

Atomistic modeling and machine learning for neutron scattering data analysis

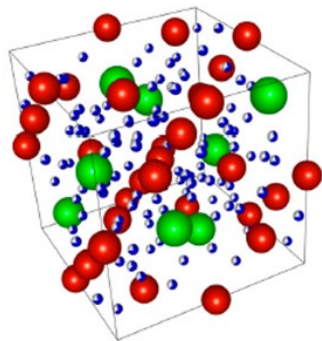
Yongqiang (YQ) Cheng

Spectroscopy Section
Neutron Scattering Division
Oak Ridge National Laboratory

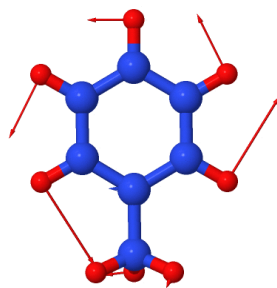
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Atomistic modeling in neutron scattering

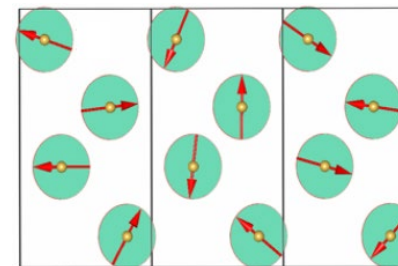
- Essential role in neutron data analysis and interpretation



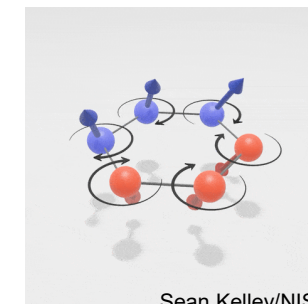
Atomic structure



Vibrational dynamics



Magnetic structure



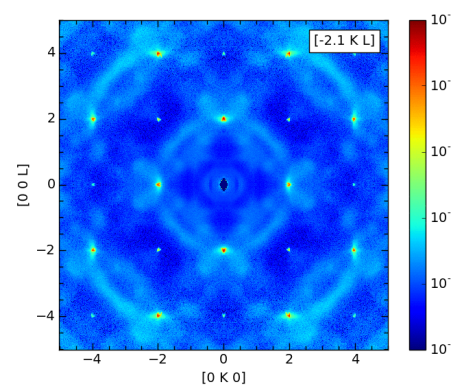
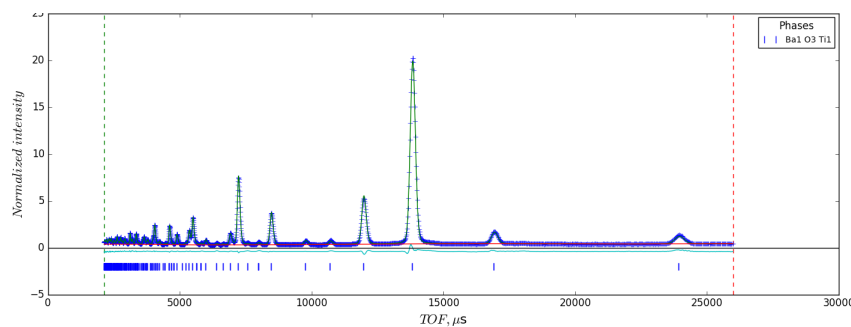
Sean Kelley/NIST

