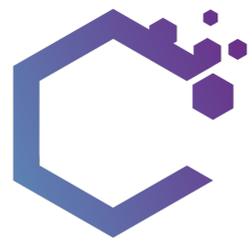


Machine learning to analyse data from ab initio molecular dynamics simulations

Morgane VACHER

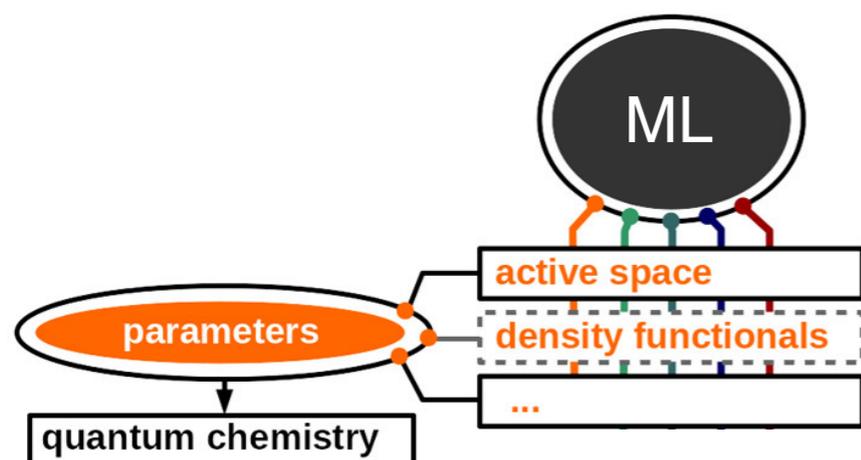


CEISAM

Chimie et Interdisciplinarité
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Machine learning & quantum chemistry



JCTC Journal of Chemical Theory and Computation

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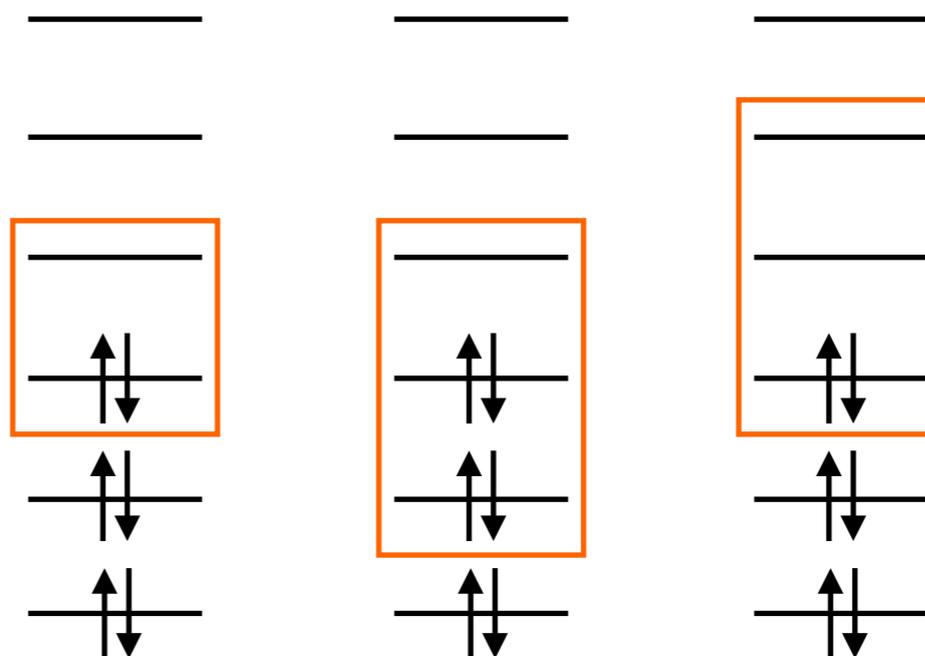
Article

Automation of Active Space Selection for Multireference Methods via Machine Learning on Chemical Bond Dissociation

WooSeok Jeong,^{||} Samuel J. Stoneburner,^{||} Daniel King, Ruye Li, Andrew Walker, Roland Lindh, and Laura Gagliardi*

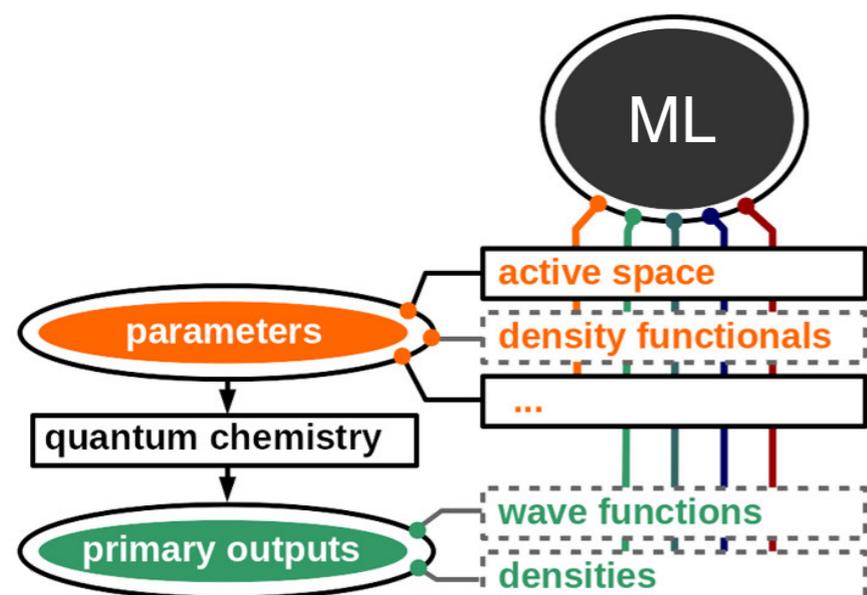
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What active space to choose?

Machine learning & quantum chemistry



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Article

Artificial Neural Networks Applied as Molecular Wave Function Solvers

Peng-Jian Yang,^{*} Mahito Sugiyama,^{*} Koji Tsuda,^{*} and Takeshi Yanai^{*}



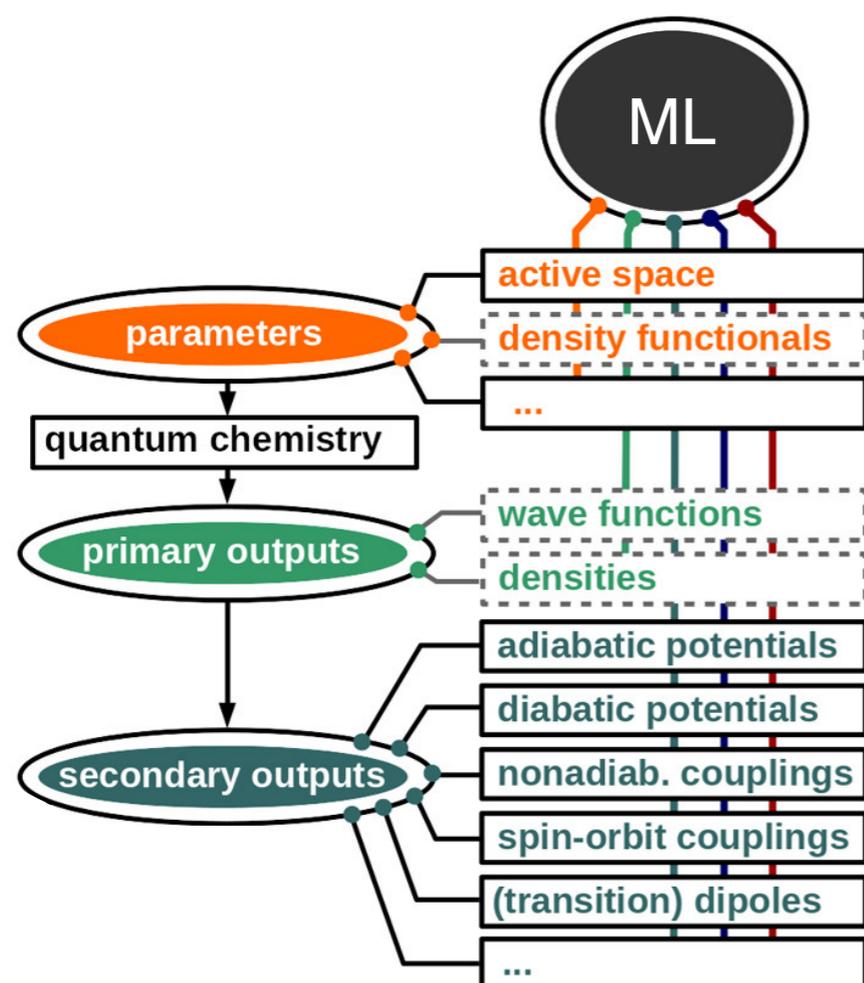
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$$\Psi = \sum_{\nu} C_{\nu} \Psi_{\nu} ?$$

Machine learning & quantum chemistry



The Journal of
Chemical Physics

Hierarchical machine learning of potential energy surfaces

Cite as: J. Chem. Phys. **152**, 204110 (2020); <https://doi.org/10.1063/5.0006498>
Submitted: 04 March 2020 . Accepted: 06 May 2020 . Published Online: 27 May 2020

Pavlo O. Dral , Alec Owens , Alexey Dral , and Gábor Csányi

COLLECTIONS

Paper published as part of the special topic on [Machine Learning Meets Chemical Physics](#)
Note: This paper is part of the JCP Special Topic on Machine Learning Meets Chemical Physics.



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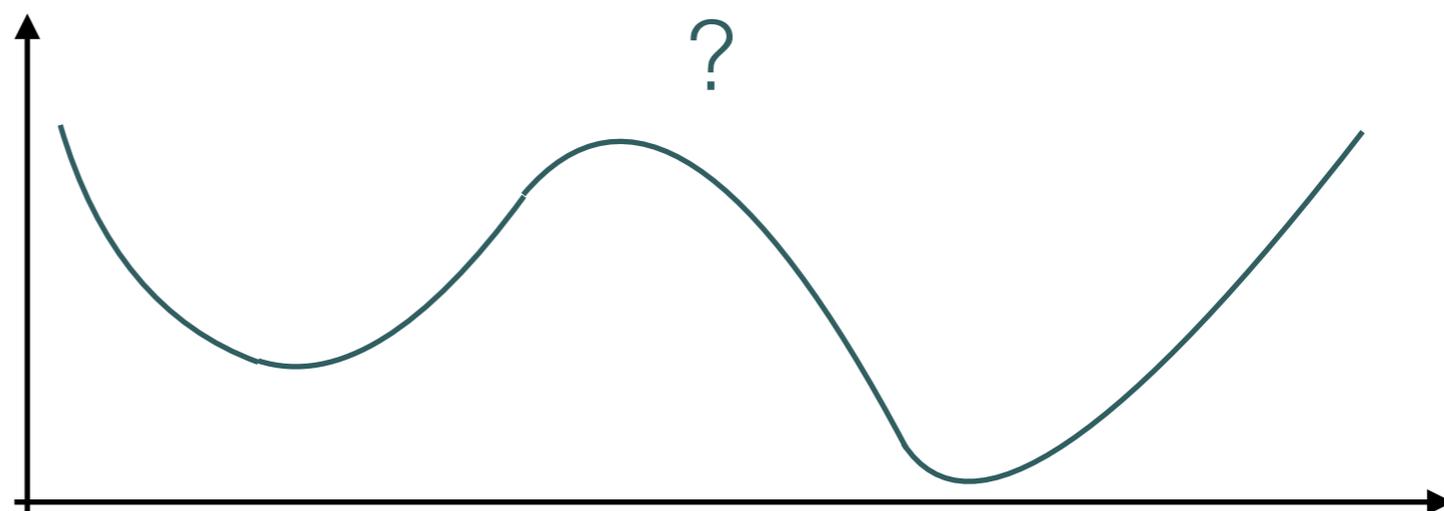


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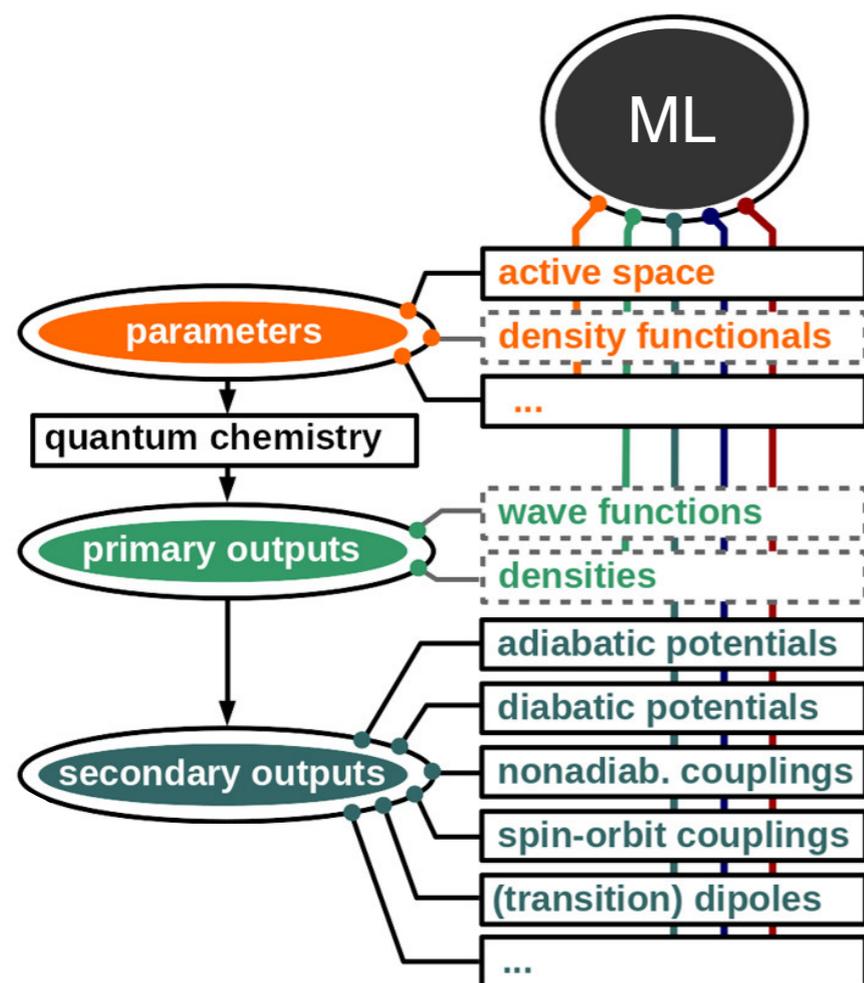
CrossMark

Potential energy



Nuclear coordinate

Machine learning & quantum chemistry



The Journal of
Chemical Physics

Hierarchical machine learning of potential energy surfaces

Cite as: J. Chem. Phys. **152**, 204110 (2020); <https://doi.org/10.1063/5.0006498>

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Note: This paper is part of the JCP Special Topic on Machine Learning Meets Chemical Physics.



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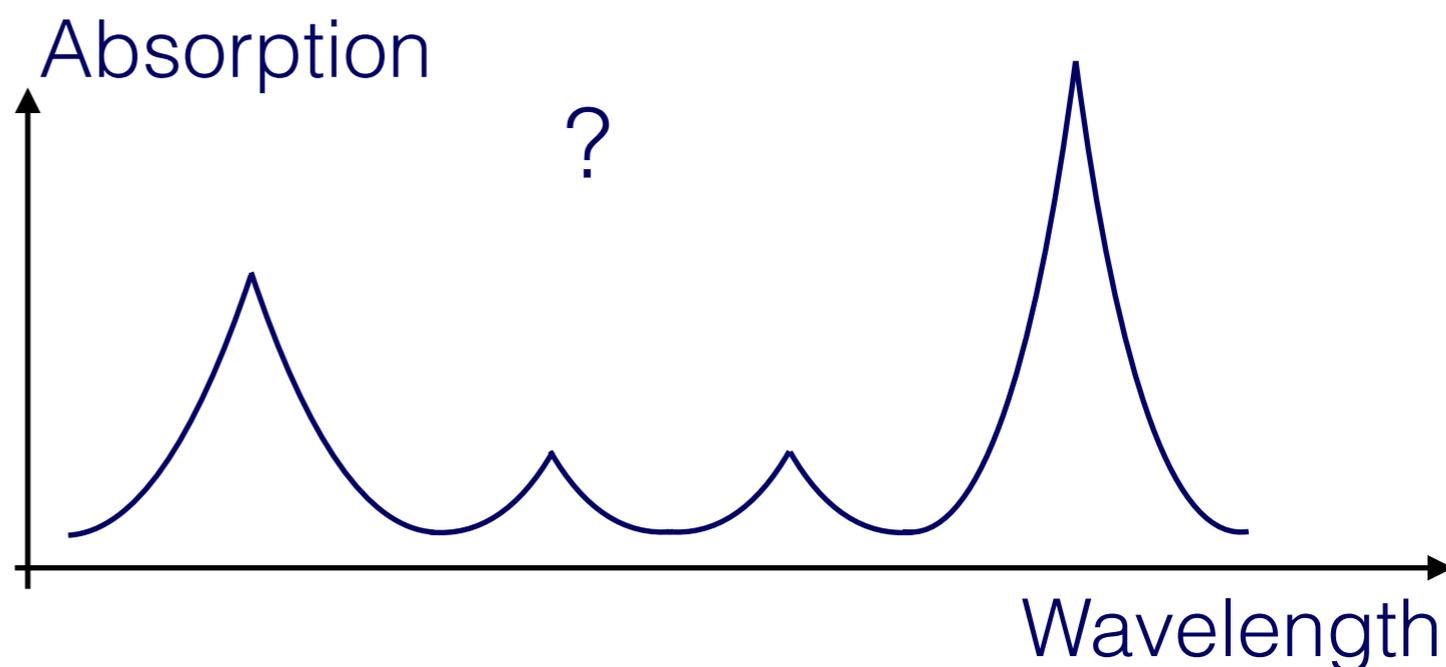
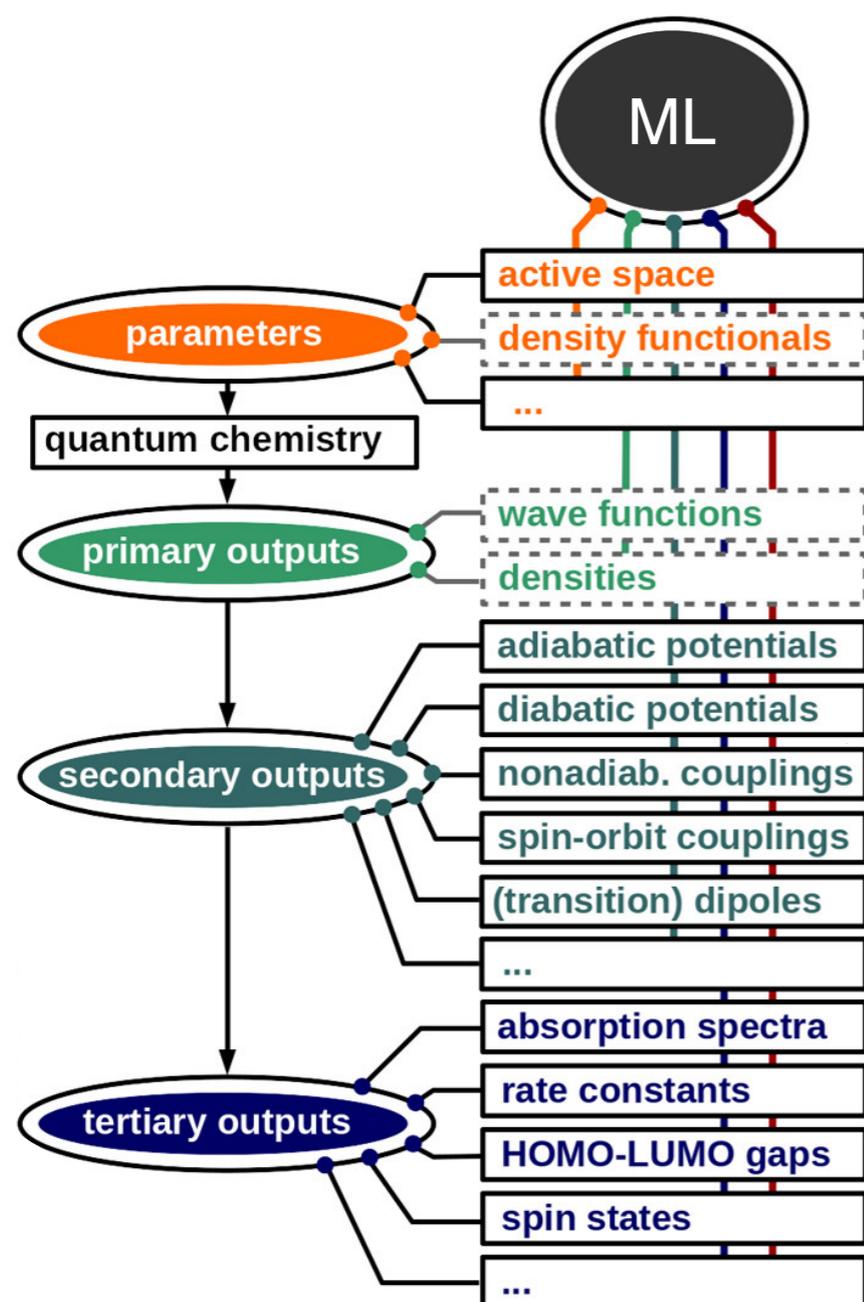
Nonadiabatic Excited-State Dynamics with Machine Learning

