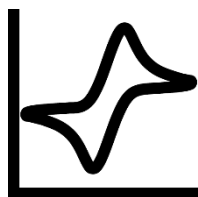


Accelerating optimization in synthetic chemistry through ML approaches

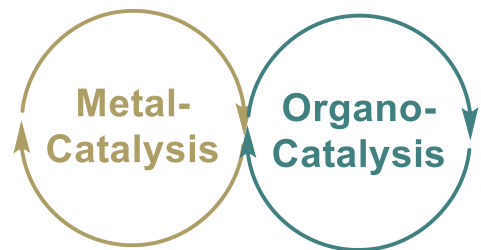


Dr Laurence Grimaud
laurence.grimaud@ens.psl.eu

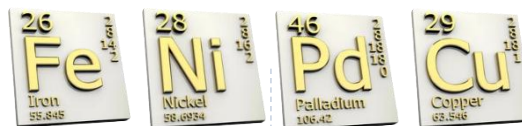




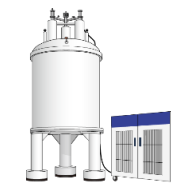
Catalysis



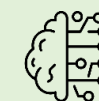
Methods & Mechanisms



Mechanistic Studies



Isocyanides : Photocatalysis and Electrosynthesis



Machine Learning



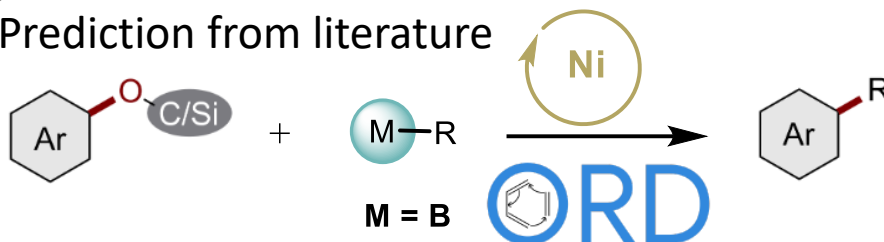
Predicted yields, properties
Accelerating optimization

AI in our lab

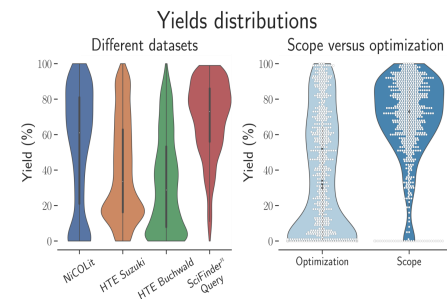


Pr Rodolphe
Vuilleumier (ENS)

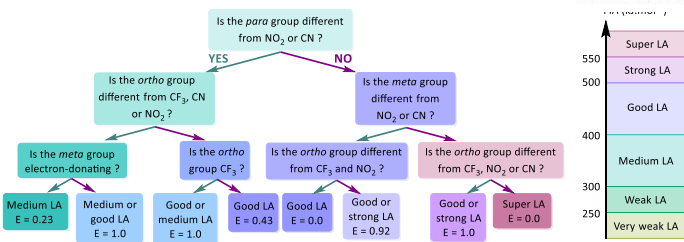
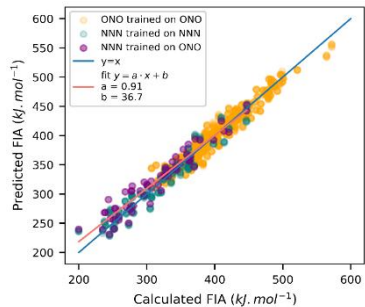
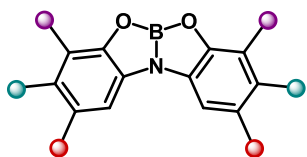
Prediction from literature



J. Am. Chem. Soc., **2022**, *144*, 14722

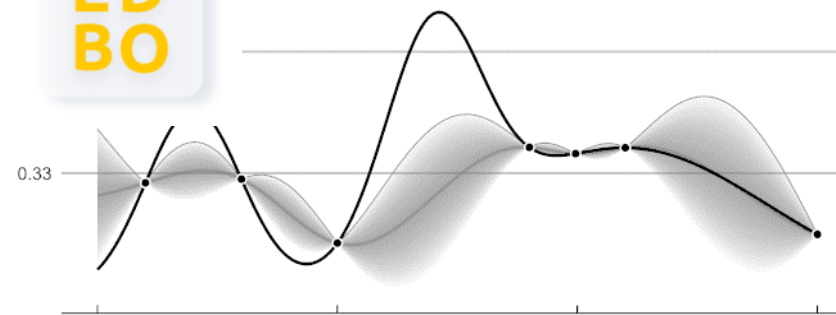
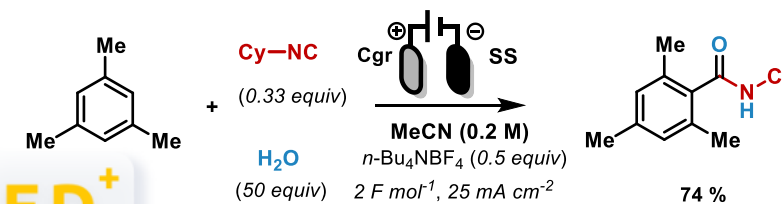


Prediction of Properties



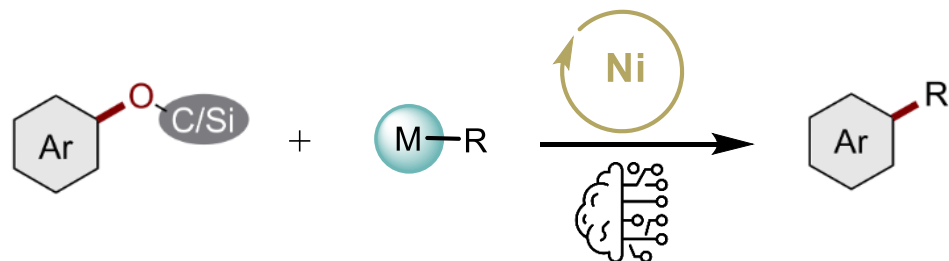
Digital Discovery **2025**, *4*, 3623

Bayesian Optimisation



C. R. Chim. **2026**, accepted. DOI: 10.5802/crchim.431

Predicting reaction yields from a literature-based reaction dataset



Prediction of the yield:

- ✓ Reduced cost
- ✓ Reduced time
- ✓ Reduced resources



Jules Schleinitz



Maxime Langevin

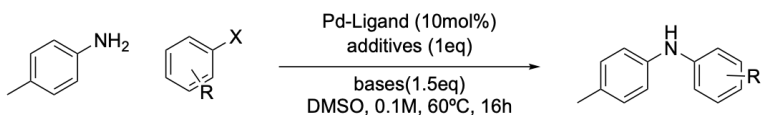


Yanis Smail & Benjamin Wehnert

Chemistry Literature for ML yield prediction ?

How to access quality data ?

HTE

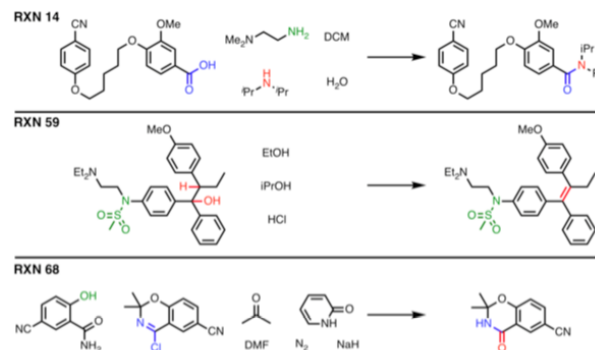


- ✗ Very specific dataset
small chemical space
- ✓ Low report bias
- ✓ Good ML performances

D. Perera, J. W. Tucker, S. Brahmabhatt, C. J. Helal, A. Chong, W. Farrell, P. Richardson, N. W. Sach, *Science* 359, 429 (2018).

D. T. Ahneman, J. G. Estrada, S. Lin, S. D. Dreher, A. G. Doyle, *Science* 360, 186 (2018)

USPTO



- ✓ Very broad dataset
Huge chemical space
- ✗ High report bias towards high yields
- ✗ Poor ML performances

D. M. Lowe, *Ph.D. thesis, University of Cambridge (2012)*

Literature data

CAS
SciFinder[®]

Reaxys[®]
An expert-curated chemistry database

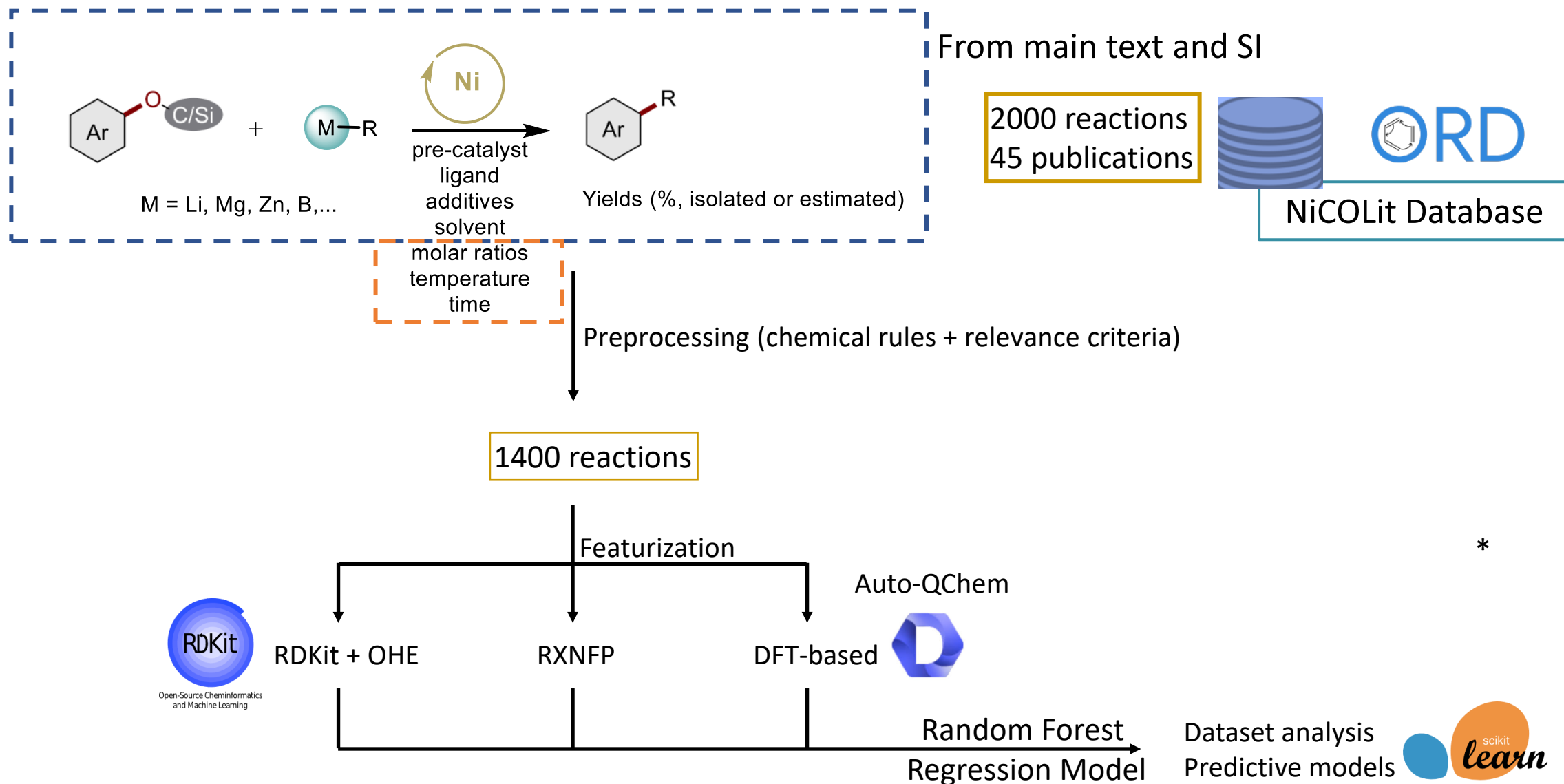


- ✓ Very broad dataset
Huge chemical space
- ✗ High report bias

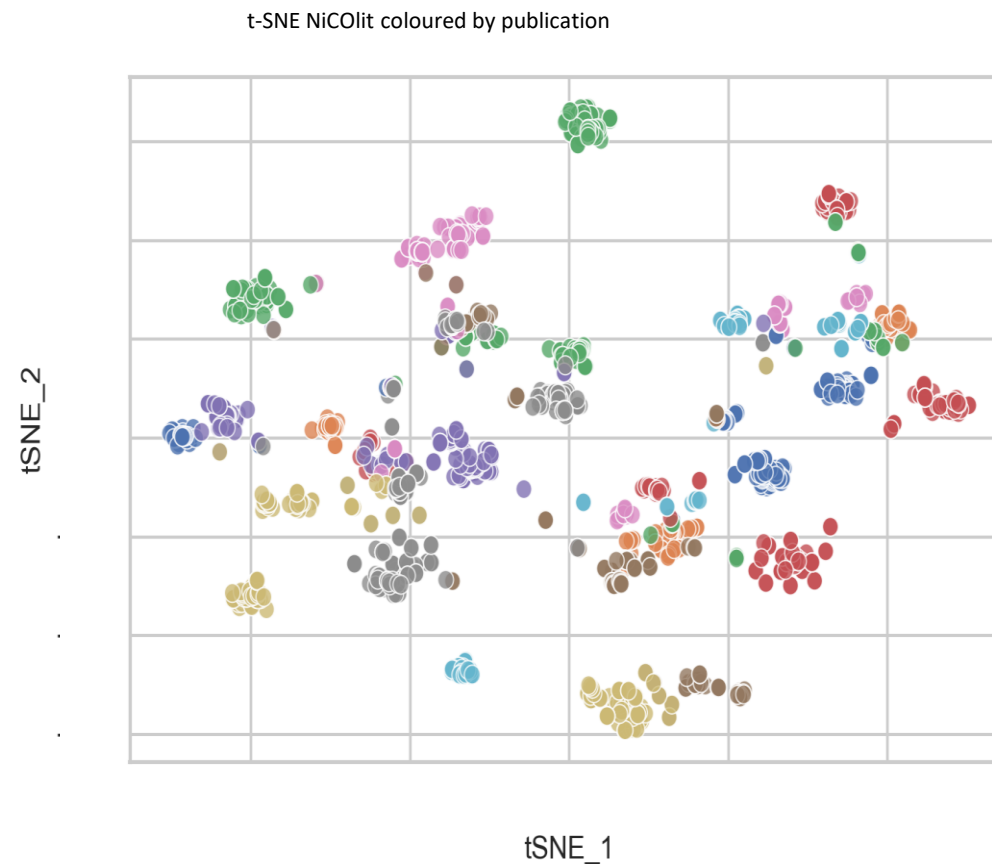
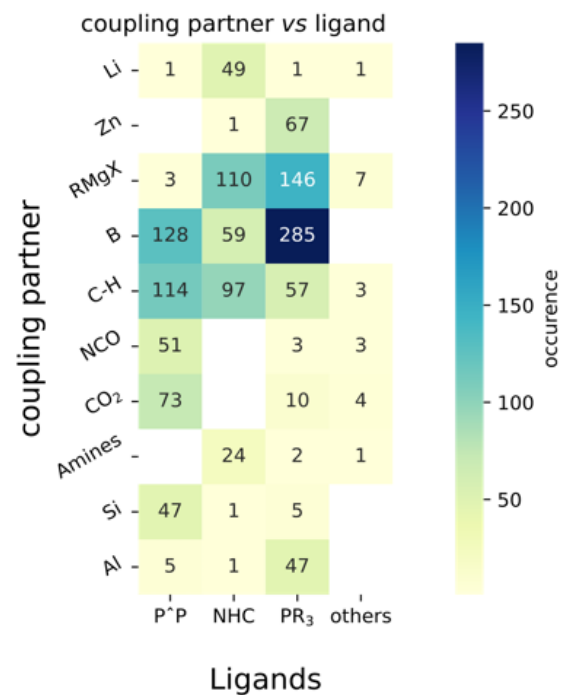
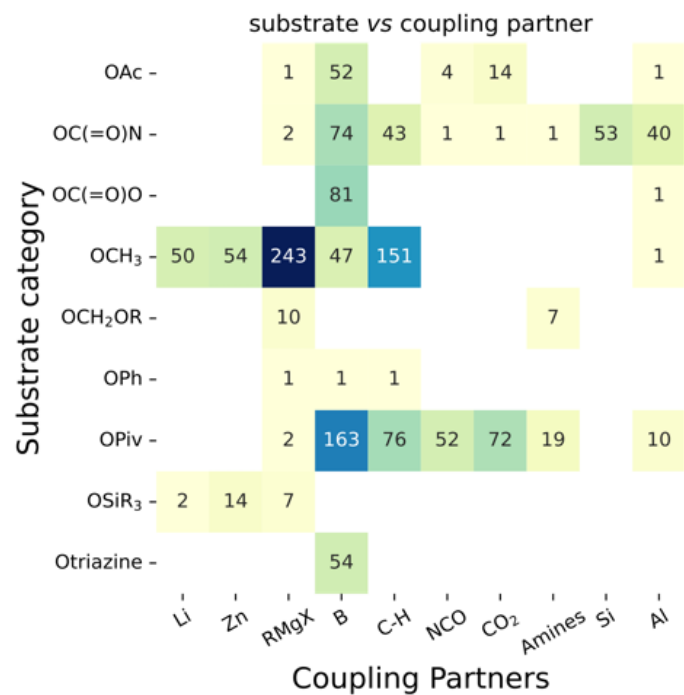
?

