Non-Adiabatic Excited States Dynamics with Machine Learning



[1] Long timescale surface hopping dynamics with deep NNs

SHARC with multi-layer feed-forward NNs

- · Use NNs instead of QM calculations to predict energies, gradients, couplings and dipole moments
- Relationships between the nuclear coordinates and the corresponding electronic properties are learned from a training set

Training set generation and adaptive sampling for excited states

- Each data point is one set of nuclear coordinates and its associated set of quantities computed with a reference method.
- Initial training set based on normal mode scans and then switch to an adaptive sampling scheme that automatically identifies untrustworthy regions not covered by the initial training set.
- Whenever the different NNs make different predictions, the corresponding geometry is assumed to lie in a conformational region with too few training points \rightarrow expand the training set by computing the quantum chemistry data for this geometry.
- During the run, threshold for the error between the NNs is adapted (×0.95) until the conformational space is sampled to make accurate predictions without any reference calculation.



Results for CH₂NH₂+

- MAE of 0.057 and 0.099 between NNs and two reference methods (MR-CISD with different b.s.).
- Very low comp. cost. so a much larger number of trajectories (3,846) was simulated than with standard OM methods (90).
- Long time scale excited-state dynamics (up to 1 ns, 10⁴ times longer than OM).
- 10 ps trajectory in less than 6 hours on 1 core (300x faster than ref. OM).
- Correct identification of the Cis.



[2] Pure deep learning vs. ab initio non-adiabatic excited state dynamics

Feed-forward deep NNs with Zhu-Nakamura TSH method for pure ML non-adiabatic dynamics

- Aim: explore topology of S_0 and S_1 PESs and the S_0/S_1 conical intersection of CH₂NH.
- DNNs model where PES of the molecule is expressed as sum of energies of constituent atoms.



⇐ Schematic model of the DNNs: 4 hidden layers, 3 atoms. Atom coordinates R_i are transformed into a set of input vectors D_{ii}. Parameters of the DNNs for an atom are optimised iteratively

Energies as: $E = \sum_{i} E_{i}$ with $E_{i} = \mathbb{F}_{i}^{out} \left[\mathbb{F}_{i}^{out} \left(\mathbb{F}_{i}^{out} \left(\dots \left(\mathbb{F}_{i}^{out} \left(\left\{ \boldsymbol{d}_{i}^{0} \right\} \right) \right) \right) \right] \right]$

Two individual DNN models trained independently for both S₁ and S₀ PESs of CH₂NH on CASSCF data calculated for the same set of molecular coordinates.

Final DNN models are trained on 90,000 ab initio data points prepared using molecular dynamics simulations.

S₀ and S₁ energy profiles calculated from the trained DNN models fully overlap with CASSCF.

 S_1/S_0 CI topology well reproduced (see 2D and 3D PES \Rightarrow)

Results for DNNs

- S₁-S₀ gap same well reproduced at all hopping and Franck-Condon regions
- TD S₀ and S₁ populations match *ab-initio* ones
- S_1 to S_0 hopping starts at same time (55 fs)
- Similar distribution of hopping points





150

60 90 120 H2C1N4H5 (degree)

120

60 90 120 H2C1N4H5 (degree)

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