Pavlo O. Dral,^{*,†} Mario Barbatti,^{*,‡} and Walter Thiel^{*,†}

[†]Max-Planck-Institut für Kohlenforschung, Kaiser-Wilhelm-Platz 1, 45470 Mülheim an der Ruhr, Germany

[‡]Aix Marseille Univ, CNRS, ICR, Marseille, France

Machine learning & quantum chemistry



THE JOURNAL OF
PHYSICAL CHEMISTRY A

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Article

A Deep Neural Network for the Rapid Prediction of X-ray Absorption Spectra

C. D. Rankine, M. M. M. Madkhali, and T. J. Penfold*



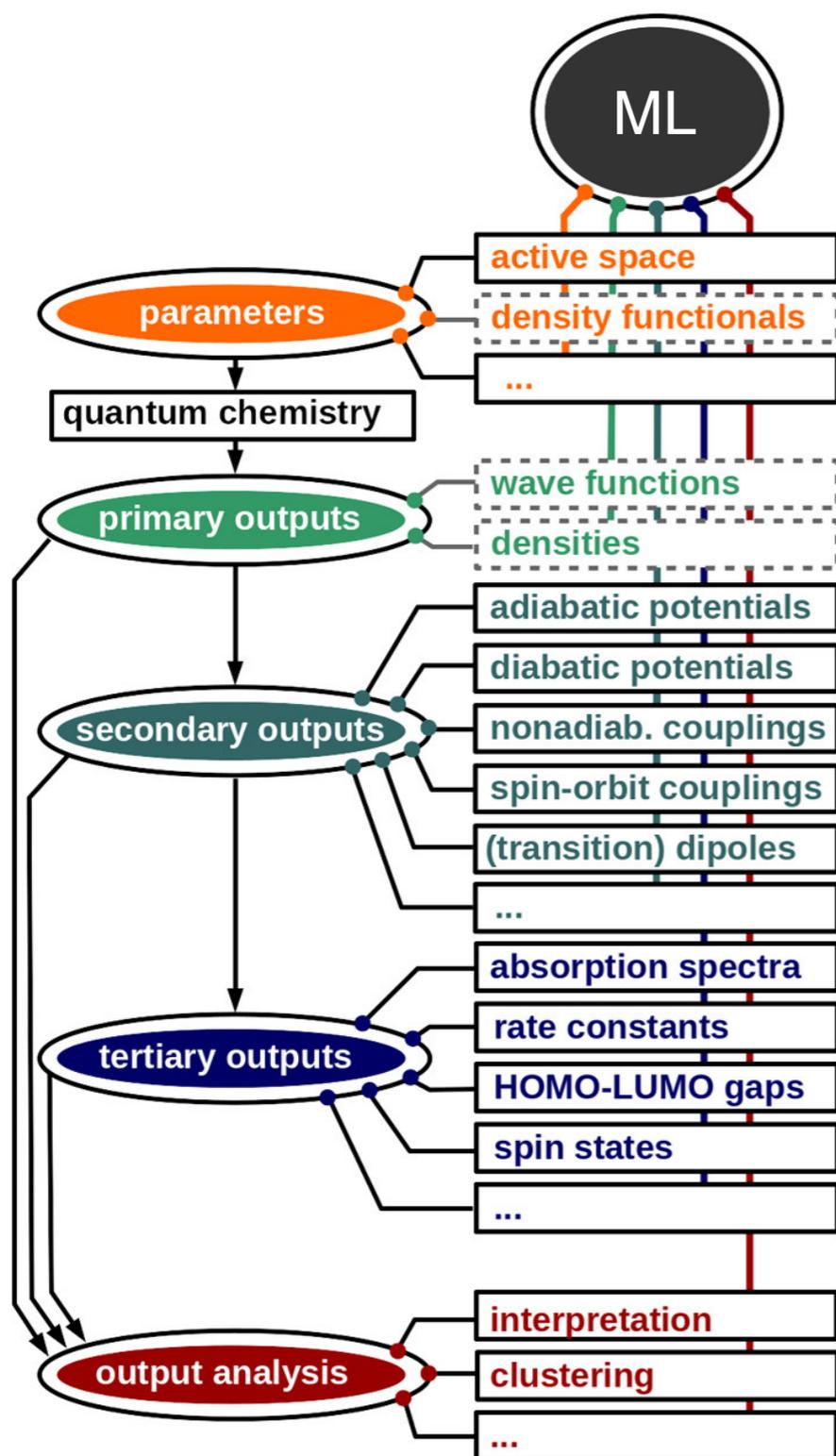
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Machine learning & quantum chemistry

Can we use machine learning algorithms to help the interpretation of AIMD simulations and to extract physical insights?



Chemical
Science

EDGE ARTICLE



Cite this: *Chem. Sci.*, 2019, 10, 2298

All publication charges for this article have been paid for by the Royal Society of Chemistry

How machine learning can assist the interpretation of *ab initio* molecular dynamics simulations and conceptual understanding of chemistry†

Florian Häse, ^a Ignacio Fdez. Galván, ^b Alán Aspuru-Guzik, ^{cde} Roland Lindh ^b and Morgane Vacher ^{*b}

ICPEAC2019

IOP Publishing

Journal of Physics: Conference Series

1412 (2020) 042003

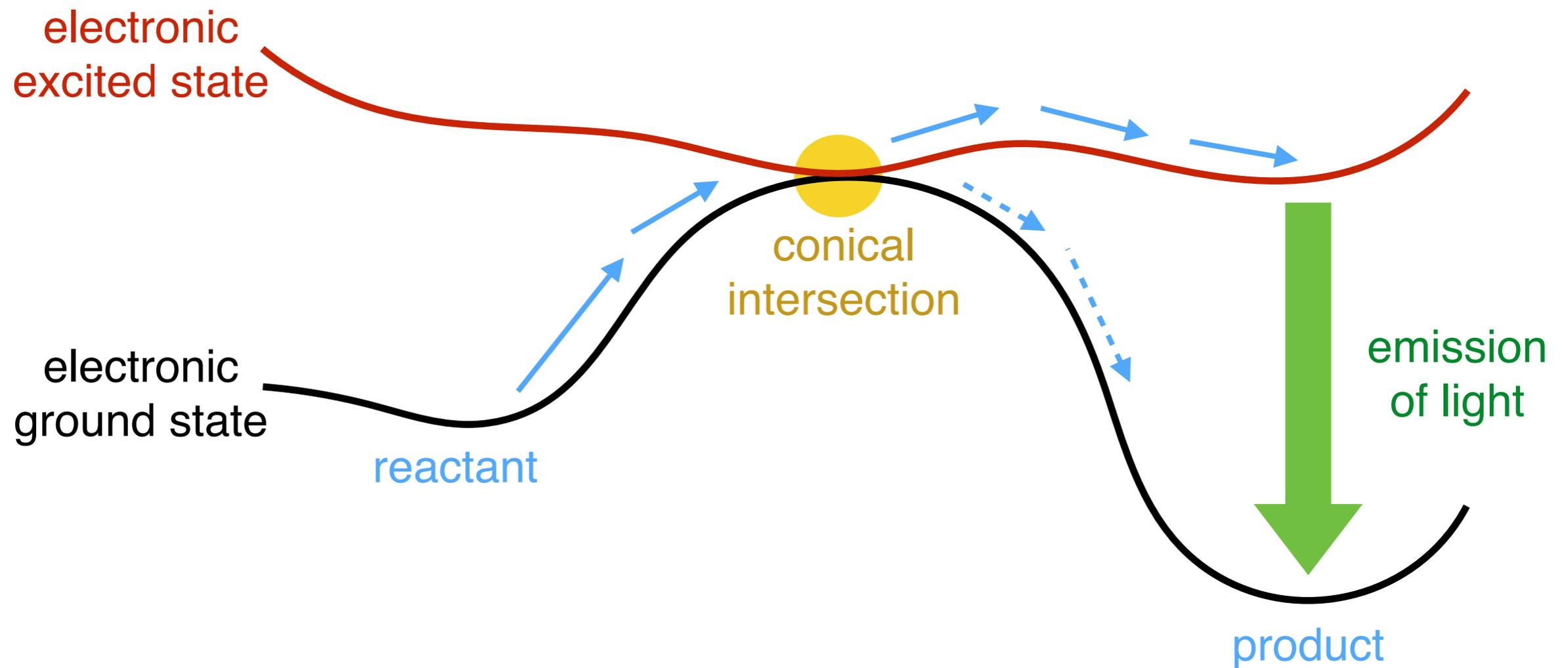
doi:10.1088/1742-6596/1412/4/042003

Machine learning for analysing *ab initio* molecular dynamics simulations

Florian Häse,^{1,2,3,4} Ignacio Fdez. Galván,⁵ Alán Aspuru-Guzik,^{2,3,4,6} Roland Lindh⁵ and Morgane Vacher⁷

What is chemiluminescence?

Definition: Emission of light (luminescence) as the result of a chemical reaction



Chemiexcitation

Population of an excited state as the result of a chemical reaction

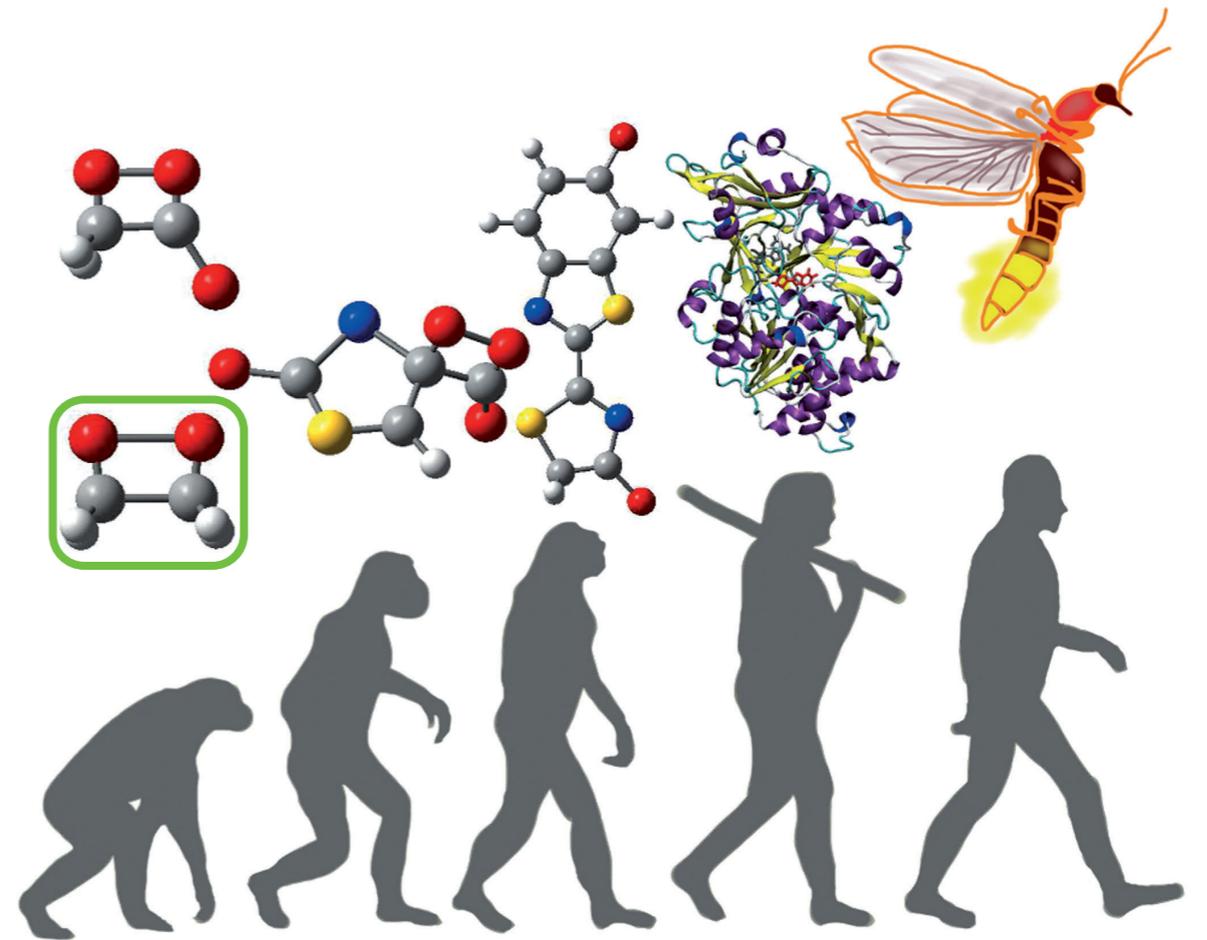
What is chemiluminescence?



→ Communication to attract partners, hunting to lure preys, defence to avoid predators

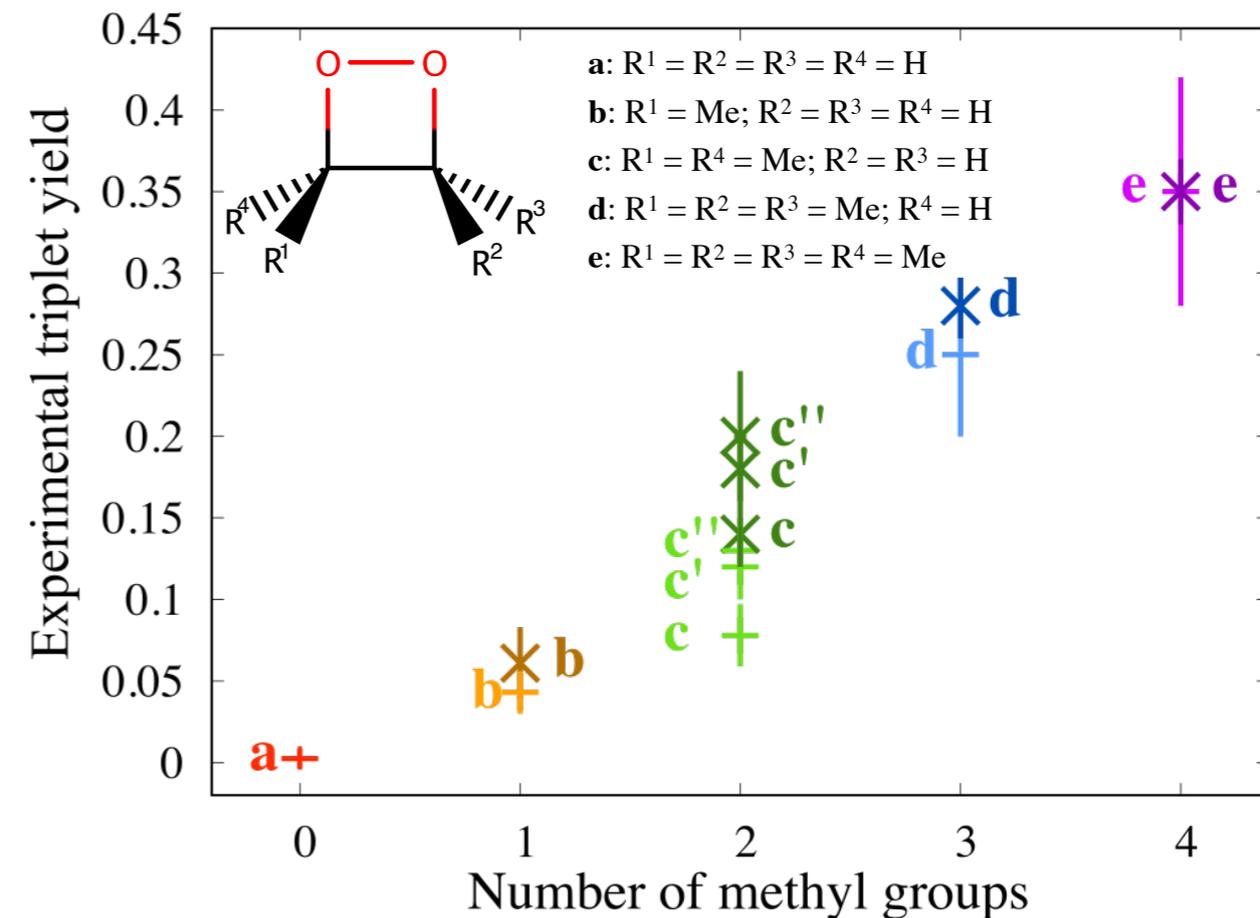
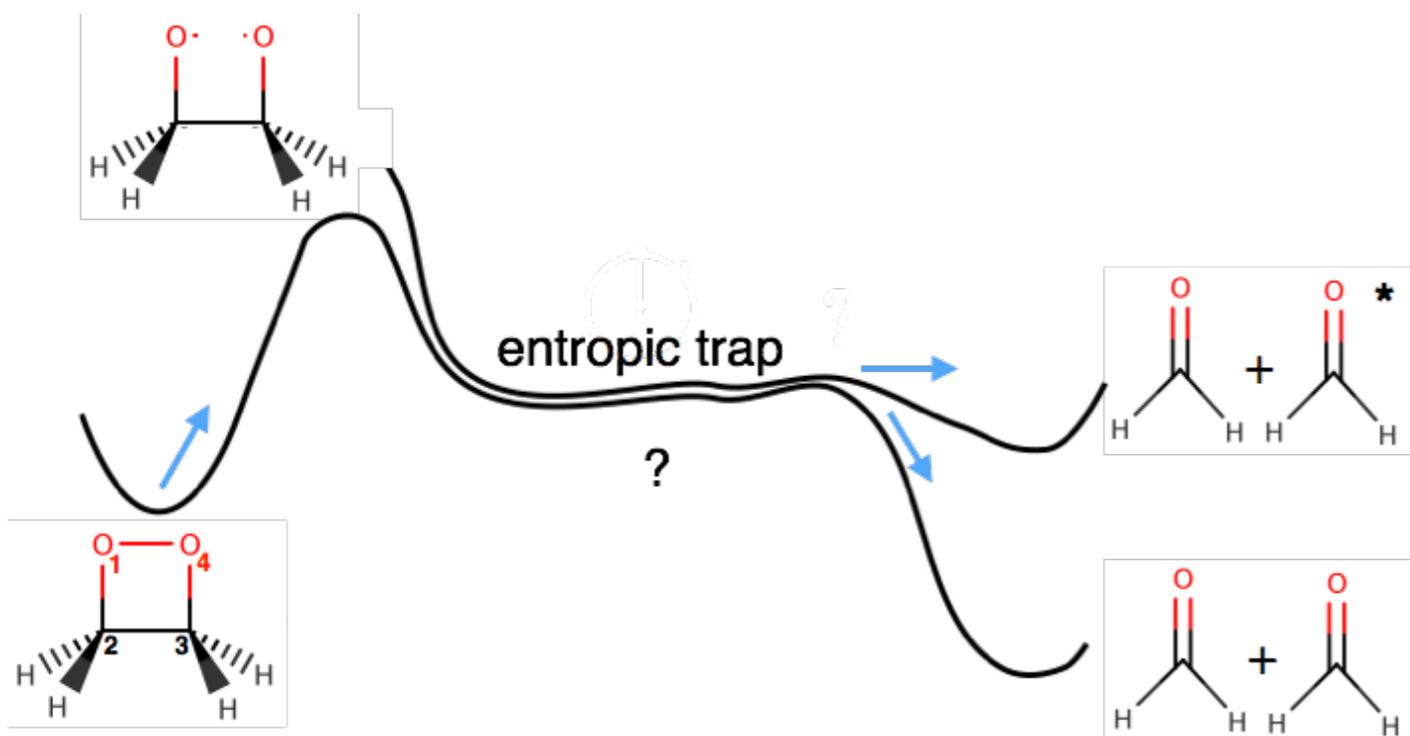
→ In vivo imaging in medicine, biosensing for environmental pollutants, food industry, etc.