Beker, W.; Roszak, R.; Wołos, A.; Angello, N. H.; Rathore, V.; Burke, M. D.; Grzybowski, B. A. *J. Am. Chem. Soc.* **2022**, 10.1021/jacs.1c12005
Strieth-Kalthoff, F.; Sandfort, F.; Kühnemund, M.; Schäfer, F. R.; Kuchen, H.; Glorius, F. *Angew. Chem. Int. Ed.* **2022**, 10.1002/anie.202204647

Manually extracted and curated database

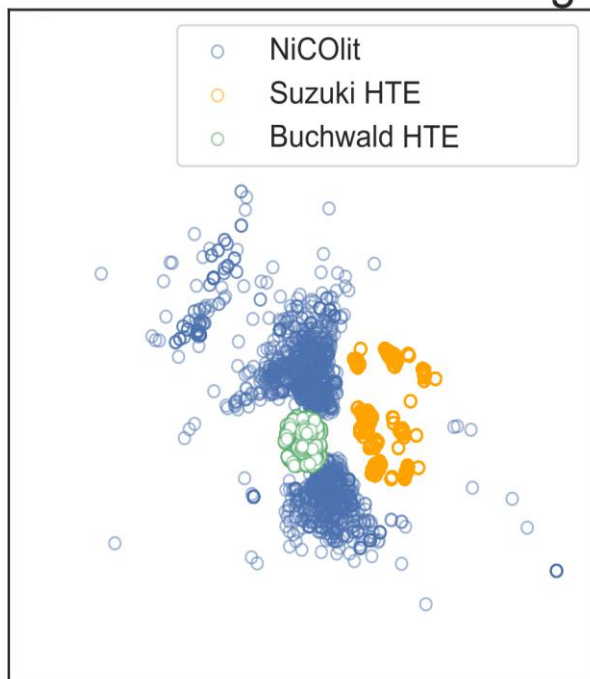


Specific combinations and minimal overlap between publications

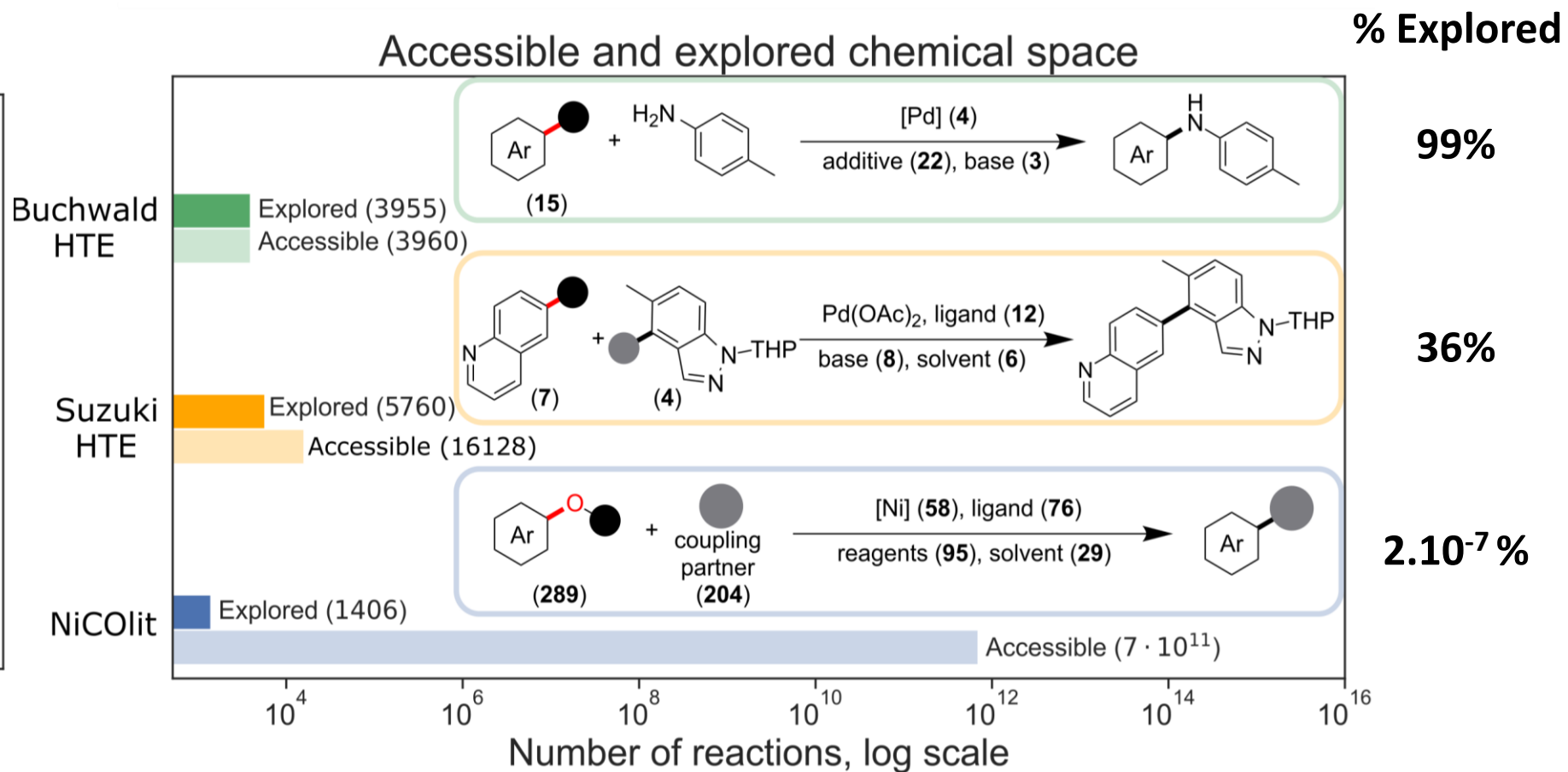


Comparison with HTE

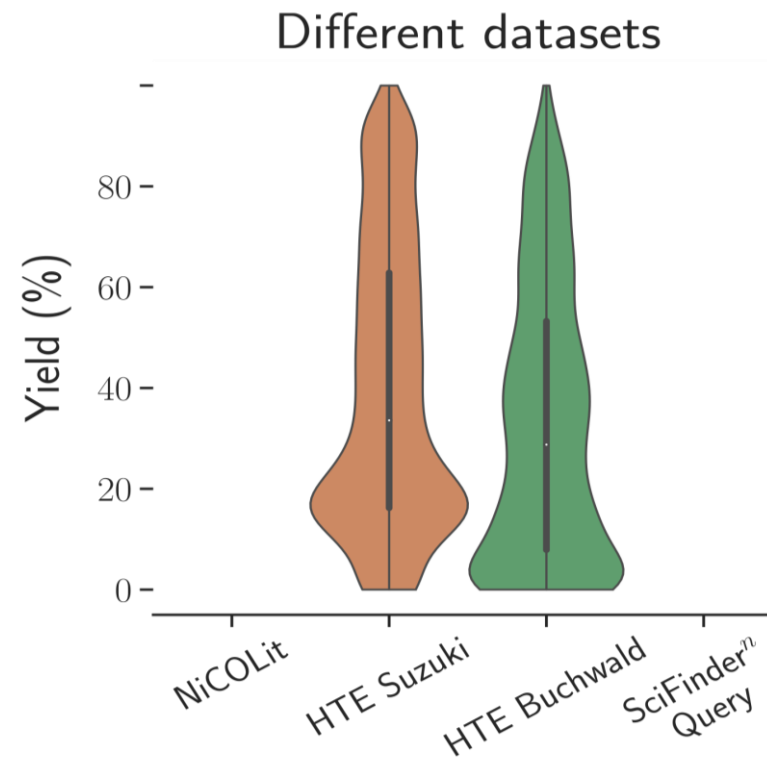
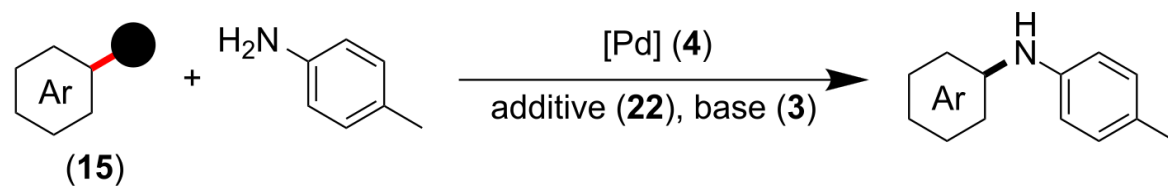
Multi-Dimensional Scaling



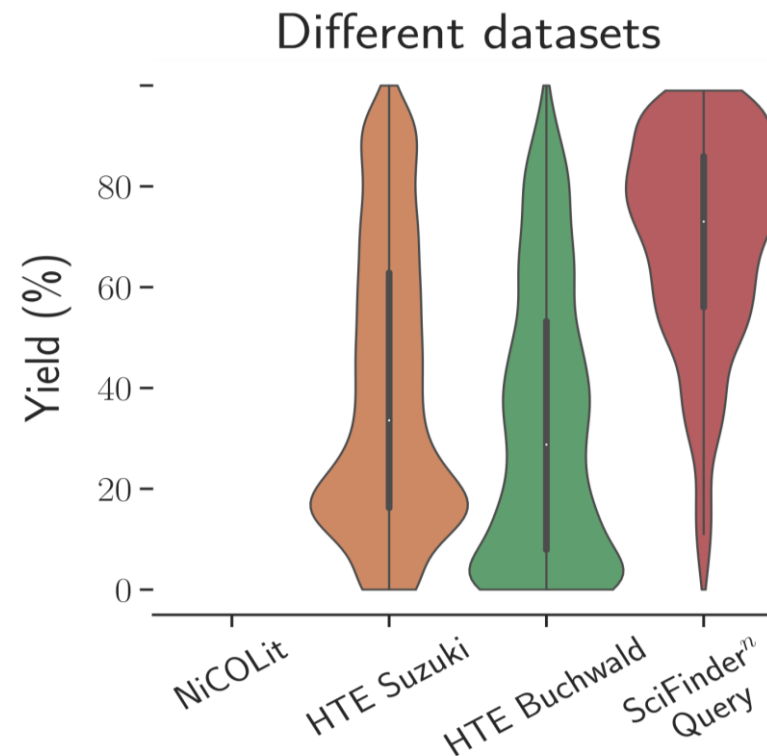
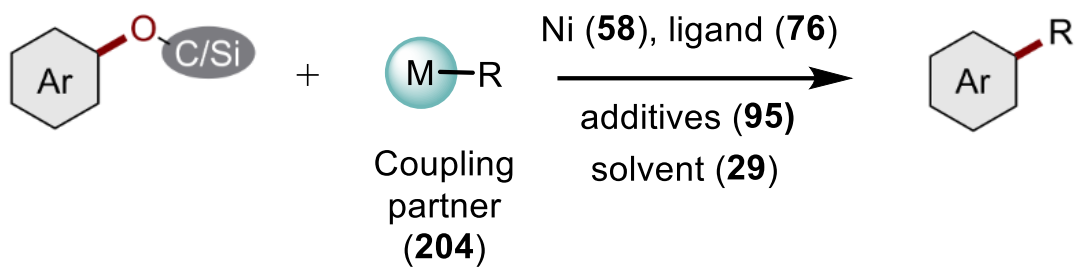
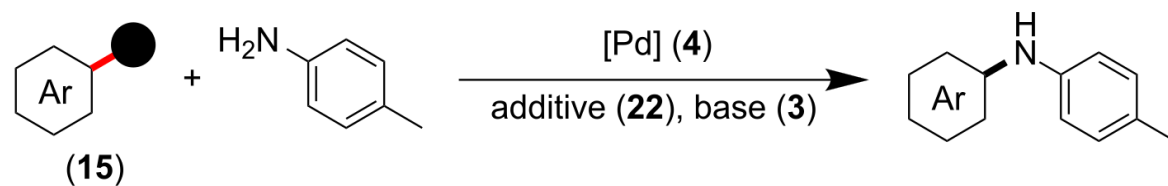
Analysis with RXNFP featurization



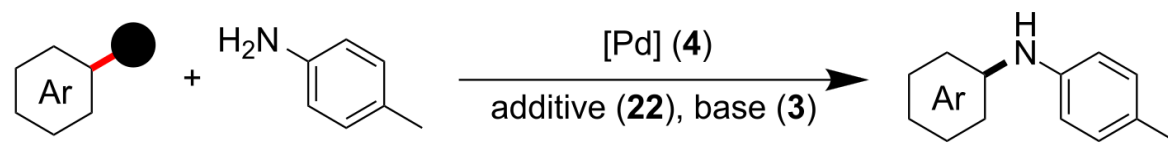
Yields distribution



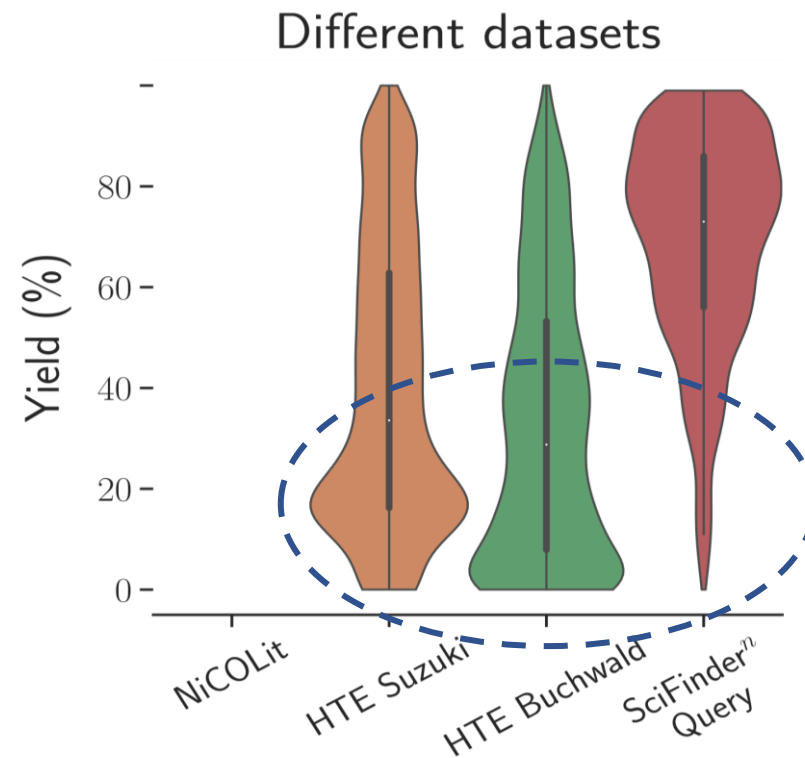
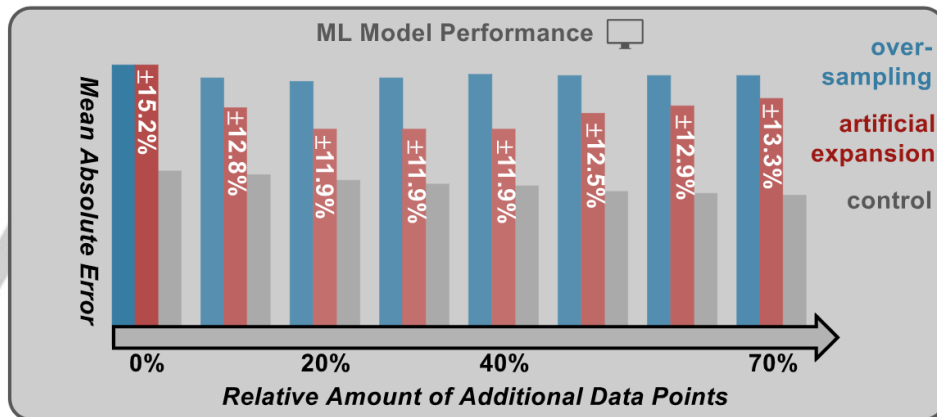
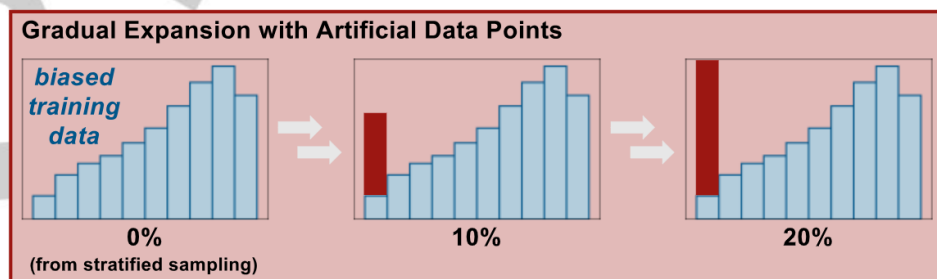
Yields distribution



