

# Integrating Data Science Tools into Molecular Design in Electrocatalysis and Energy Applications

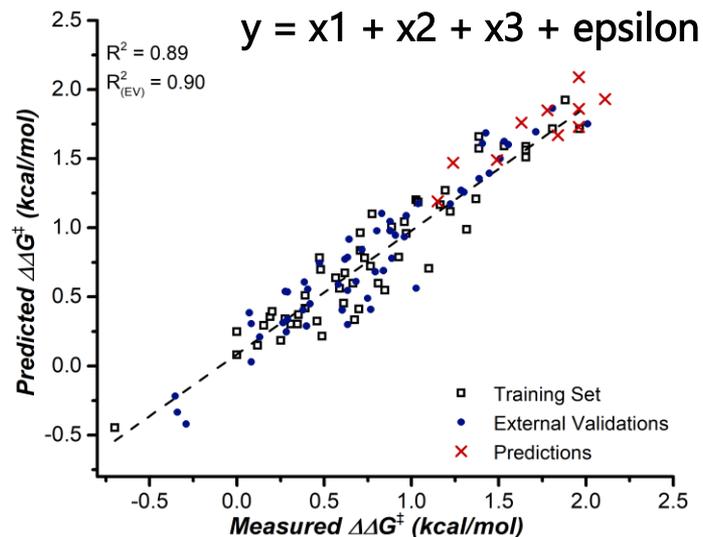


National Academy of Sciences  
Workshop on Electrochemistry  
November 19, 2019  
@Sigman\_Lab

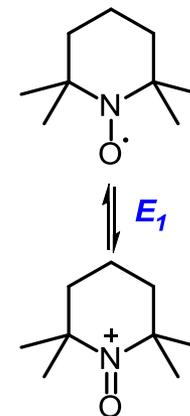
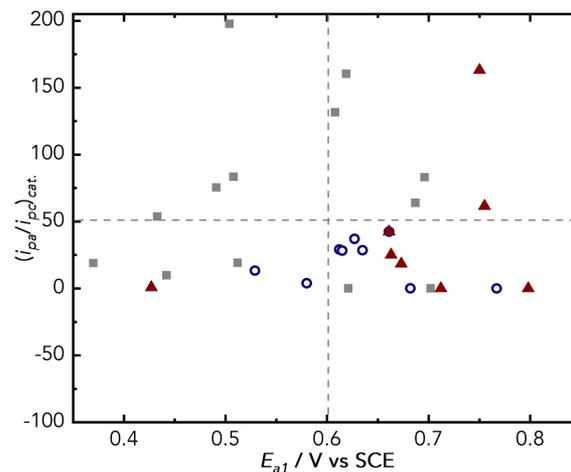


# Outline of talk

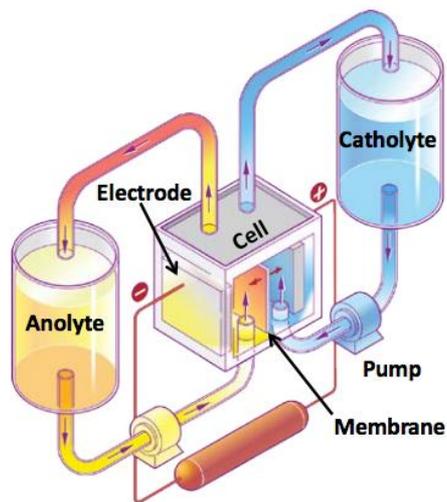
## introduction to data science



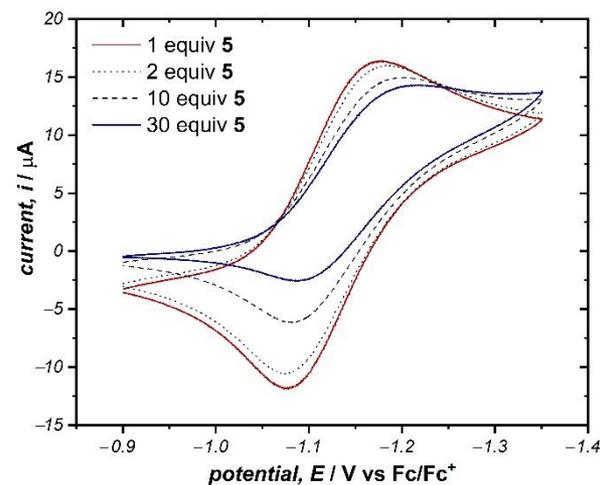
## case study 1: electrocatalysis



## case study 2: flow batteries

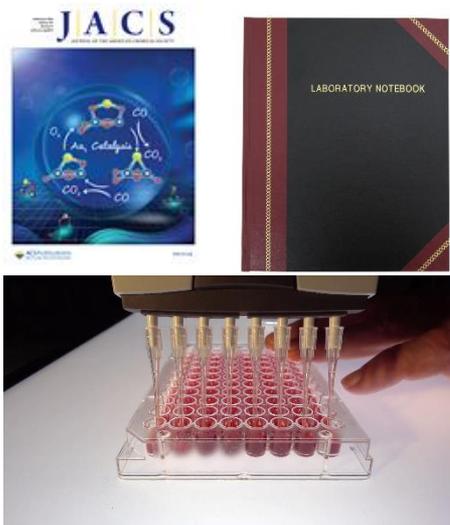


## future applications and thoughts



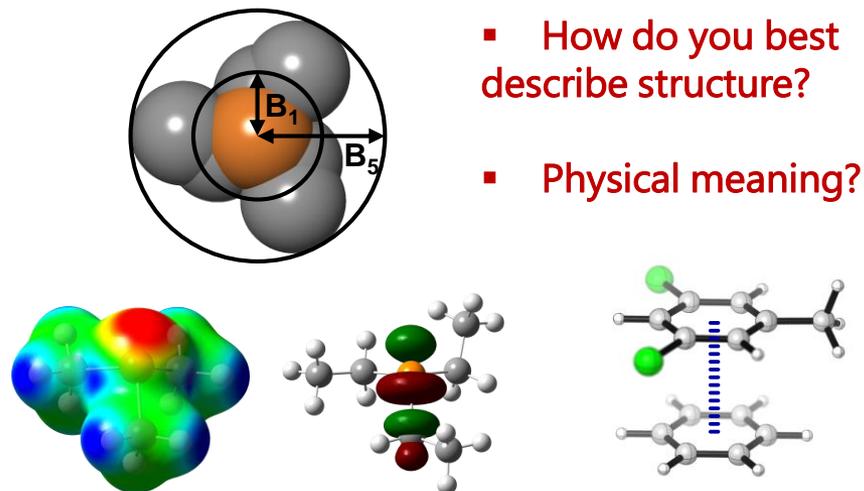
# Data science meets physical organic chemistry

## empirical data collection and mining

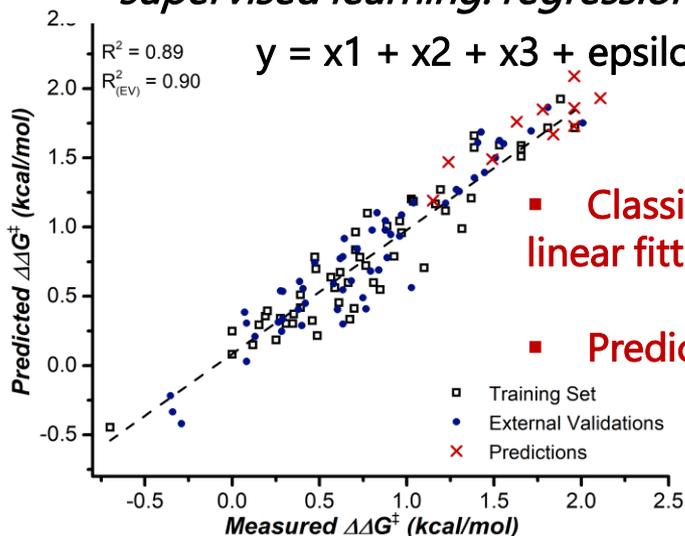


- No wasted data
- Use substrate & catalyst variation
- Data set size?
- Data set quality?

## molecular featurization and property sets

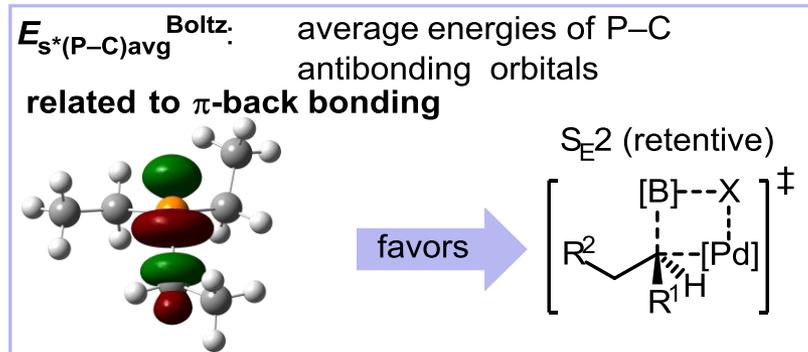


## supervised learning: regression tools



- Classification, linear fitting, or ML?
- Predictive?

## transfer learning?

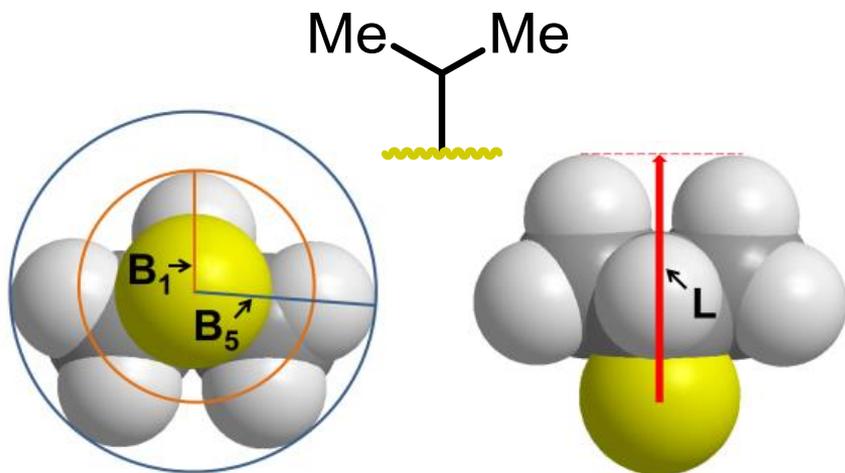


- Conversion of math to mechanism?
- Translate to new systems

# Our typical molecular features

## steric parameters used: Sterimol

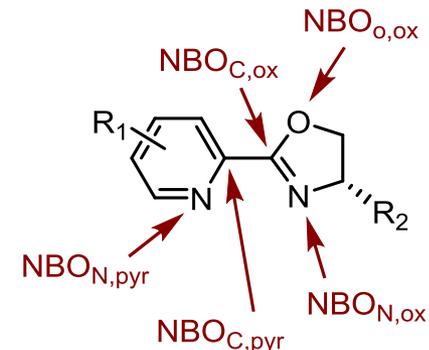
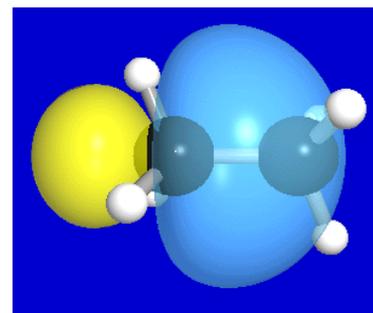
- Verloop developed in 1970's
- Three parameters
  - $L$  is maximum length
  - $B_1$  is minimal radius perpendicular to  $L$
  - $B_5$  is maximum radius perpendicular to  $L$
  - $L$  &  $B_5$  are not independent



- Other parameters
  - Torsion angles, distances, % Vbur etc...

