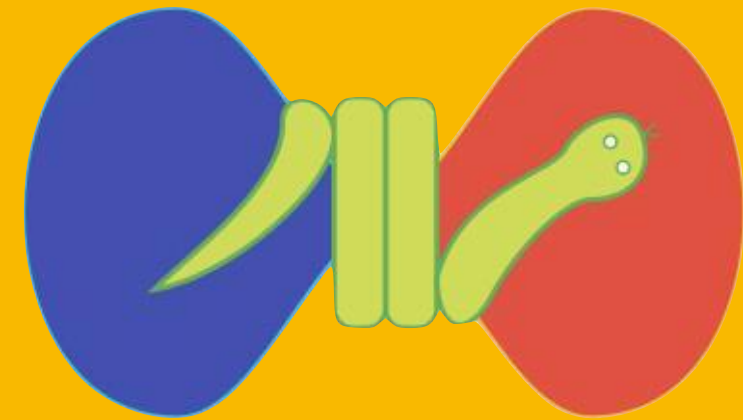
# Software from PRG



Embedded Quantum ESPRESSO  
[eqe.rutgers.edu](http://eqe.rutgers.edu)

s(TD)DFT

2016-2021



DFTpy  
[dftpy.rutgers.edu](http://dftpy.rutgers.edu)

(TD)OF-DFT

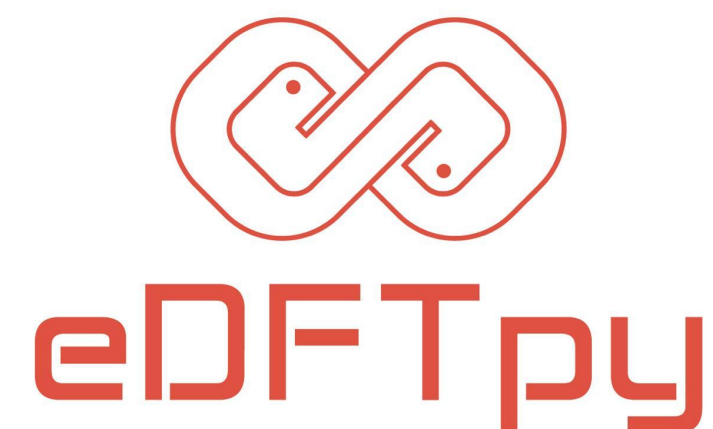
2019-present



QEpy  
<https://gitlab.com/shaoxc/qepy>

KS-DFT

2020-present



Embedded DFTpy  
[edftpy.rutgers.edu](http://edftpy.rutgers.edu)