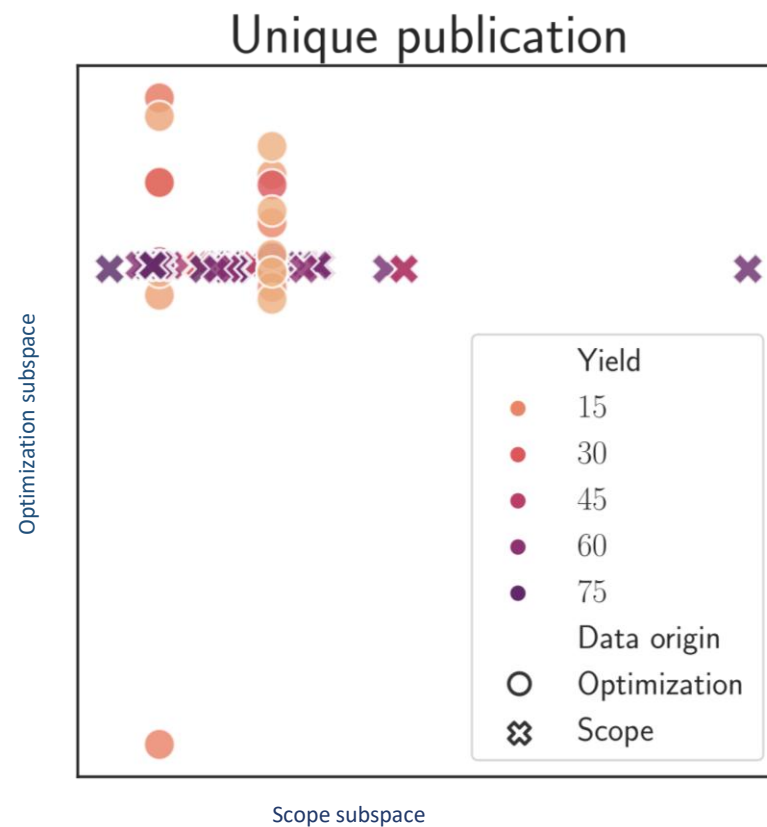
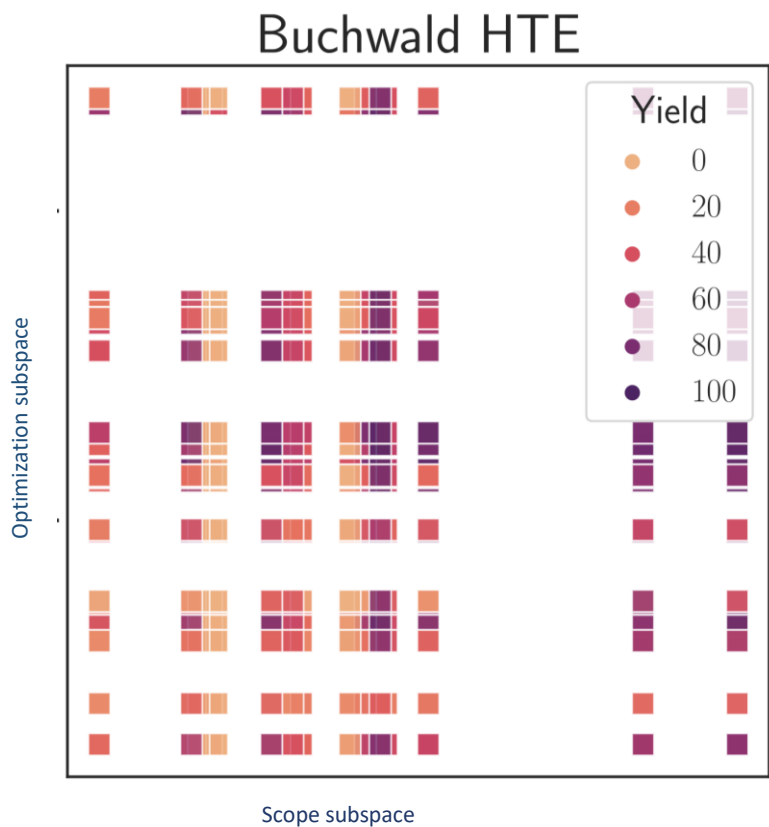
Yields distribution



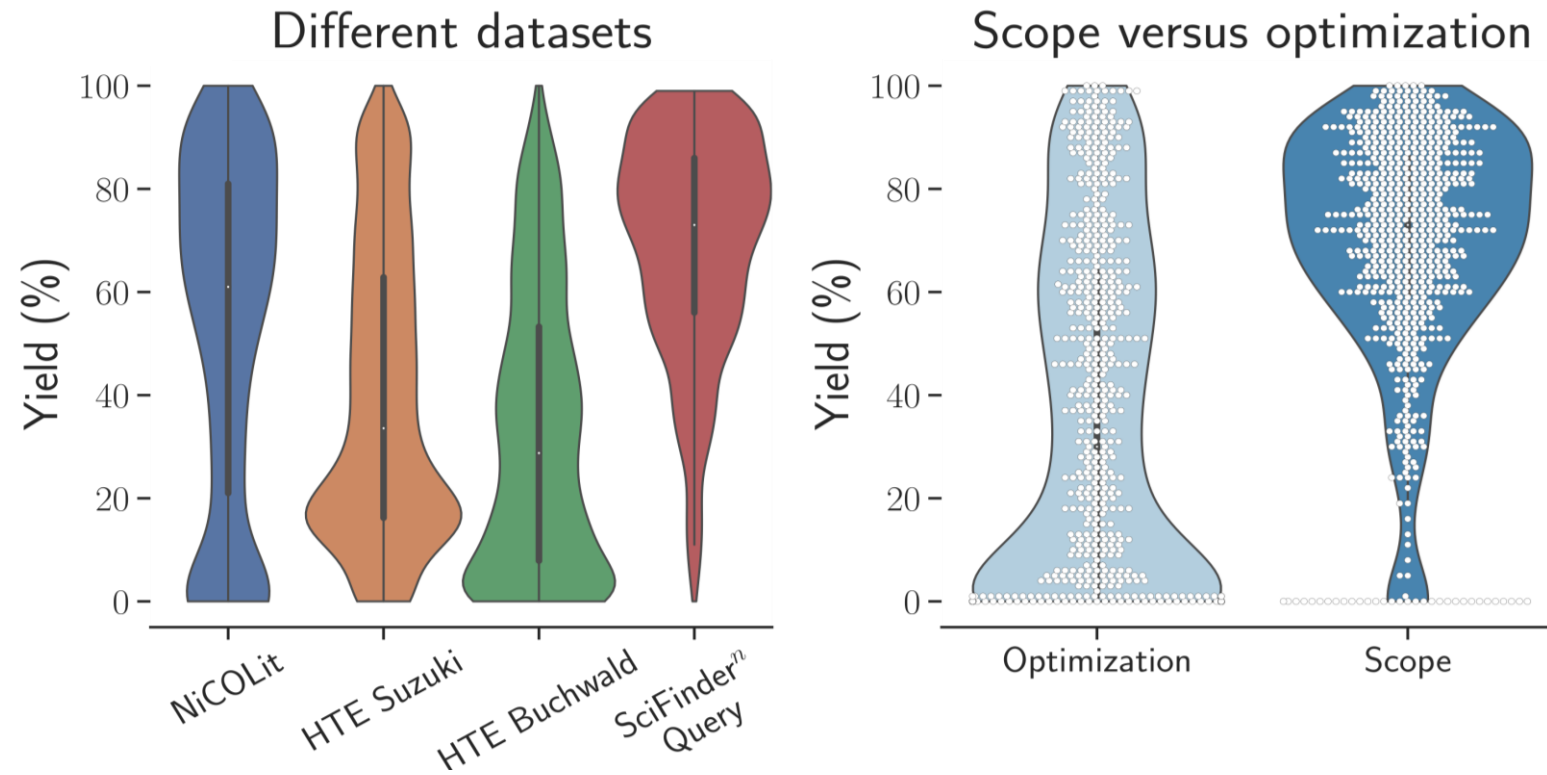
(15)



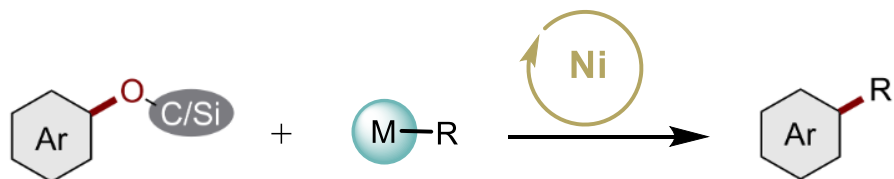
Comparison with HTE



Yields distributions

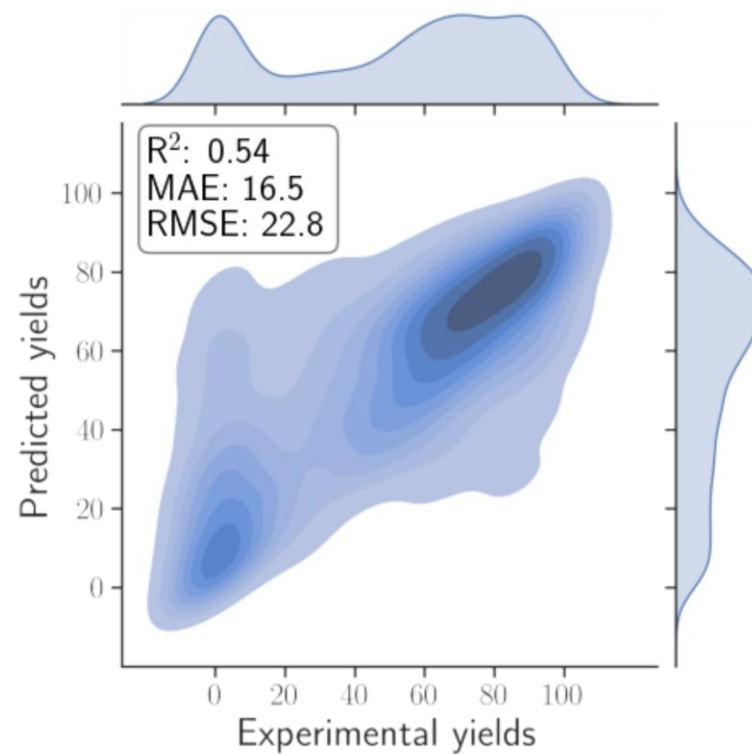
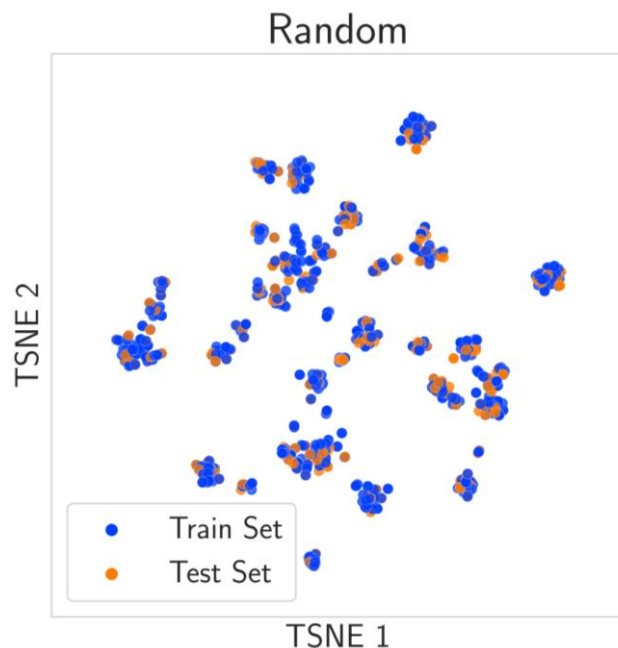
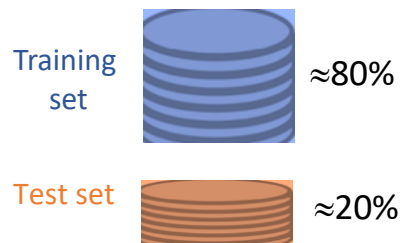


Performances of the model on a random split



M = Li, Mg, Zn, B,...

