Kohn-Sham Hamiltonian Mapping Approach with Machine-Learning

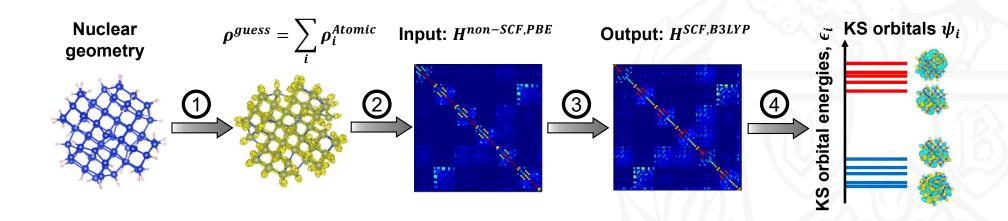
CompChemCyberTraining Workshop, July 2024

Mohammad Shakiba SUNY Buffalo Akimov Research Group





Kohn-Sham Hamiltonian mapping workflow



University at Buffalo The State University of New York

Kohn-Sham Hamiltonian mapping workflow

- Step 1 (data generation):
 - Generate a precomputed nuclear trajectory with either PBE or xTB (similar to what is done in typical NA-MD simulations in nanoscale systems)
 - Generate guess (xTB or PBE atomic guess) and target Hamiltonian (hybrid functional) for a set of random geometries of the precomputed trajectory (high-throughput)
- Step 2 (training the models):
 - Select the partitioning of the input and target Hamiltonian matrices
 - Equal partitioning
 - Atomic partitioning
 - Train multiple models for each partition with the generated data
- Step 3 (use the model):
 - Generate guess Hamiltonians for all geometries and use the trained models to generate the target Hamiltonian matrices and molecular orbitals (high-throughput)

Kohn-Sham Hamiltonian mapping workflow

- Step 1 (data generation):
 - Generate a precomputed nuclear trajectory with either PBE or xTB (similar to what is done in typical NA-MD simulations in nanoscale systems)
 - Generate guess (xTB or PBE atomic guess) and target Hamiltonian (hybrid functional) for a set of random geometries of the precomputed trajectory (high-throughput)
- Step 2 (training the models):
 - Select the partitioning of the input and target Hamiltonian matrices
 - Equal partitioning
 - Atomic partitioning
 - · Train multiple models for each partition with the generated data
- Step 3 (use the model):
 - Generate guess Hamiltonians for all geometries and use the trained models to generate the target Hamiltonian matrices and molecular orbitals (high-throughput)

Data generation (distribute_jobs.py):

```
# General variables
params['prefix']
params['trajectory xyz file']
params['user steps']
params['njobs']
params['nprocs']
params['remove raw outputs']
params['submit template']
params['software load instructions']
params['submit exe']
# Guess calculations
params['do guess']
params['guess dir']
params['guess input template']
params['guess software']
params['guess_software exe']
params['guess mpi exe']
# Reference calculations
params['do ref']
```

```
params['reference_dir']
params['reference_input_template']
params['reference_software']
params['reference_software_exe']
params['reference_mpi_exe']

# Distribute the single-point calculations
distribute_jobs(params)
```

Training the models (1 train.py):

```
# General variables
params['prefix']
params['path to input mats']
params['path to output mats']
params['path to trajectory xyz file']params['save ml mos']
params['path to sample files']
params['input proprty']
params['output proprty']
# Models properties
params['kernel']
params['degree']
params['alpha']
params['qamma']
params['scaler']
params['partitioning method']
params['npartition']
params['memory efficient']
params['train parallel']
```

```
# Saving models
params['save models']
params['path to save models']
params['save ml hams']
params['save ao overlap']
# Error analysis
params['do error analysis']
params['save ref eigenvalues']
params['save ref eigenvectors']
params['path to save ref mos']
params['compute ml total energy']
params['write wfn file']
params['path to save wfn files']
params['cp2k ml input template']
# Overlap and time-overlap
calculations
params['compute overlap']
params['nprocs']
params['is periodic']
```

```
params['A cell vector']
params['B cell vector']
params['C cell vector']
params['periodicity type']
params['translational vectors']
params['lowest orbital']
params['highest orbital']
params['res dir']
# Distribute the single-point
calculations
models, models error, input scalers,
output scalers = train(params)
```

Use the model (2_distribute_jobs.py):

Let's do the calculations!