Spin dynamics

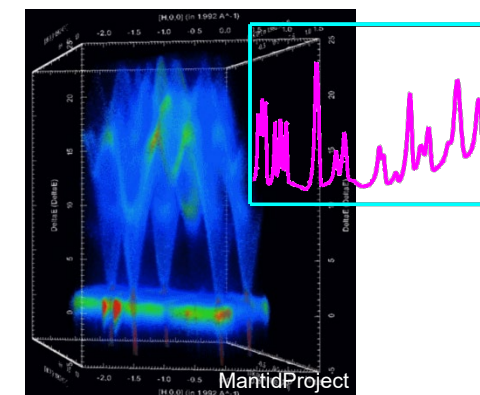
Diffraction

Diffuse scattering

Spectroscopy



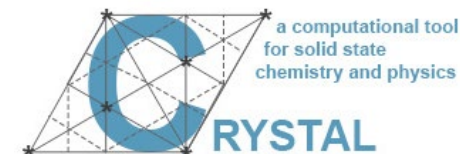
Yaohua Liu



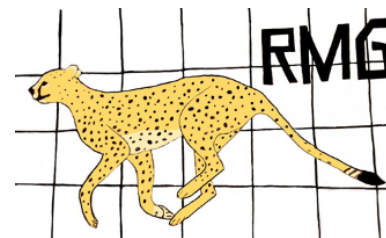
MantidProject

Bridging theory and INS experiments

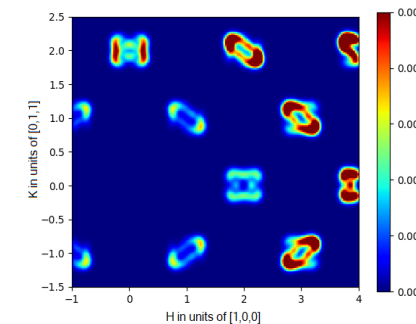
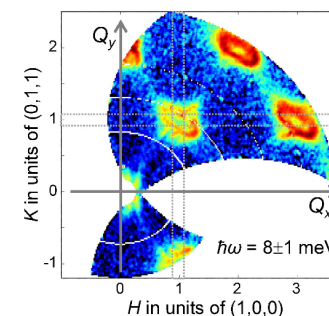
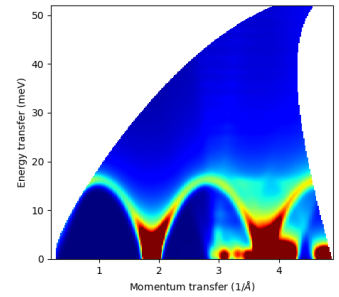
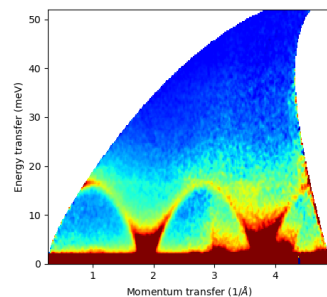
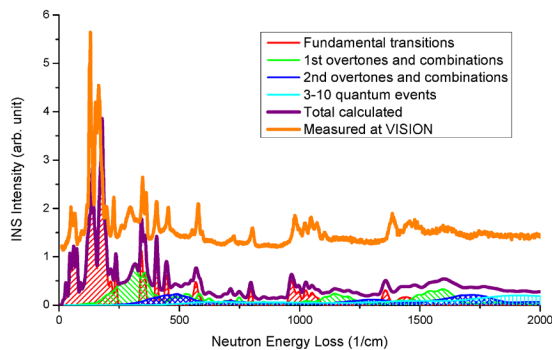
Common atomistic modeling tools