with Harper, K. C.; Bess, E. N. *Nature Chem.* 2012, 366

## standard electronic parameters



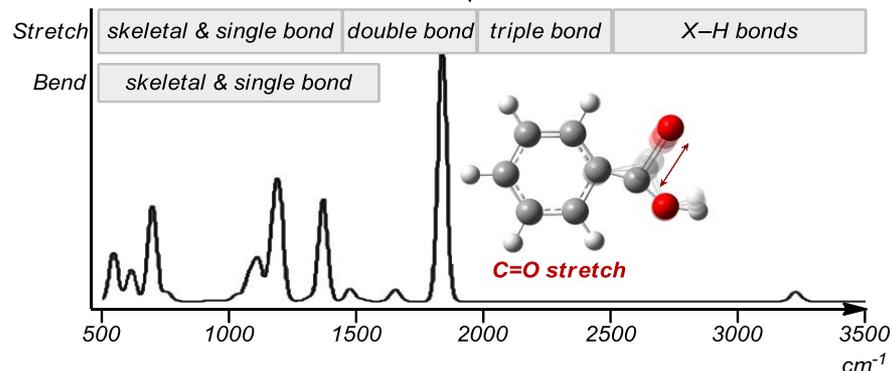
NBO

'natural bonding orbital'

Reed, A. E.; Weinhold, F. *J. Chem. Phys.*, 1983, 78, 4066

## hybrid parameters

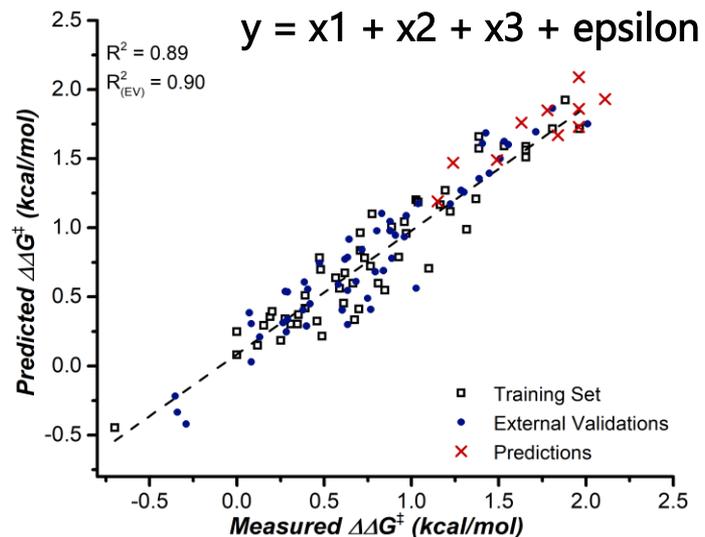
$$\nu = \frac{1}{2\pi c} \sqrt{\frac{k}{\mu_{red}}}$$



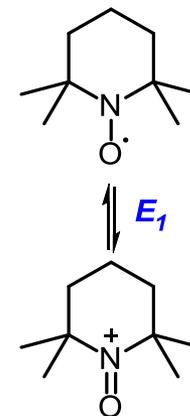
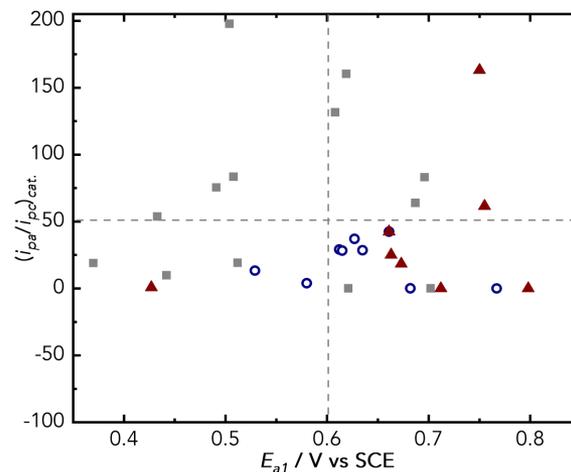
With Milo, A.; Bess, E. N. *Nature* 2014, 507, 210  
 Jones, R. N.; et. Al. *Can. J. Chem.* 1957, 35, 504

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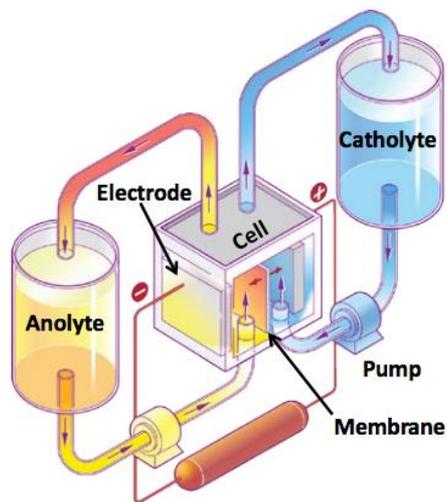
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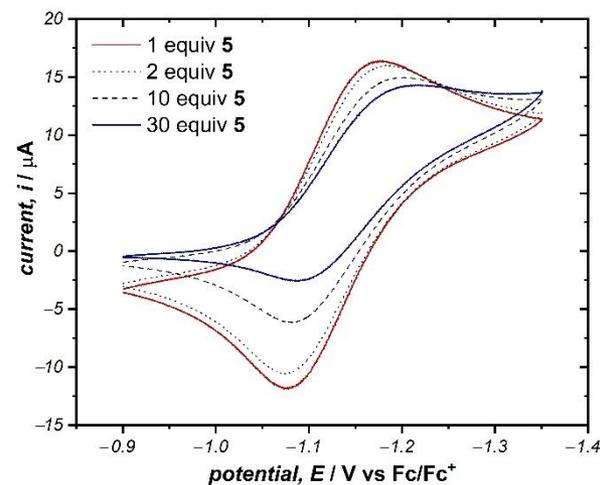
## case study 1: electrocatalysis



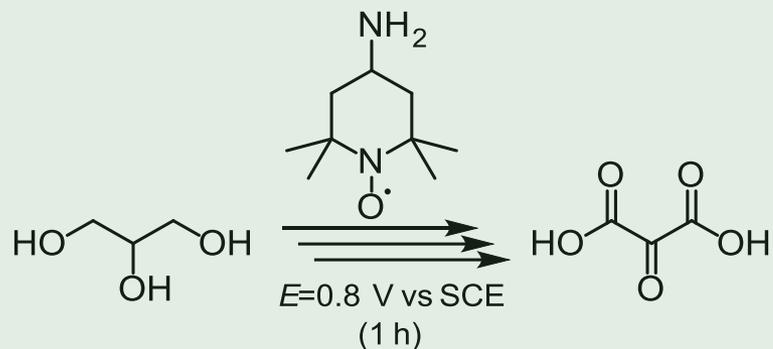
## case study 2: flow batteries



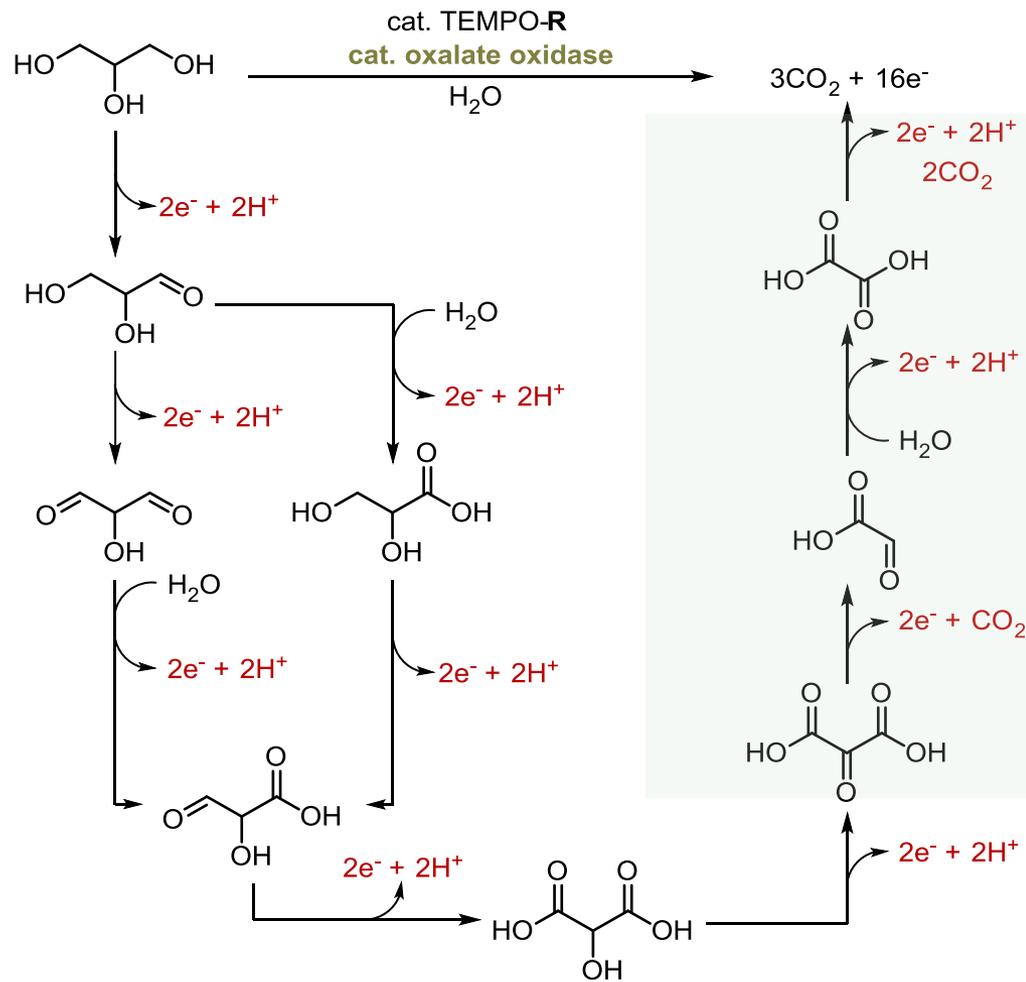
## future applications and thoughts



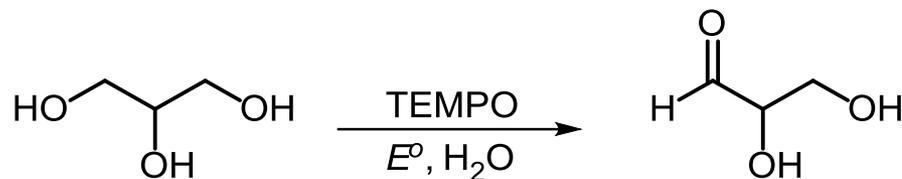
# Designing electrocatalytic oxidation cascades

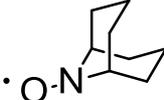
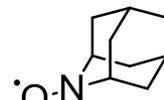
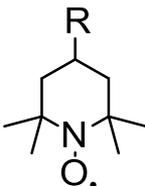


- Complete oxidation of glycerol to CO<sub>2</sub> was achieved using a hybrid catalytic system
- As many as 16 electrons were collected per molecule of glycerol
- *TEMPO-NH<sub>2</sub> was found to exhibit anomalous catalytic properties that allow for expanded pH range*