s(TD)DFT

2020-present



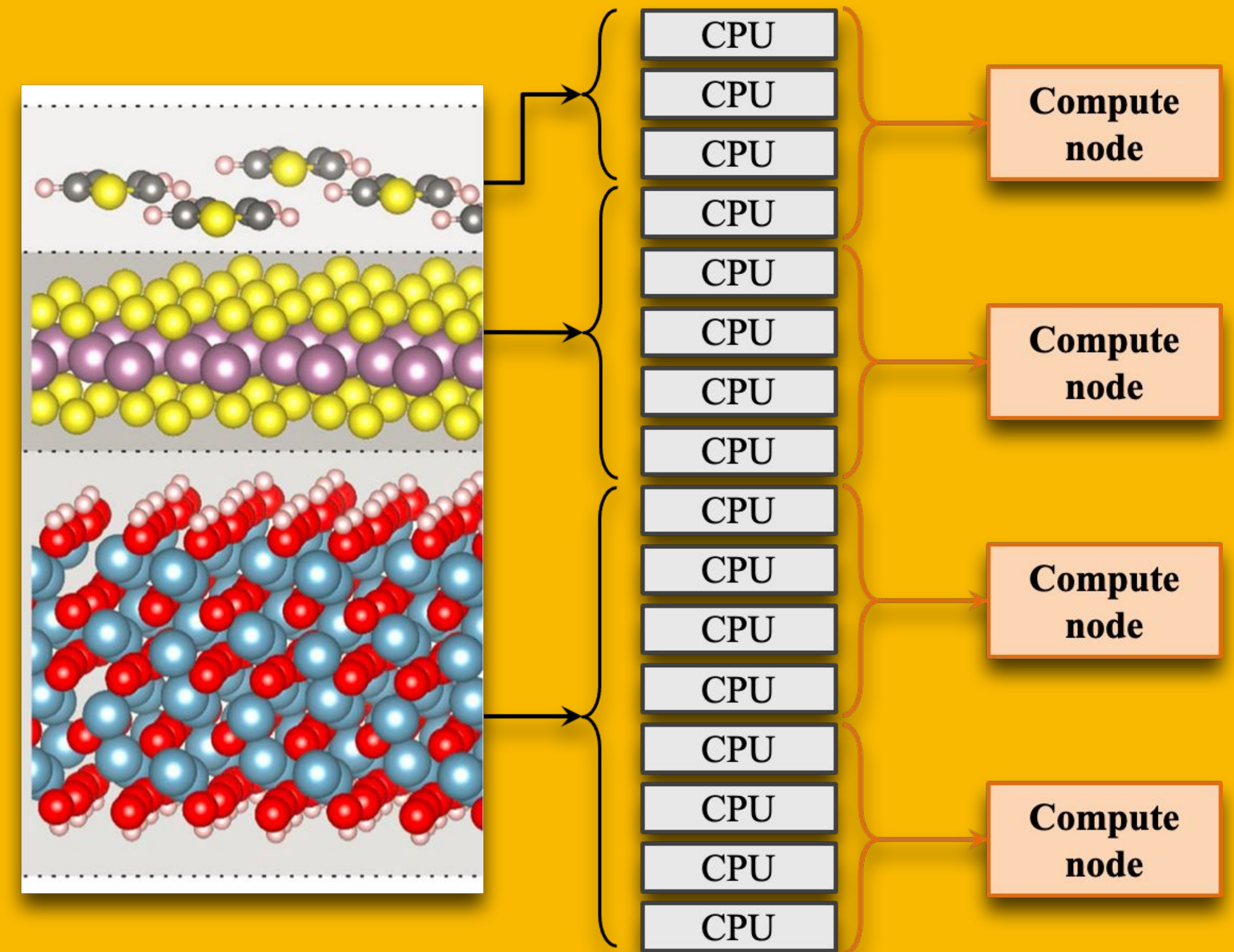
# Density Embedding

Has an Achille's heel

- ⦿ Requires self-consistency across all subsystems
- ⦿ Requires at least  $\#CPUs \geq \#subsystems$
- ⦿ Requires exascale computers to tackle the mesoscale



## sDFT vs computer architecture



# Machine Learning

## The Electronic Structure

✓ Learn quantities rich in information

- ◉ Wavefunction?
- ◉ Electron density?

✓ 1-rdm and/or 2-rdm

✓ Rest on rigorous grounds

→ **Short and insightful:** von Lilienfeld & Burke, **Nat. Commun.** 11, 4895 (2020)

## Maps

→ Carleo, Noé, **Nat. Rev. Chem.** 7, 692 (2023)

→ Shao, Paetow, Tuckerman & Pavanello **Nat. Commun.** 14, 6281 (2023)

→ Sager-Smith & Mazziotti, **JACS** 144, 18959 (2022)