NWCHEM
HIGH-PERFORMANCE COMPUTATIONAL
CHEMISTRY SOFTWARE

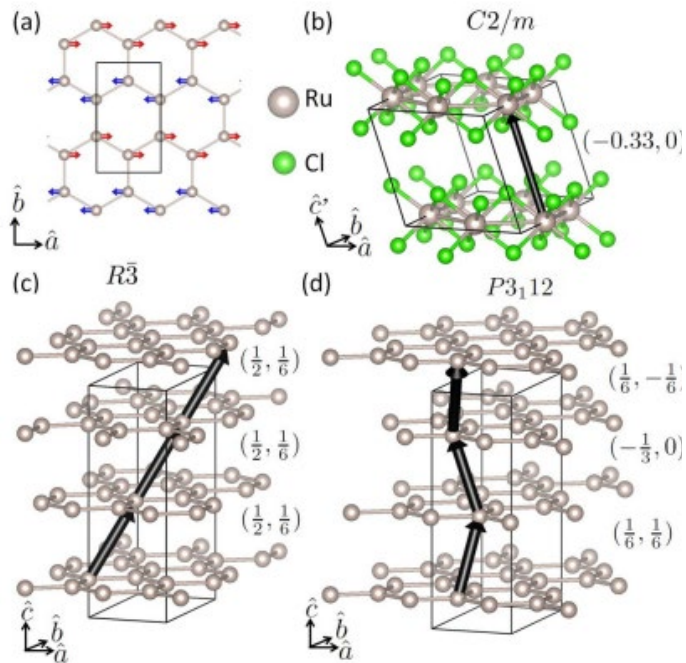


OCLIMAX

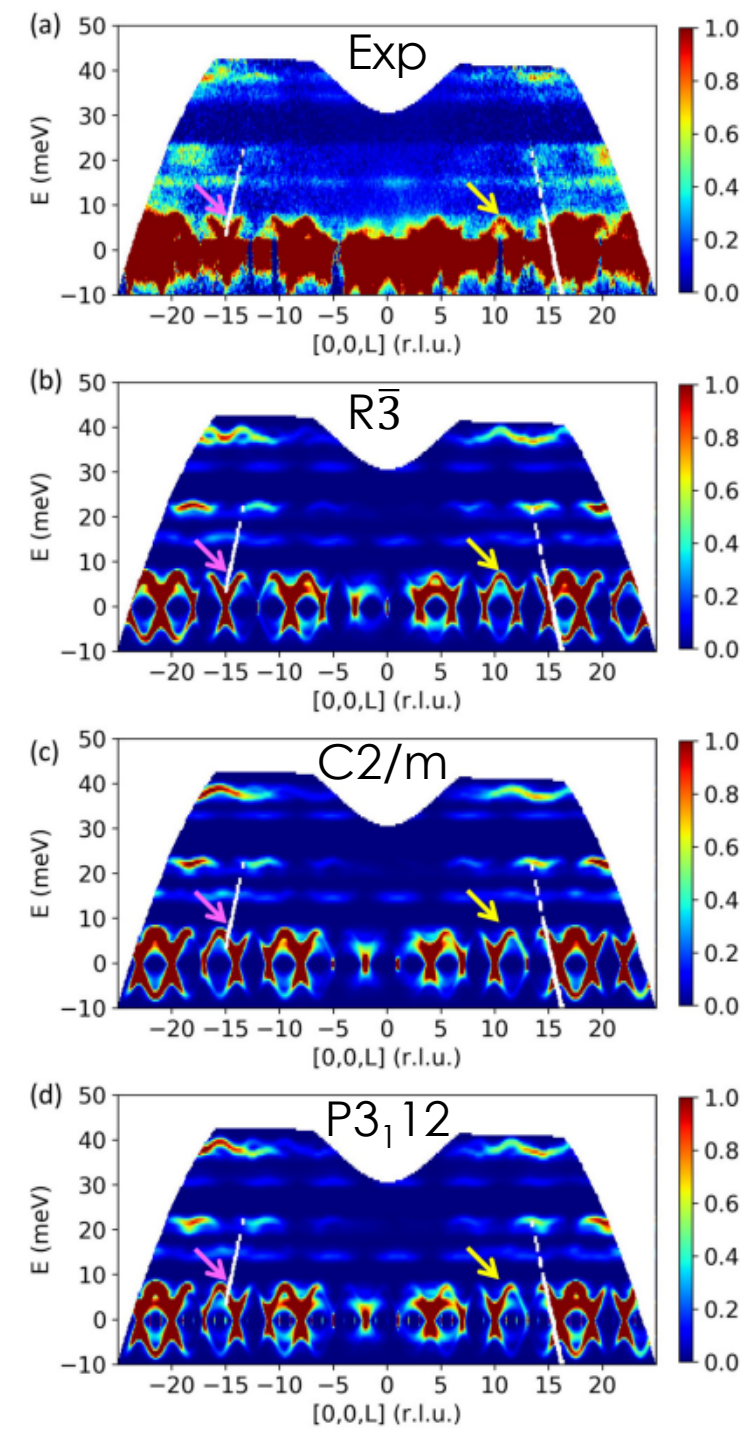
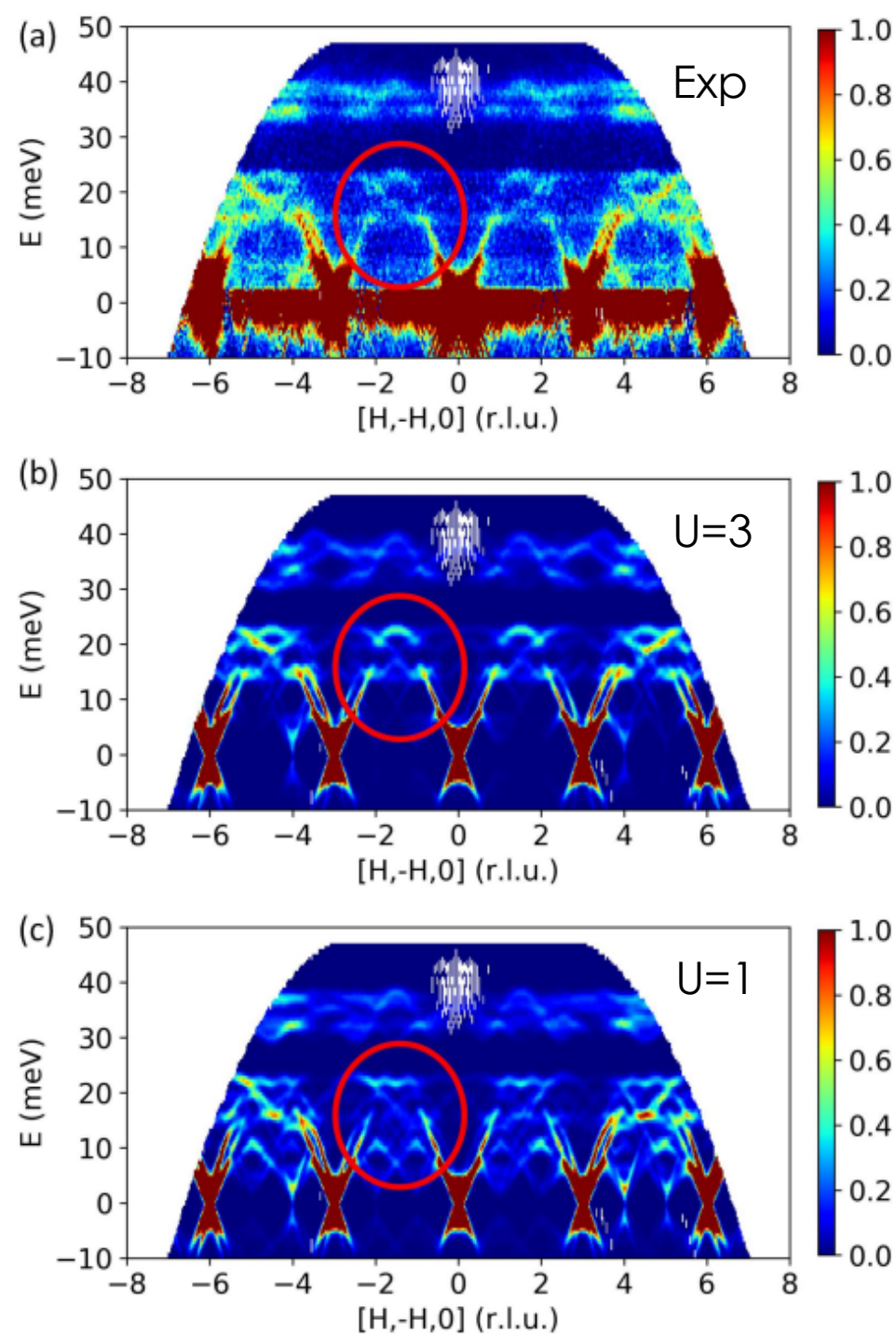


VISION, CNCS, HYSPEC, SEQUOIA, ARCS and many other neutron spectrometers.