Structures of model compounds



Chemiexcitation in 1,2-dioxetane

Decomposition into fundamental or excited formaldehyde molecules



→ Yield of triplet excited states > yield of singlet excited states ✓

→ Increase in the chemiexcitation yield upon methyl substitution ?

Theoretical approach

Ab initio molecular dynamics simulations

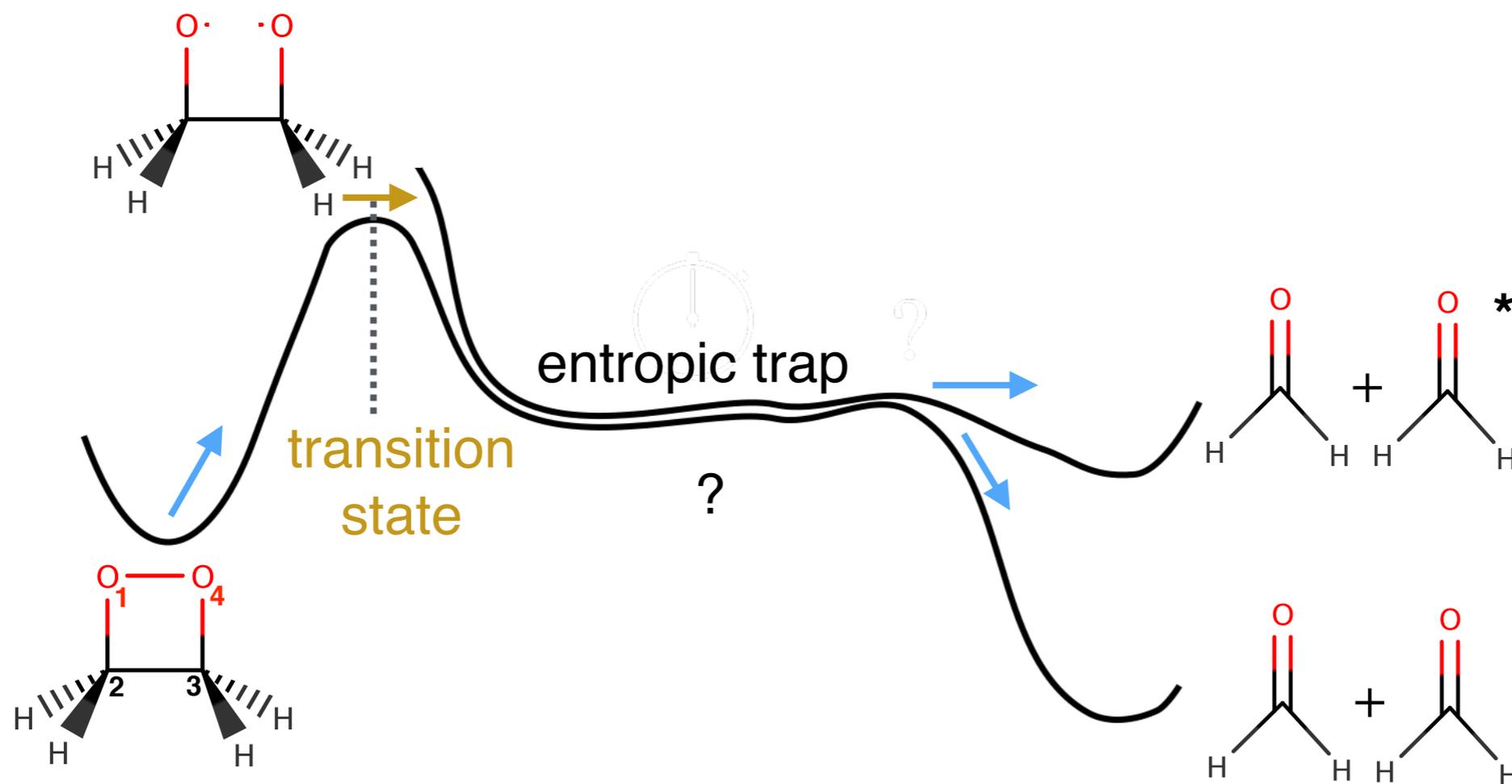
- Born-Oppenheimer dynamics
- non-adiabatic dynamics (surface hopping) including 4 singlet states

Electronic structure method

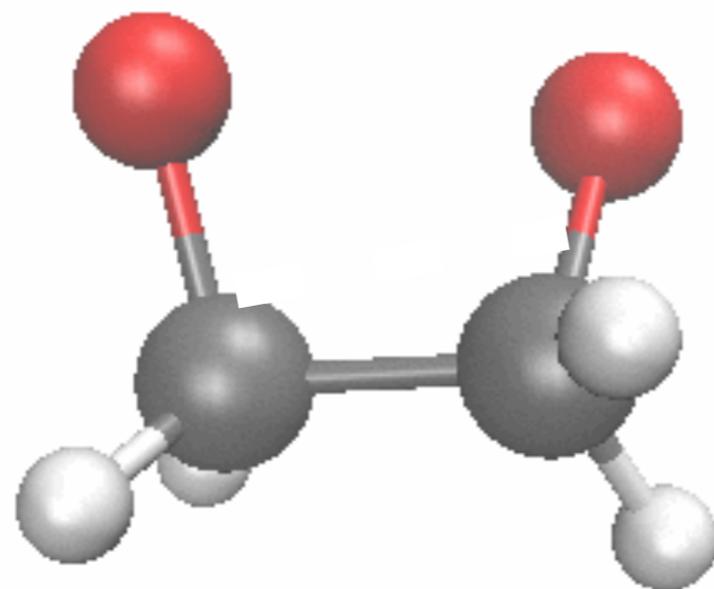
- CASSCF(12-in-10)
- ANO-RCC-VTZP basis set

Initial conditions

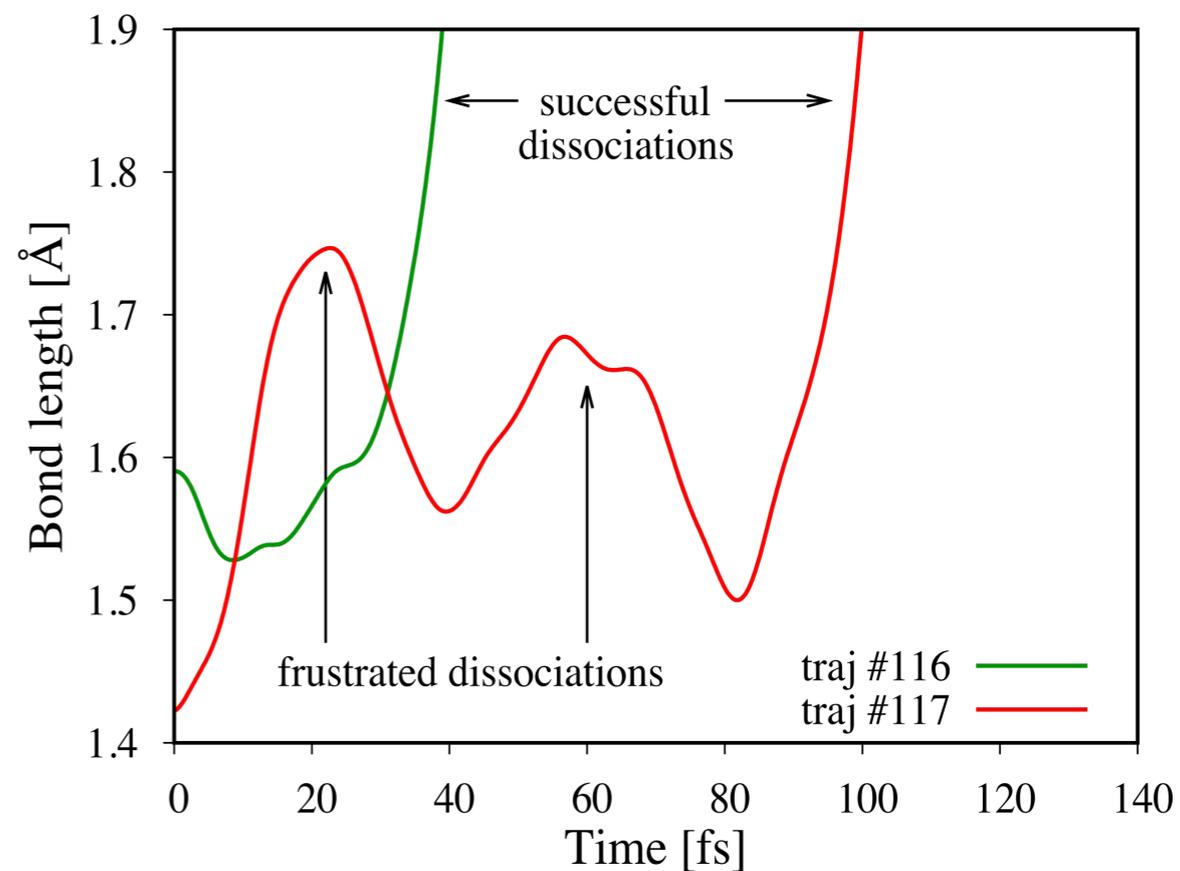
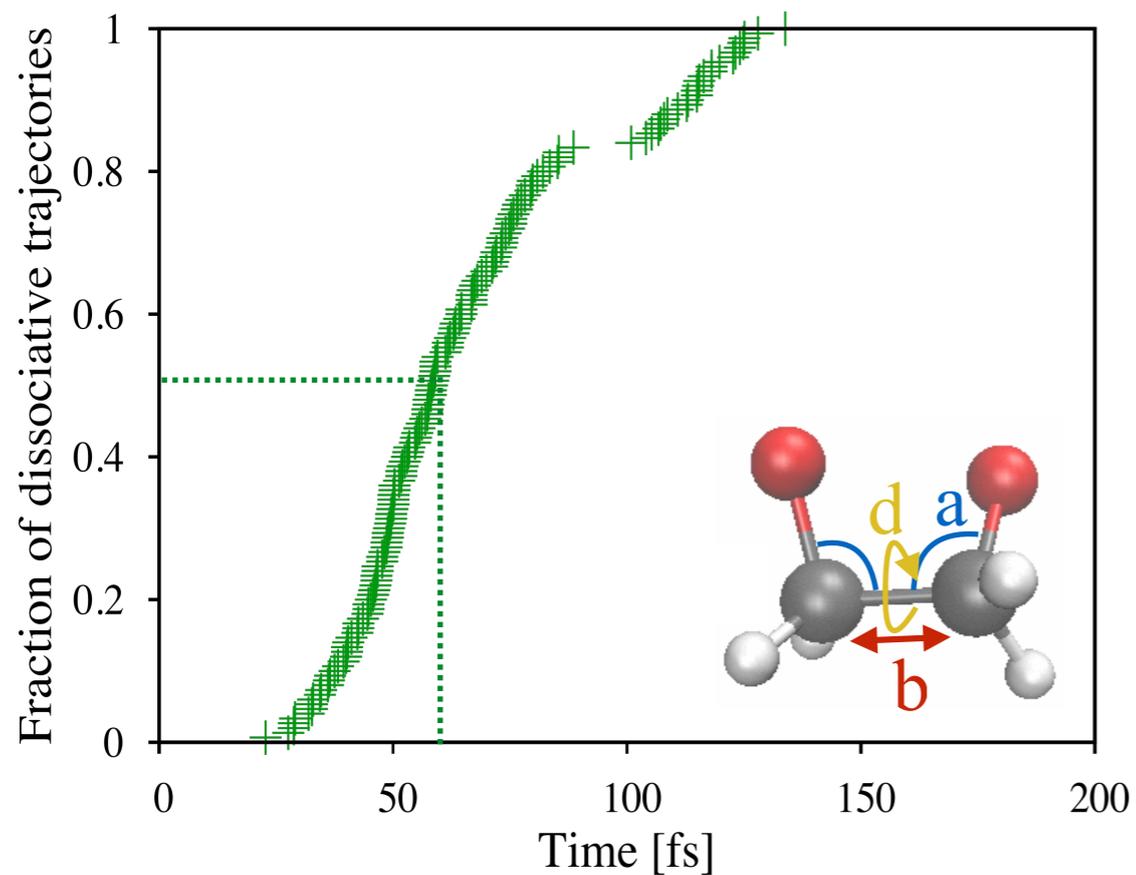
- Transition state geometry with 1kcal/mol kinetic energy in the forward direction
- 150 trajectories sampled from the Wigner distribution (Newton-X package)