# TEMPO-NH<sub>2</sub> and how do we adjust properties

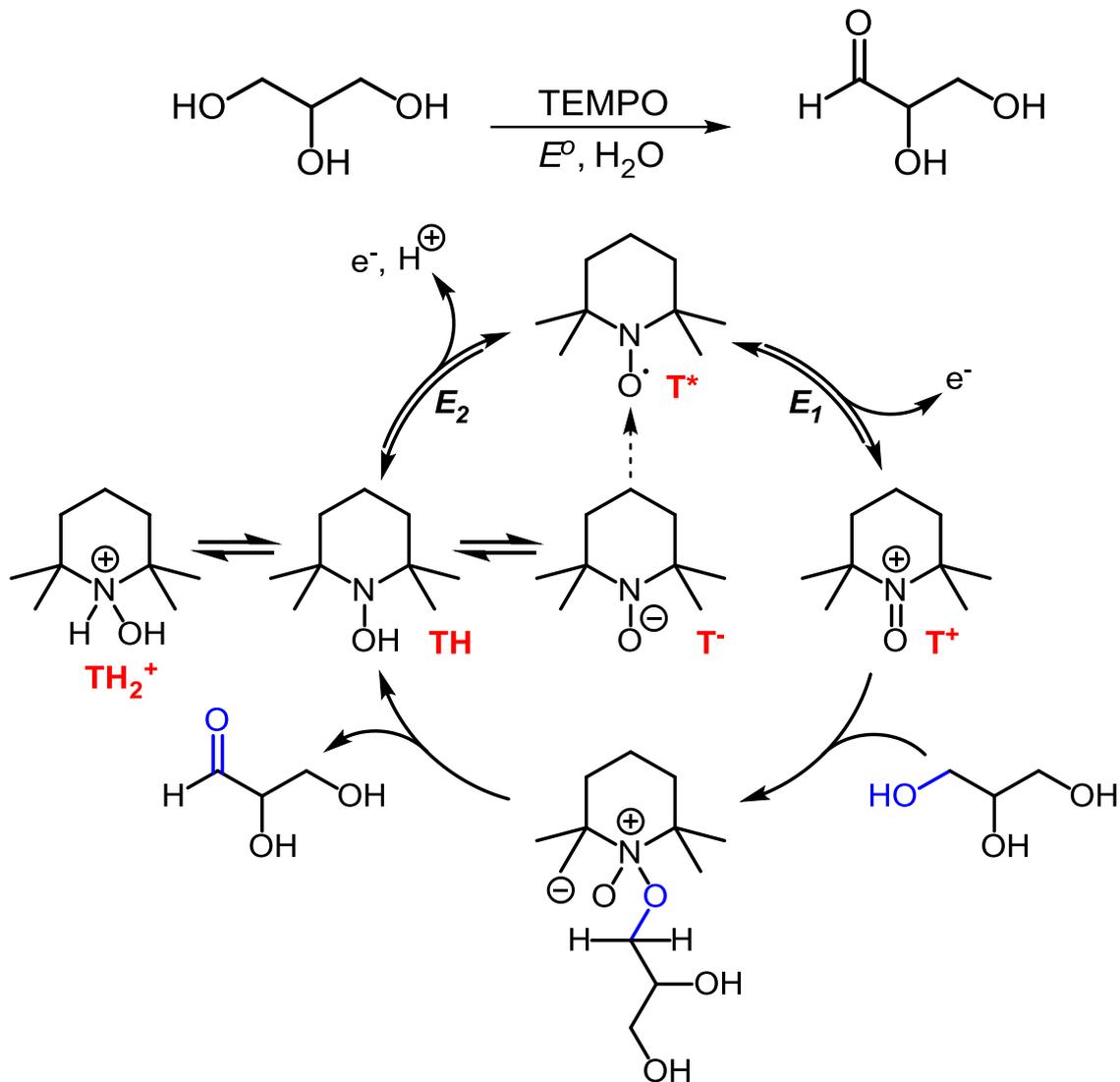


	Electrochemical Potential $E_{1/2}$ / V vs SCE	Catalytic Activity $J_{max}$ / $\mu\text{A cm}^{-2}$	
➡ AZADO	0.466	855	
➡ ABNO	0.485	801	ABNO
TEMPO	0.499	282	
TEMPO-COOH	0.548	224	
TEMPO-OH	0.583	507	
➡ TEMPO-NH <sub>2</sub>	0.623	1453	AZADO
TEMPO=O	0.685	0	
TEMPO-NHC=OMe	0.603	274	
TEMPO-OMe	0.493	297	
Me-AZADO	0.403	313	
			TEMPO-R

**GOAL: predict catalytic activity, eliminate the need for catalyst screening**

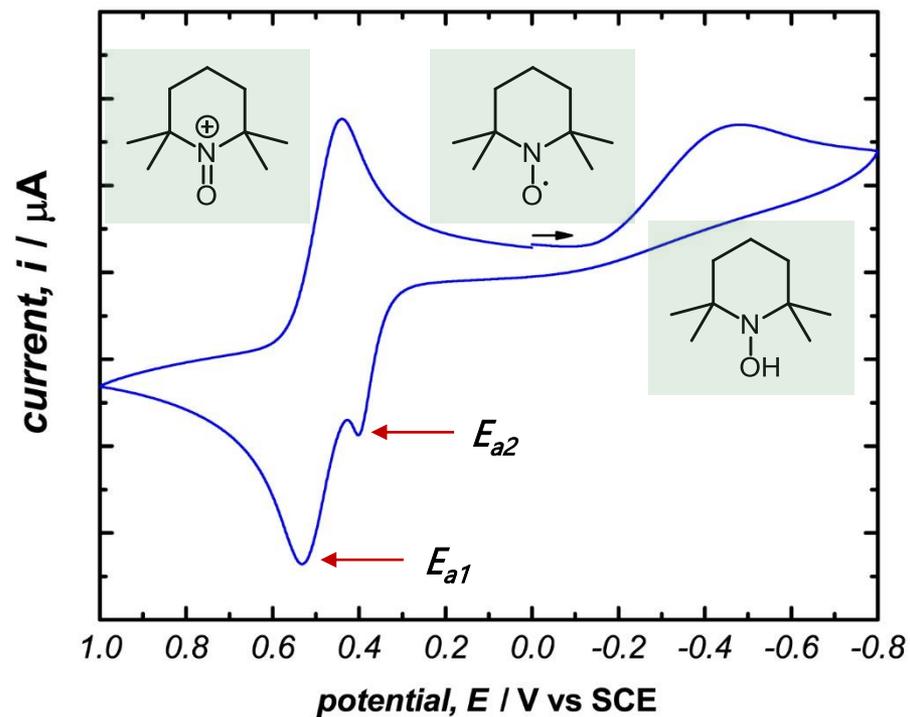
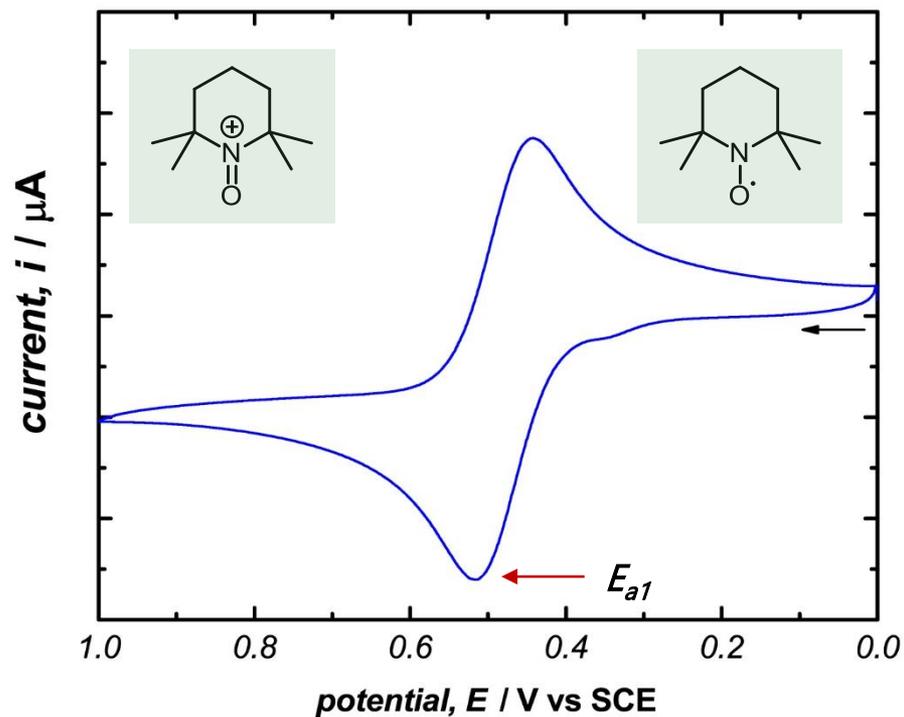
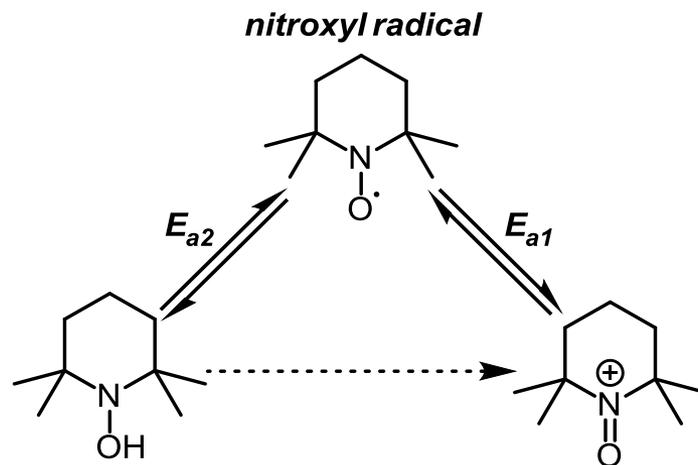
- need a better understanding of structure-function relationships
- enable design of TEMPO derivatives for various diverse applications

# Initiate study by considering the mechanism

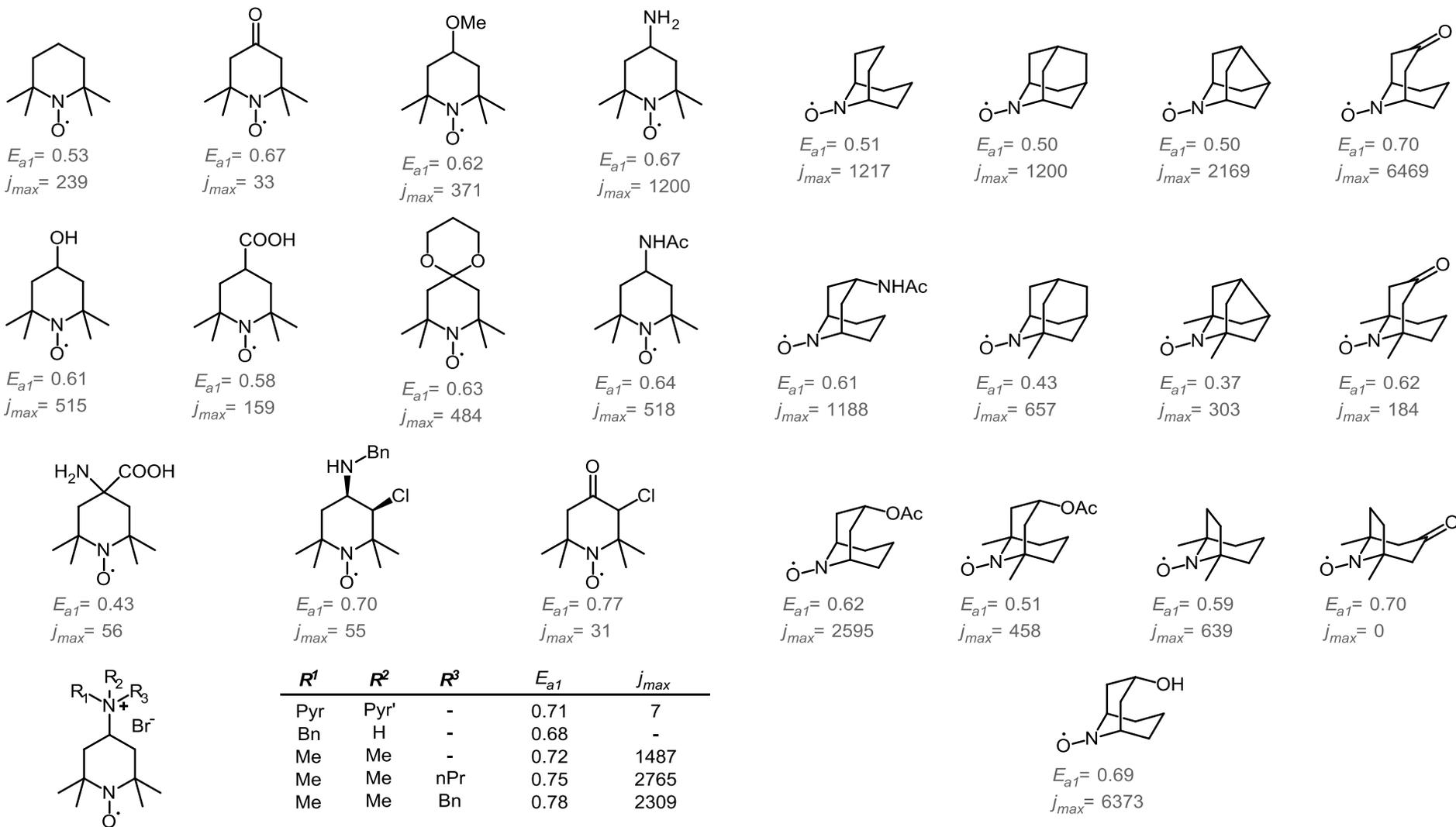
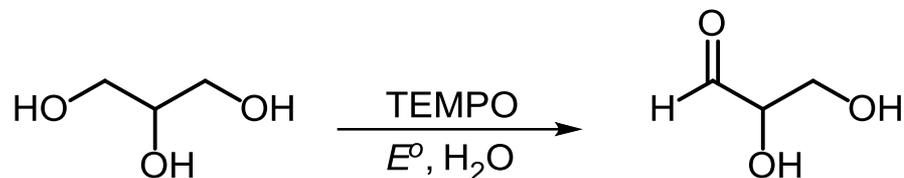