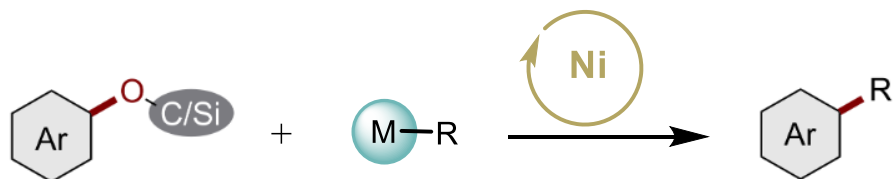
DFT featurization



Comparison to literature
HTE $R^2 = 0.8$
USPTO $R^2 < 0.2$

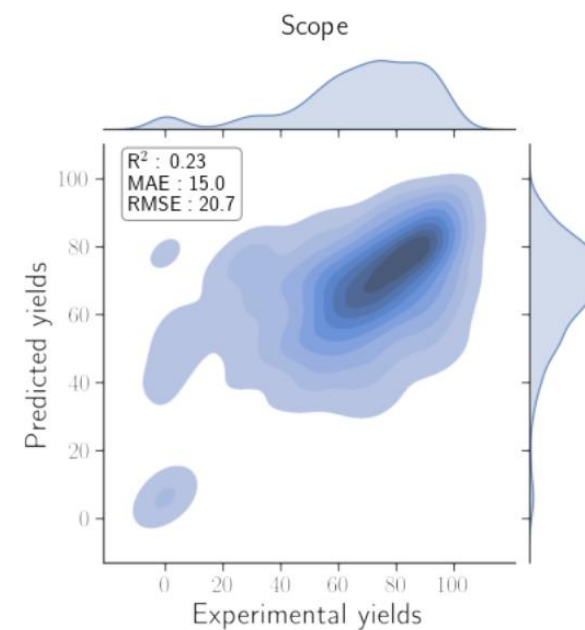
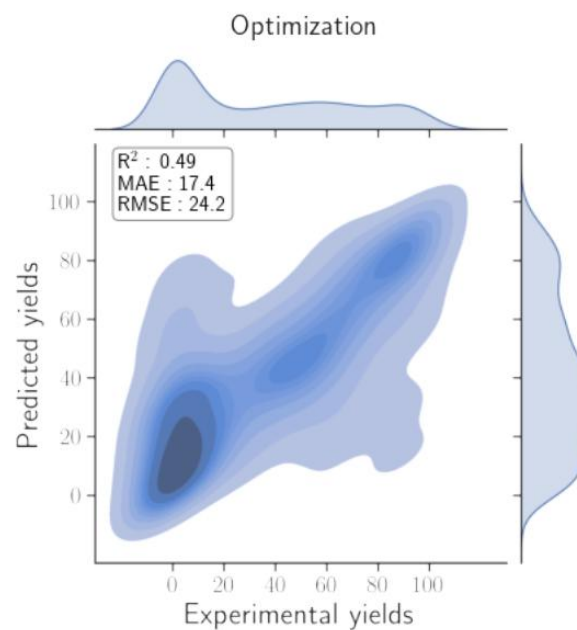
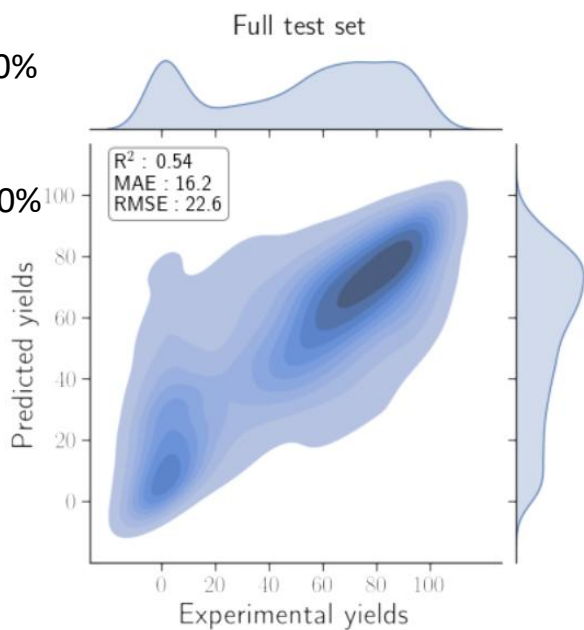
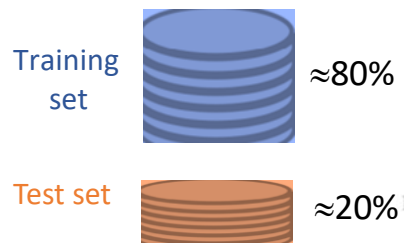
RDKit FP and DRFP $R^2 0.50$
RXNFP $R^2 0.37$

The importance of failed experiments

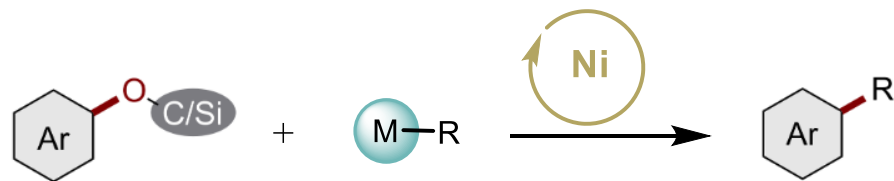


M = Li, Mg, Zn, B,...

DFT featurization

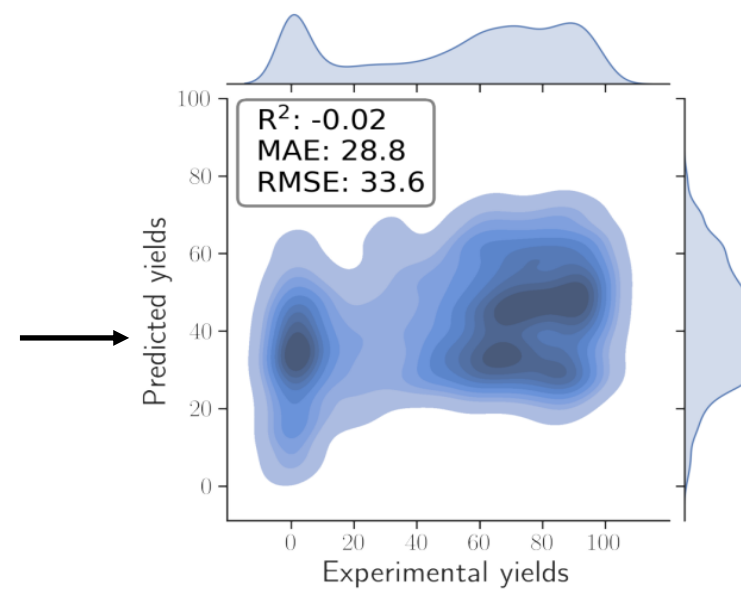
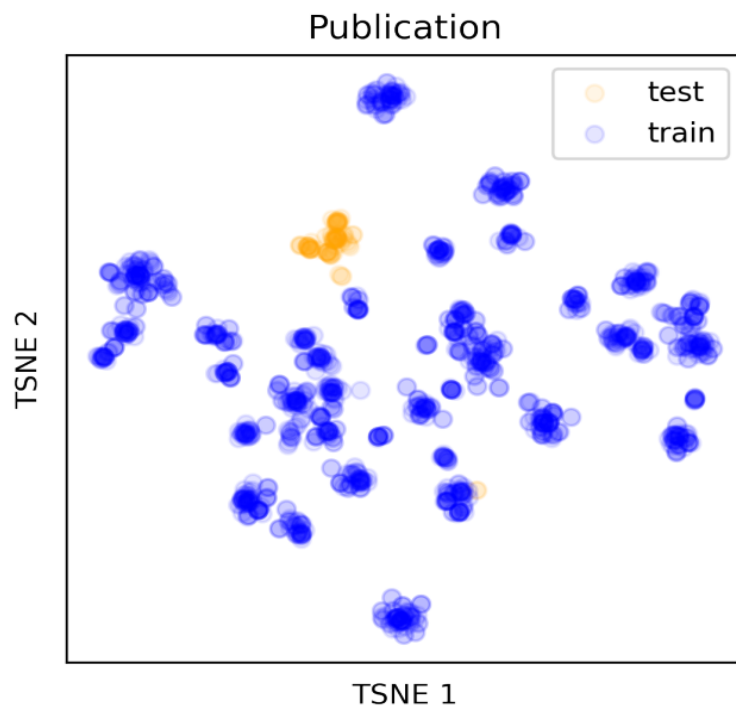
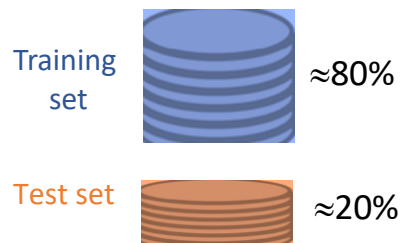


Performances for a out-of-sample publication



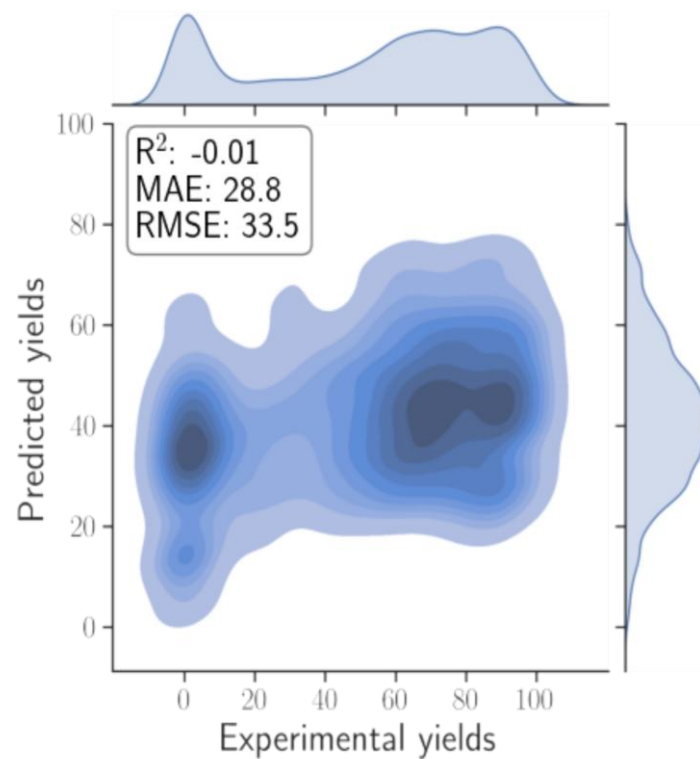
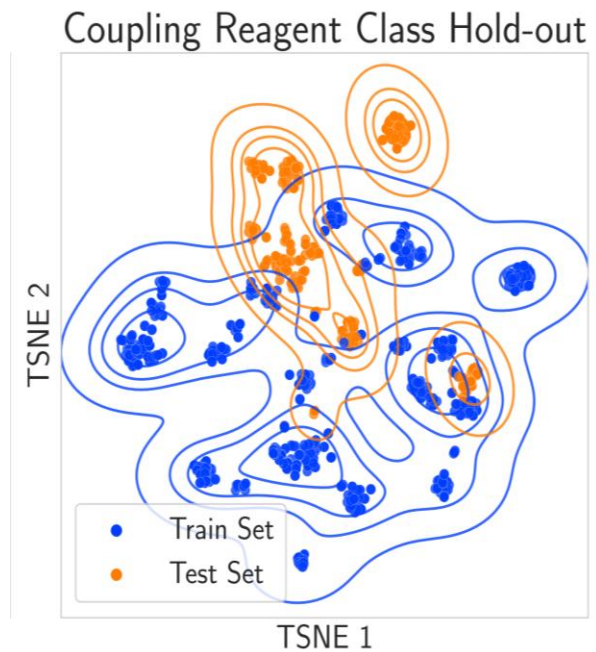
M = Li, Mg, Zn, B,...

DFT featurization



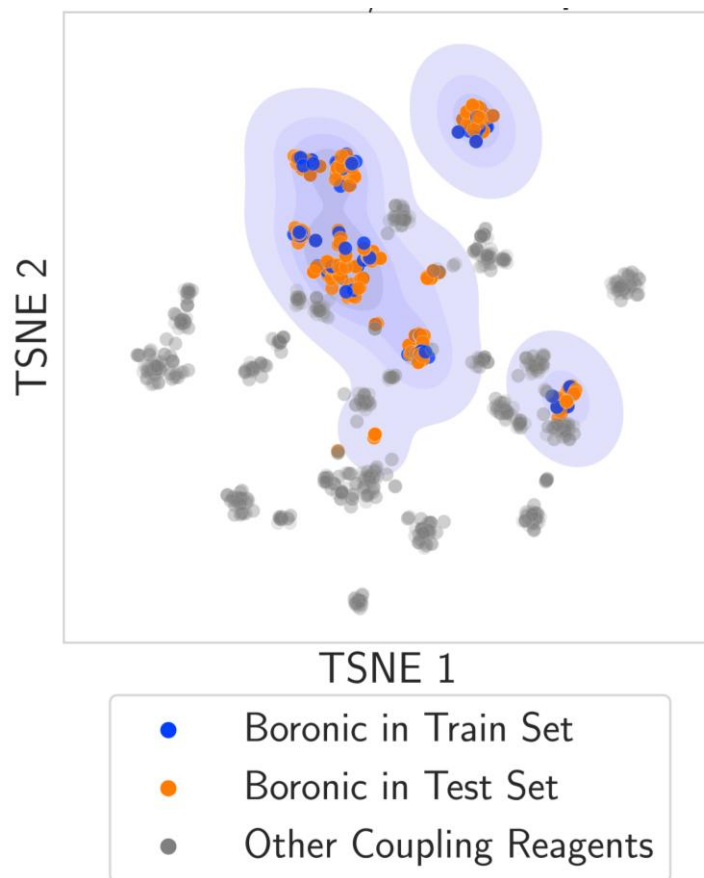
Performances for a out-of-sample coupling partner

DFT featurization



Performances on a restricted dataset with similar coupling partners

DFT featurization



Coupling partner	R^2	Number of reactions	Number of publications
B	0.47	472	11
C-H	0.59	271	3
RMgX	0.51	266	5
CO ₂	0.52	87	1
Zn	0.54	68	2
NCO	0.39	57	1
Al	0.20	53	1
Si	0.64	53	1

Similar to the prediction on the whole NiCOLit database

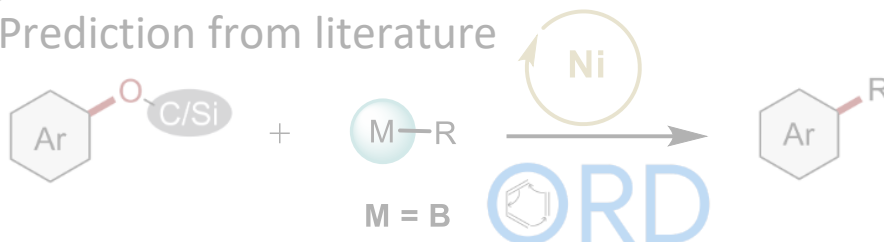
on Buchwald HTE data: $R^2 = 0.59$ for 98 data points

AI in our lab

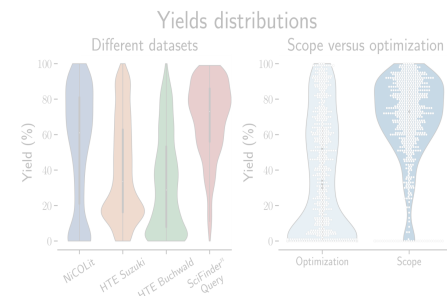


Pr Rodolphe
Vuilleumier (ENS)

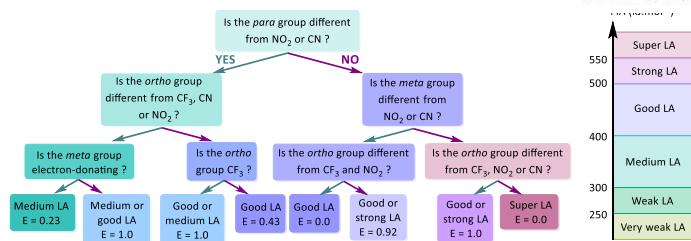
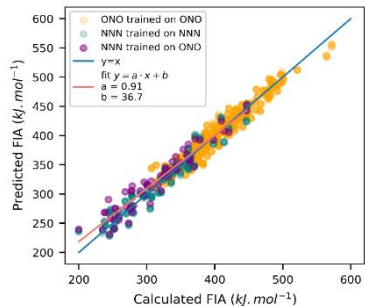
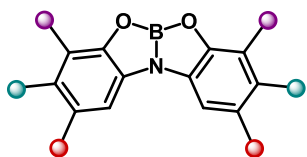
Prediction from literature



J. Am. Chem. Soc., 2022, 144, 14722



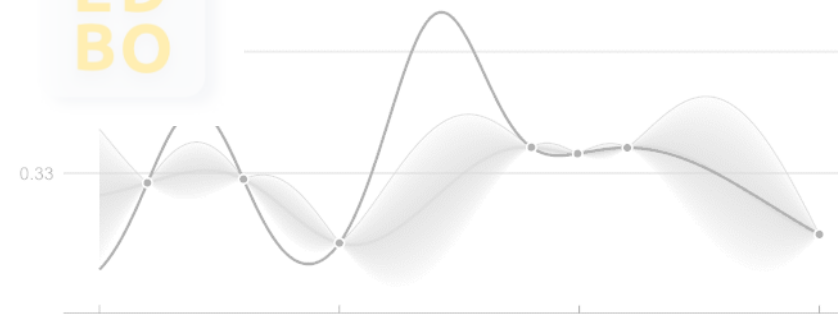
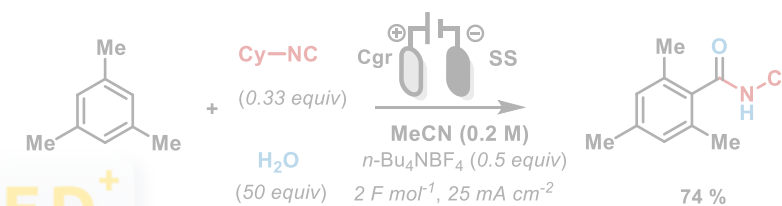
Prediction of Properties