Single crystal RuCl_3

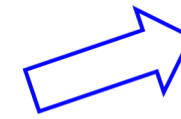


S. Mu et al. Phys. Rev. Res.,
4, 013067 (2022)



Two grand challenges

- The model is not good enough for the science
 - Time and/or length scale limitations
 - Accuracy and efficiency trade-off
- The analysis is not easy enough for the users
 - Computing resources
 - Learning curve



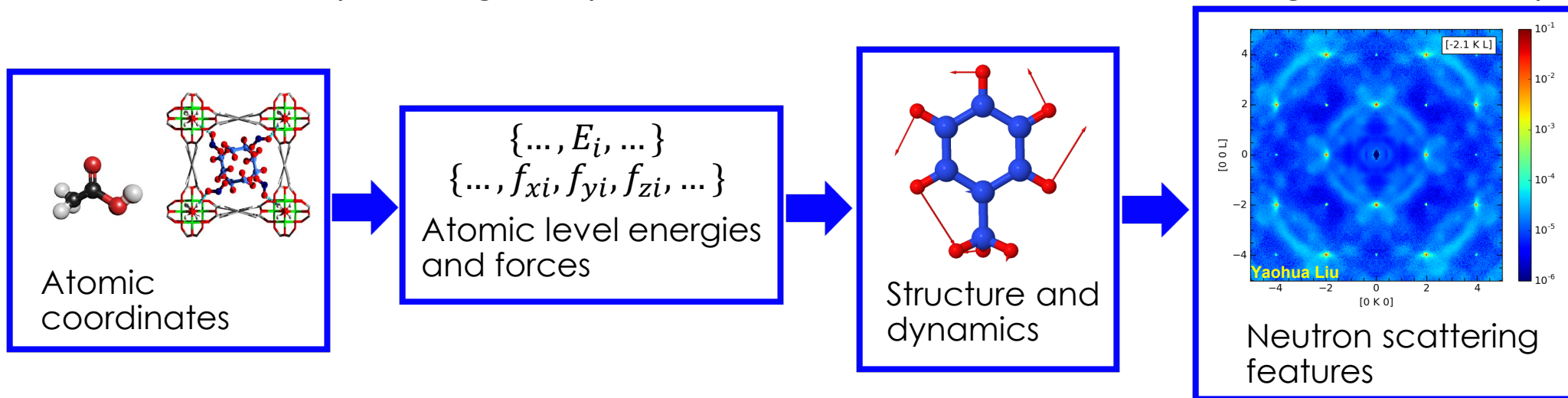
How much we
can learn



How many people
can use it

How to predict neutron scattering features from an atomistic model?

- ❖ What dictates the (nonmagnetic) features we see in a neutron scattering experiment (ideally)?



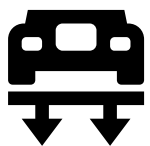
- ❖ Given a structure, how to obtain the energies and forces (easily/quickly and accurately)?

- ✓ Traditional approach based on density functional theory (DFT)



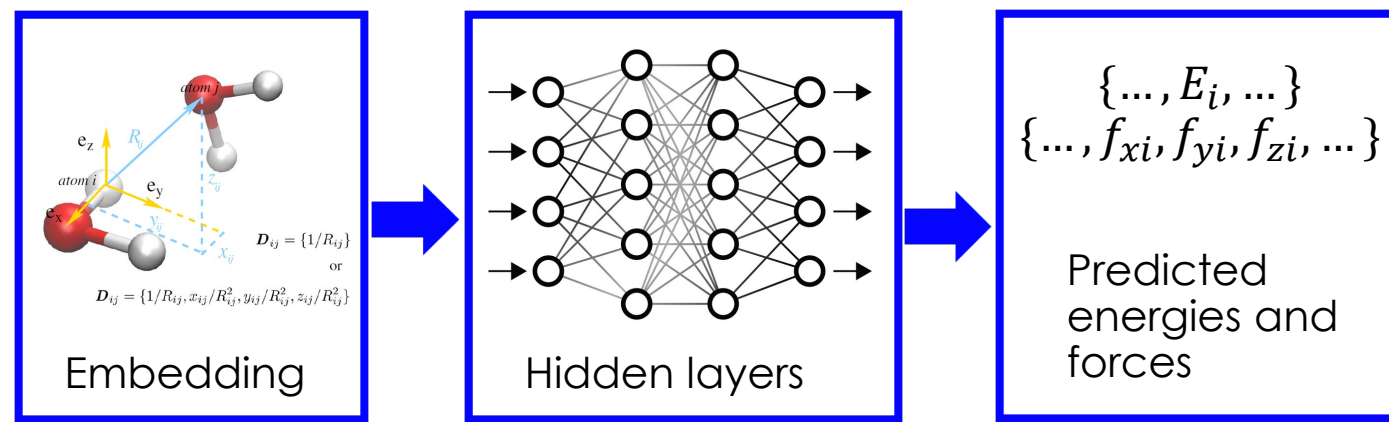
Accurate but slow/small

or classical force-fields



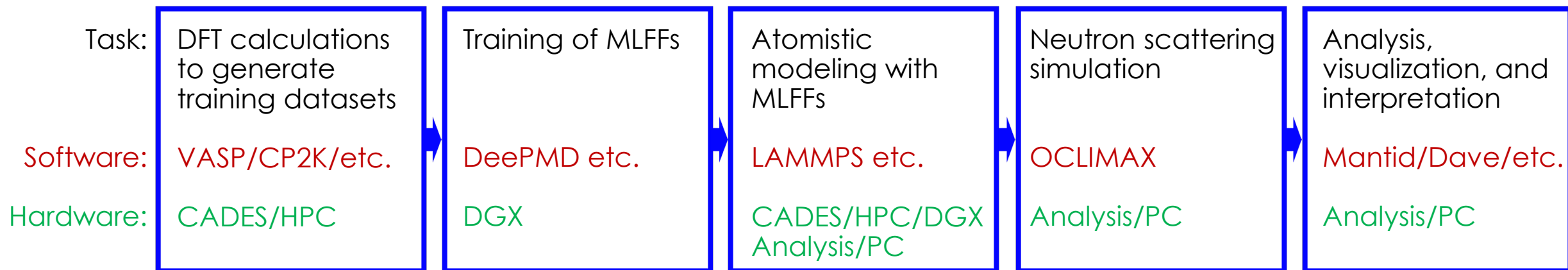
Fast/large but crude

- ✓ Machine learning force field (MLFF)