- The nature of  $E_2$  is not well understood
- $E_1$  and  $E_2$  can be accessed electrochemically

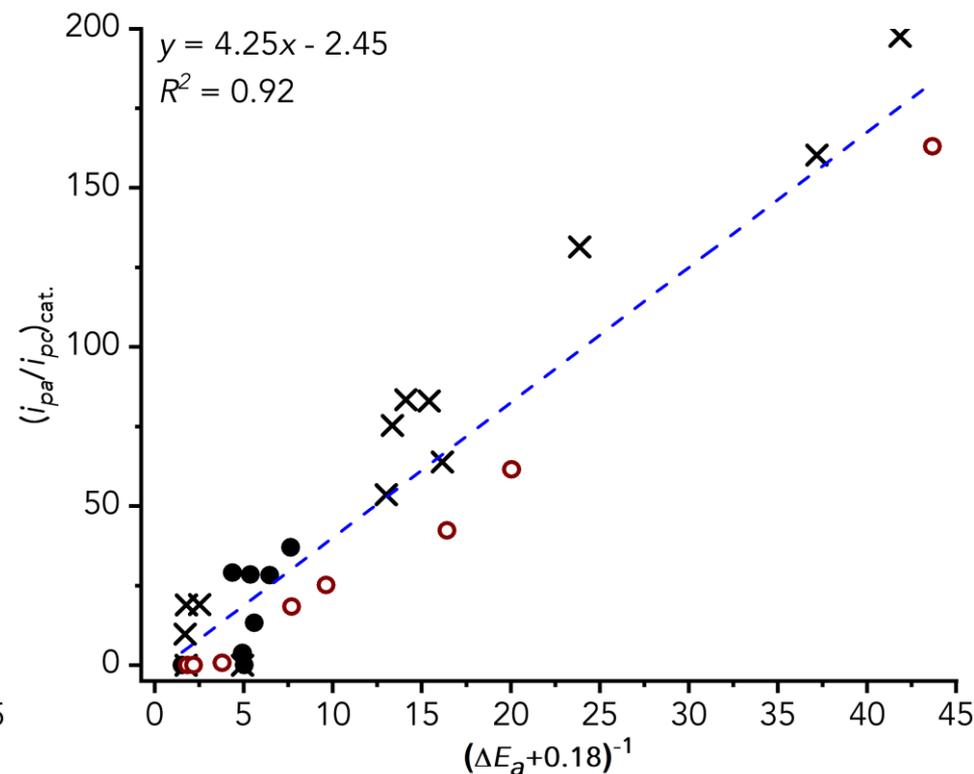
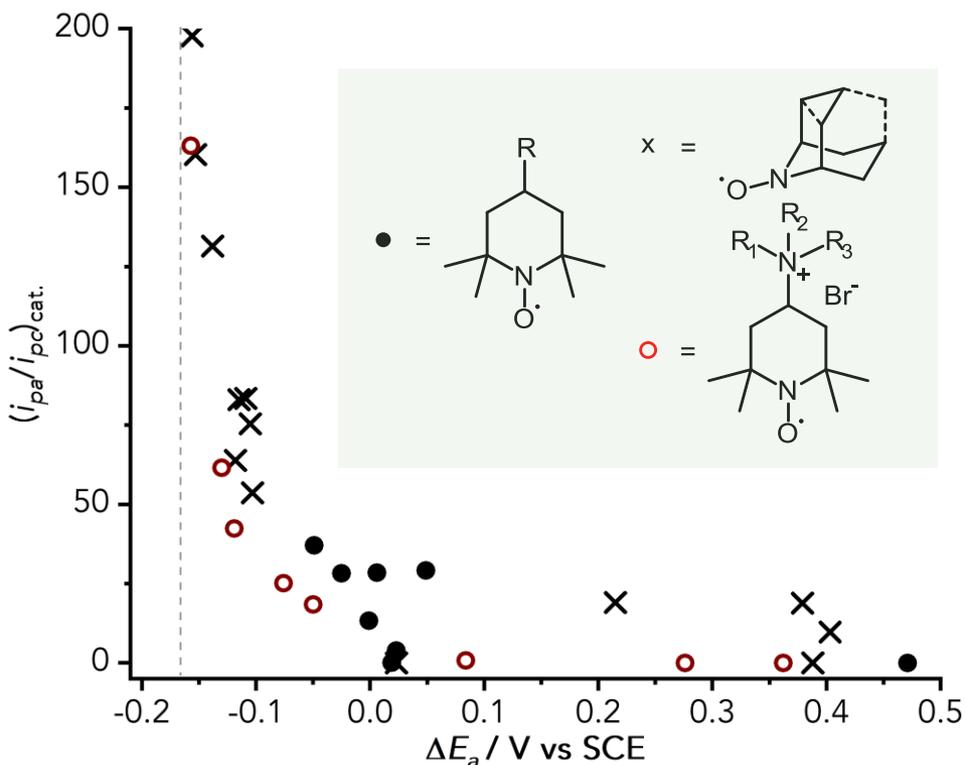
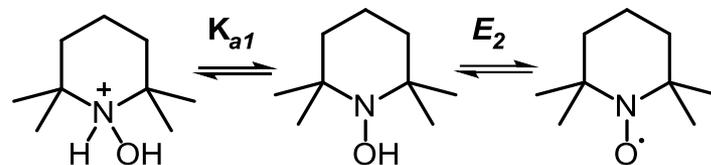
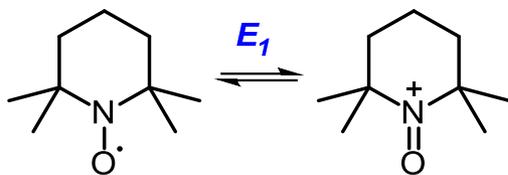
# TEMPO exists in three oxidation states



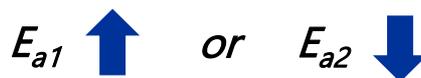
# Evaluation of a broad range of TEMPO derivatives



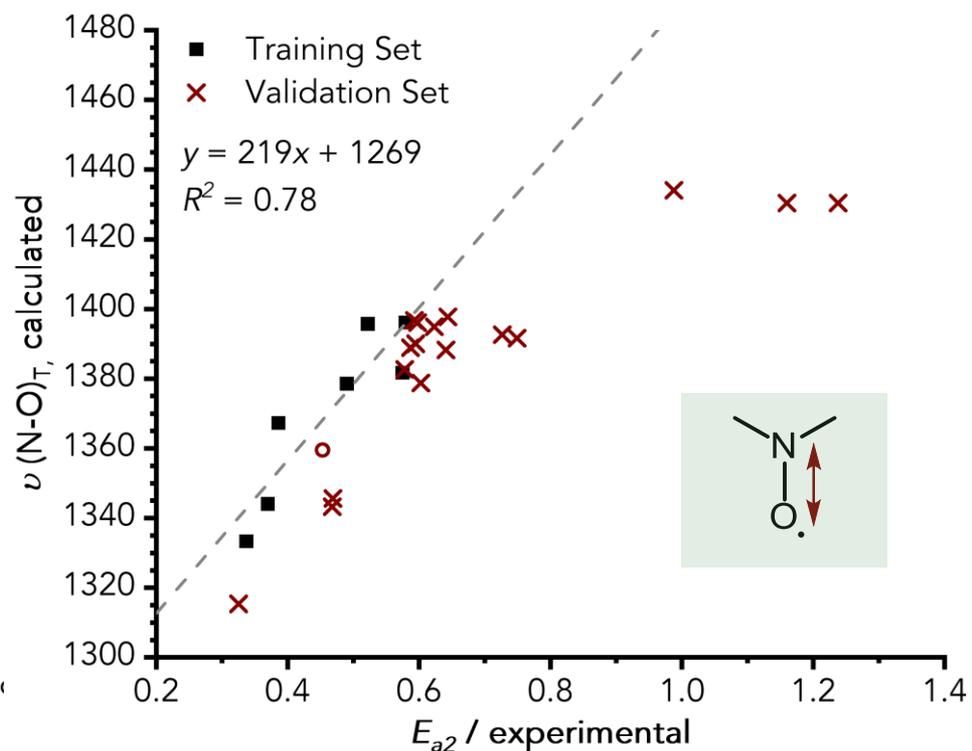
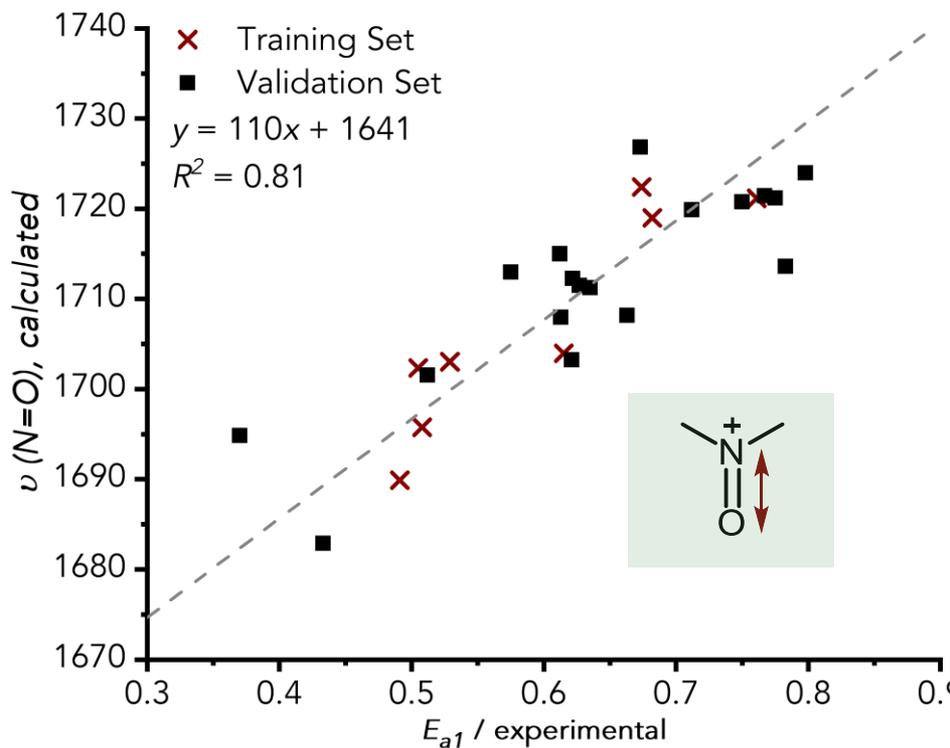
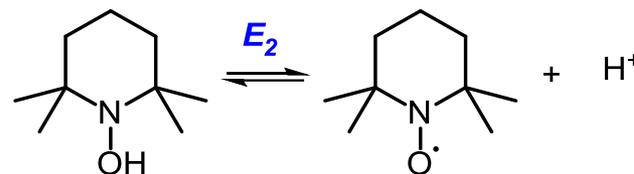
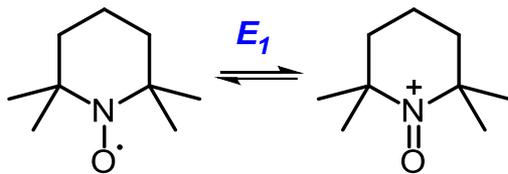
# Correlation found between $E_2$ - $E_1$ and catalysis