Dissociation of 1,2-dioxetane



Dissociation of 1,2-dioxetane



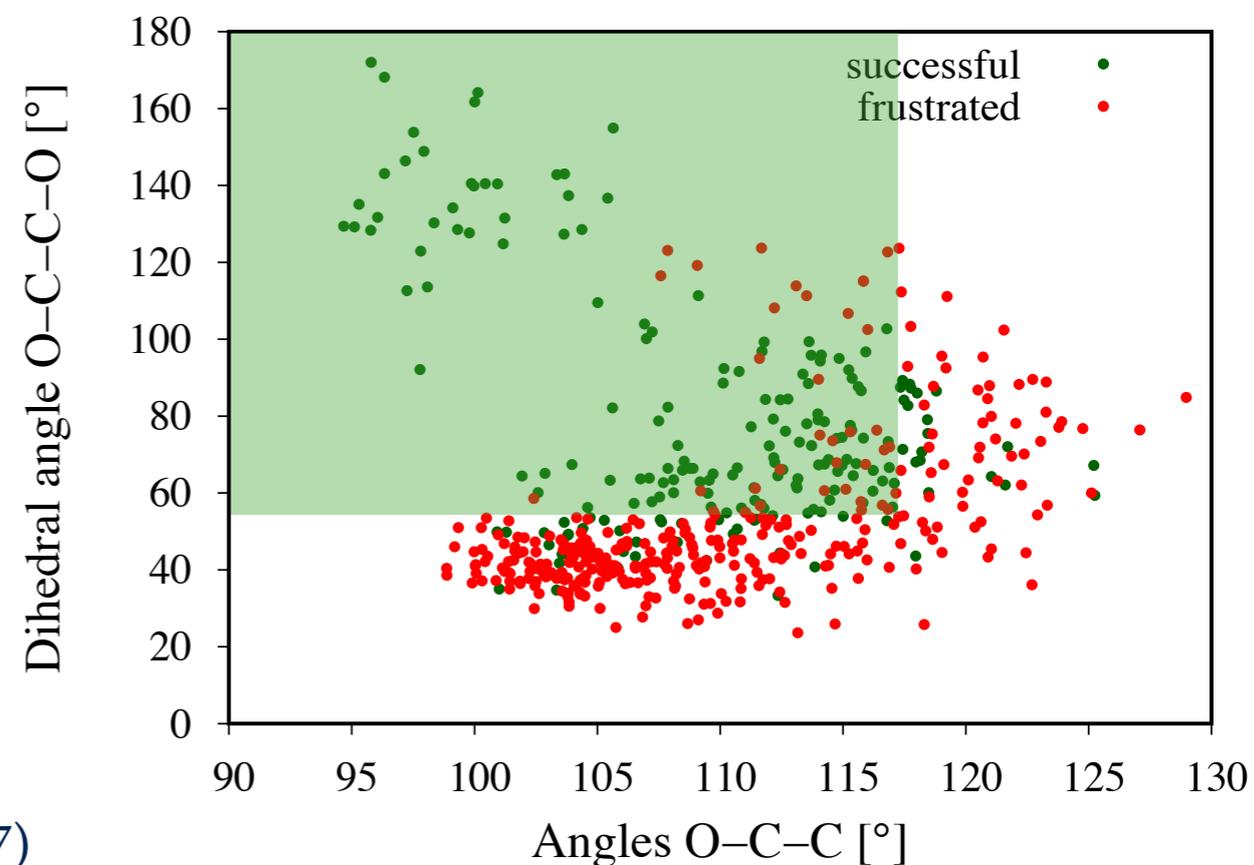
→ Dissociation time scale

between $t = 25$ fs and $t = 140$ fs
half-time of 59 fs

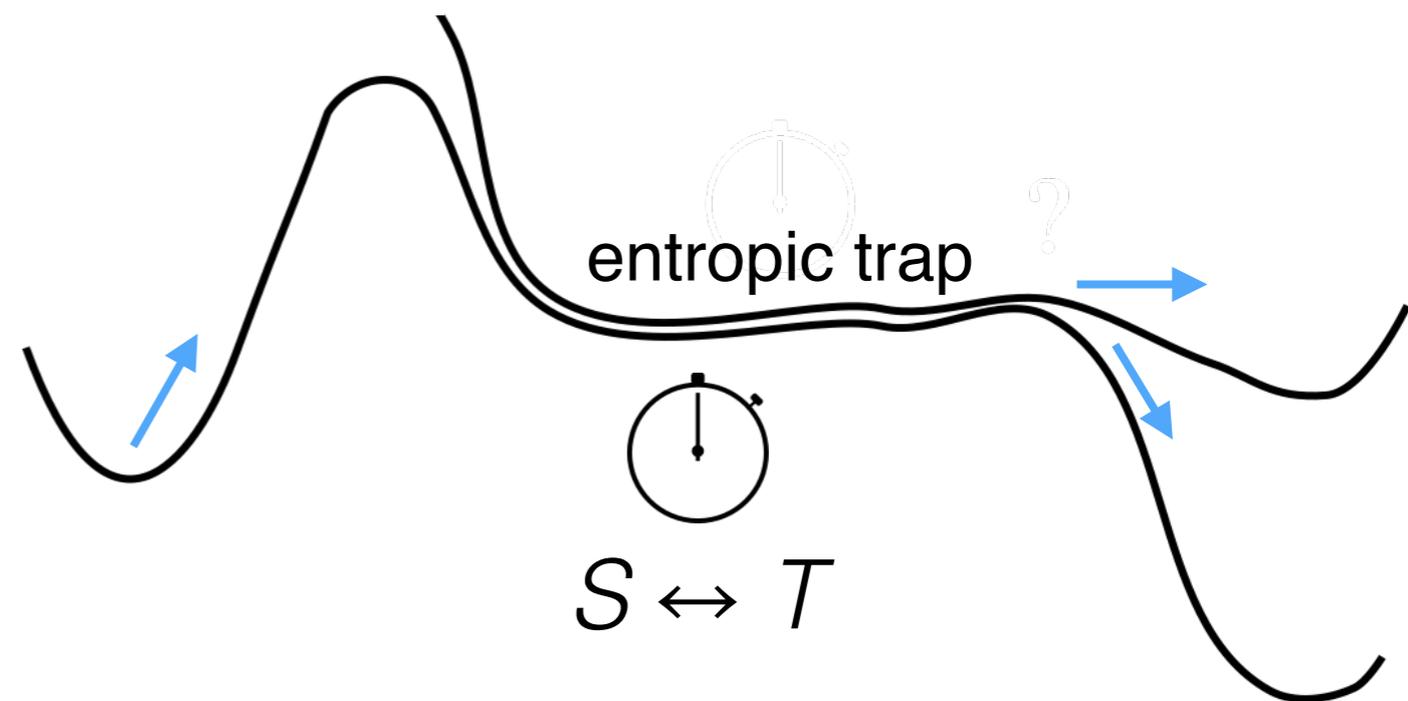
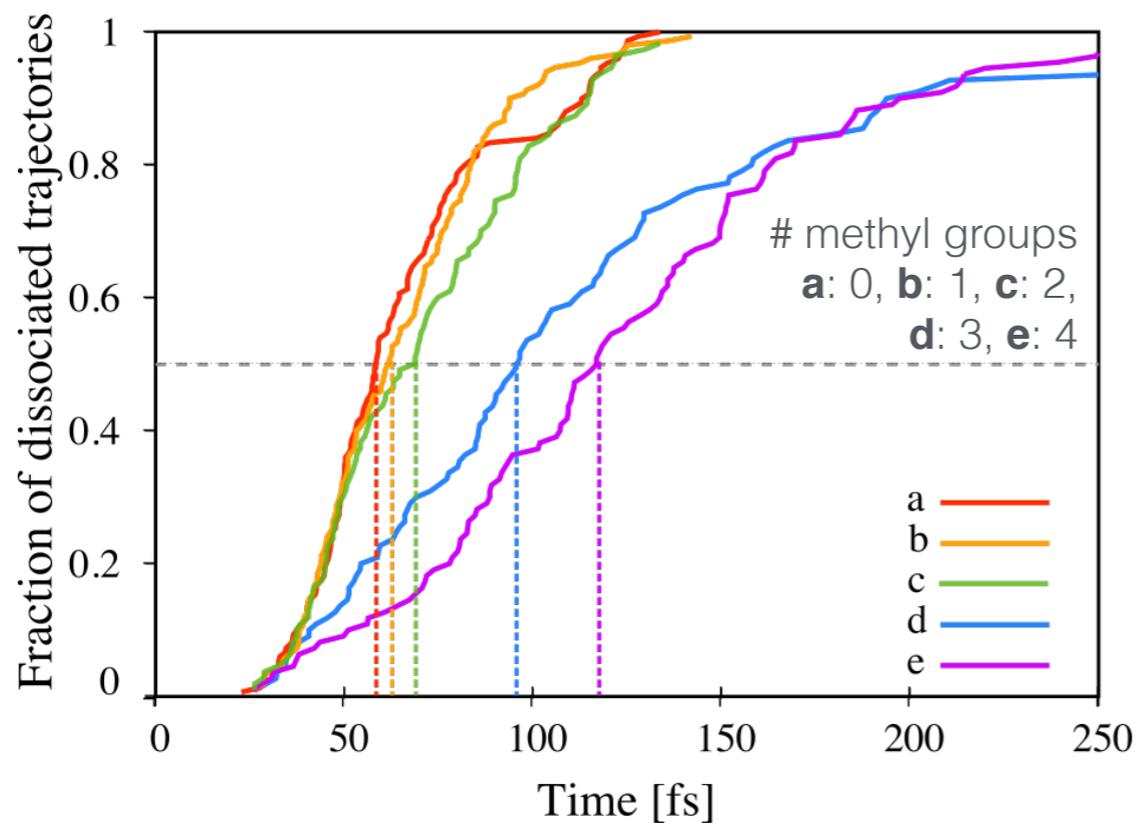
→ Geometrical conditions necessary

O-C-C-O dihedral $> 55^\circ$

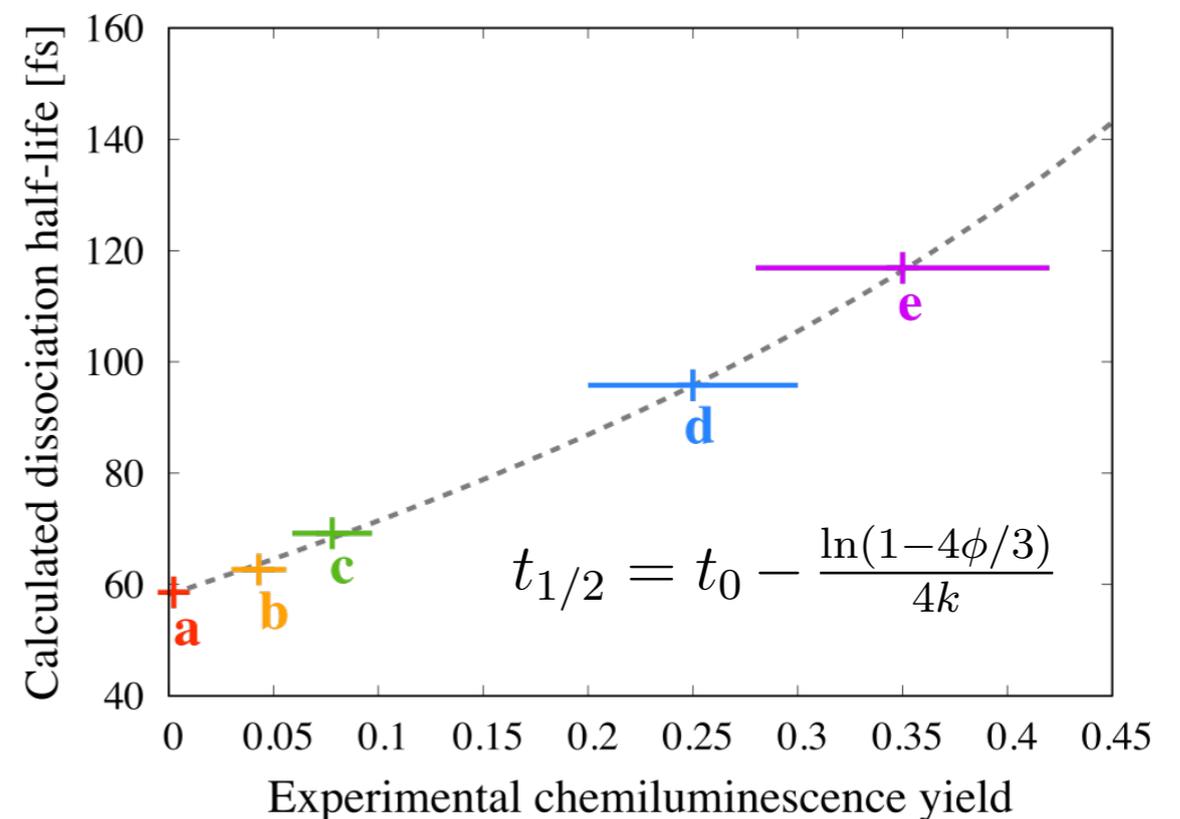
O-C-C angle $< 117^\circ$



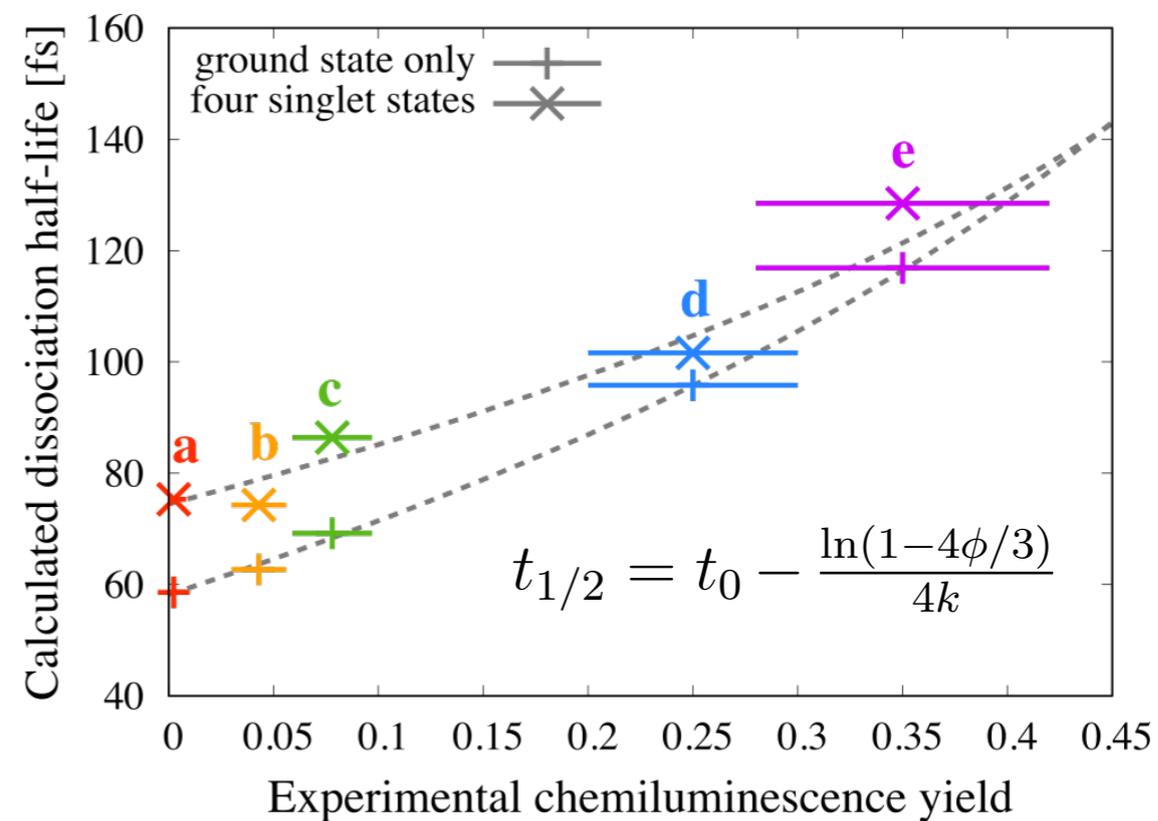
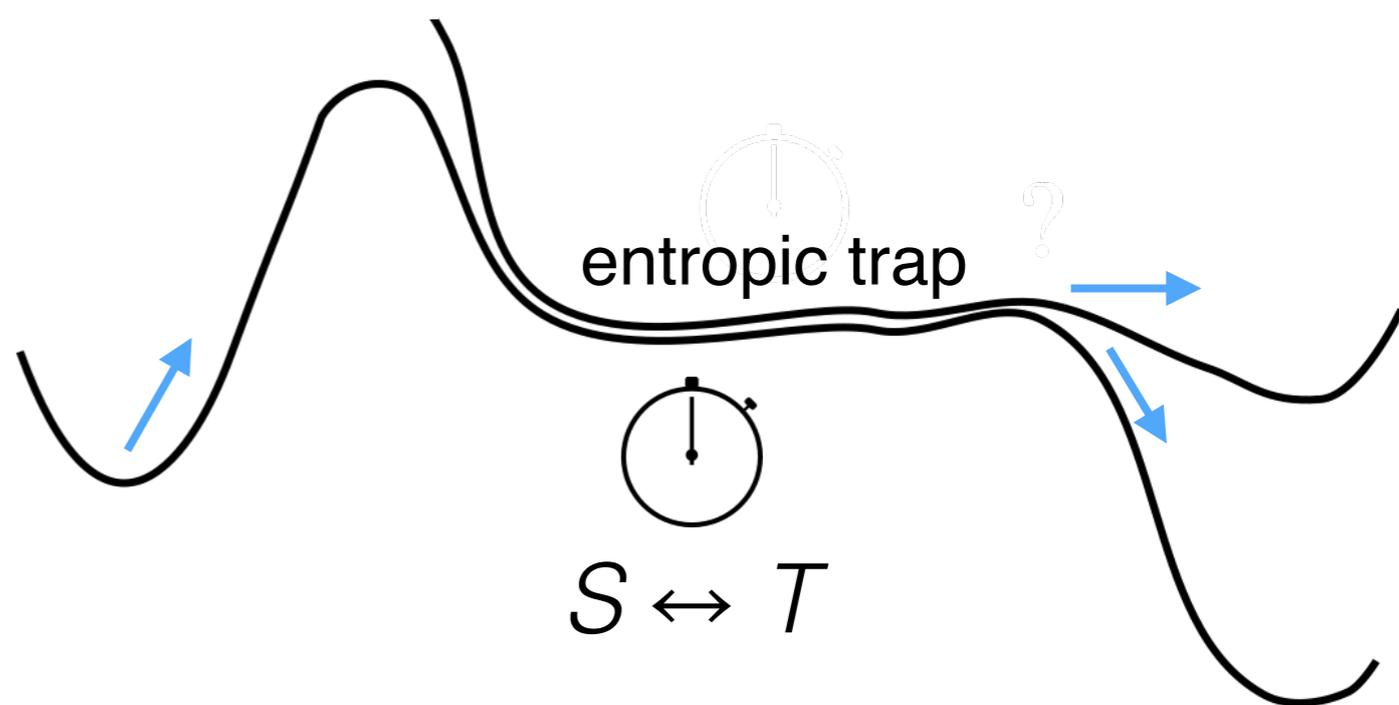
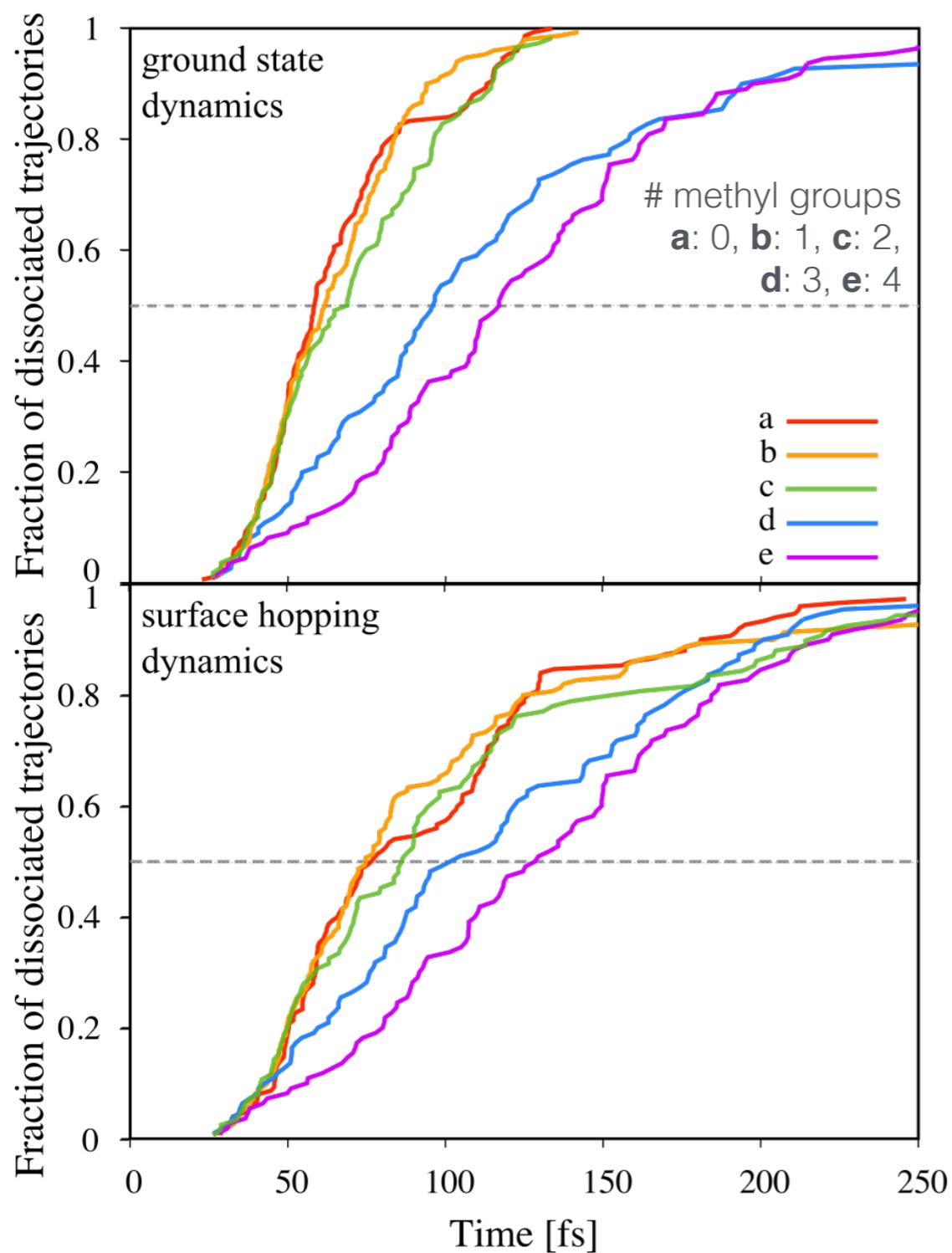
Effect of methyl substitution



➔ The longer the system stays in the entropic trap, the more population is transferred from S to T and the higher the chemiexcitation yield is.