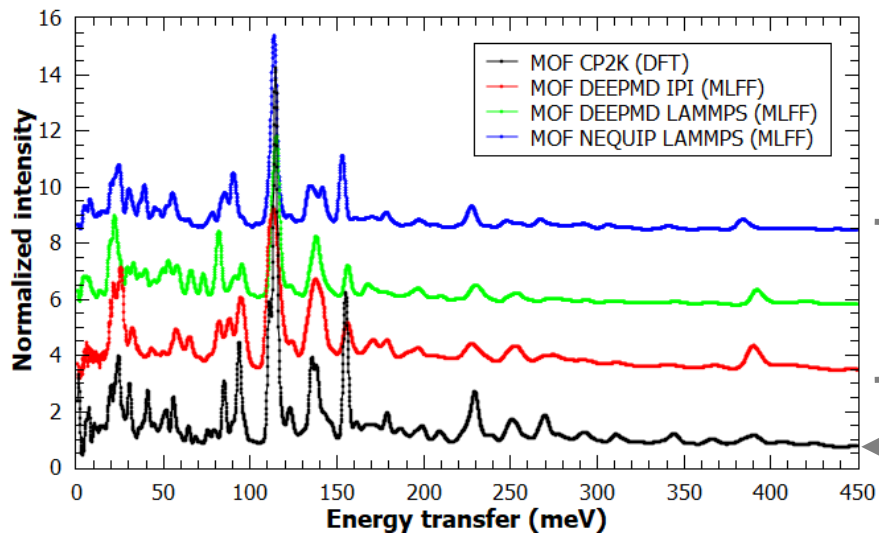
Fast/large with near DFT accuracy

Development and application of MLFFs in neutron scattering



DeepMD: Zhang et al. Phys. Rev. Lett. 120, 143001 (2018)
NequIP: Batzner et al. <https://arxiv.org/abs/2101.03164> (2021)

- ✓ Simulation of vibration and INS spectra of complex materials



MLFF: Minutes on PC

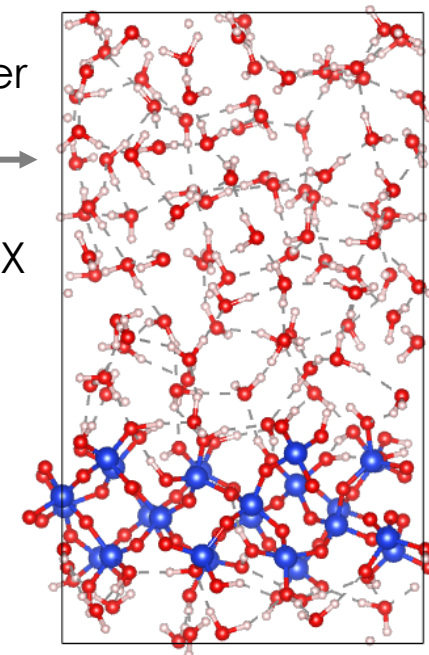
DFT: Days on CADES

- ✓ Simulation of diffusion and QENS in heterogeneous systems

DFT: 1,000 steps per day on CADES

MLFF: 10,000 steps per minute on DGX

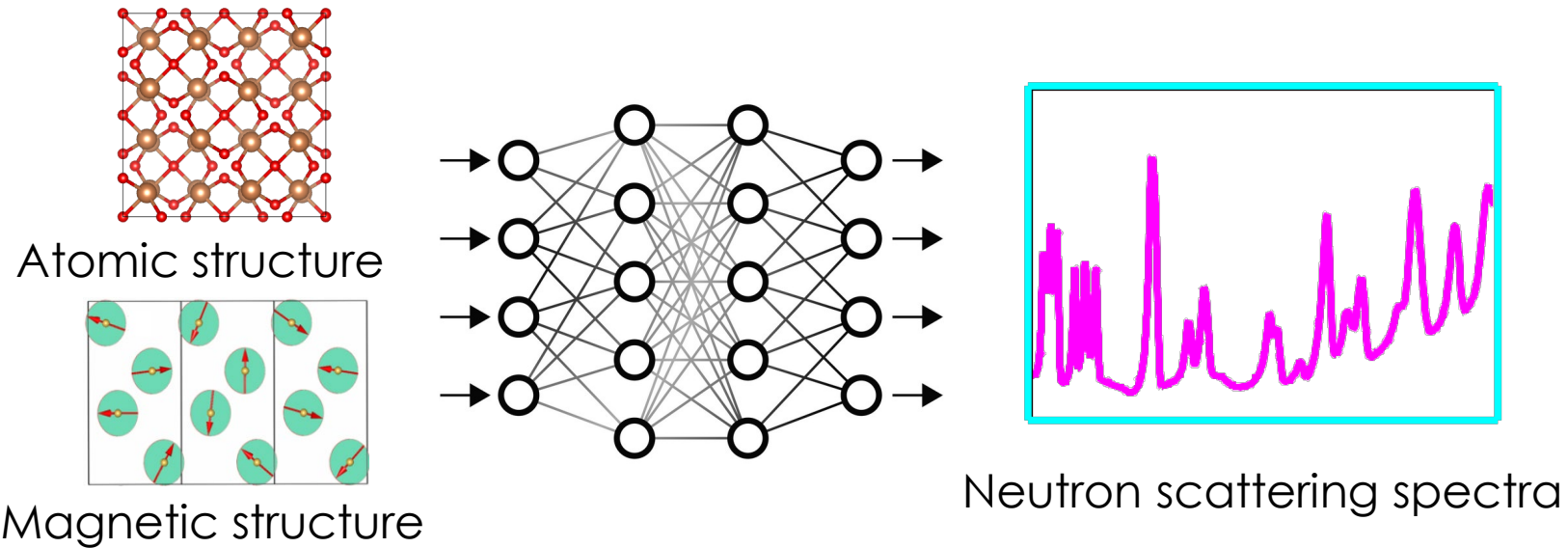
10,000 speedup and linear scaling with size, while inheriting spectroscopic accuracy from DFT