Digital Discovery 2025, 4, 3623



Bayesian Optimisation



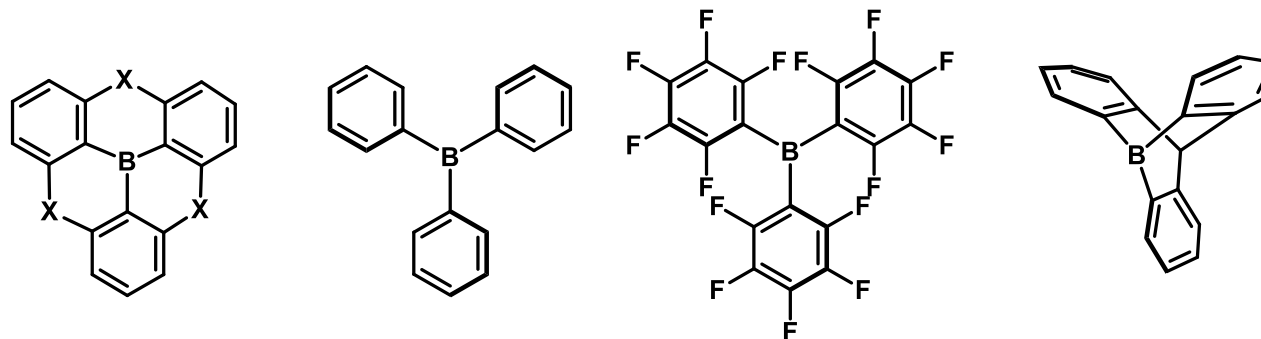
C. R. Chim. 2026, accepted. DOI: 10.5802/crchim.431

Predicting properties in low data regime: Lewis acidity

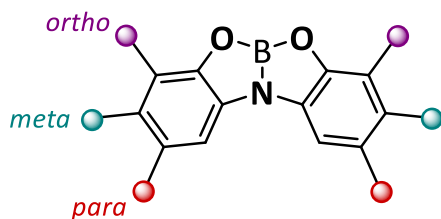


Juliette Fenogli

Boron-based Lewis acids



Using ML in low data regime



With models close to statistical analysis to perform XIA

- To get more insights into the qualitative concept of LA
- To design new LA

Massey, A. G.; Park, A. J. *J. Organomet. Chem.*, 1964, **2**, 245

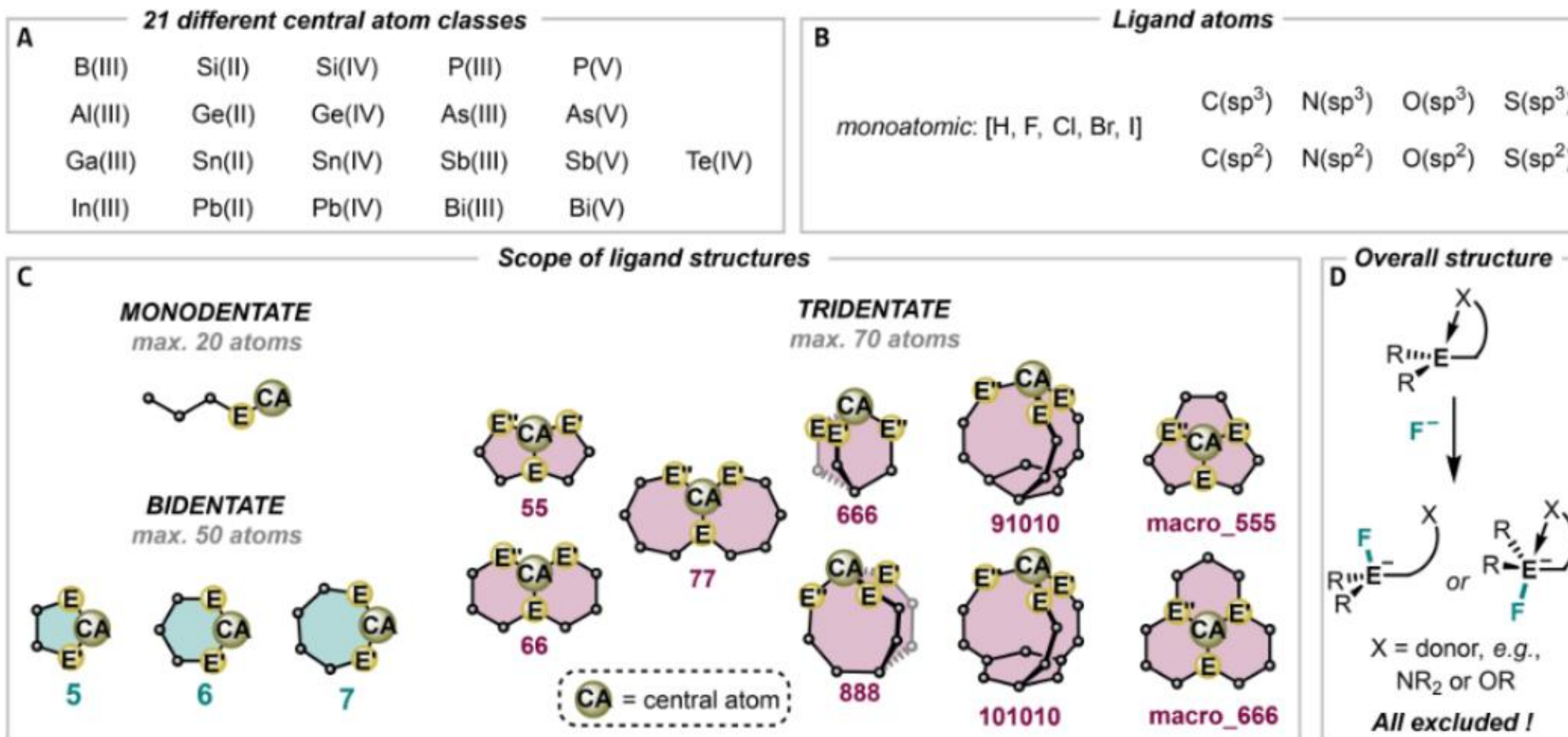
Alharbi, M. M.; Van Ingen, Y.; Roldan, A.; Kaehler, T.; Melen, R. L. *Dalton Trans.* 2023, 52, 1820

Ben Saida, A.; Chardon, A.; Osi, A.; Tumanov, N.; Wouters, J.; Adjieufack, A. I.; Champagne, B.; Berionni, G. *Angew. Chem. Int. Ed.* **2019**, *131*, 17045

Huang, K.; Dutton, J. L.; Martin, C. D. *Chem. Eur. J.* **2017**, *23*, 10532

ML for predicting Lewis acidity

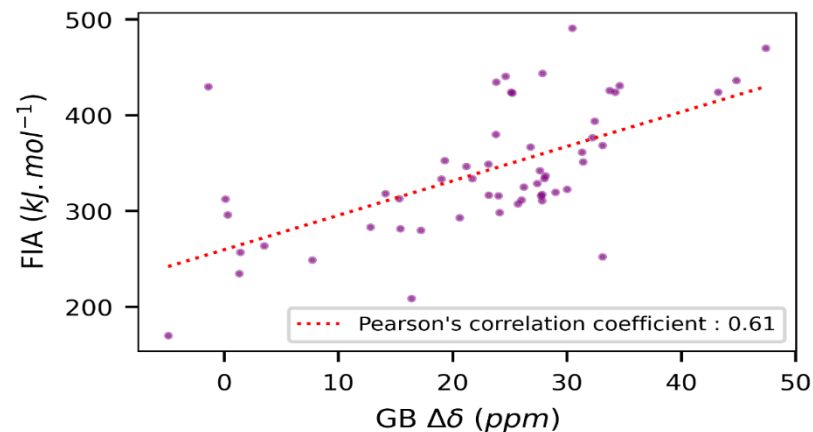
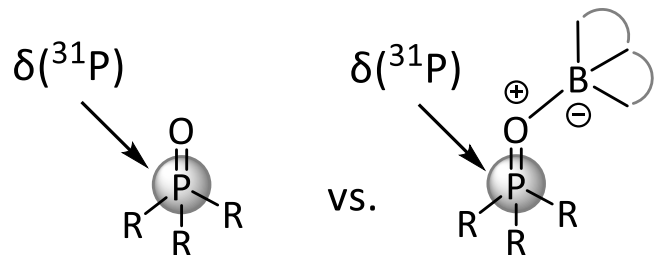
Predicting FIA using graph neural network



49 000 molecules !

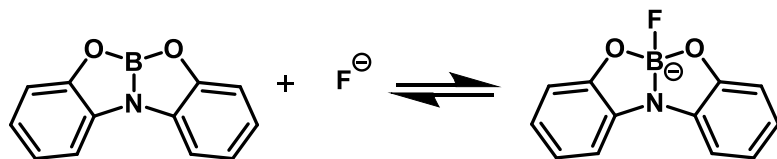
Lewis acidity determination

Experimental determination: Gutmann-Beckett NMR displacement

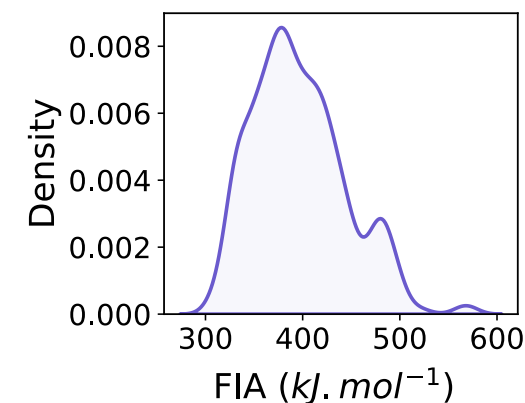
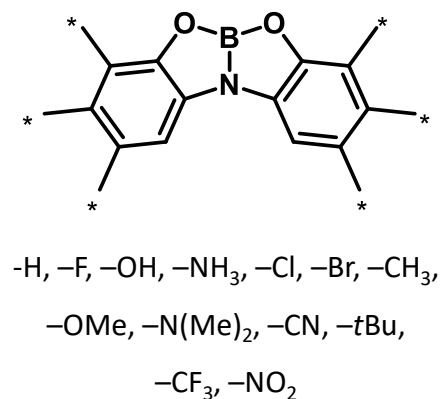


Theoretical determination: Fluoride ion affinity

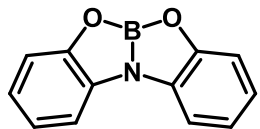
For a reliable database based on DFT calculations (M062X/6-31G(d))



$$\Delta_r H^\circ = -\text{FIA}$$



Molecular descriptors



SMILES : c12c(OB3Oc4c(N32)cccc4)cccc1

Molecular representation

Molecular descriptors

Training data

Cheminformatics

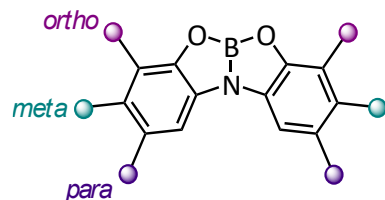


DFT-calculated

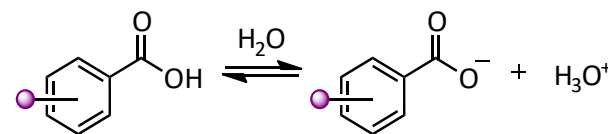


Method : M06-2X/6-31g

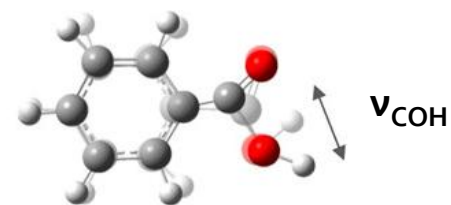
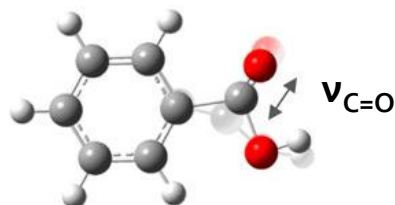
Hammett-extended



Global parameters	Dipolar moment, frontier orbitals energies, absolute electronegativity...
Atomic parameters for B	Charge, valence, buried volume...



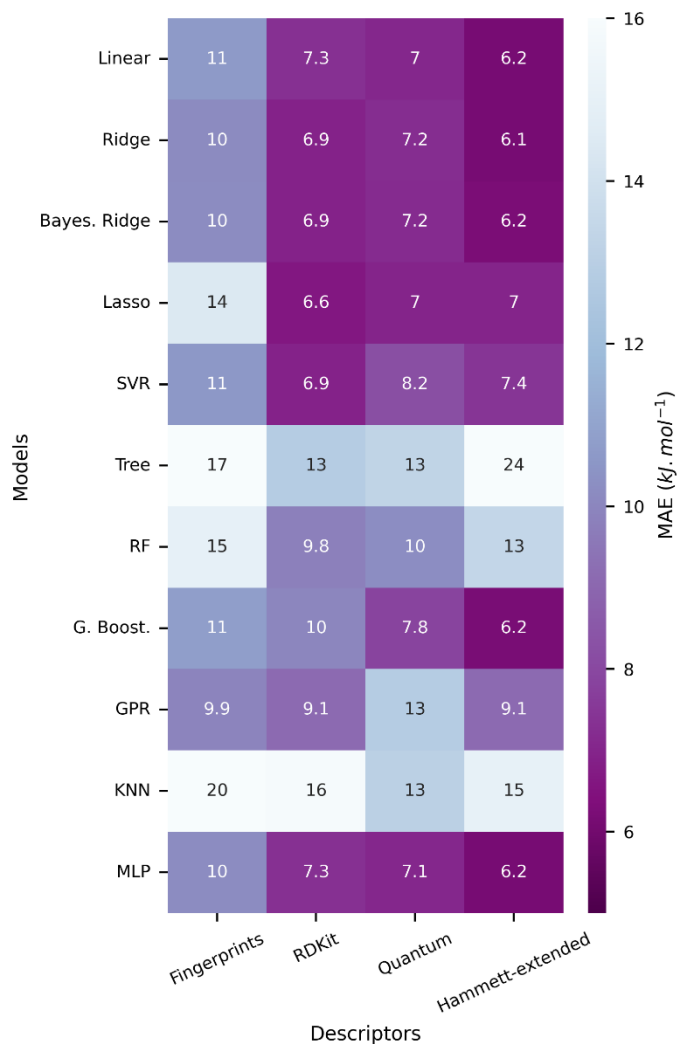
Hammett σ constants	σ_{mv} , σ_p
Steric parameters	Sterimol B1 , B5 and L for <i>o</i> , <i>m</i> & <i>p</i> Torsional angle : $\theta_{tor,o}$
IR parameters	$\nu_{C=O}$, ν_{COH} , $I_{C=O}$, I_{COH} for <i>o</i> , <i>m</i> & <i>p</i>
NBO charges	NBO_C , $NBO_{=O}$, NBO_O , NBO_H for <i>o</i> , <i>m</i> & <i>p</i>