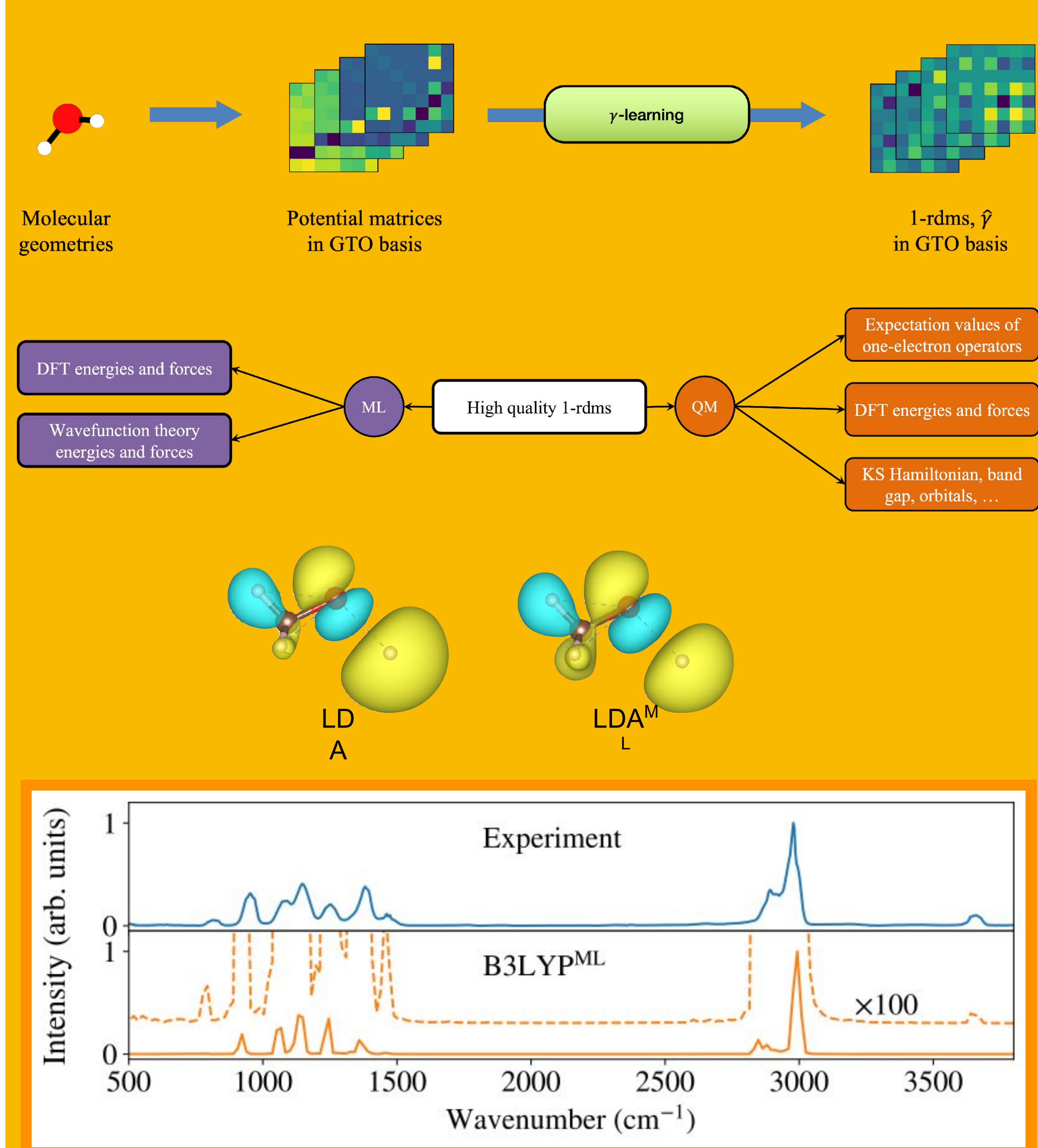
→ Tuckerman, Burke, Müller et al. in **Nat. Commun.** (2017, 2020)

→ Glover, Tuckerman et al. **Nat. Commun.** 13, 7044 (2022)

→ Ceriotti et al. in **J. Chem. Phys.** (2019, 2021), **JCTC** (2021, 2023), **PRB** (2020)...