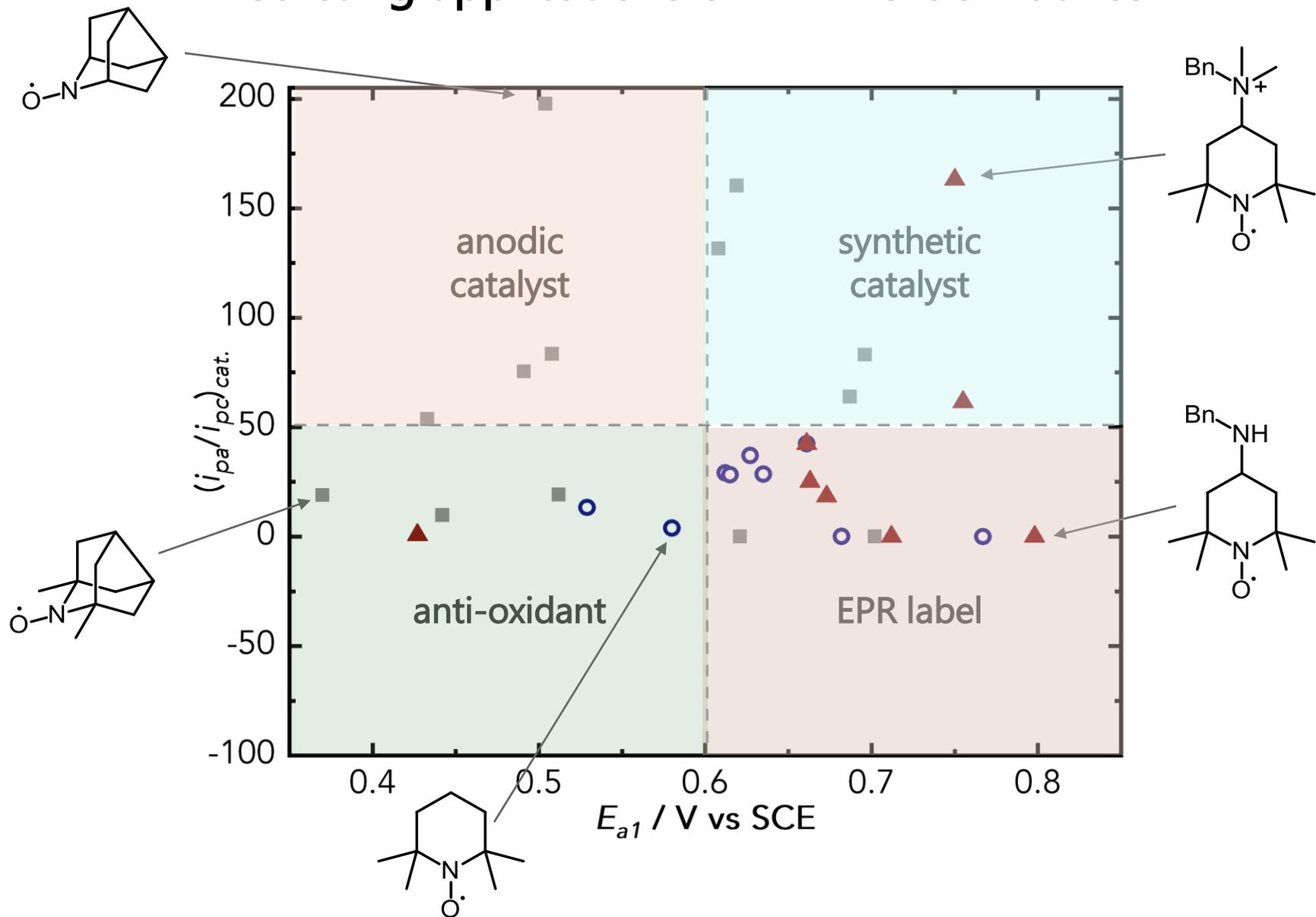
Activity increases if:



# Correlating both $E_1$ and $E_2$ with molecular features



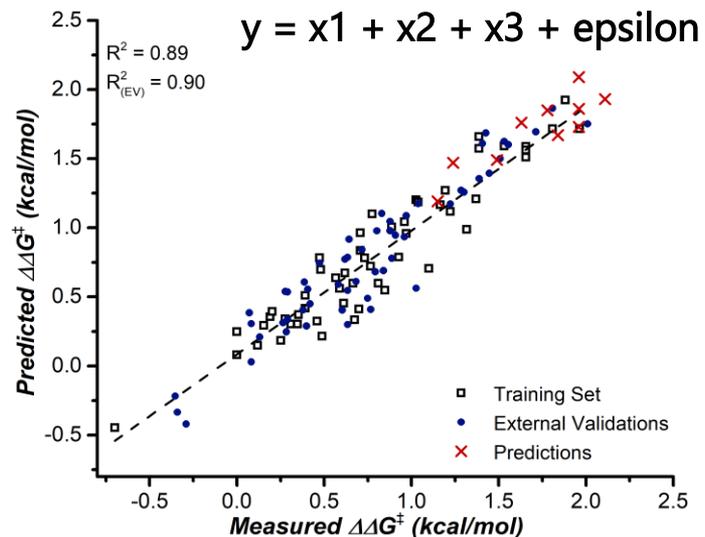
# Predicting applications of TEMPO derivatives



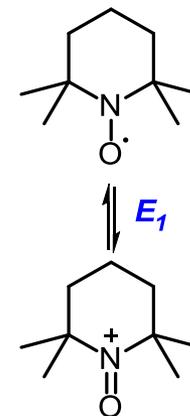
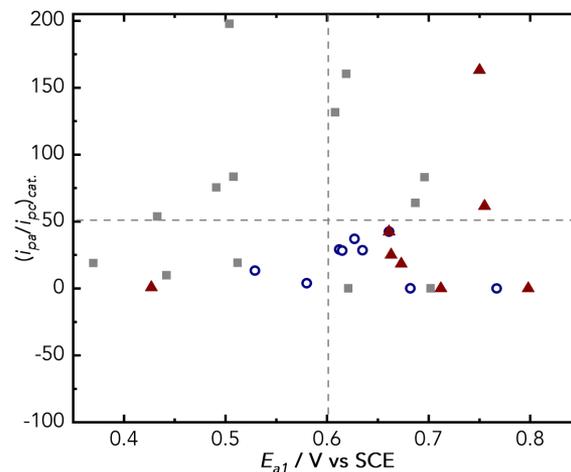
Applications: Lancaster, L.; Hickey, D. P.; Sigman, M. S.; Minter, S. D.; Wheeldon, I. *Chem. Commun.* **2018**, *54*, 491;  
F. Macazo, D.P. Hickey, S. Abdellaoui, M.S. Sigman, S.D. Minter *Chem. Comm.*, **2017**, *53*, 10310;  
D.P. Hickey, R. D. Milton, D. Chen, M. Sigman, S.D. Minter, *ACS Catalysis*, **2015**, *5*, 5519.

# Outline of talk

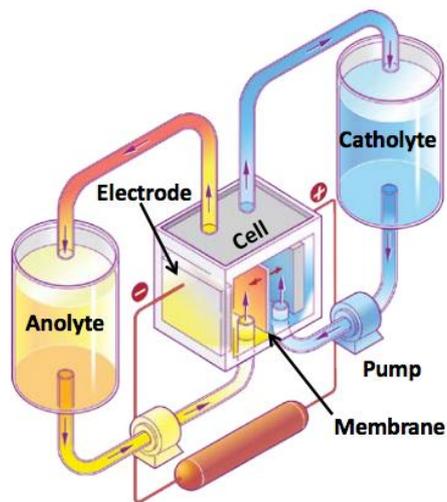
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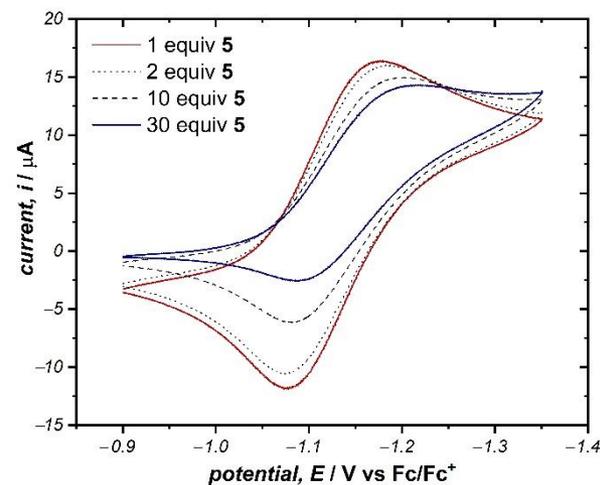
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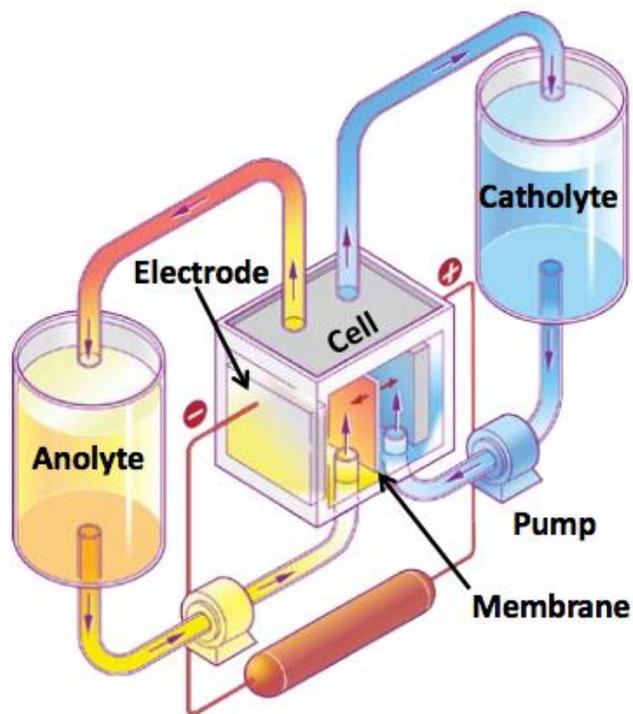
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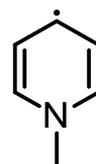
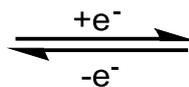
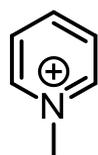
## future applications and thoughts



# Designing improved electrolytes for flow batteries



*Anolyte:*

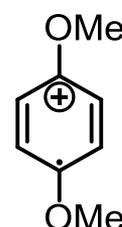
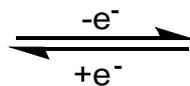
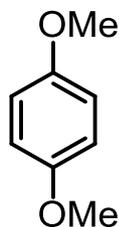


