

# EXCITED STATE MACHINE LEARNING FOR CHROMOPHORES IN COMPLEX ENVIRONMENTS

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### Overview

A major challenge in modern materials modelling techniques is the prediction of the optical properties of chromophores in complex environments. This problem is inherently multiscale. Consider a system such as a dye in solvent: the optical properties dependant on photoexcited processes act on a ps-ns timescale, the dye needs to be sampled on a long ns- $\mu$ s timescale, coupled with the long-ranged solvent interactions on a scale of 10s of nm.

Progress on the prediction of optical properties has been made using linear-scaling time-dependant  $DFT^{8,11}$ . However, the need for sampling over large time-scales combined with large length-scales means the computational demand remains very high. This project will use Machine Learning (ML) to attempt to accelerate the current state-ofthe-art techniques used in optical properties prediction.



Fig. 1: Catechol

### Goals

As an initial target for this project a protocol for generating excited state potential energy surfaces (PES) of organic molecules will be produced. An exemplar system that will be treated as a case study for this project is photodissociation of the molecule catechol  $^{10,4}$ .

[1] Bartók, A. P., et al. 2010, 'Gaussian approximation potentials: the accuracy of quantum mechanics, without the electrons.', Physical review letters 104 13, 136403. [2] Cole, D., et al. 2020, 'A machine learning based intramolecular potential for a flexible organic molecule', Faraday Discuss pp. -, URL: http://dx.doi.org/10.1039/D0FD00028K [3] Dral, P. O. 2019, 'Mlatom: A program package for quantum mechanics, without the electrons.', Physical review letters 104 13, 136403. [2] Cole, D., et al. 2020, 'A machine learning Journal of computational chemistry and the electrons.', Physical review letters 104 13, 136403. [2] Cole, D., et al. 2020, 'A machine learning based intramolecular potential for a flexible organic molecule', Faraday Discuss pp. -, URL: http://dx.doi.org/10.1039/D0FD00028K [3] Dral, P. O. 2019, 'Mlatom: A program package for quantum mechanics, without the electrons.', Physical review letters 104 13, 136403. [2] Cole, D., et al. 2020, 'A machine learning based intramolecular potential for a flexible organic molecule', Faraday Discuss pp. -, URL: http://dx.doi.org/10.1039/D0FD00028K [3] Dral, P. O. 2019, 'Mlatom: A program package for quantum mechanics, without the electrons.', Physical review letters 104 13, 136403. [2] Cole, D., et al. 2020, 'A machine learning' Journal of computational chemistry and the electrons.', Physical review letters 104 13, 136403. [2] Cole, D., et al. 2020, 'A machine learning' Journal of computational chemistry and the electrons.', Physical review letters 104 13, 136403. [2] Cole, D., et al. 2020, 'A machine learning' Journal of computational chemistry and the electrons.', Physical review letters 104 13, 136403. [2] Cole, D., et al. 2020, 'A machine learning' Journal of computational chemistry and the electrons.', Physical review letters 104 13, 136403. [2] Cole, D., et al. 2020, 'A machine learning' Journal of computational chemistry and the electrons.', Physical review letters 104 13, 136403. [2] Cole, D., et al. 2020, 'A machine learning' Journal of computational [4] Gerhards, M., et al. 1996. Structure and vibrations of catechol h2o(d2o) in the s0 and s1 state. [5] Khorshidi, A. and Peterson, A. A. 2016, 'Amp: A modular approach to machine learning and quantum chemistry with a deep neural network for molecular wavefunctions', Nature Communications10. [7] Schutt, K. T., et al. 2019, "Schnetpack: A deep learning toolbox for atomistic systems." Journal of physical chemistry. A1234, 873-880. 9] Westermayr, J., et al. 2020, 'Combining schnet and share The schnare machine learning approach for excited state dynamics', The journal of physical reviewletters 114 23, 233001. [11] Zuehlsdorff, T. J. and Isborn, C. M. 2019, 'Modeling absorption of ultraviolet light', Physical reviewletters 114 23, 233001. [11] Zuehlsdorff, T. J. and Isborn, C. M. 2019, 'Modeling absorption of ultraviolet light', Physical reviewletters 114 23, 233001. [11] Zuehlsdorff, T. J. and Isborn, C. M. 2019, 'Modeling absorption of ultraviolet light', Physical reviewletters 114 23, 233001. [11] Zuehlsdorff, T. J. and Isborn, C. M. 2019, 'Modeling absorption of ultraviolet light', Physical reviewletters 114 23, 233001. [11] Zuehlsdorff, T. J. and Isborn, C. M. 2019, 'Modeling absorption of ultraviolet light', Physical reviewletters 114 23, 233001. [11] Zuehlsdorff, T. J. and Isborn, C. M. 2019, 'Modeling absorption of ultraviolet light', Physical reviewletters 114 23, 233001. [11] Zuehlsdorff, T. J. and Isborn, C. M. 2019, 'Modeling absorption of ultraviolet light', Physical reviewletters 114 23, 233001. [11] Zuehlsdorff, T. J. and Isborn, C. M. 2019, 'Modeling absorption of ultraviolet light', Physical reviewletters 114 23, 233001. [11] Zuehlsdorff, T. J. and Isborn, C. M. 2019, 'Modeling absorption of ultraviolet light', Physical reviewletters 114 23, 233001. [11] Zuehlsdorff, T. J. and Isborn, C. M. 2019, 'Modeling absorption of ultraviolet light', Physical reviewletters 114 23, 233001. [11] Zuehlsdorff, T. J. and Isborn, C. M. 2019, 'Modeling absorption of ultraviolet light', Physical reviewletters 114 23, 233001. [11] Zuehlsdorff, T. J. and Isborn, C. M. 2019, 'Modeling absorption of ultraviolet light', Physical reviewletters 114 23, 233001. [11] Zuehlsdorff, T. J. and Isborn, C. M. 2019, 'Modeling absorption of ultraviolet light', Physical reviewletters 114 23, 233001. [11] Zuehlsdorff, T. J. and Isborn, C. M. 2019, 'Modeling absorption of ultraviolet light', Physical reviewletters 114 23, 233001. [11] Zuehlsdorff, T. J. and Isb

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# **Investigating ML Toolkits**

#### 1. $AMP^5$

2. SchNetPack<sup>7</sup>: in particular SchNOrb<sup>6</sup> and SchNarc<sup>9</sup>

3.  $MLatom^3$ 

4. GAP<sup>1</sup>: with particular interest in recent work on organic molecules<sup>2</sup>

# **Binding Curve**

- be investigated.





# **Excited State PES**

• Training Neural Network potentials off DFT data for Ground and Excited States of catechol

• Some preliminary results shown in Fig. 2



## Future...

• Using a Machine Learned PES, the binding curve for the H<sup>+</sup>dissociation of catechol following absorption from UV-light will

• Enhanced sampling will be necessary to retrain around the dissociation pathway to improve the binding curve and PES.

Fig. 3: Exploring the Dissociation Pathway. As we extend the O-H bond length of catechol, we move along the red arrow, however we must also explore the sides of this potential (blue arrows).

### • Further investigations into solvents • Prediction of excited state lifetimes using MLMD