Opportunities

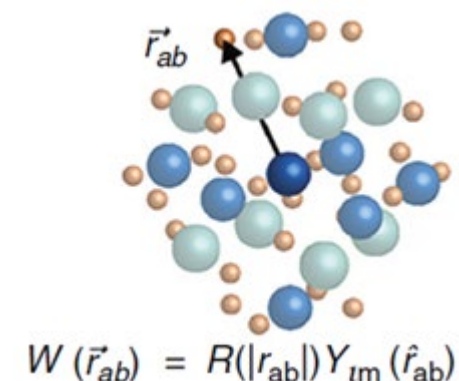
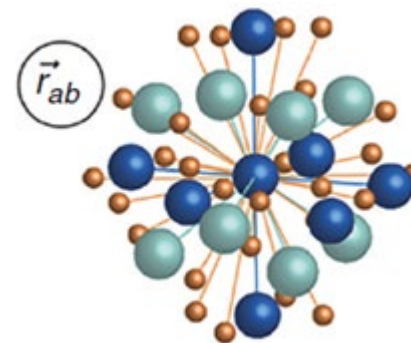
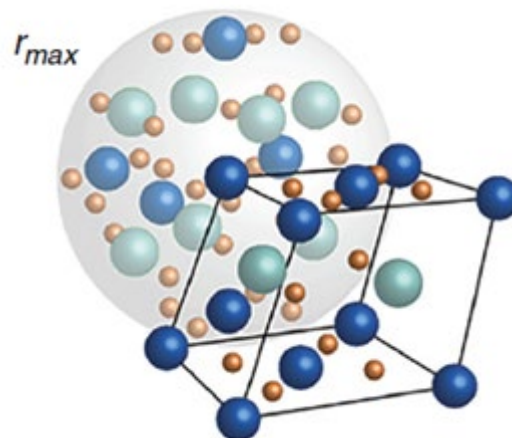
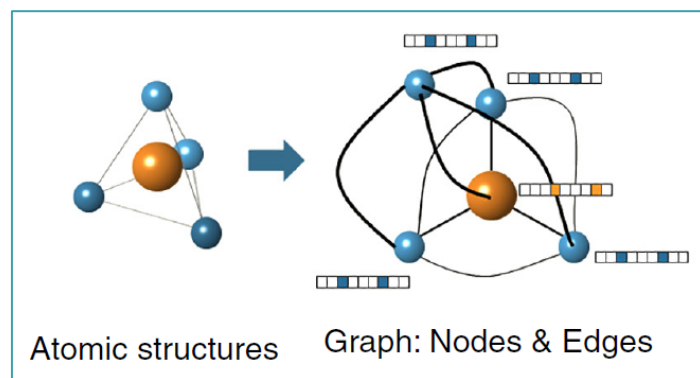
- Disordered/high-entropy materials
- Defects, surface, interface, domain boundaries
- Diffuse scattering (structural and thermal)

To tackle challenge 2: Neural networks connecting structure and neutron scattering data



Representation of structure

- Euclidean neural network (e3nn)



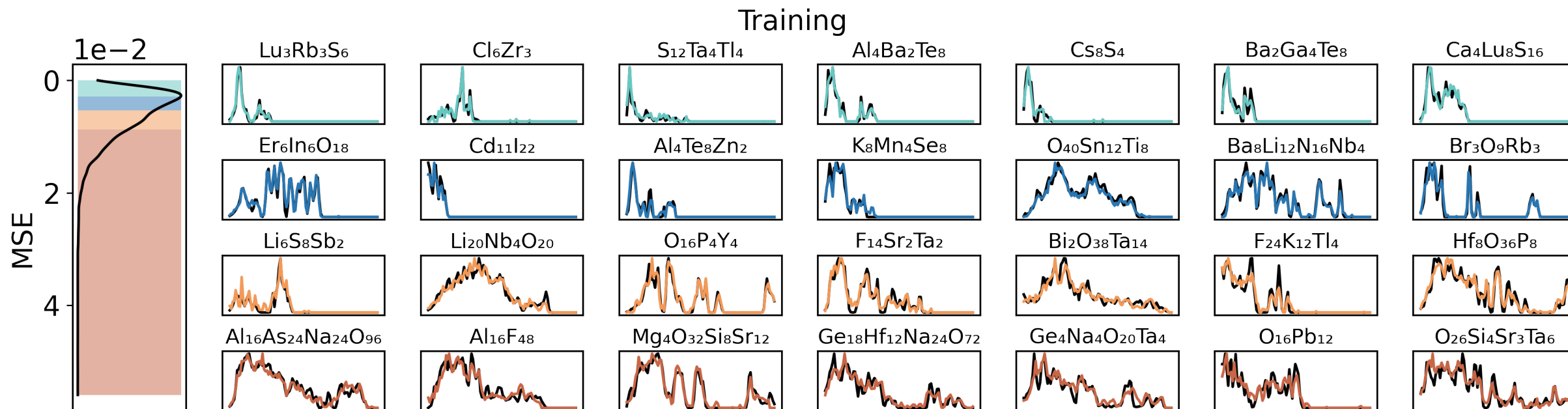
Equivariant neural network for 3D
translation, rotation, inversion