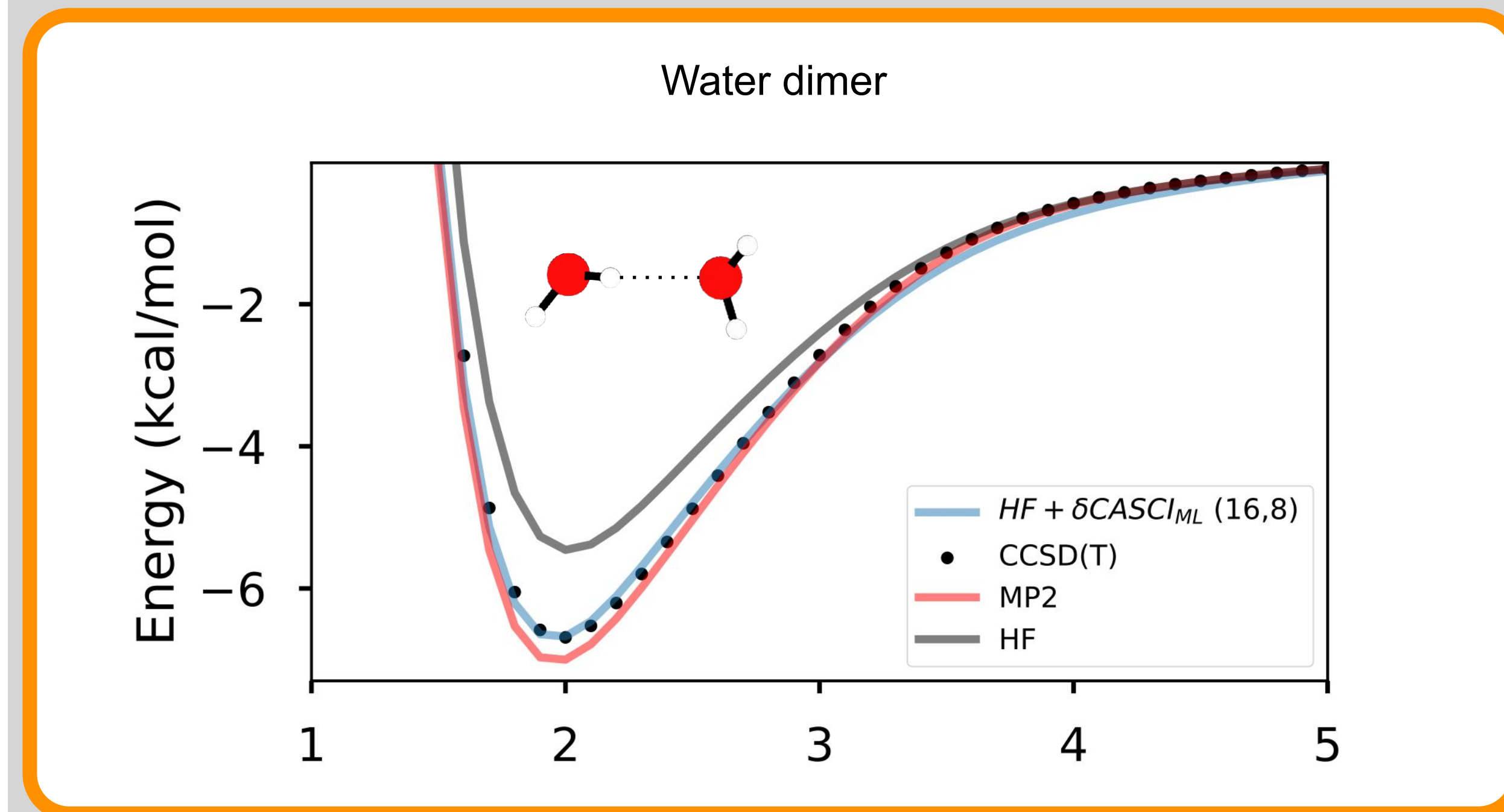
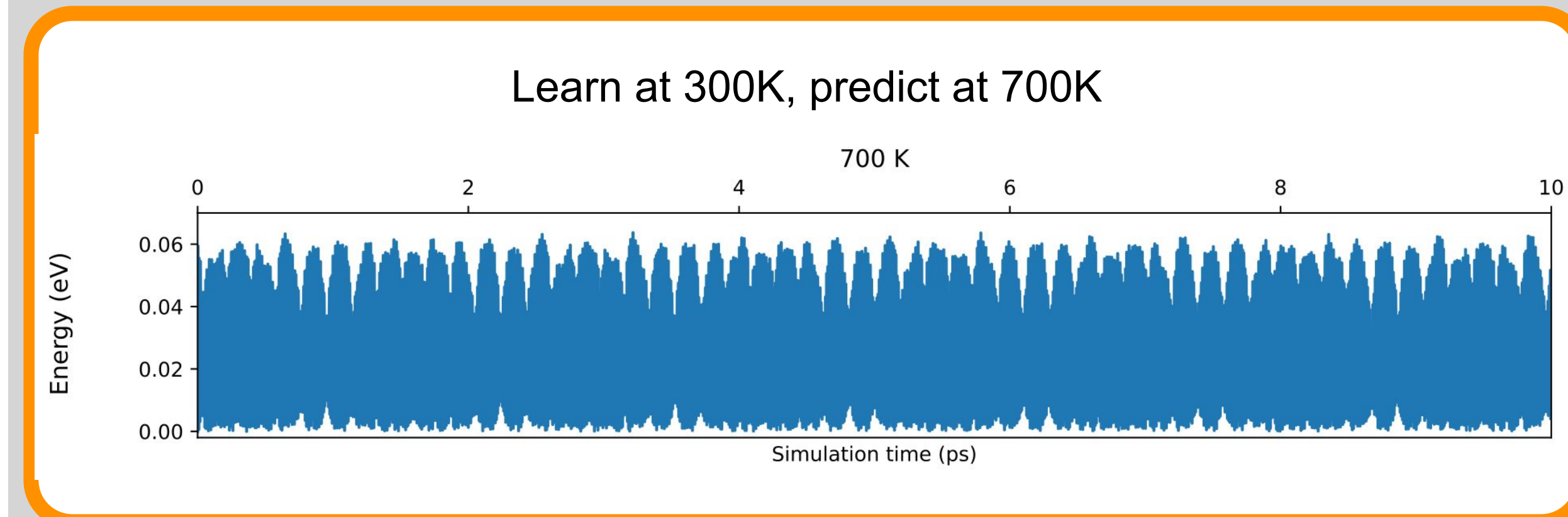
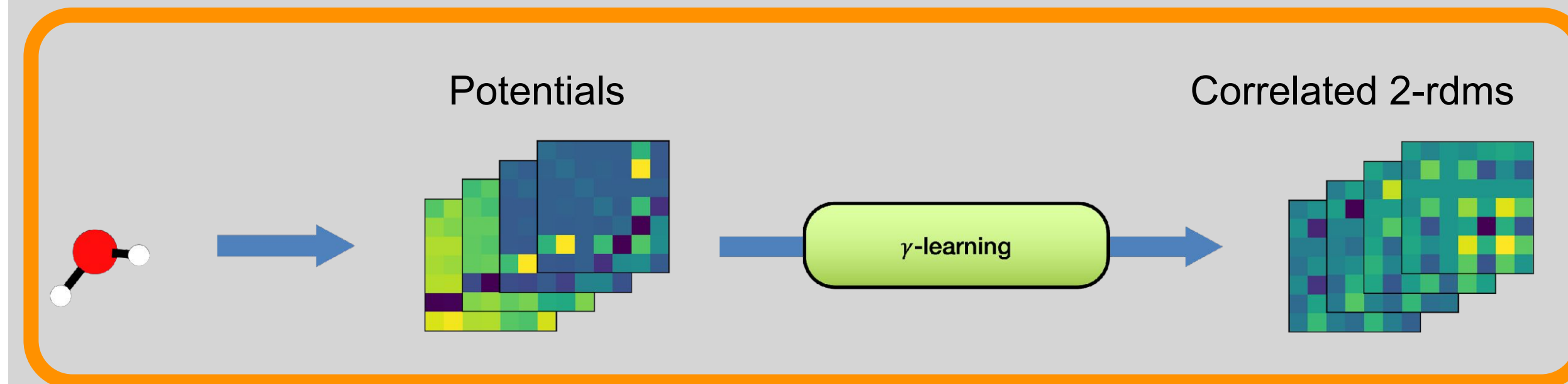
# Learning 1-rdms