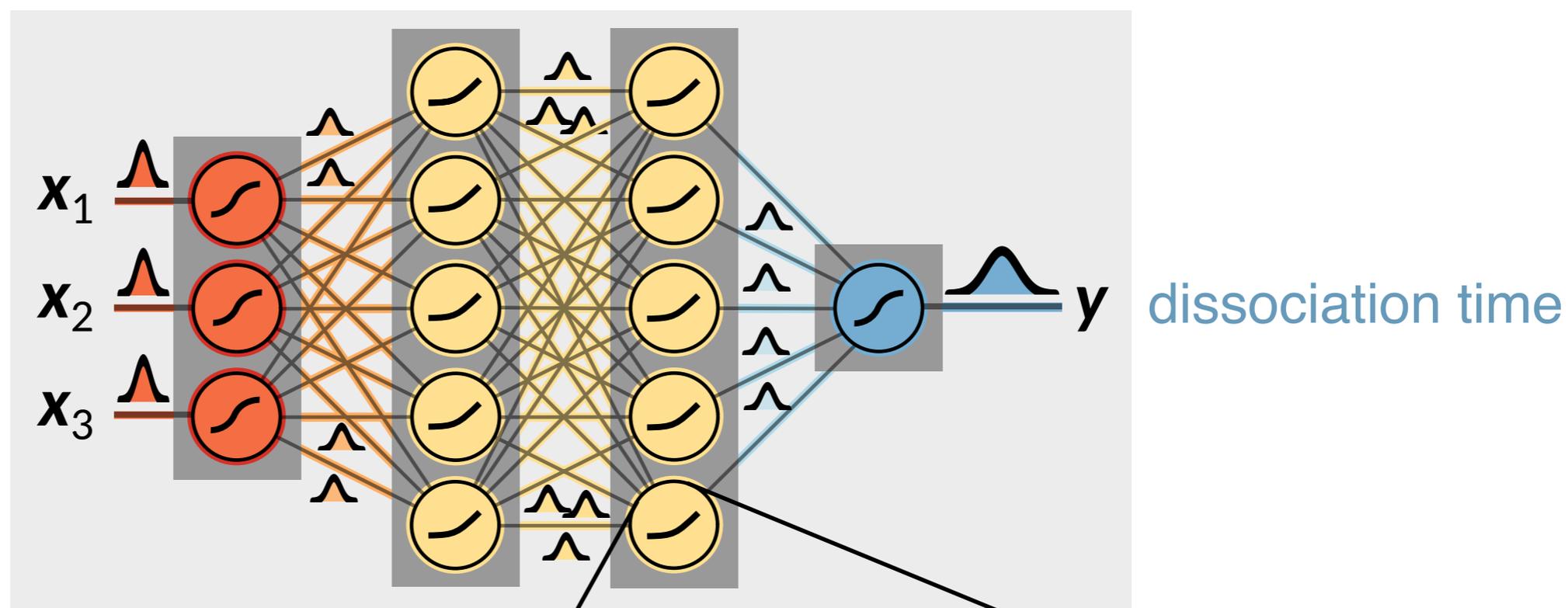
Effect of methyl substitution



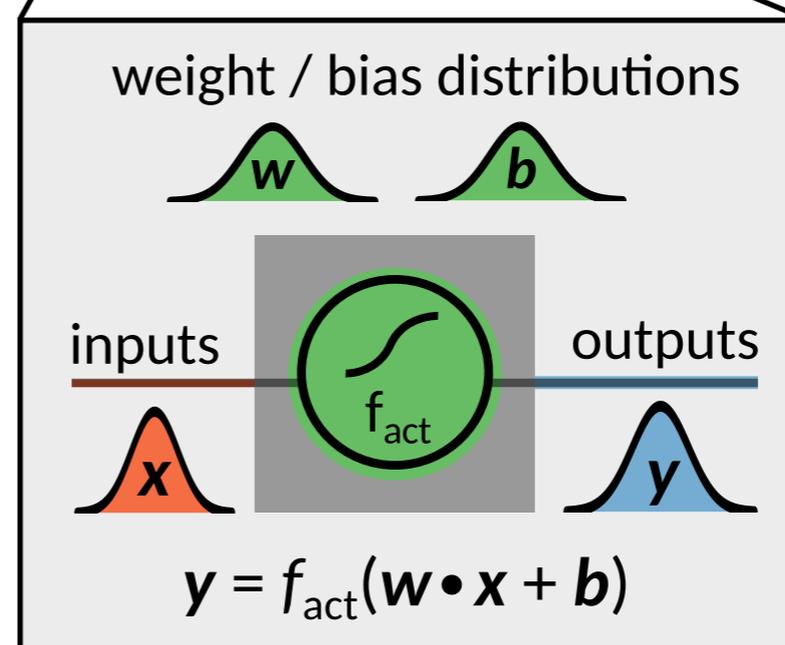
Prediction of dissociation time

BNN1:
initial nuclear
geometry

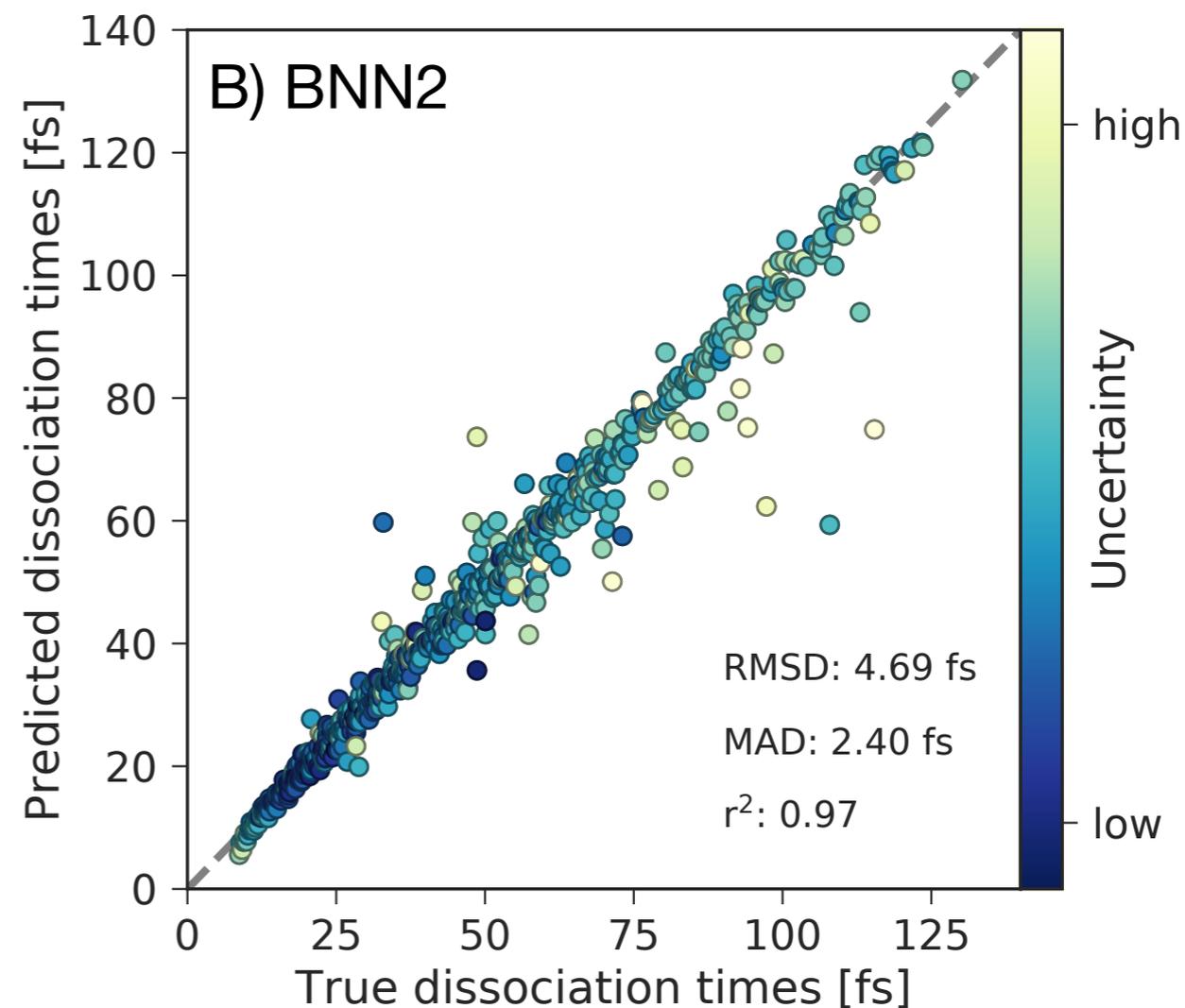
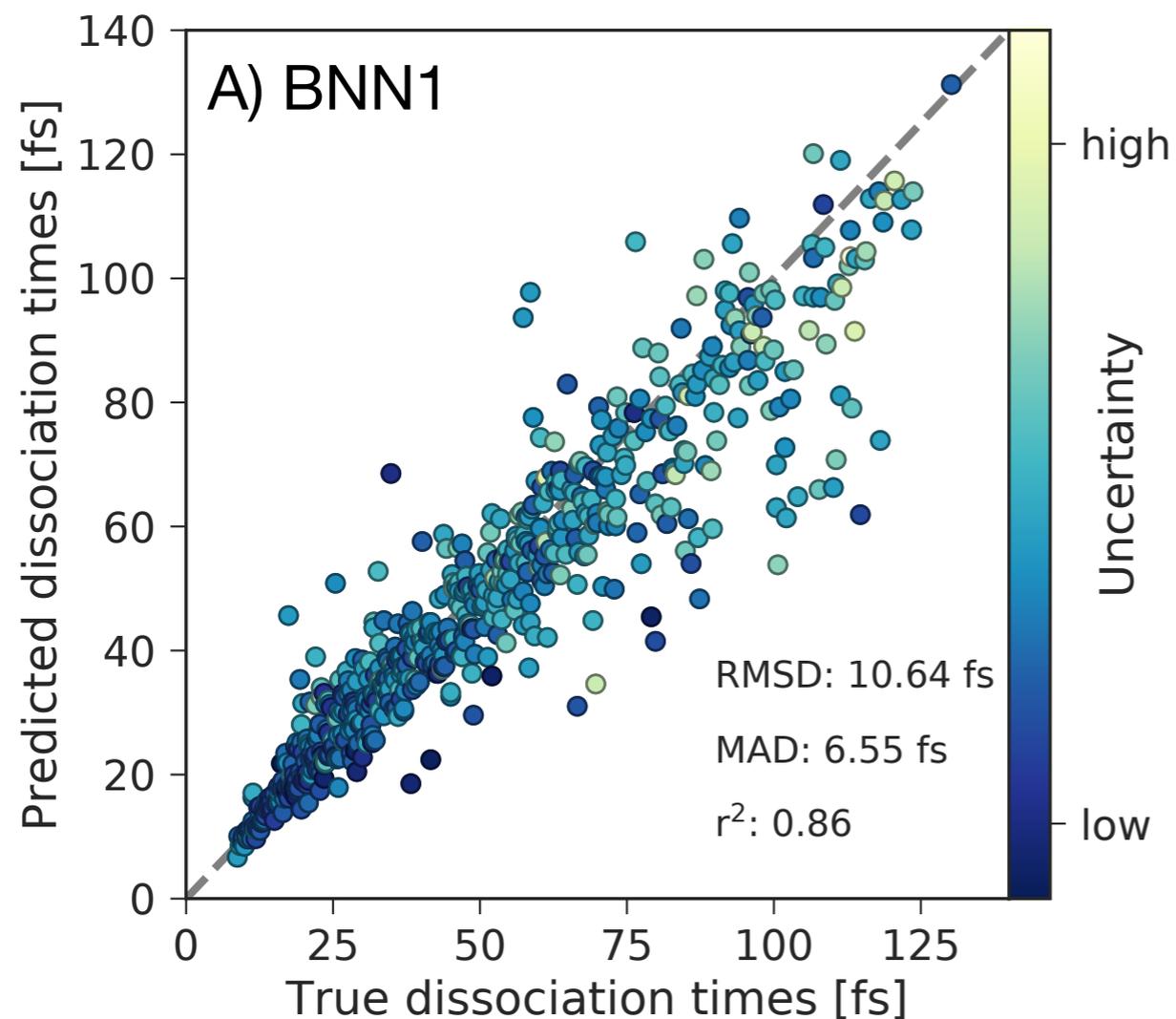
BNN2:
+ nuclear
velocities



4 layers of 130 neurons
Activation function: Leaky ReLU

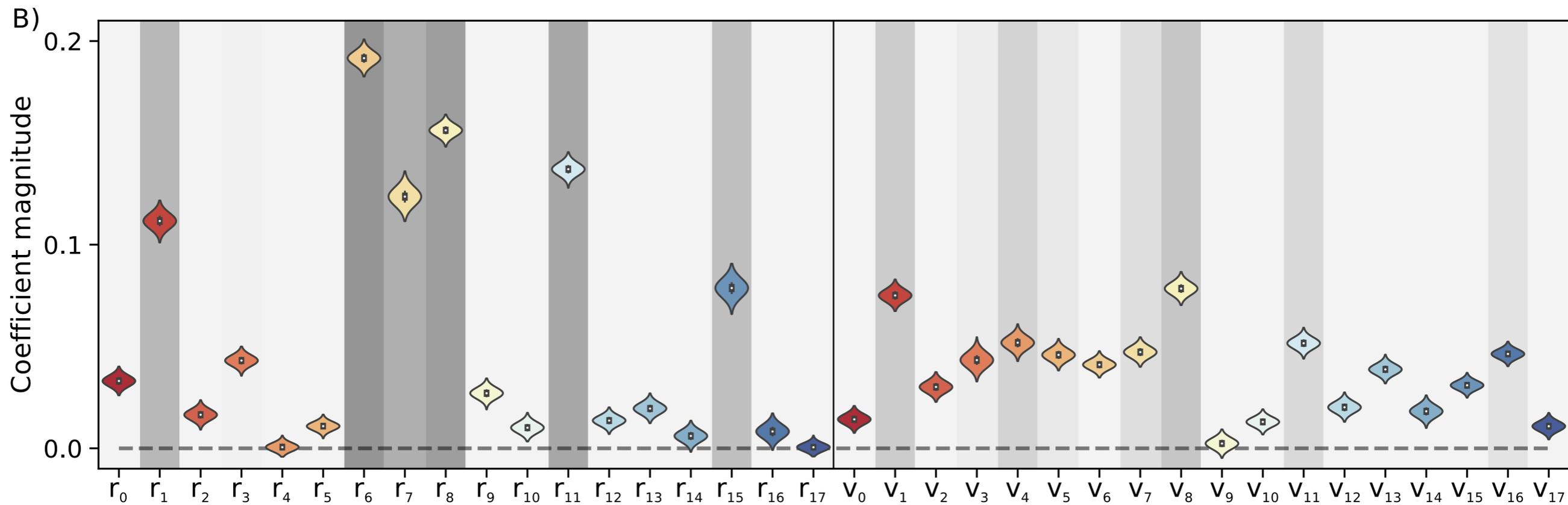
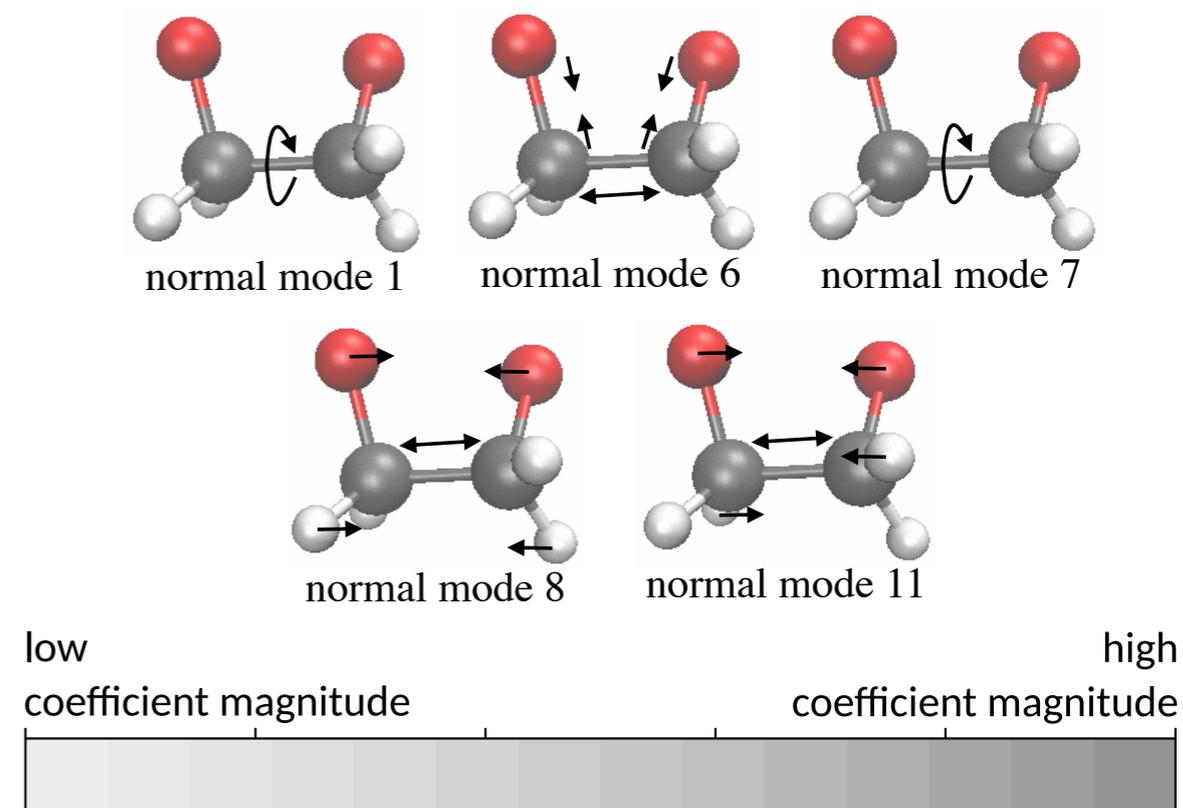
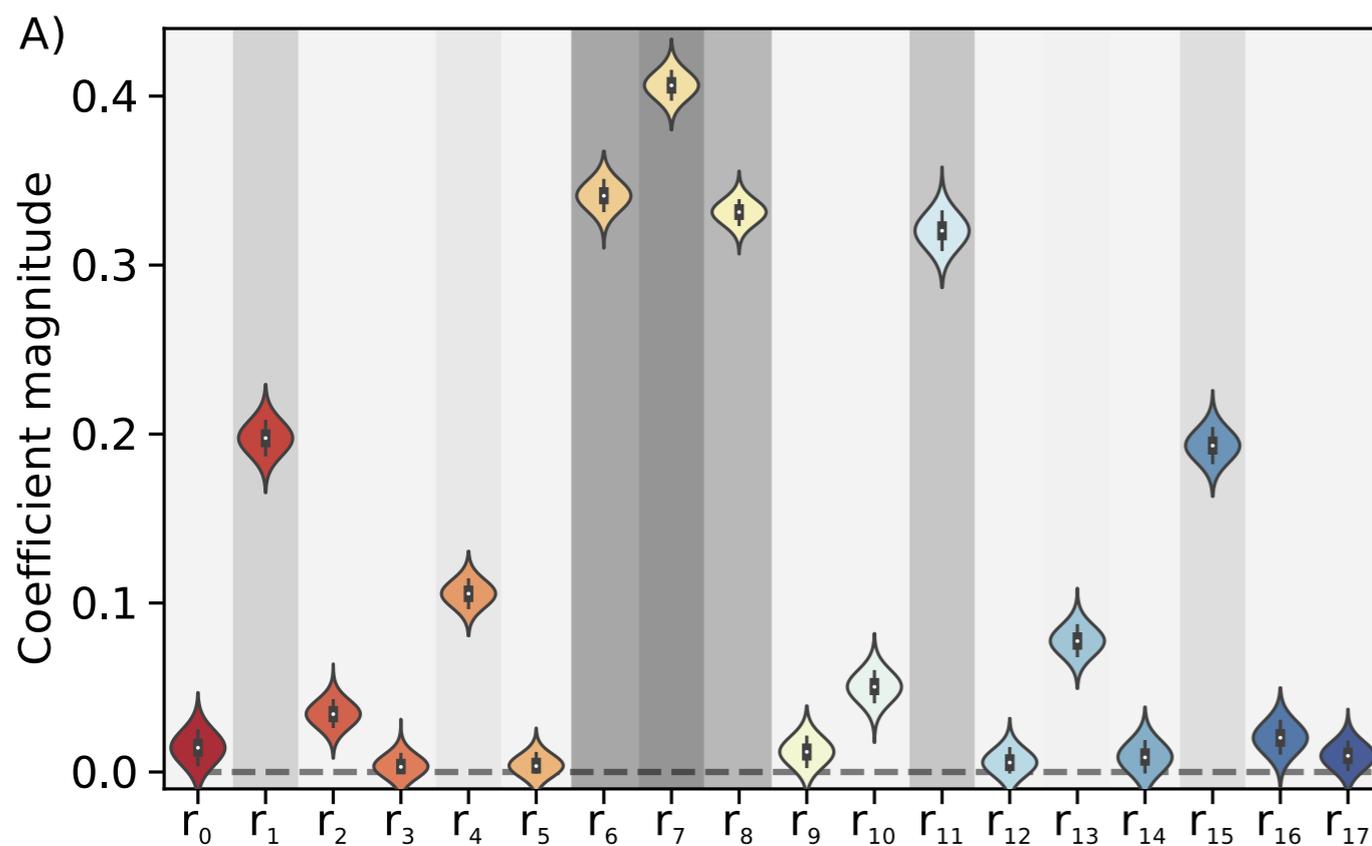