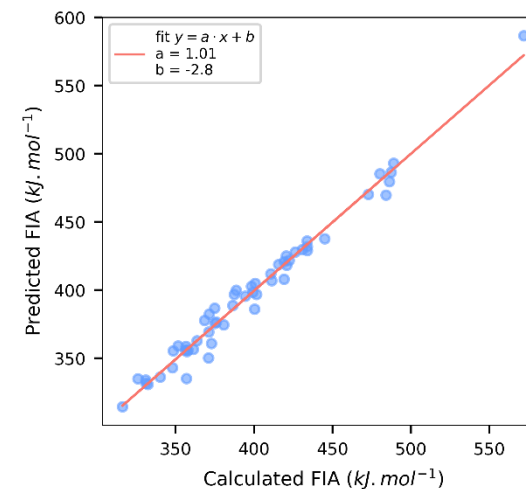
⇒ 244 concatenated features

Model construction

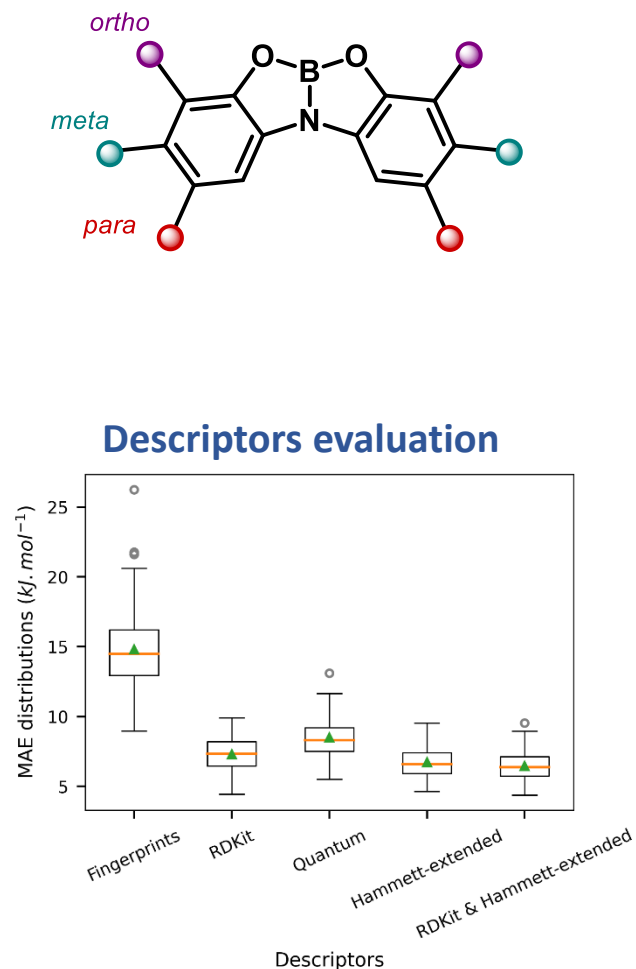
Test set



Optimized model: Linear Regression



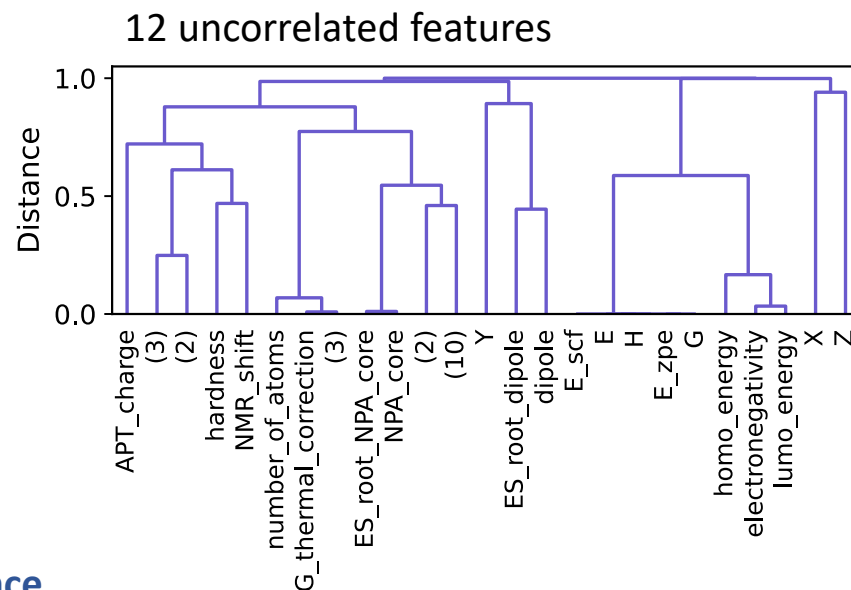
MAE about 5 kJ.mol⁻¹



➡ Regression models offer an optimal balance between interpretability and prediction accuracy

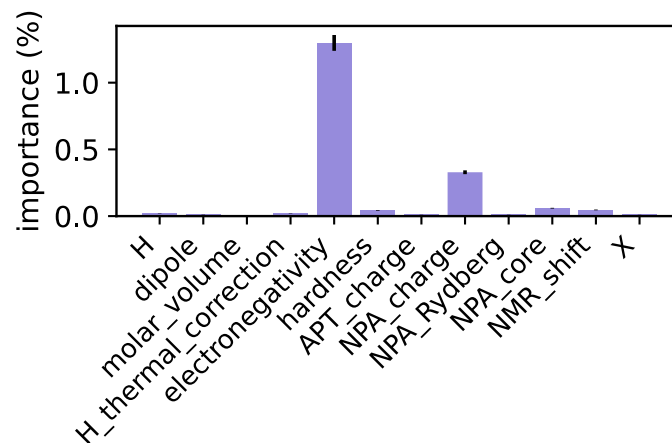
Interpretability: finding the key feature of LA

Hierarchical clustering



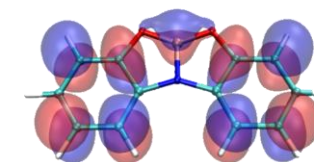
With DFT descriptors

Permutation importance



Absolute electronegativity

$$\chi = -1/2 (E_{HOMO} + E_{LUMO})$$

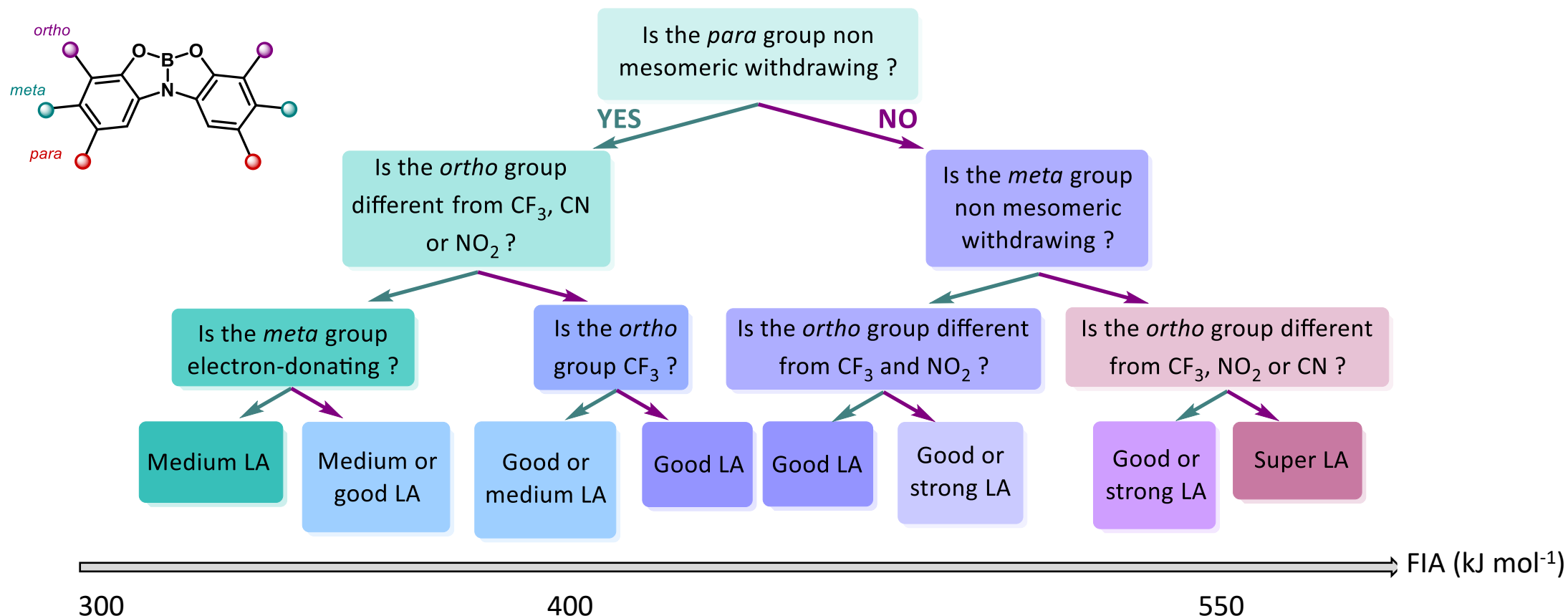


➔ Unexpectedly Lewis Acidity is more influenced by MO interactions than by Coulombic interactions (Hard acidity)

A classification to help design

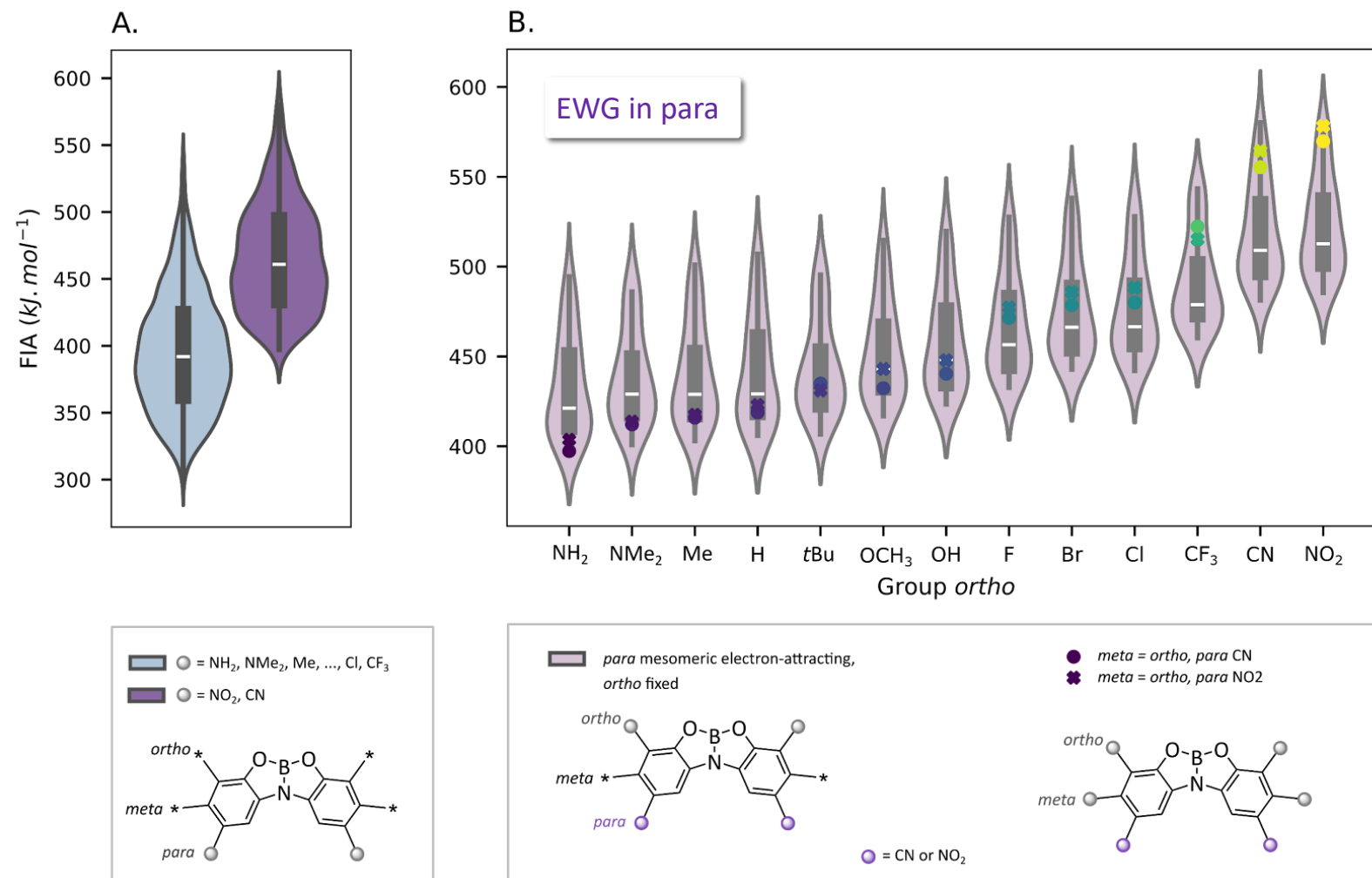
Decision tree with 3 questions

With Hammett-extended descriptors

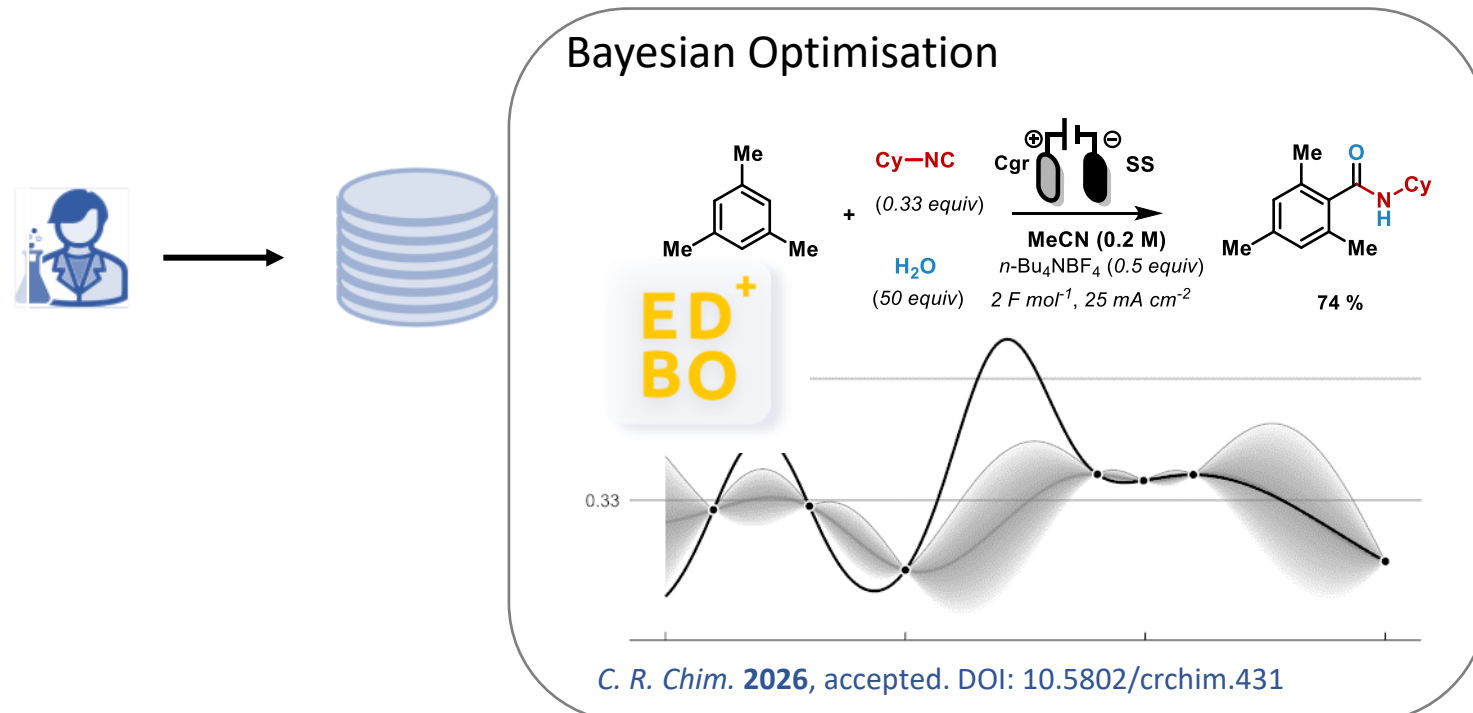
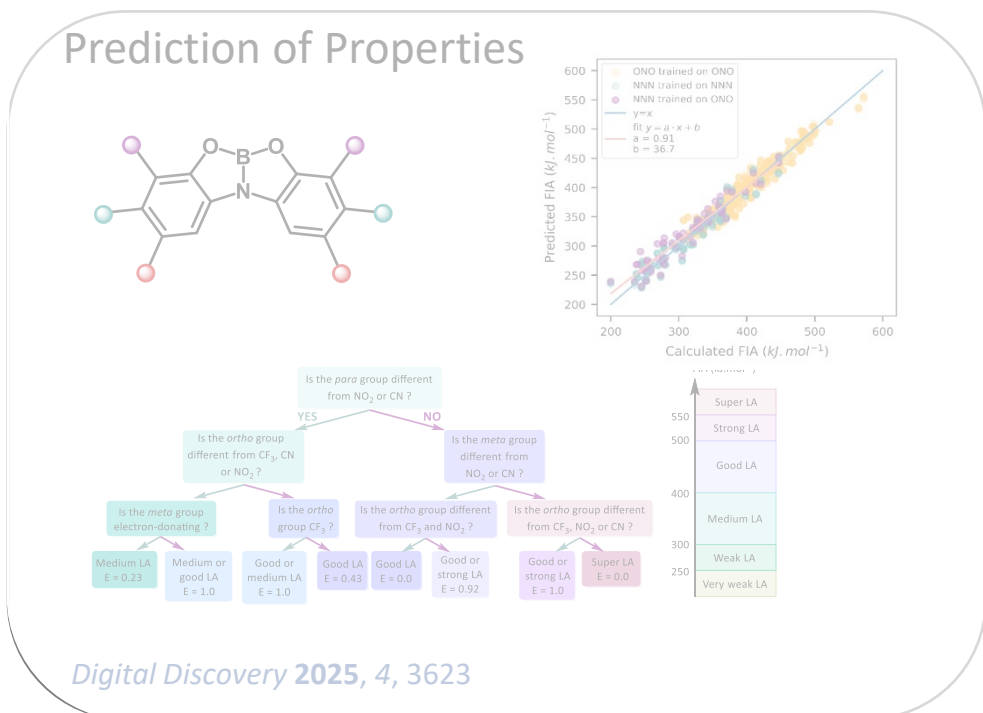
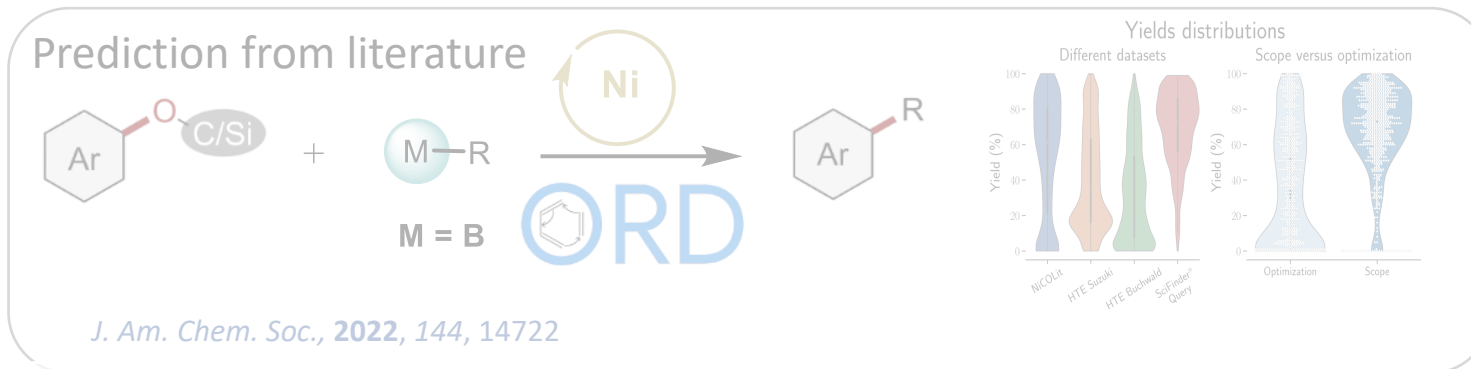