Discharged

Charged

$$E_{1/2} = -1.4 \text{ V vs Ag/Ag}^+$$

*Catholyte:*



Discharged

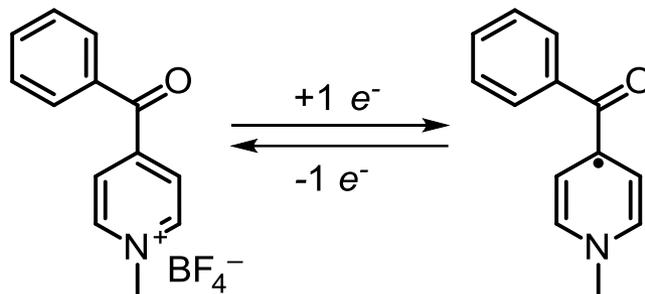
Charged

$$E_{1/2} = 0.8 \text{ V vs Ag/Ag}^+$$

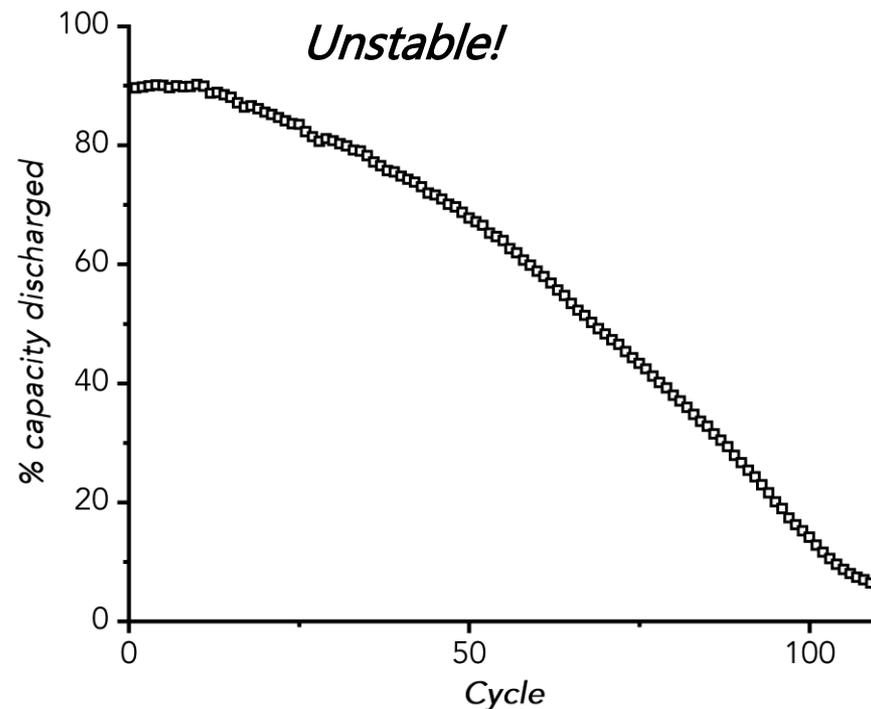
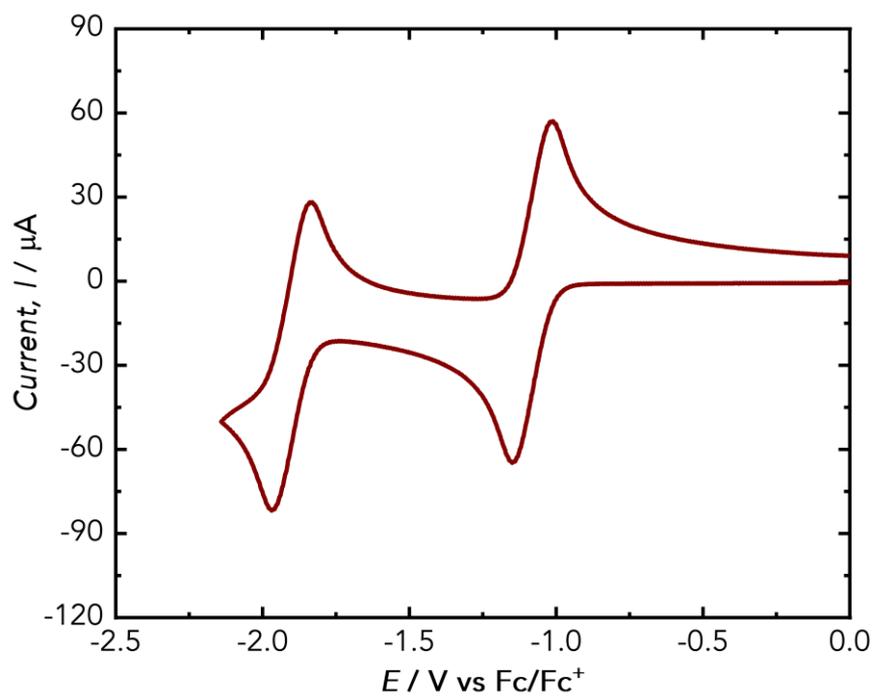
*Essential requirements for anolyte/catholyte:*

- *Stable in charged and discharged states*
- *Molecules need to store a significant amount of energy*

# Identification of a promising anolyte candidate

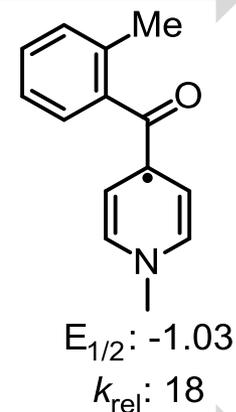
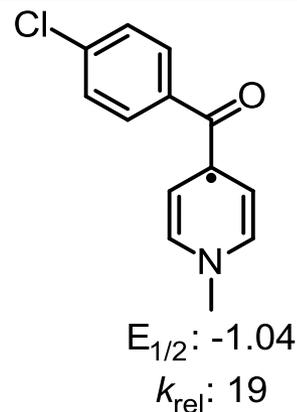
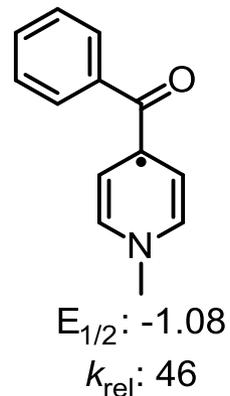
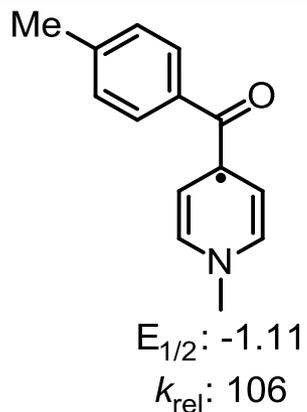
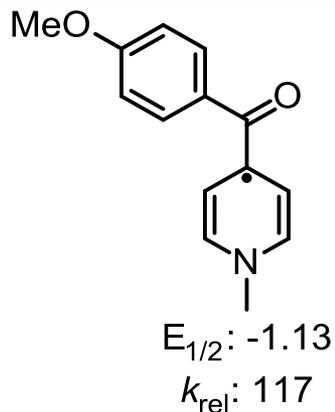


*Low potential (1.12V)  
reversible redox*



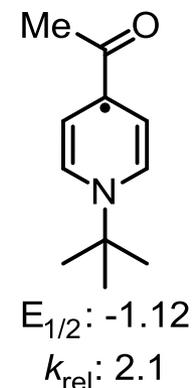
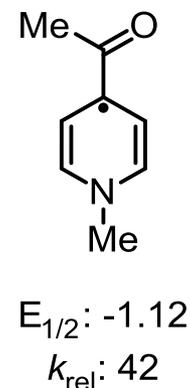
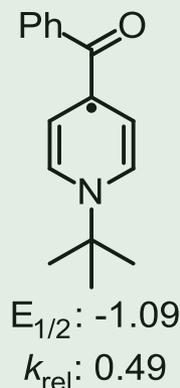
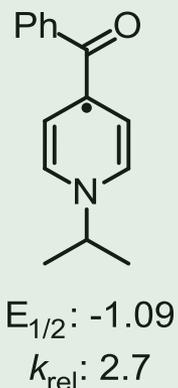
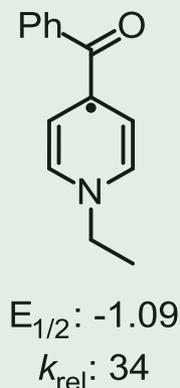
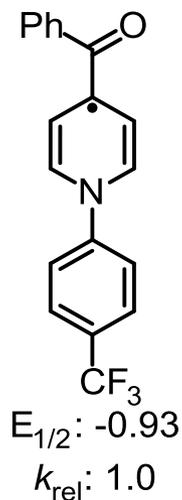
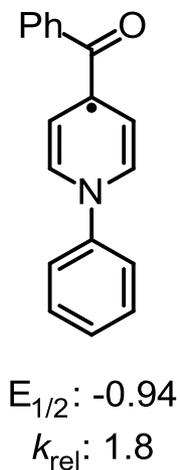
# Training set design

*Decreased Energy*



*Increased Persistence*

*Mechanistic and structural hint*



*similar potential*  
*increased persistence*

# Developing a statistical model of stability

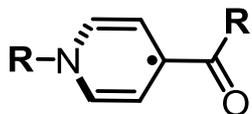
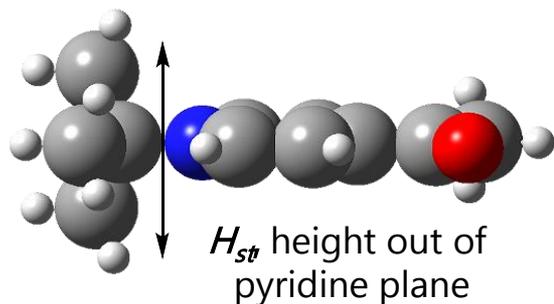
## *Parameters evaluated:*

- *IR frequencies, NBO charges,*
- *Sterimol steric parameters*
- *Charton steric parameters*
- *Electrochemical potential (computed)*

# Developing a statistical model of stability

## Parameters evaluated:

- IR frequencies, NBO charges,
- Sterimol steric parameters
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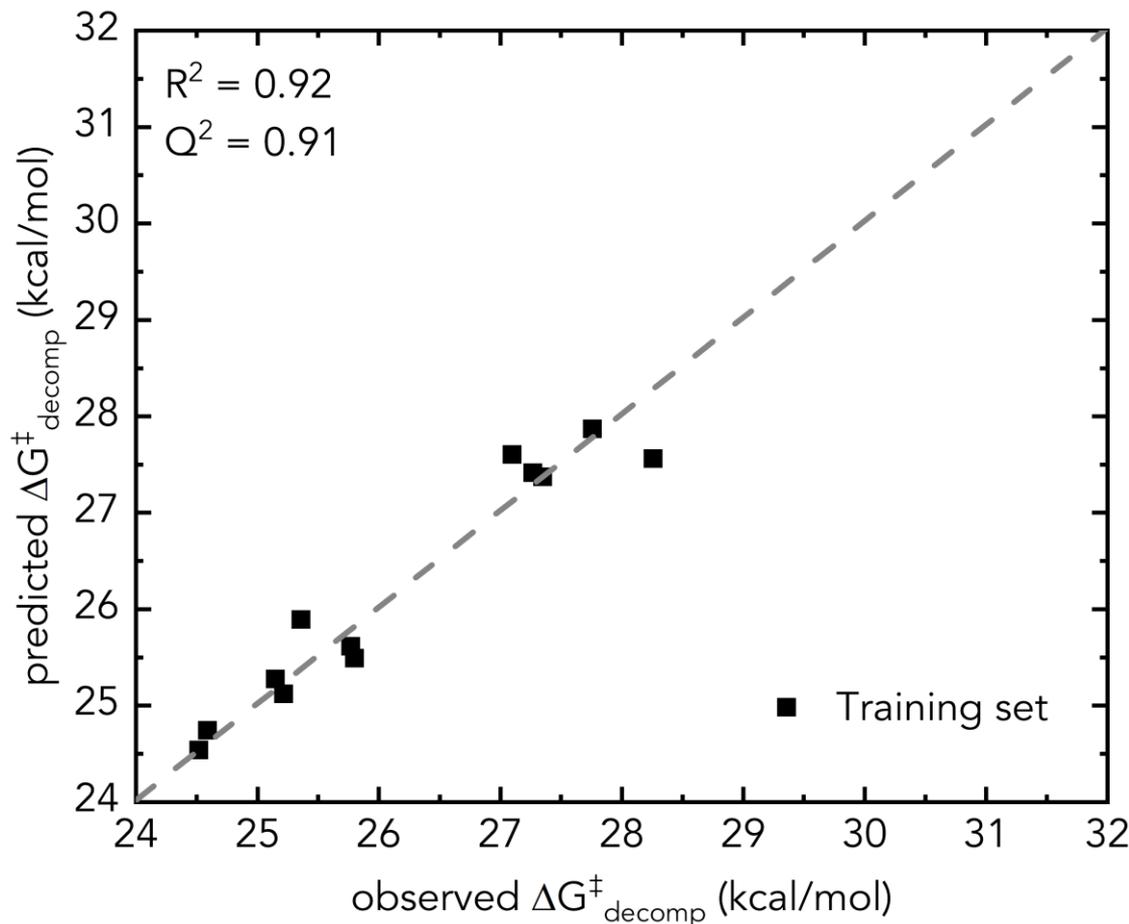
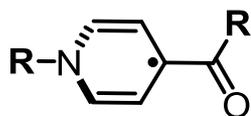
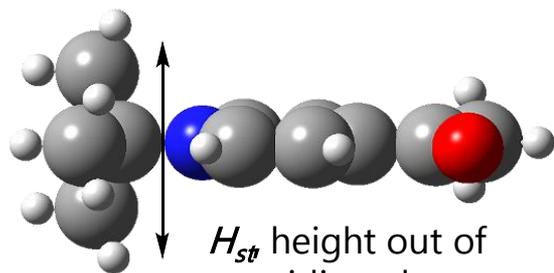
$$\Delta G_{decomp} = 0.49 E_{1/2(\text{computed})} + 1.17 H_{st} + 0.07$$