Prediction of dissociation time



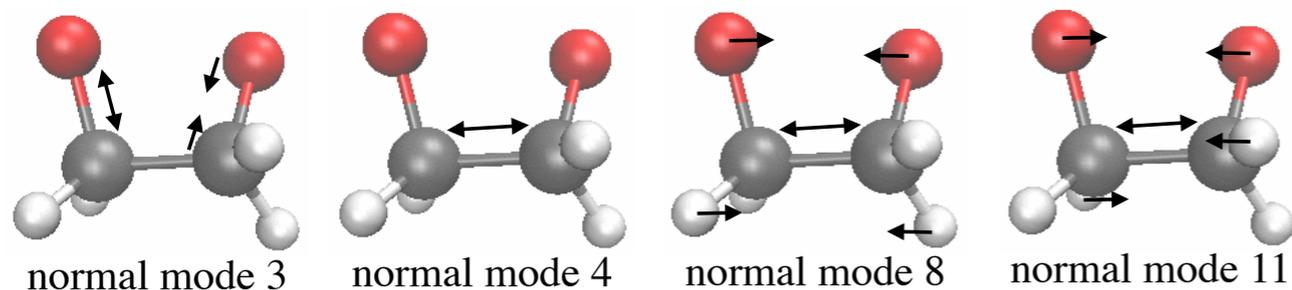
→ Accurate predictions of the dissociation times of 1,2-dioxetane

Analysis of the trained BNN 1

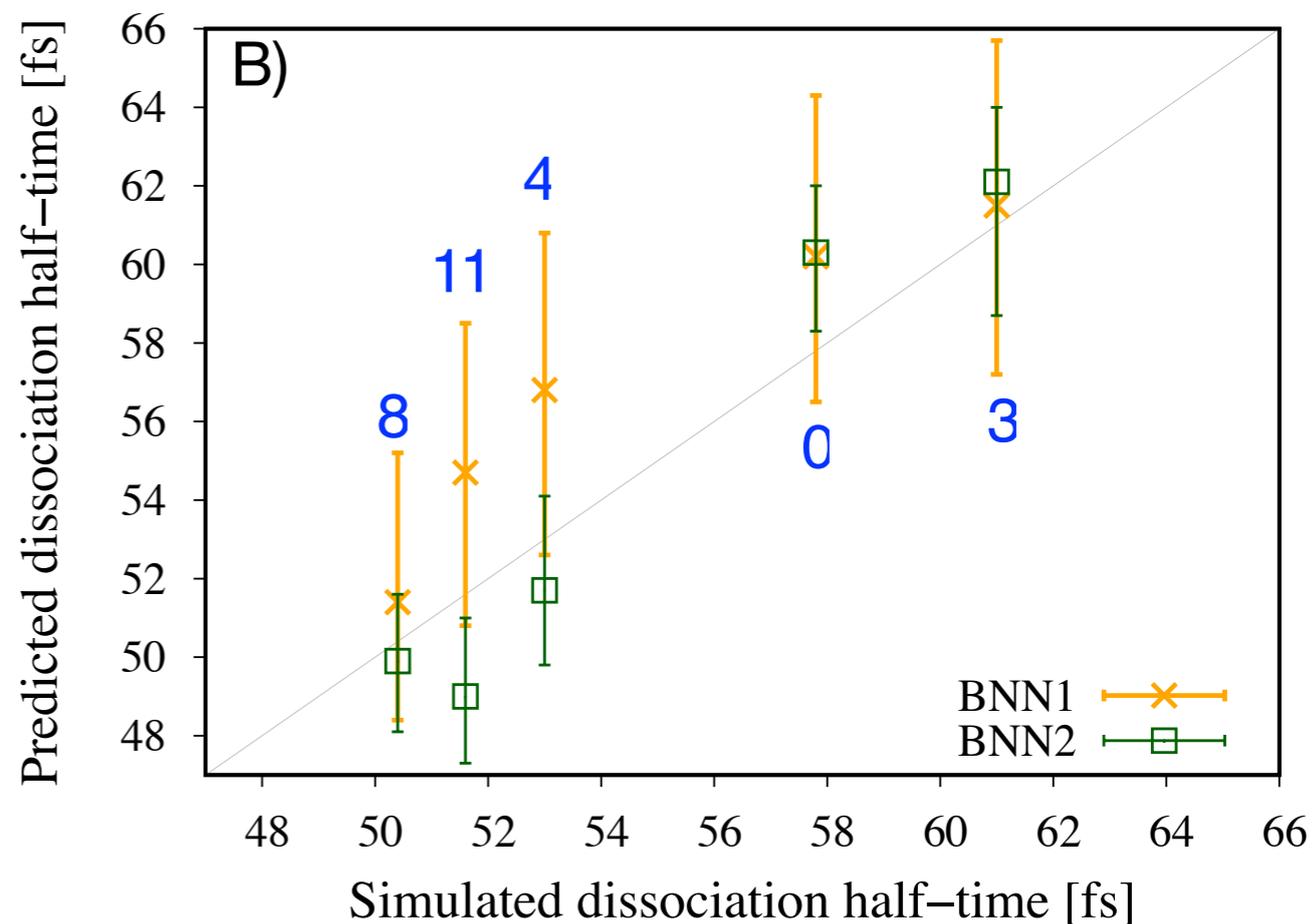
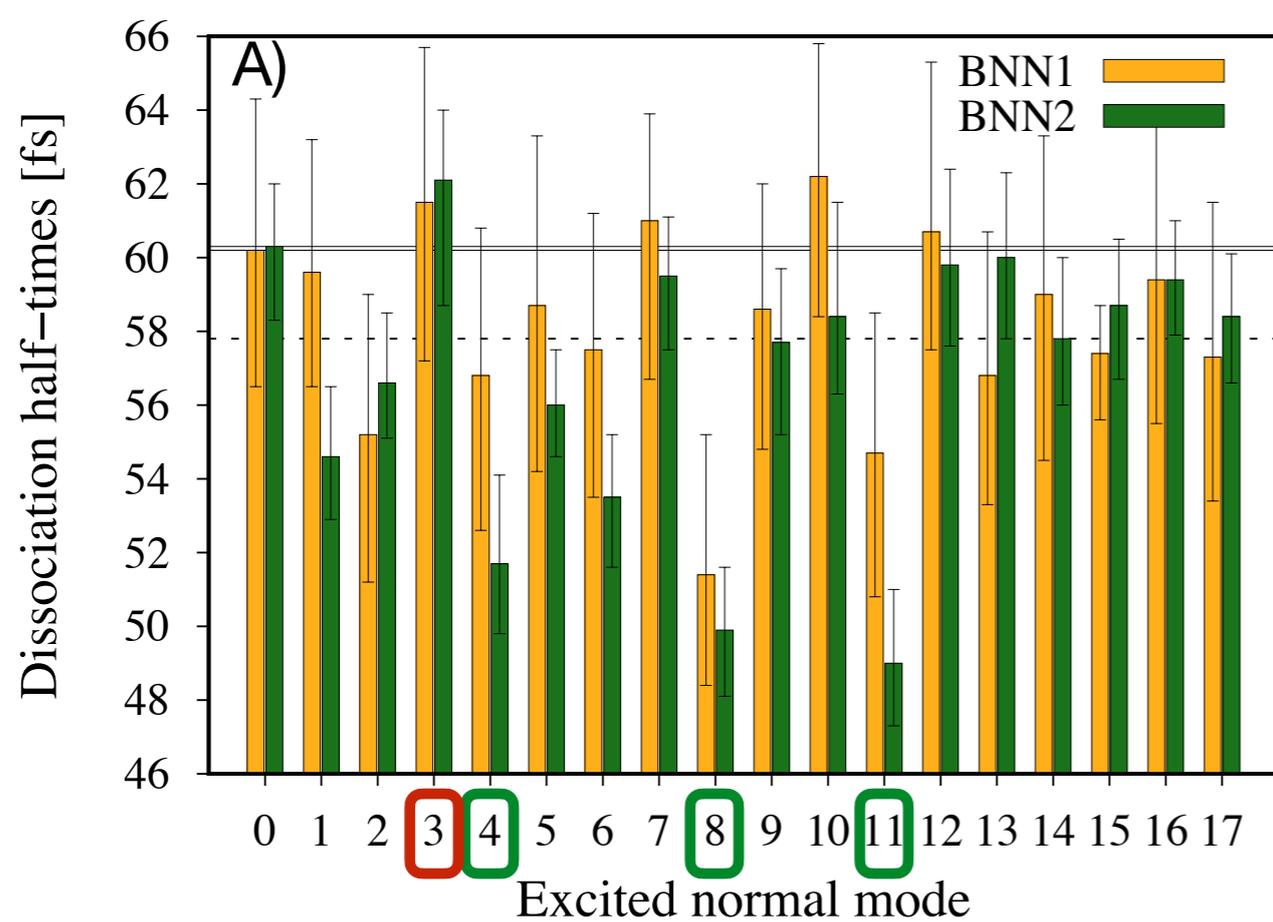


Analysis of the trained BNN 2

- ❖ Predictions of dissociation times for vibrational excited states

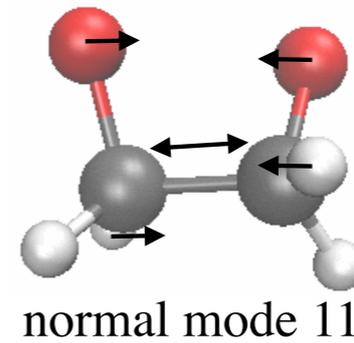
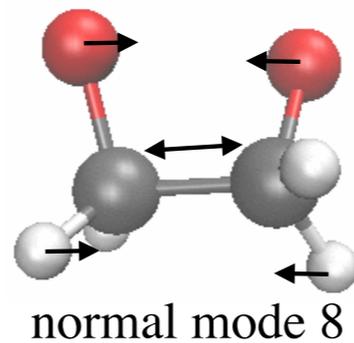
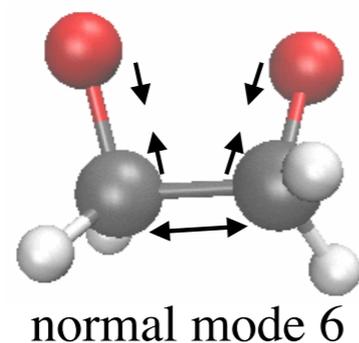


Ensemble	8	11	4	3
N_{frus}	1.08	1.17	1.18	1.52



Interpretation of the trained BNN

→ Correlation between nuclear coordinates and dissociation times

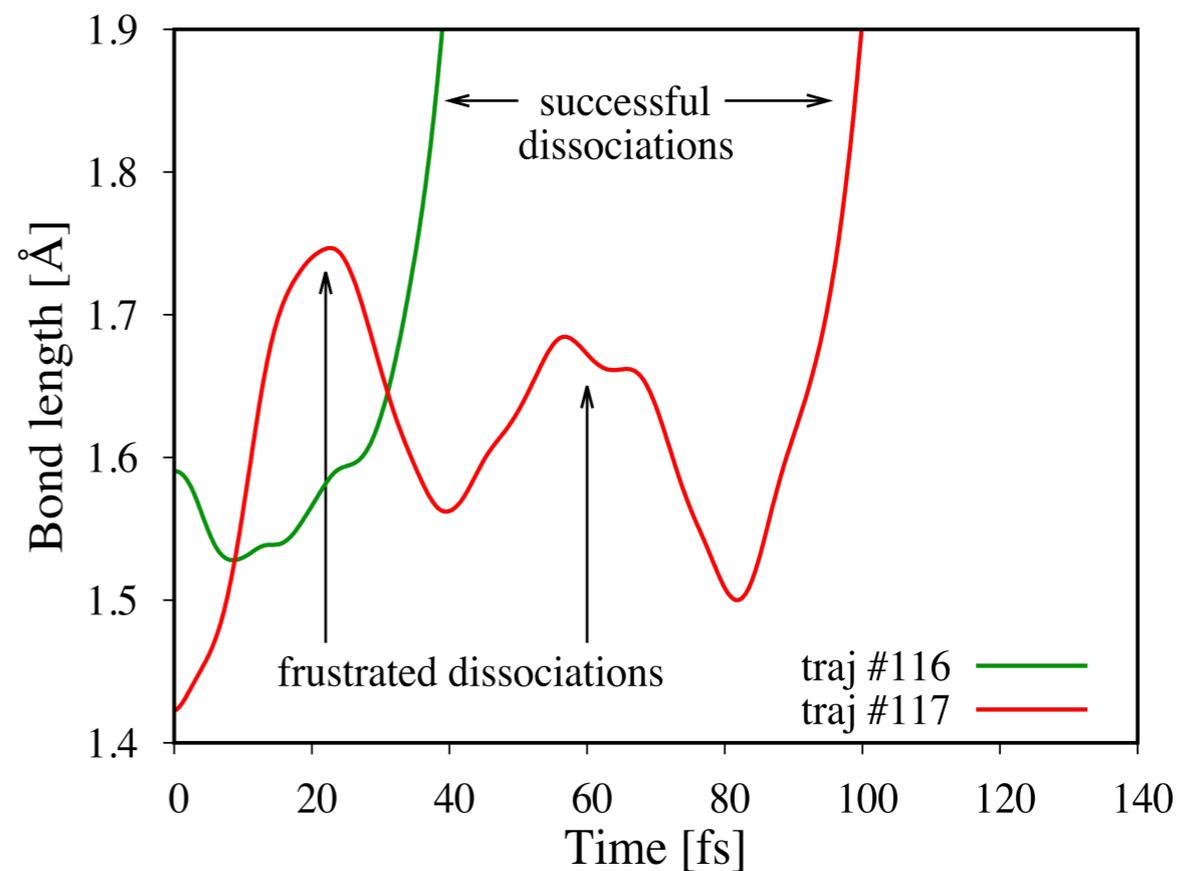
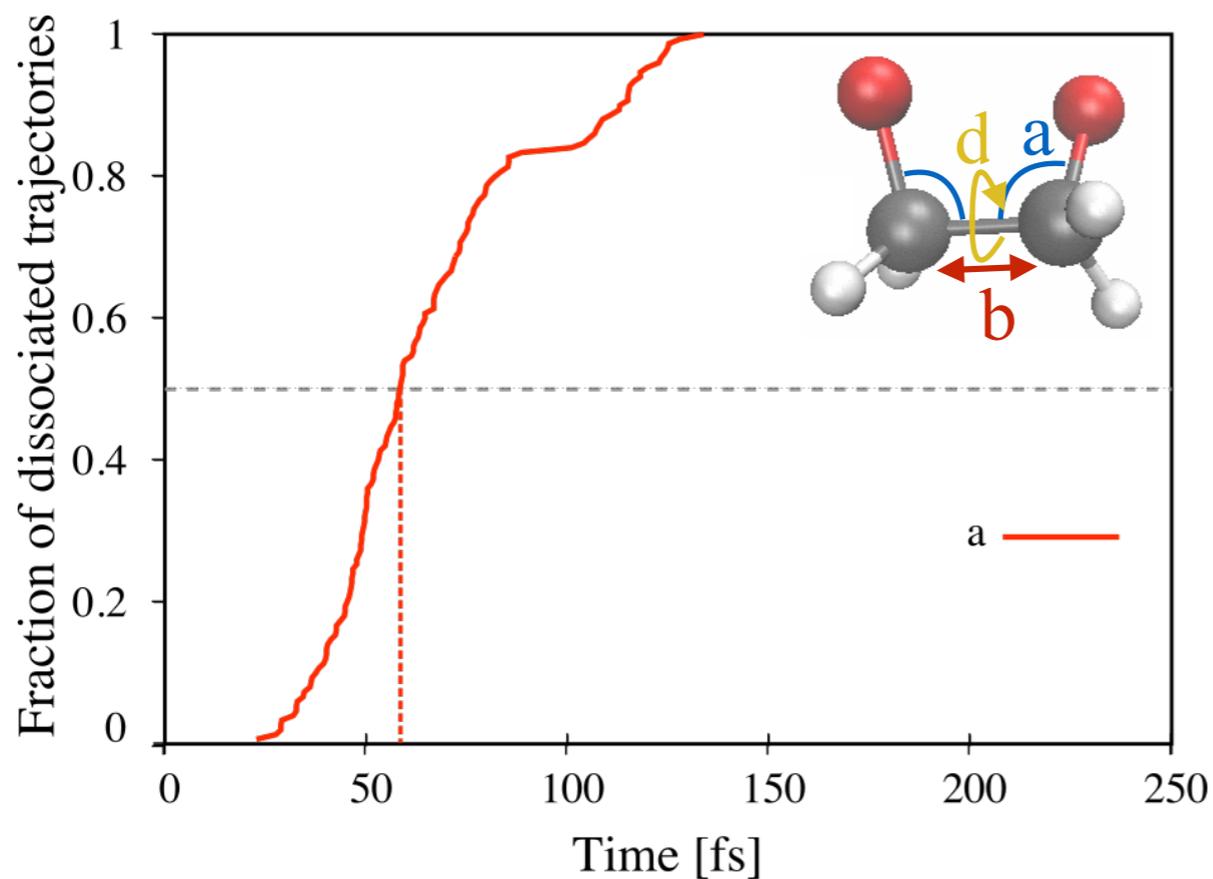


... related to empirical rules known today as:

- octet rule
- relation between bond order and bond length
- orbital hybridisation / valence shell electron pair repulsion (VSEPR) model

This is chemistry !