<https://e3nn.org/>

https://github.com/zhantaochen/phononDoS_tutorial

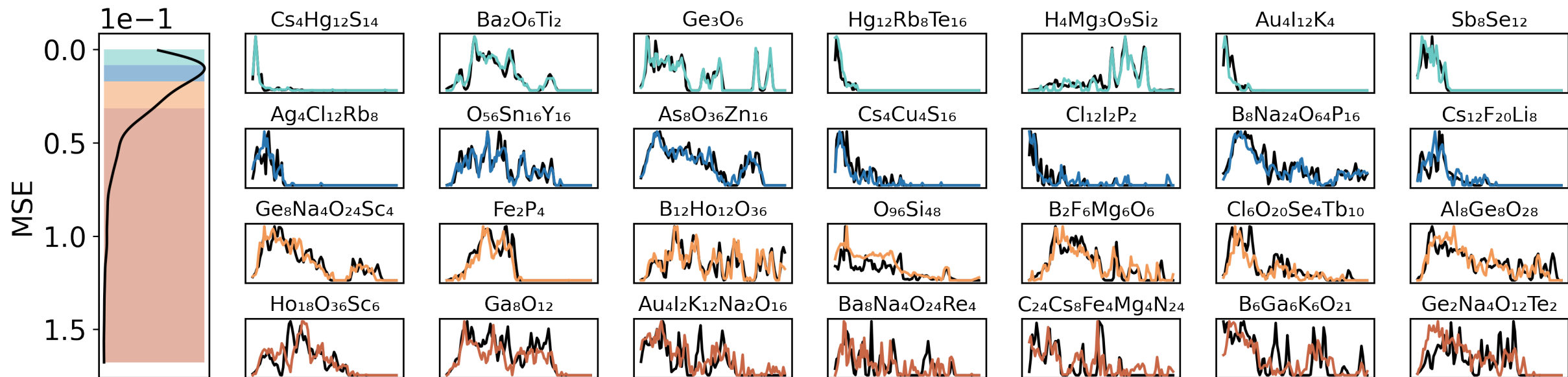
From structure to spectra (Inorganic crystals)

- Materials Project Phonon Database (~10,000 inorganic crystals, 90% training, 5% validation, 5% testing) [<http://phonondb.mtl.kyoto-u.ac.jp/>]
- Euclidean Neural Network (e3nn) [<https://e3nn.org/>]
- Simulated INS spectra were generated using VASP/Phonopy and OCLIMAX (10~1000cm⁻¹, 100 data points)

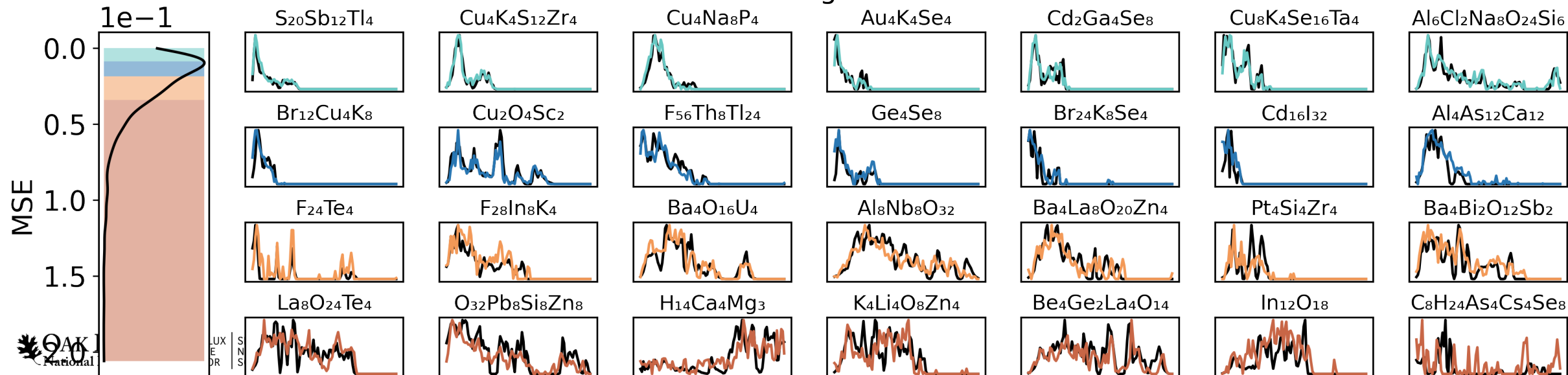


From structure to spectra (Inorganic crystals)