1. Xuecheng Shao & Nick Viot
2. Learn the map
3. Use QM machinery to
  - ✓ Calculate any , gaps ...
  - ✓ Calculate



# Learning 2-rdms

1. Jessica Martinez & Xuecheng Shao
  2. Start from HF
  3. Learn the map
  4. readily available
  5. Stable AIMDs
  6. MB expansion for the 2-rdm
- ✓ Tackle condensed phases



# QMLearn

- ✓ Xuecheng Shao, Jessica Martinez, Nick Viot
- ✓ Learn 1- and 2-rdms
- ✓ Builds training set
- ✓ Handles databases
- ✓ Surrogate QM calculations

<http://qmlearn.rutgers.edu/>

The screenshot displays the QMLearn website interface. On the left is a dark sidebar with navigation links: Contacts, Installation, Tutorials, and API QMLearn. The main content area features a 'Welcome to QMLearn!' message and a 'A snapshot of QMLearn' section. This section contains two diagrams: 'QM-Learn: Workflow' and 'QM-Learn: Code'. The workflow diagram shows a process starting from 'Molecular structure' to 'External potential', which is then processed by 'ML' to produce a '1-rdm,  $\hat{\rho}$ '. This leads to 'QM' calculations for 'Energy,  $E[\hat{\rho}]$ ', 'Forces,  $\vec{F}[\hat{\rho}]$ ', and 'Expectation values of 1-electron operators,  $\langle O_1 \rangle = \text{Tr}[\hat{O}_1 \hat{\rho}]$ '. These results are used for 'AIMD relaxations'. The code diagram shows 'Structure handler' (using ASE) and 'QM engines' (using pyscf and Psi4NUMPY). It also includes 'Init. ML', 'Database', and 'Models' components, which are supported by 'Training & Testing', 'Stores sets & models', and 'Web-accessible' features, all utilizing 'learn' and TensorFlow.

# THANK YOU



Alina Umerbekova 3:57 PM

@Michele Thank you for the num-num.py!!!

2 files ▾



👍 1 😊



Michele Pavanello 3:58 PM

hahahahahahahahahahahahahahaha

Funding



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