*electronic/thermodynamic*      *steric/kinetic*

# Developing a statistical model of stability

## Parameters evaluated:

- IR frequencies, NBO charges,
- Sterimol steric parameters
- Charton steric parameters
- Electrochemical potential (computed)



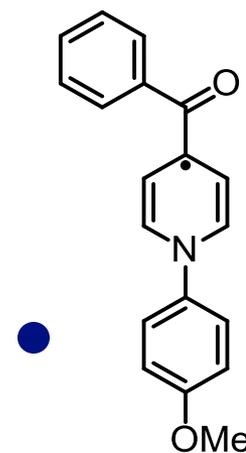
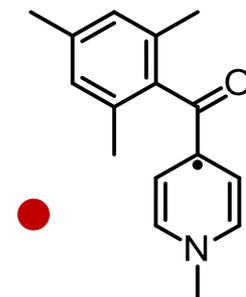
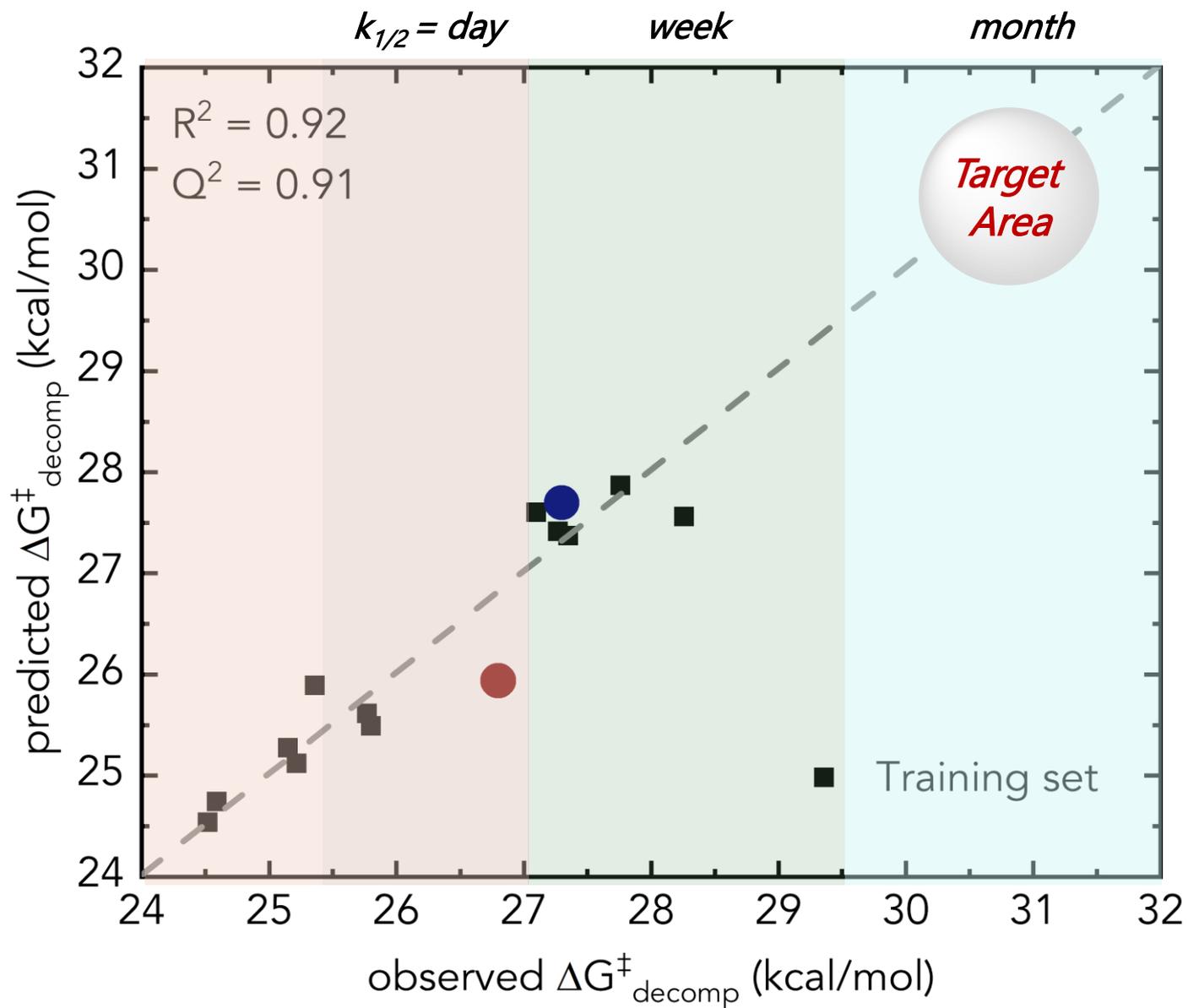
$$\Delta G_{decomp} = 0.49 E_{1/2(\text{computed})} + 1.17 H_{st} + 0.07$$

*electronic/thermodynamic*      *steric/kinetic*

Christo Sevov  
David Hickey  
Sophia Robinson

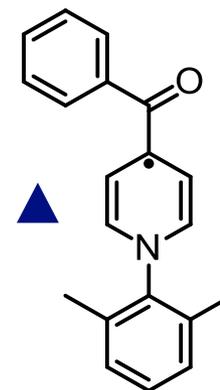
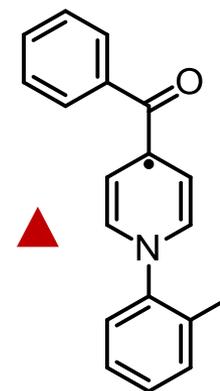
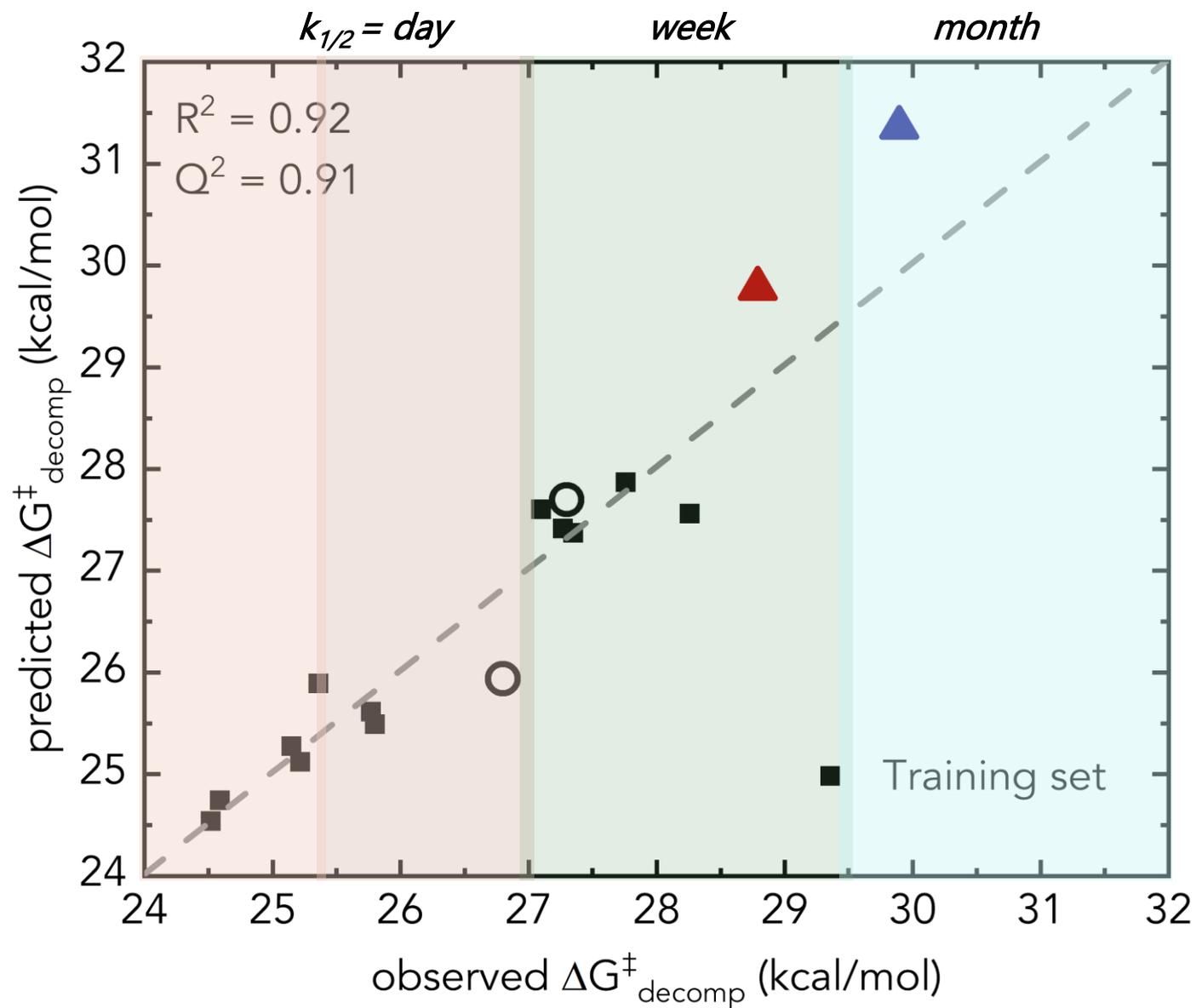
# Interpolations