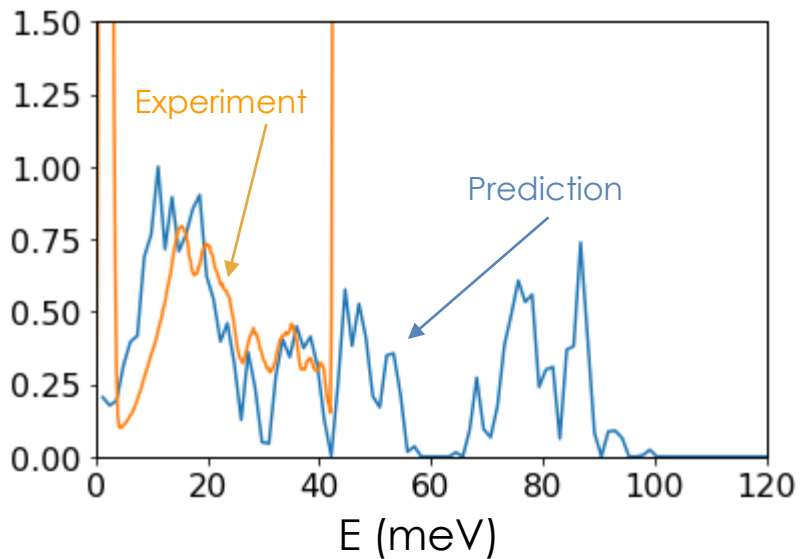
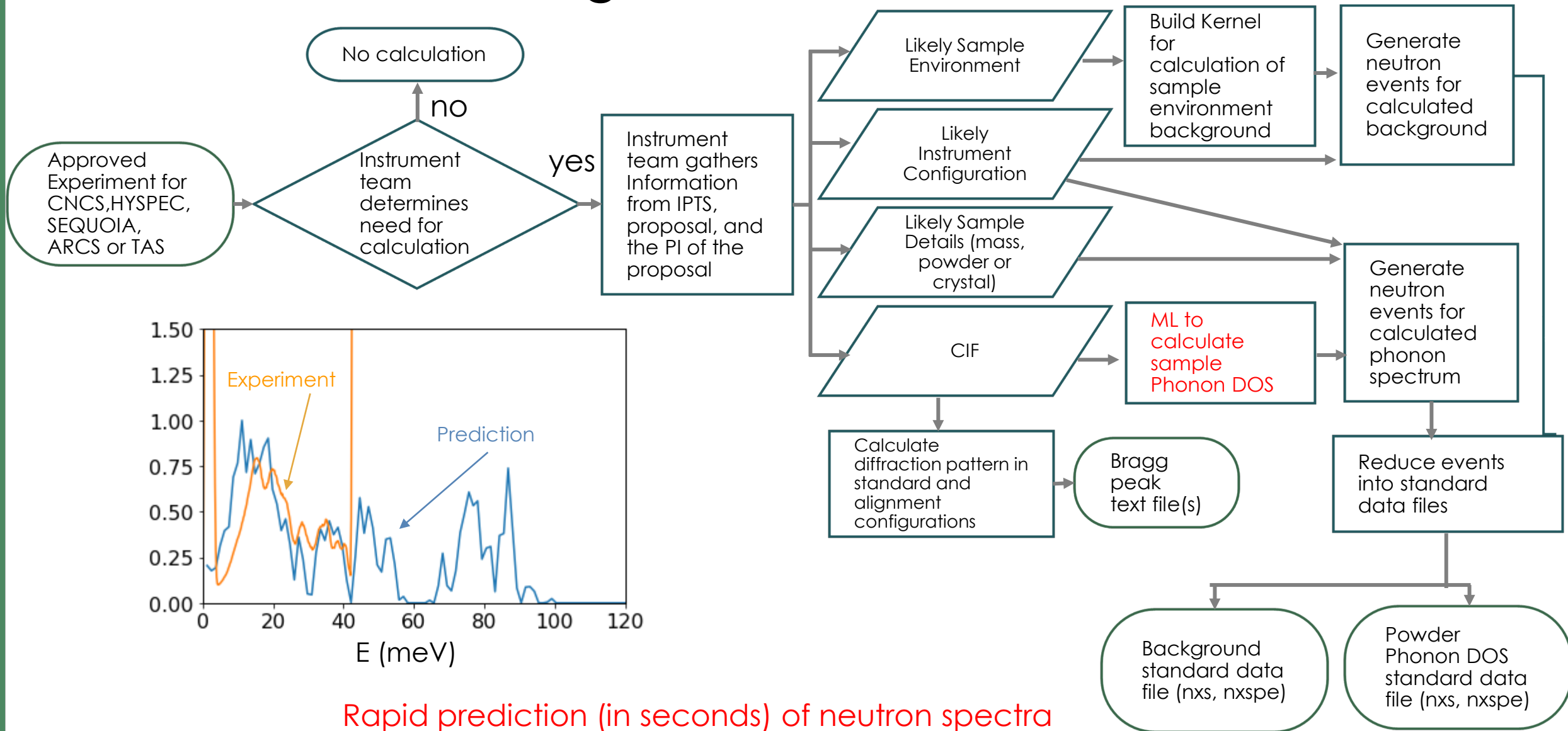
Validation



Testing



A critical link in the digital twin workflow



Rapid prediction (in seconds) of neutron spectra directly from molecular/crystal structure on a PC, for users with no modeling background.

Credit: Matt Stone

Opportunities

- Access by users either through a web interface or Analysis
- Experiment planning
- Rapid/automated data analysis and interpretation

Thank you!