“Frustrated” dissociations

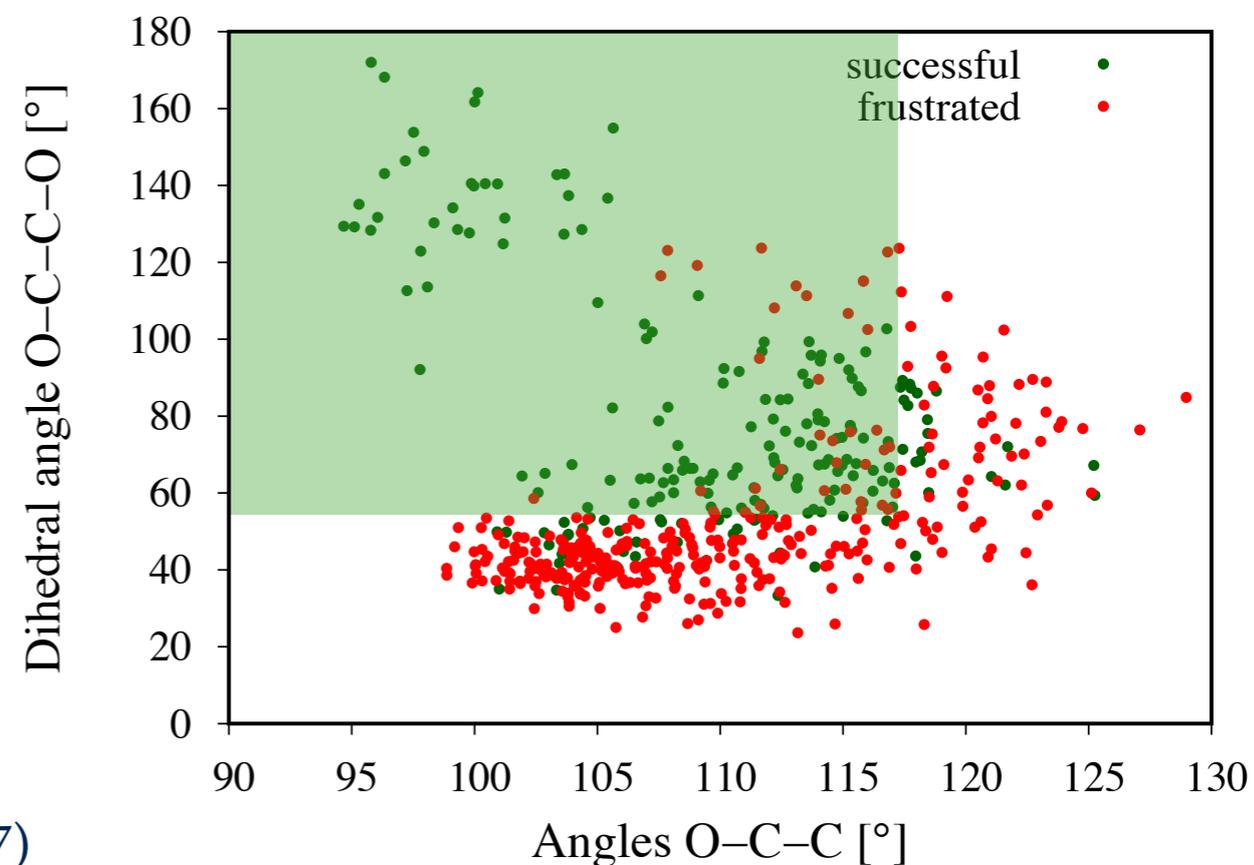


→ Dissociation time scale
between $t = 25$ fs and $t = 140$ fs
half-time of 59 fs

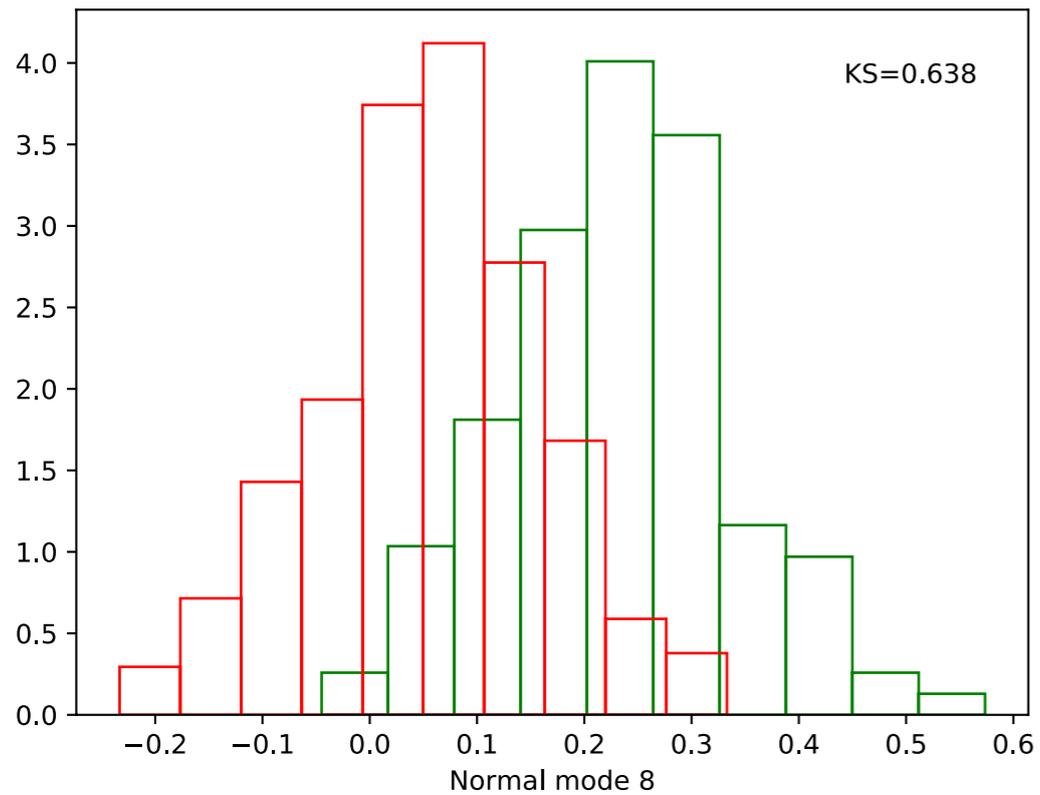
→ Geometrical conditions necessary

O-C-C-O dihedral $> 55^\circ$

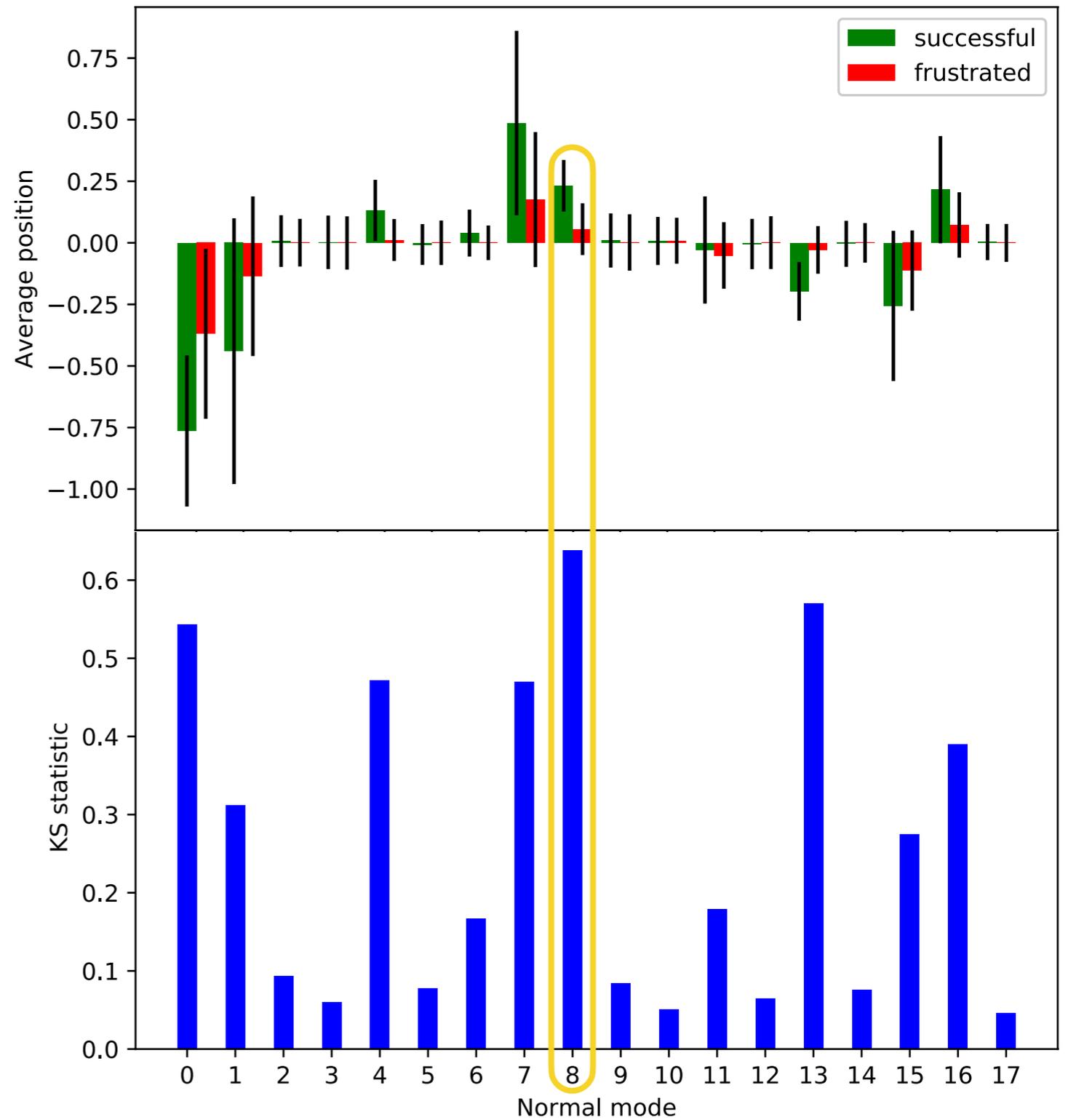
O-C-C angle $< 117^\circ$



“Frustrated” dissociations - revisited



KS = Kolmogorov–Smirnov

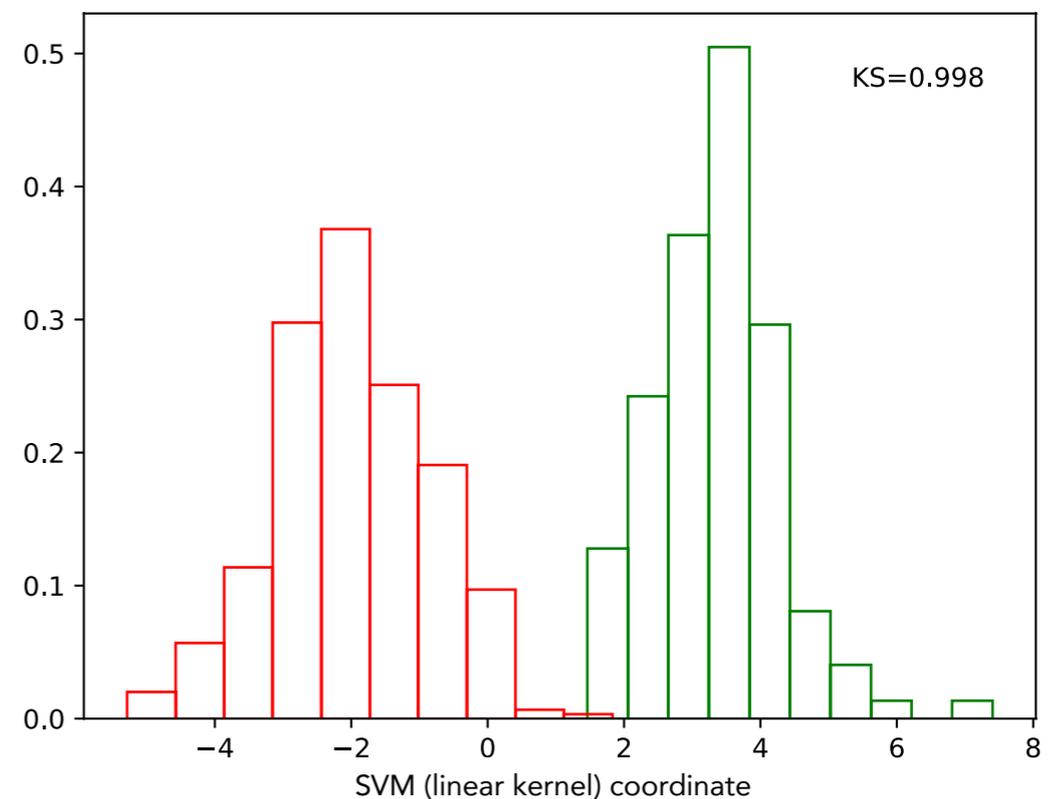
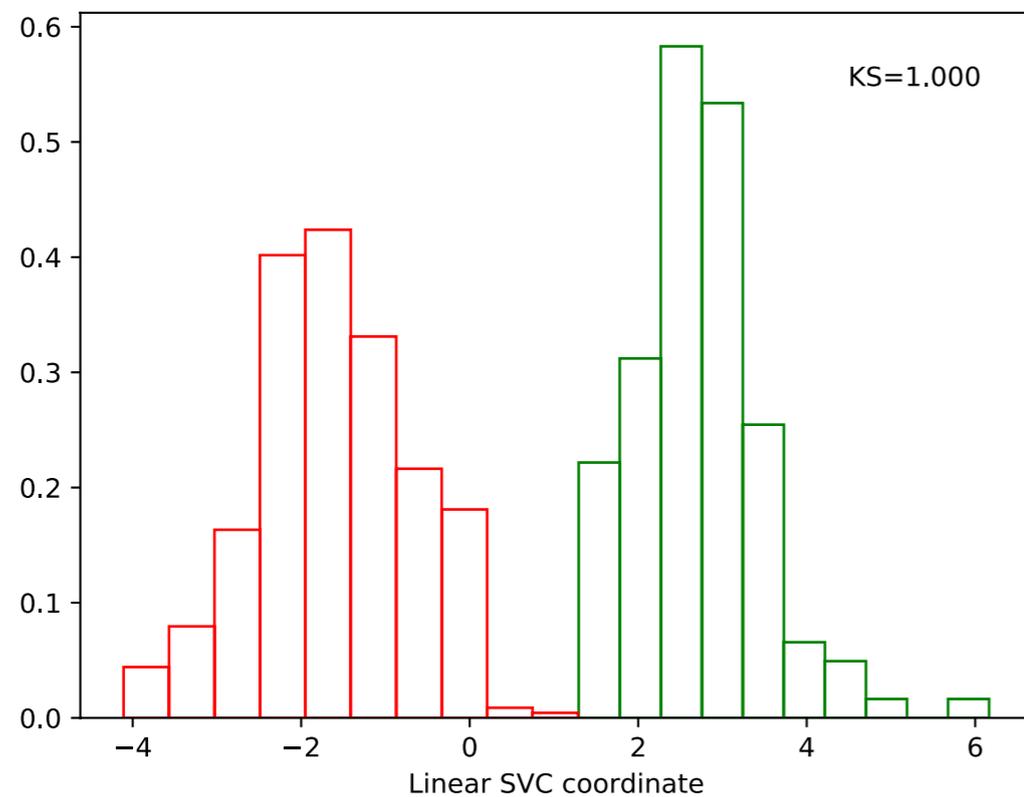
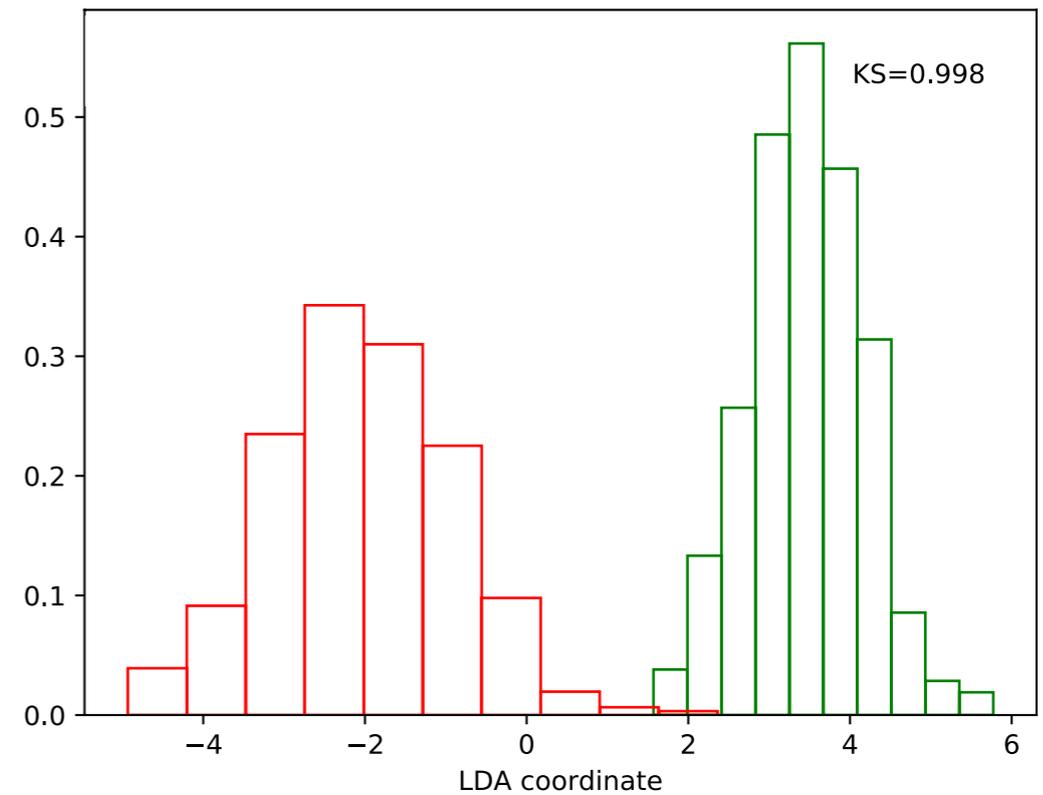
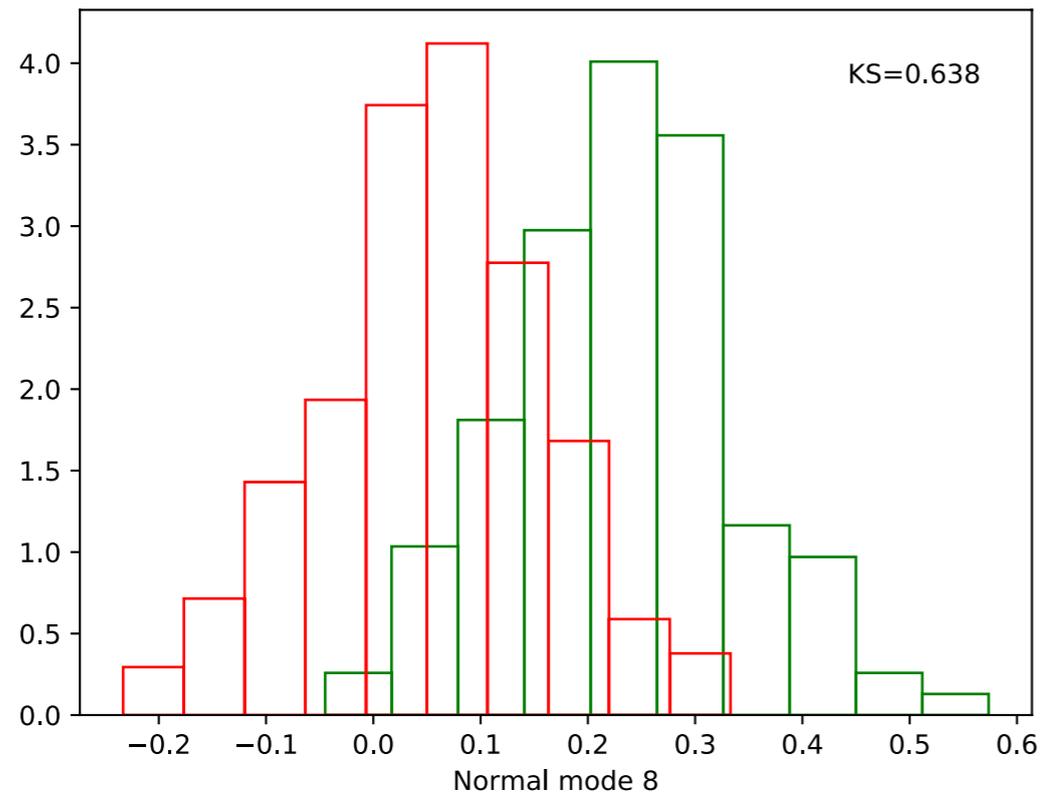