⇒ In low-data regime, ML models can accurately and interpretably predict Lewis acidity, bridging the gap between advanced ML techniques and traditional chemical intuition

Screening and Analysing the database

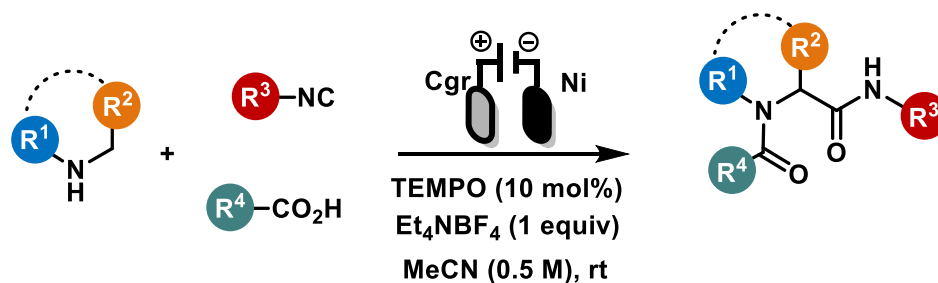


AI in our lab

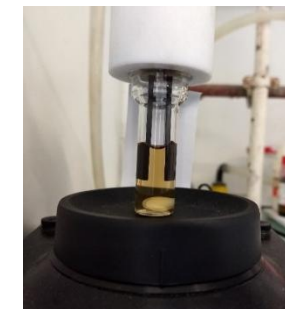




Electro-induced Ugi-Joullié coupling

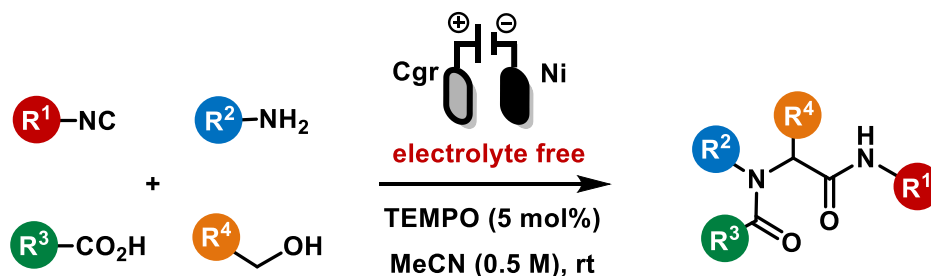


Pan, N.; Ling, J.; Zapata, R.; Pulicani, J.-P.; Grimaud, L.; Vitale, M. R. *Green Chem.* **2019**, *21*, 6194



Undivided cell

Electro-oxidative Ugi Reaction

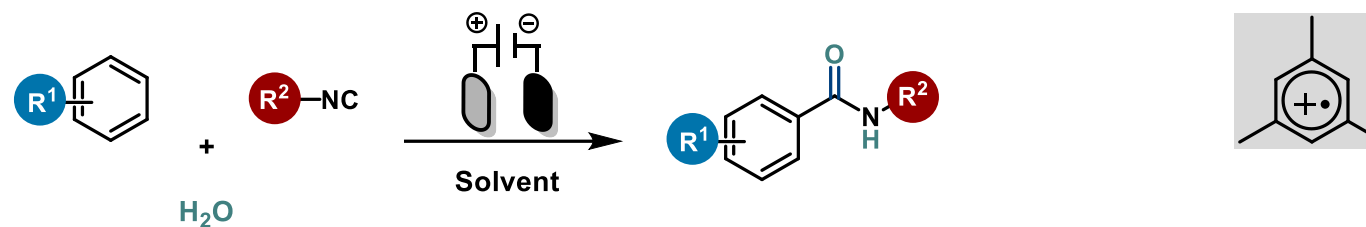


Pan, N.; Xinen Lee, M.; Bunel, L.; Grimaud, L.; Vitale, M. R. *ACS Org. Inorg. Au* **2021**, *1*, 21

For the electro-Passerini, see: Simon, A.; Bachollet, S. P. J. T.; Pan, N.; Grimaud, L.; Vitale, M. R. *Synlett* **2024**, *35*, A-E

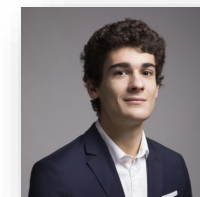
New electrophiles in IMCRs

Carbocations



For cation-pool: Yoshida *J. Am. Chem. Soc.* **2013**, *135*, 5000

For previous cyanation: Gooßen *Chem. Eur. J.* **2018**, *24*, 11288



Virgile Rouffeteau



Dr Maximilian
Fleck

Experimental conditions

Substrates' substituents

Stoichiometry

Concentration

Solvent(s)

Temperature

etc...

+

Electrosynthesis

Electrodes materials

Supporting electrolyte

(nature/quantity)

mA or Volt

Charge (e^- injected per substrate)

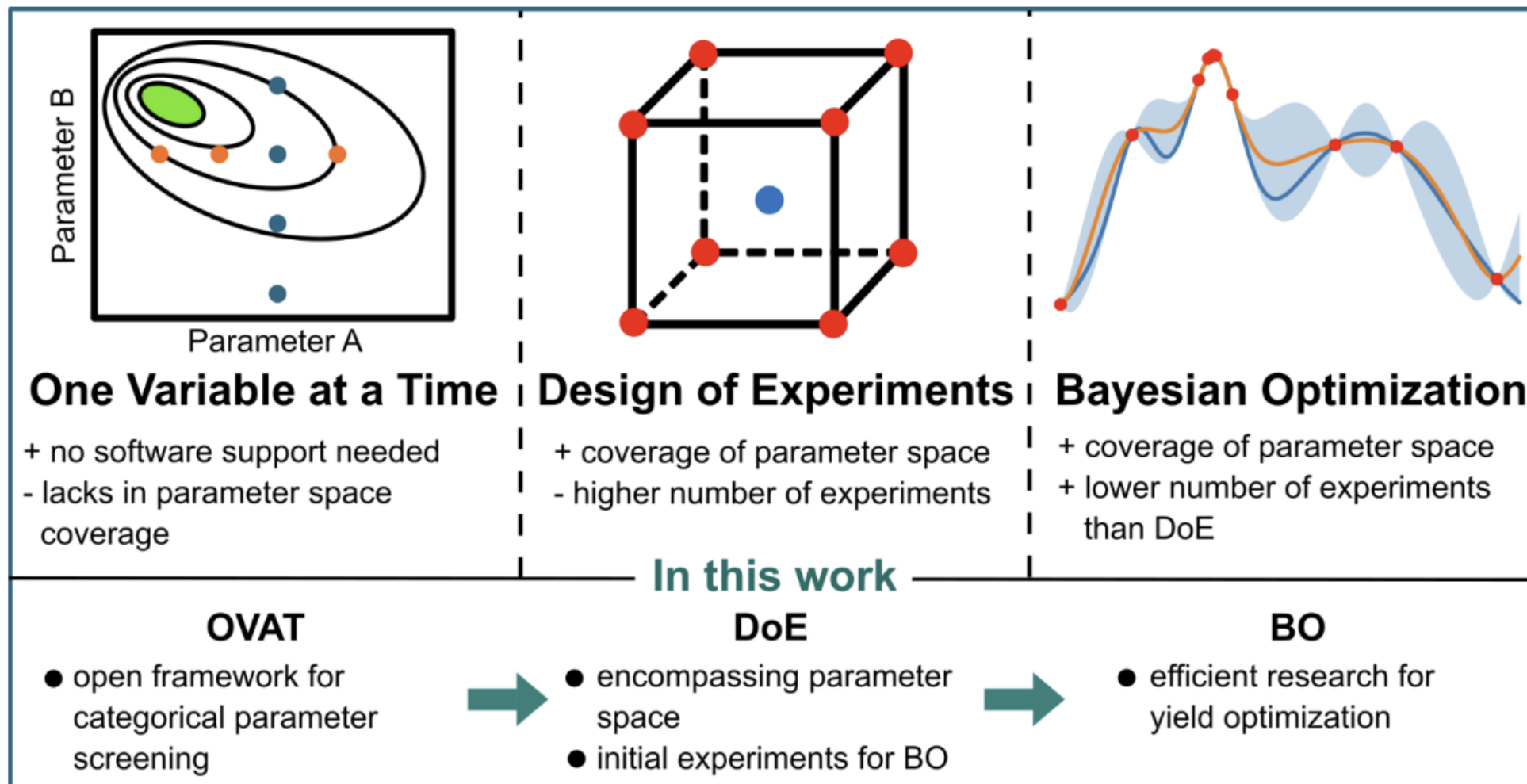
etc...

> 14 parameters

> 10^9 possible combinations

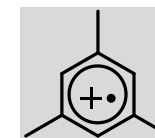
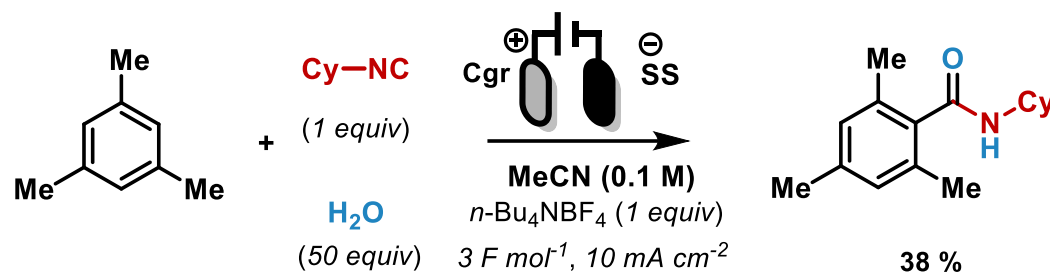


Different optimization methods



Chemical Space for Bayesian Optimization

Electro-carbamoylation of electron-rich arenes using Bayesian optimisation



✓ Output Yield (based on limiting Substrate)

✓ Definition of space

6 Parameters

	Values						
Cy-NC equivalent(s)	0.33	0.5	0.75	1	1.5	2	3
Water equivalent(s) %limiting	1	5	10	25	50		
Salt equivalent(s) %limiting	0.5	1	2				
Current Density (mA.cm ⁻²)	5	10	15	20	25		
Limiting Reagents' Concentration(M)	0.05	0.1	0.15	0.2			
Faraday per mole of arene	2	3	4	5	6		

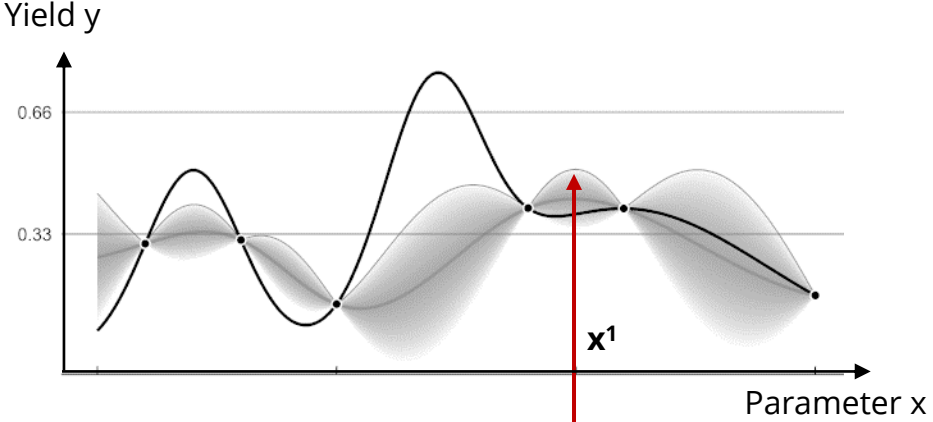
✓ Evaluation of the efficiency (NMR with ext. Std)

✓ Algorithm: EDBO+

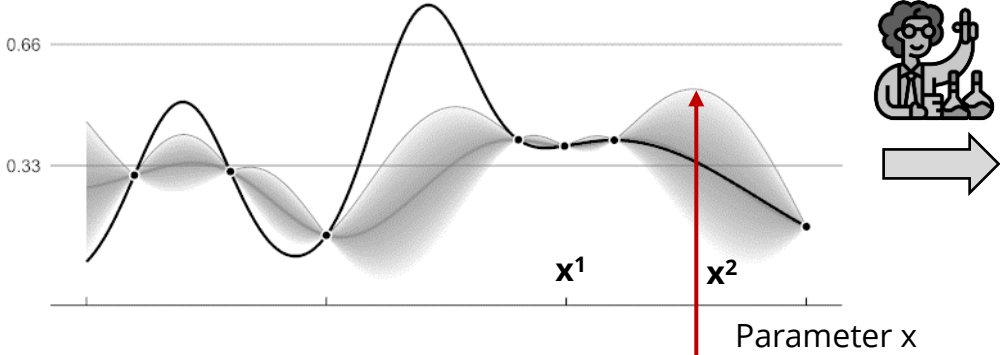


10 500 combinations !