“Frustrated” dissociations - revisited

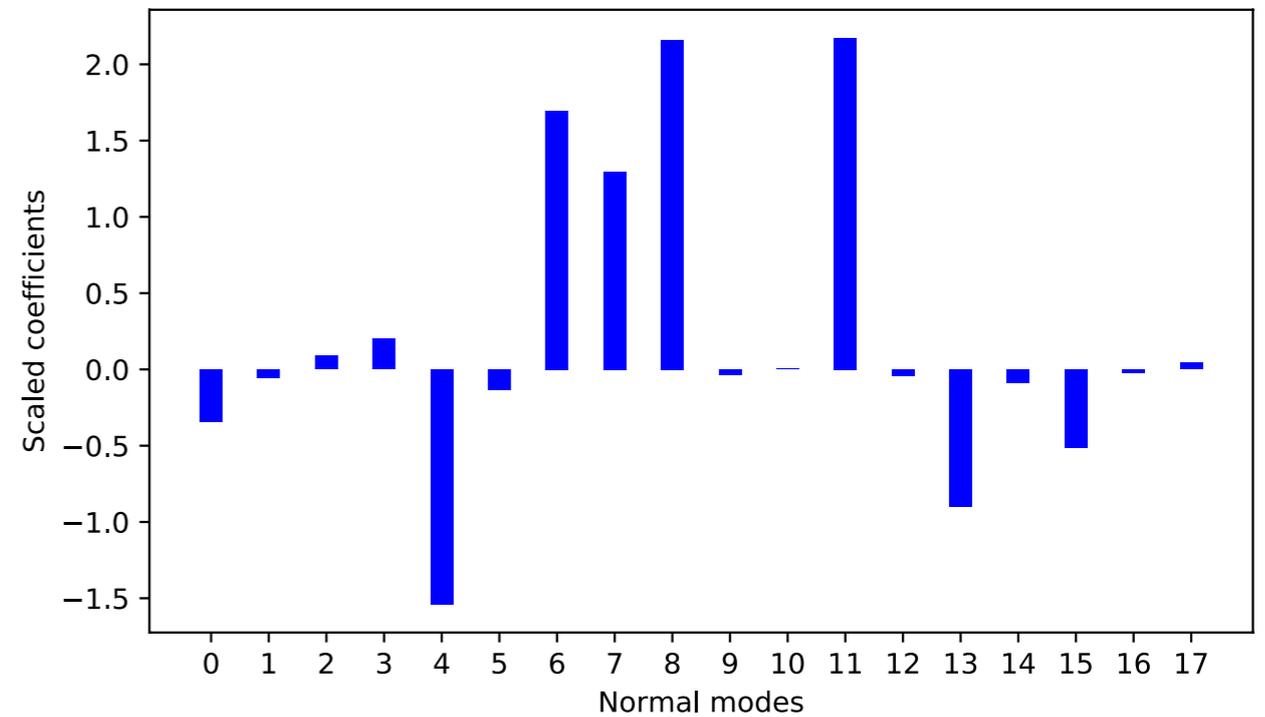
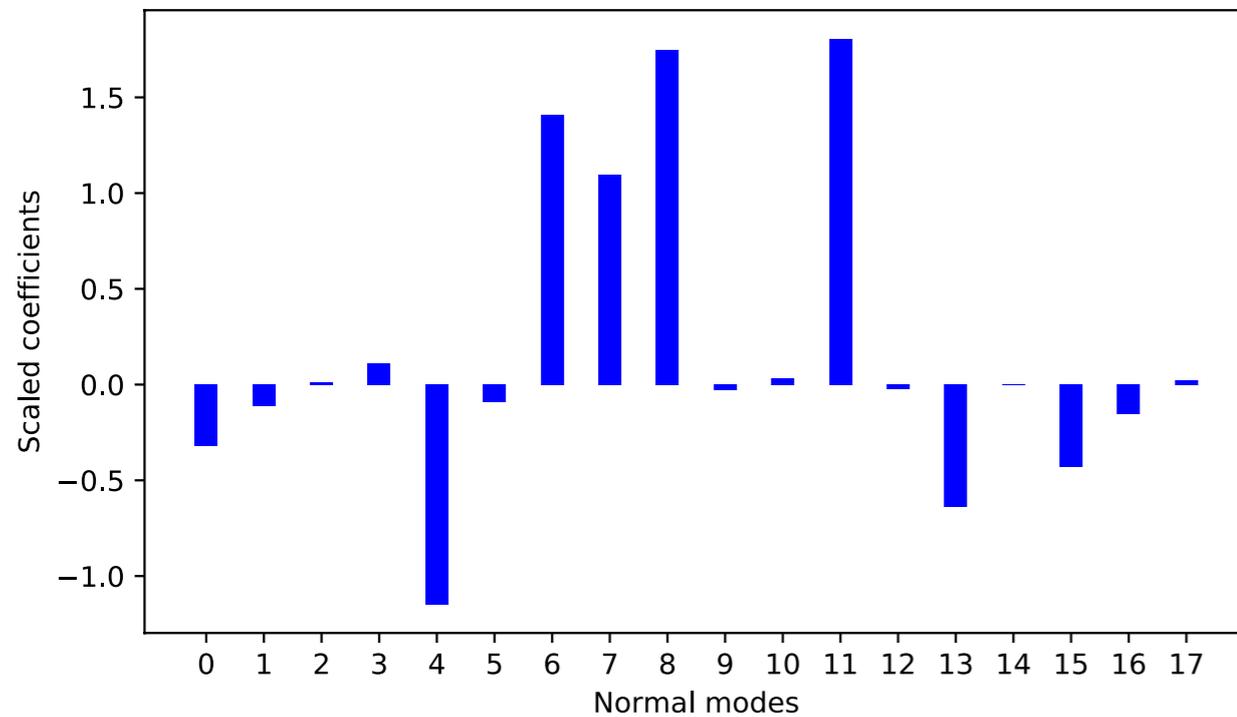
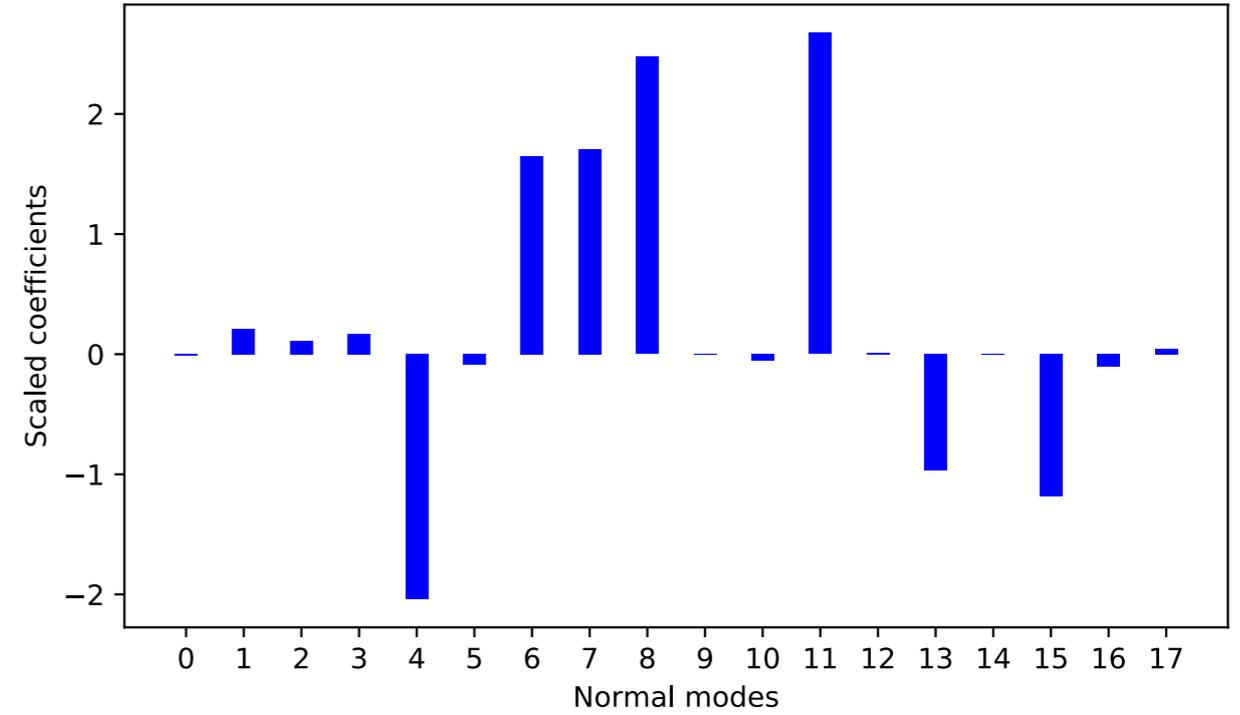
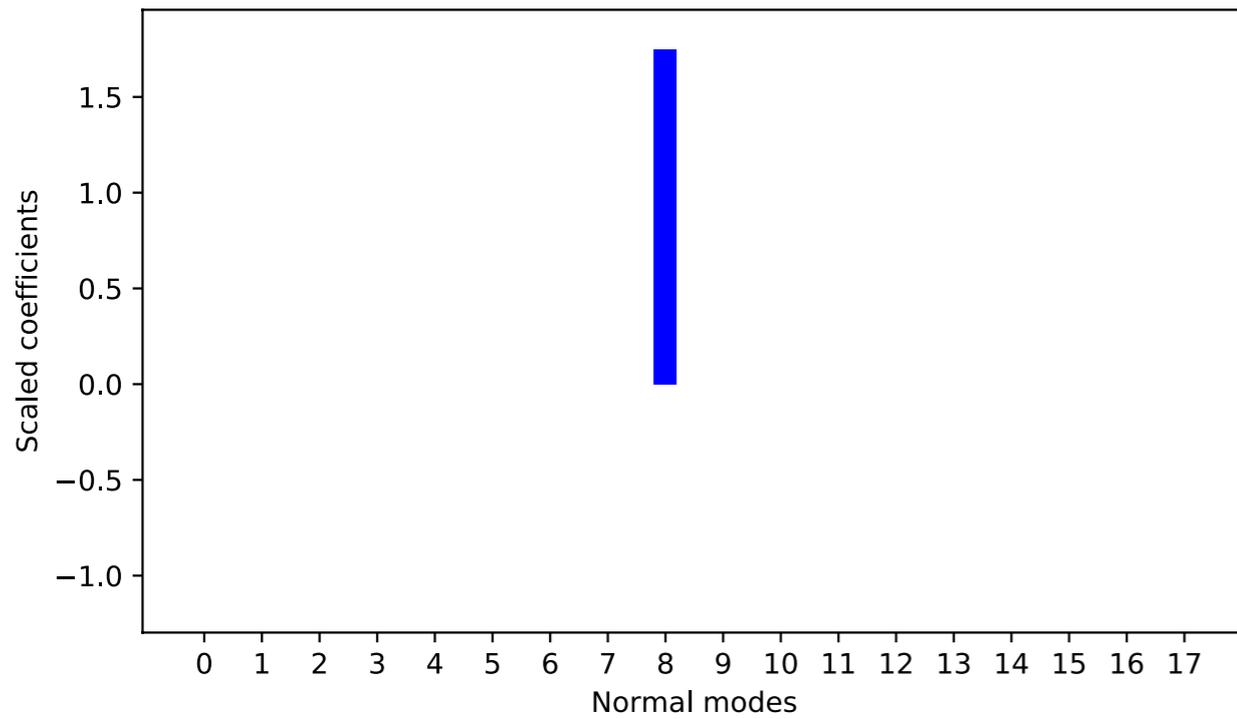
Three different standard machine learning classifiers:

- linear discriminant analysis (LDA)
- linear support vector classification (SVC)
- support vector machines (SVM) with a linear kernel

“Frustrated” dissociations - revisited

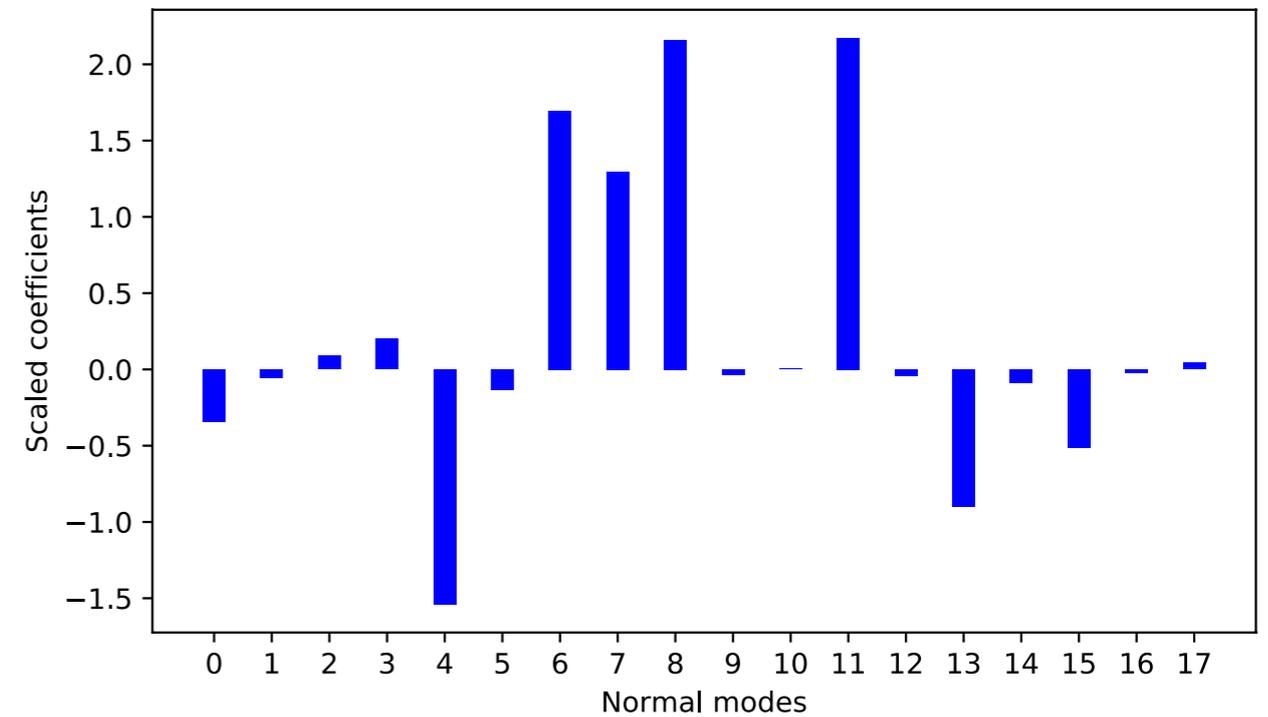
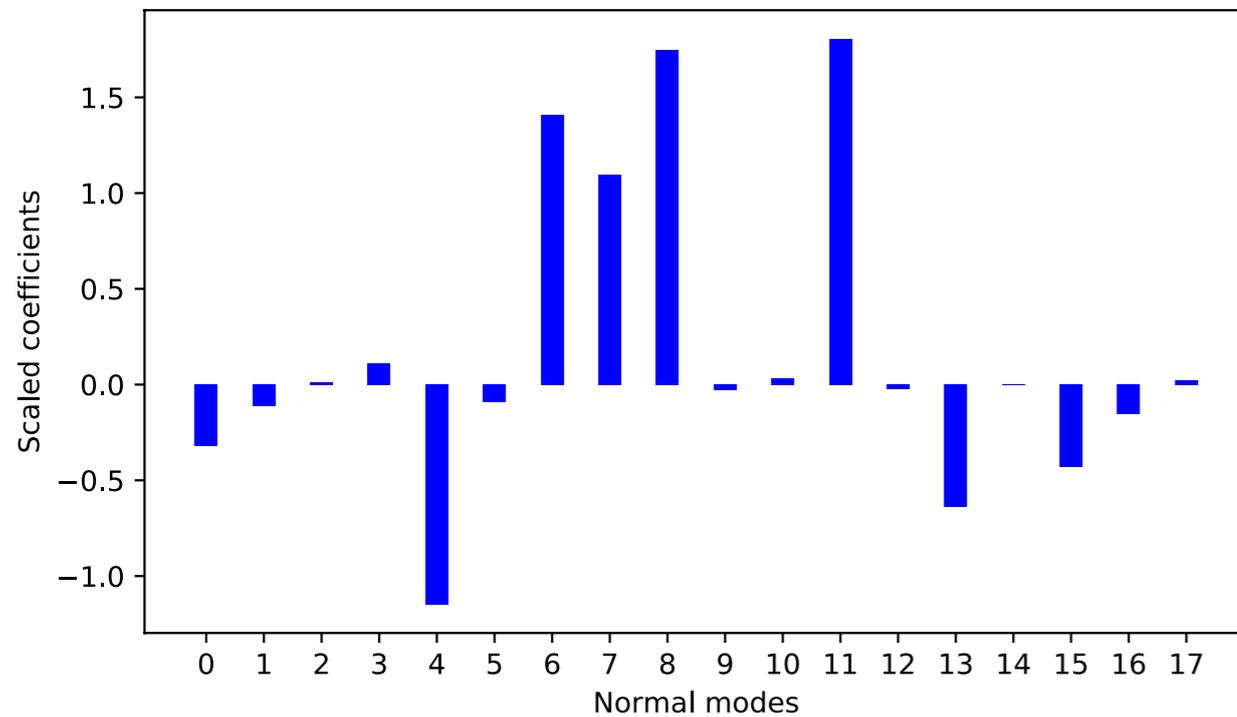
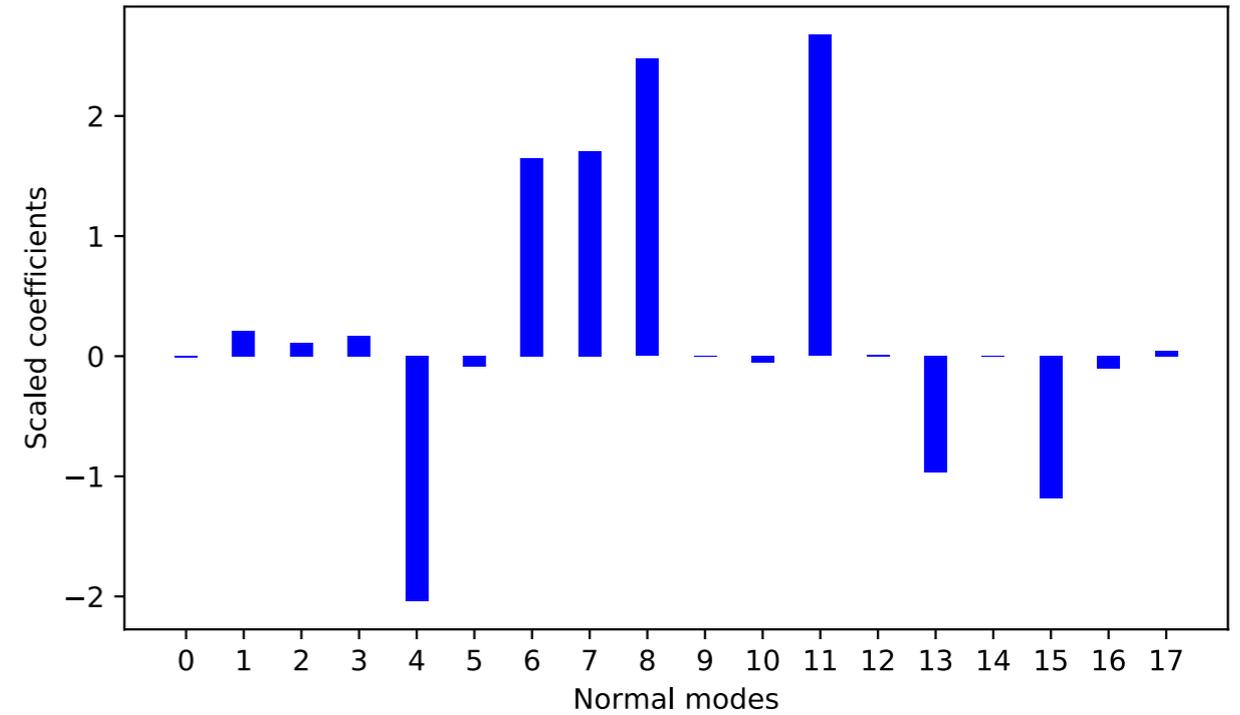


“Frustrated” dissociations - revisited



“Frustrated” dissociations - revisited

→ In-phase planarisation motion of the two formaldehyde moieties



Take home messages

- ❖ Ab initio molecular dynamics simulations are necessary to provide details into the mechanisms and yields of photochemical reactions.
- ❖ Machine learning algorithms are able to predict accurately a specific outcome quantity of AIMD simulations. In order to make accurate predictions, the models evidence empirical rules that are, today, part of the common chemical knowledge.
- ❖ Machine learning techniques are also helpful to analyse and further interpret the results produced by the AIMD simulations.
- ❖ This paves the way for new conceptual insights in chemistry where machine analysis would provide a source of inspiration for us.

Acknowledgements



Alán Aspuru-Guzik Florian Häse



Thank you!

Häse, Fdez Galván, Aspuru-Guzik,
Lindh and Vacher, *Chem. Science*,
10, 2298-2307 (2019)

Häse, Fdez Galván, Aspuru-Guzik,
Lindh and Vacher, *J. Phys. Conf. Series*,
1412, 042003 (2020)