Bayesian Optimization

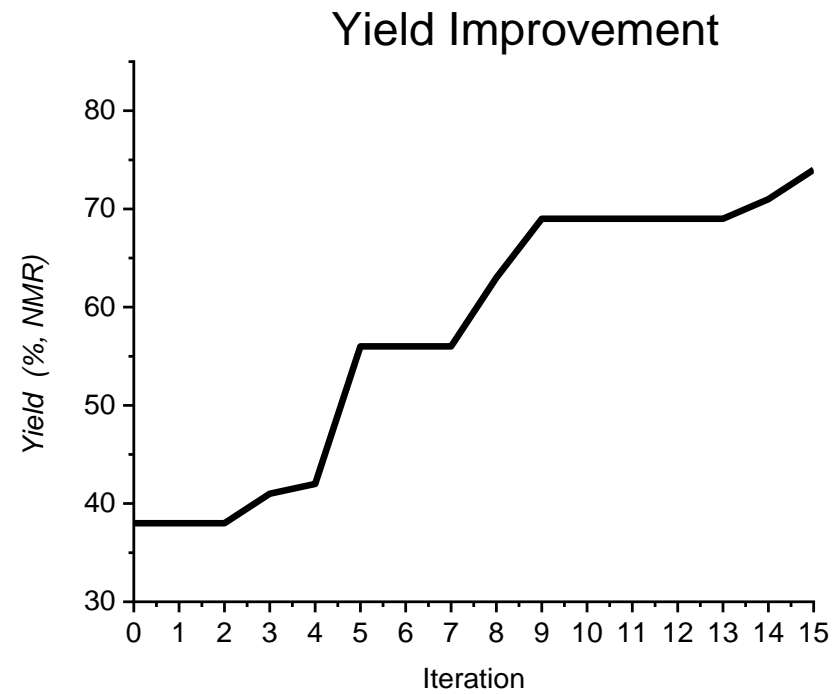
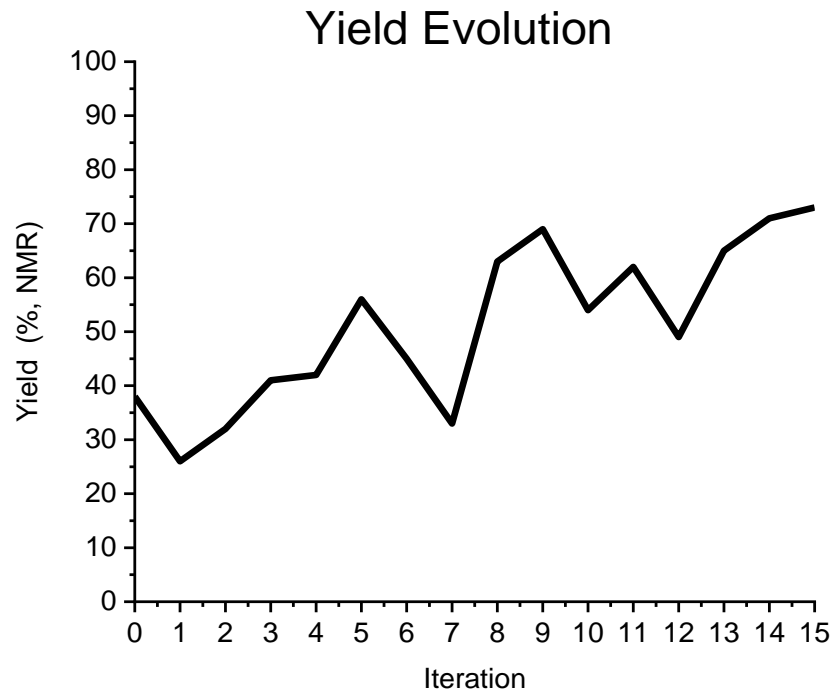
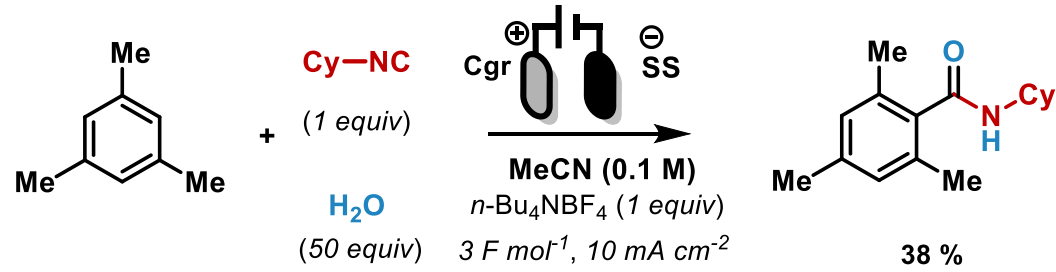


Highest peak at x^1 ,
new theoretical highest yield y^1

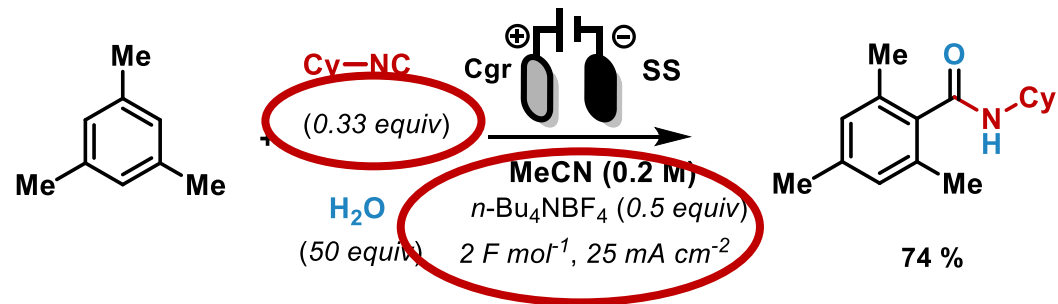
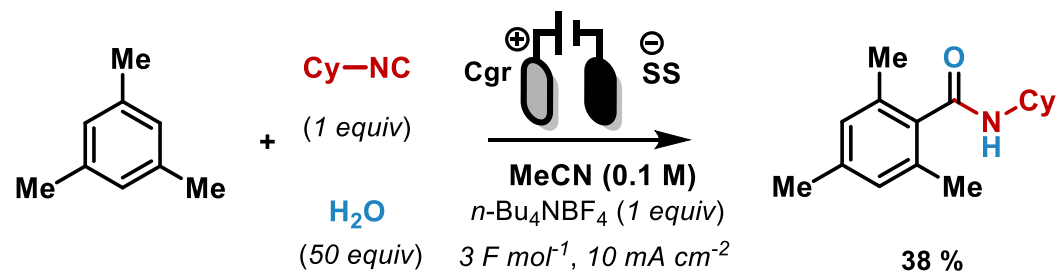


New highest peak at x^2 ,
new theoretical highest yield y^2

Bayesian Optimization for electrosynthesis

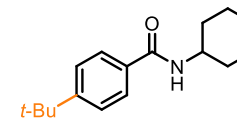
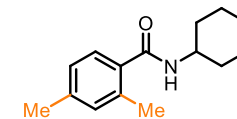
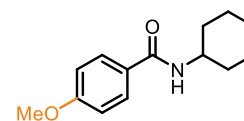
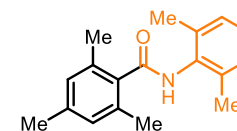
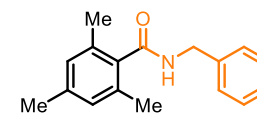
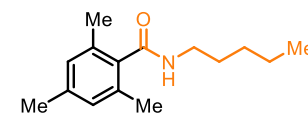


Optimized conditions



High faradic efficiency

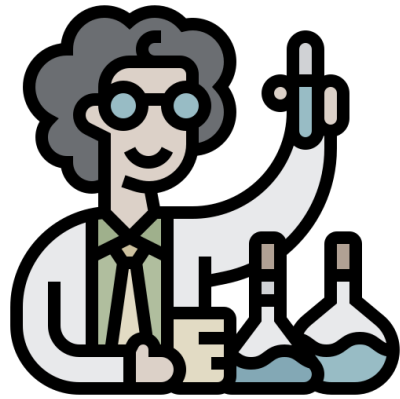
Product



EDBO

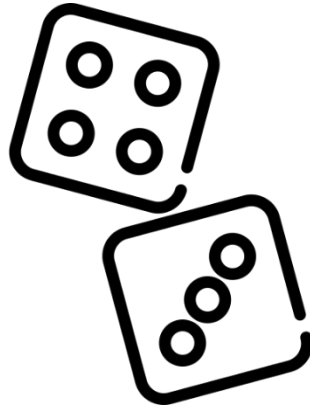


Precedents



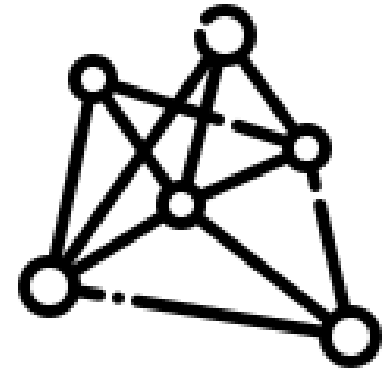
- Intuitive sampling

Majority of the literature



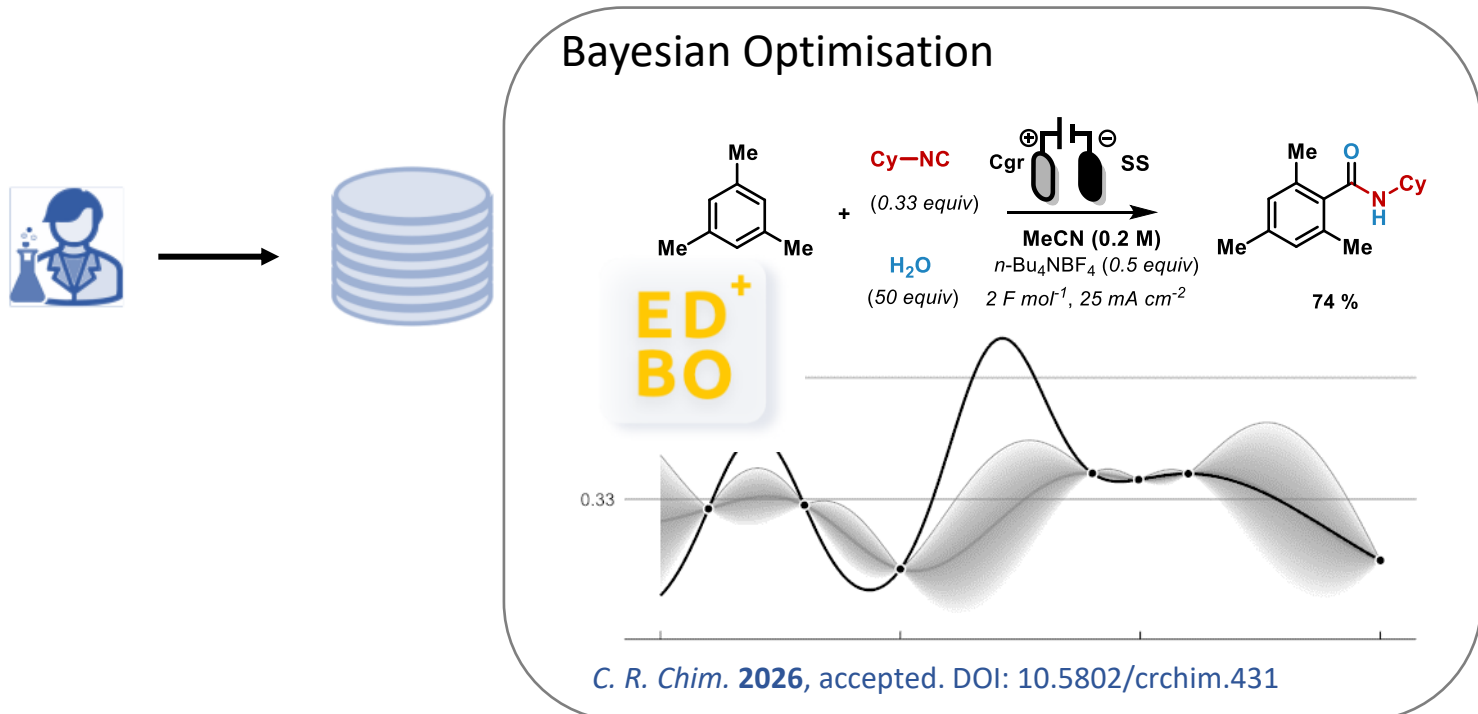
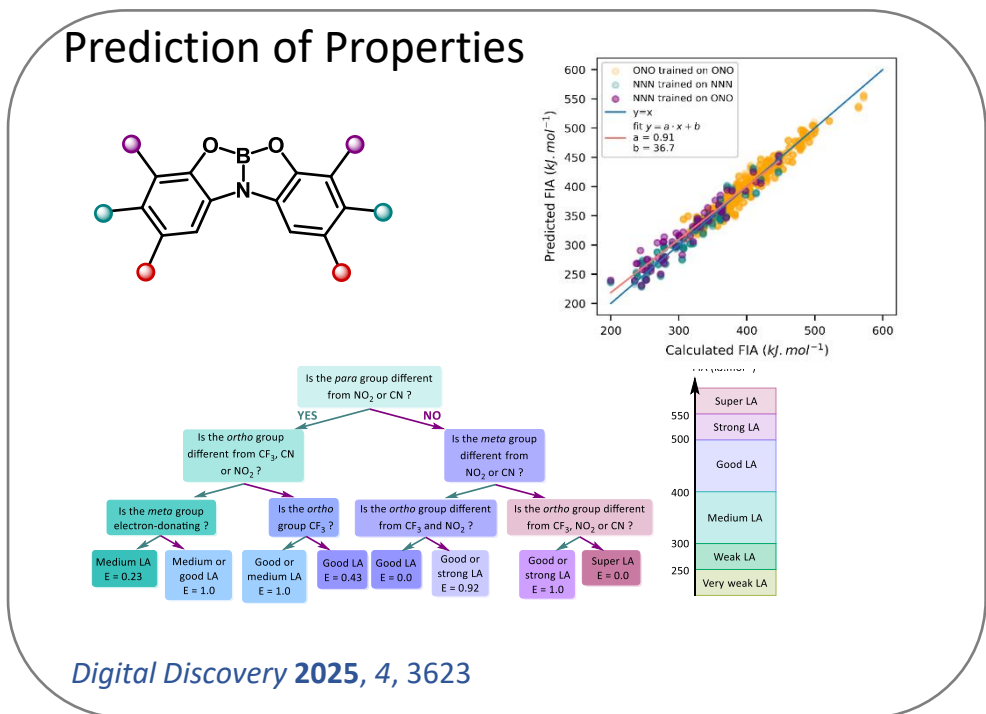
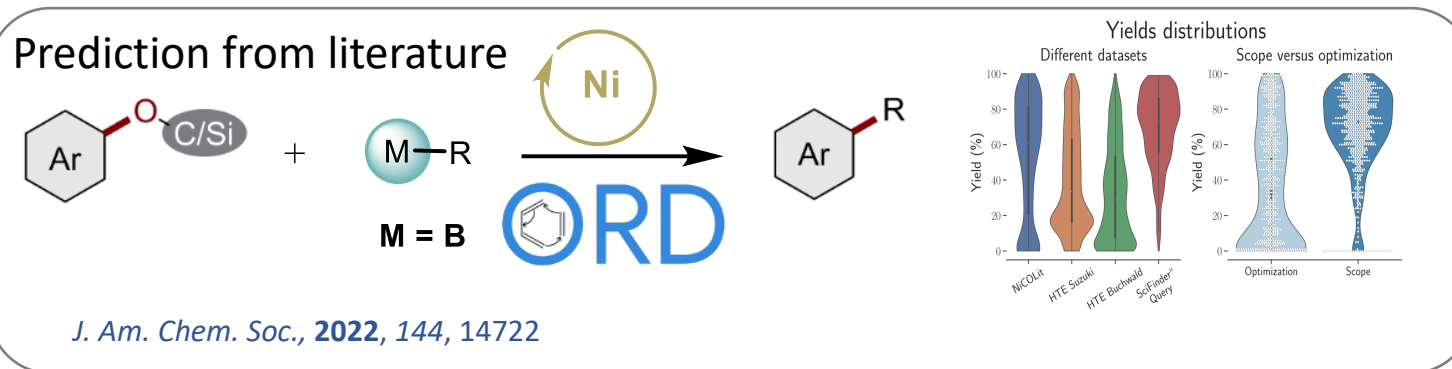
- Random sampling

Doyle *et coll*, *Nature*, **2021**, 590, 89.



- Orthogonal sampling

Felbin *et coll*, *Org. Process Res. Dev.* **2024**, 28, 1597.





Dr Maxime Vitale



Pr Rodolphe Vuilleumier



Dr Maximilian Fleck

PhD students

- Dr Na Pan
- Dr Johanne Ling
- Dr Khaoula Jaouadi
- Dr Aurélien Bailly
- Dr Jules Schleinitz
- Dr Emile Escoudé
- Dr Alexandre Simon

- Juliette Fenogli
- Virgile Rouffeteau
- Mohktar Ben Ghanem
- Louis Lengagne
- Sabry Zekhenine

Thank you !

Interns

- Dr Francesca Brunelli
- Dr Sylvestre Bachollet
- Lyse Kastner
- Elyssa Caron
- Clara Perrier
- Lilian Bourqui
- Salomé Nicolas
- Ramiro Zapata
- Louis Bunel
- Maegan Xinen Lee...