*Initial predictions: interpolations*



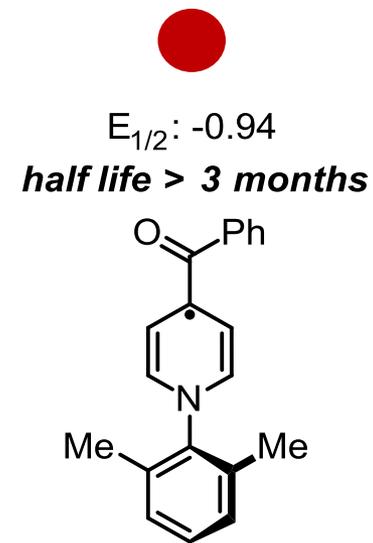
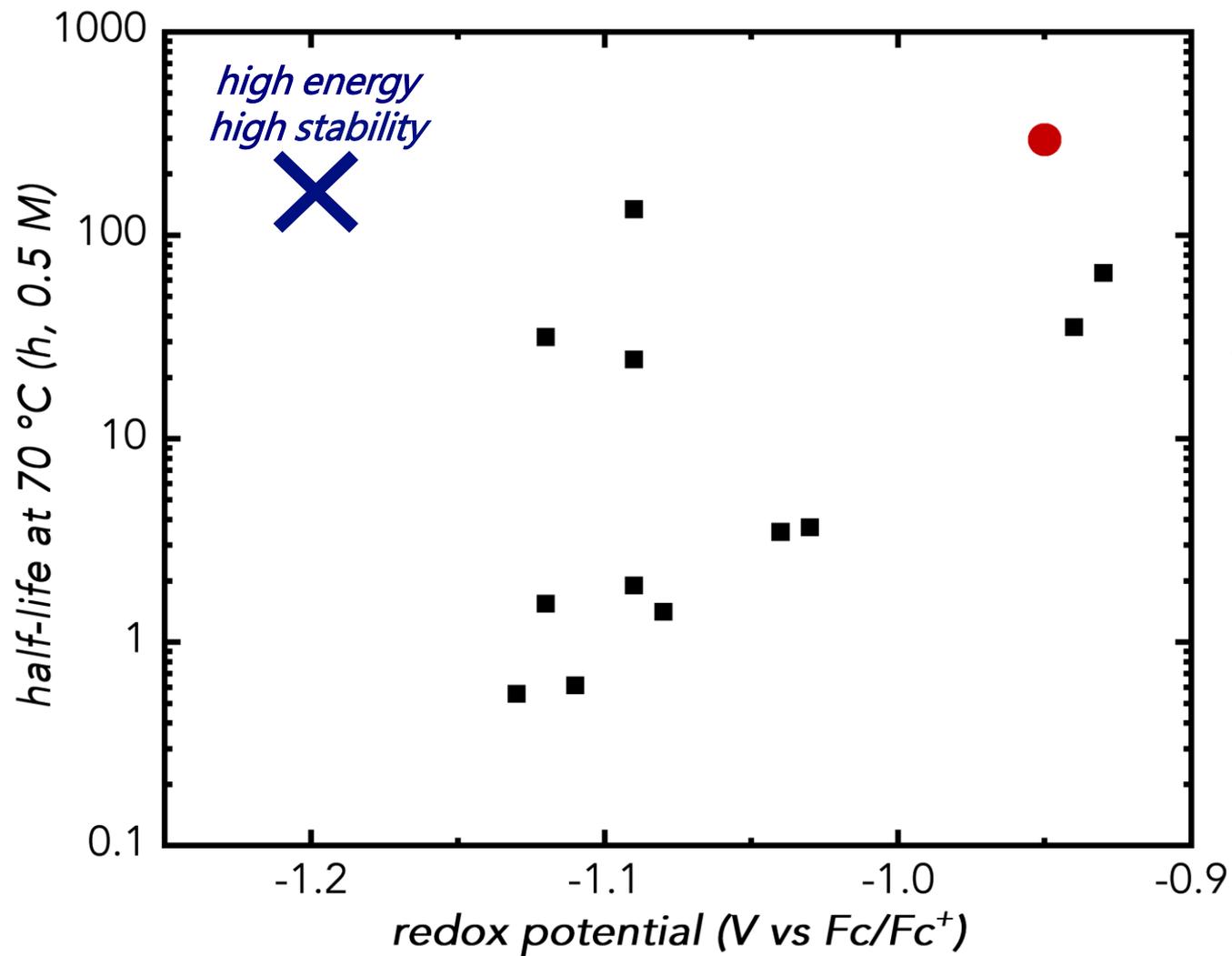
*Christo Sevov  
David Hickey  
Sophia Robinson*

# Predictions

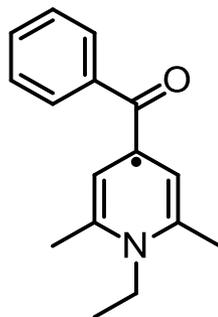
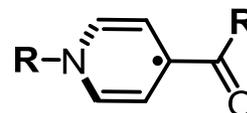
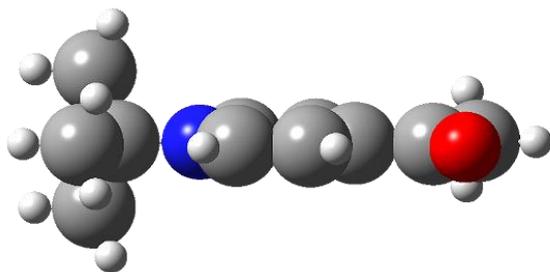


***Predicted and validated 1000-fold increase in stability!!!***

# Stability versus potential: still correlated



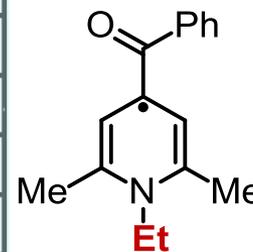
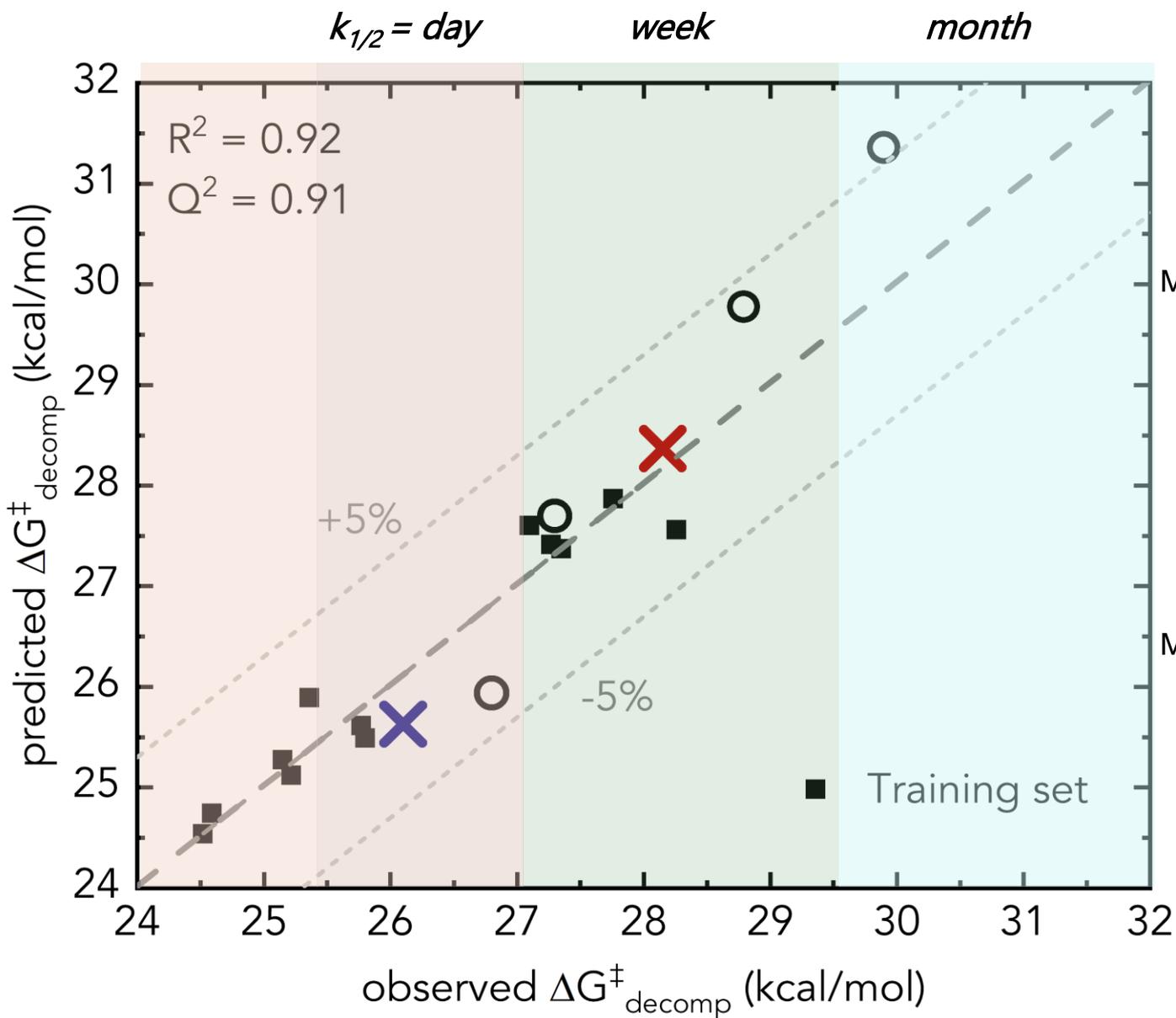
# Stability versus potential: still correlated



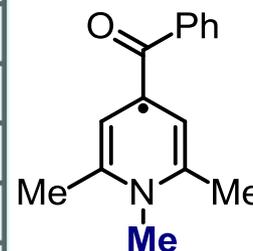
**predicted** potential: -1.23 V  
**predicted**  $\Delta G^\ddagger = 28.4$  kcal/mol

*Protect the 2,6-positions through substitution:  
Model predicts good stability and higher redox potential*

# A bit more about the model



$E_{1/2}$ : -1.21  
 $k_{\text{rel}}$ : 0.56  
**persistent**  
& **low potentia**

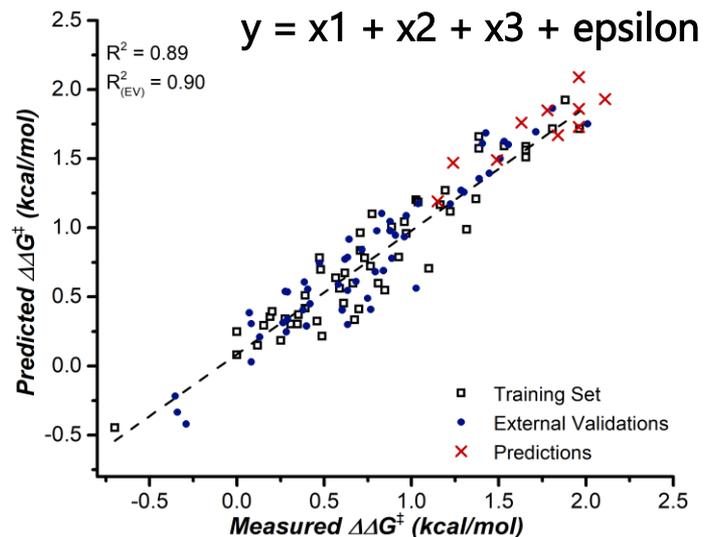


$E_{1/2}$ : -1.21  
 $k_{\text{rel}}$ : 12.0

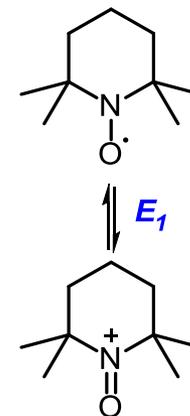
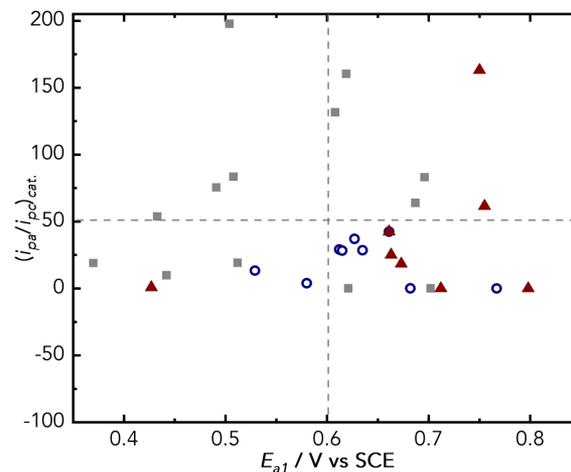


# Outline of talk

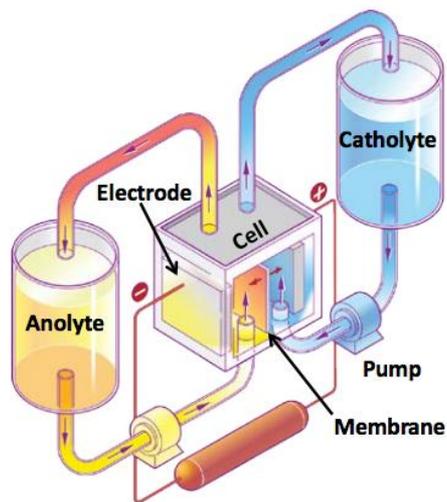
## introduction to data science



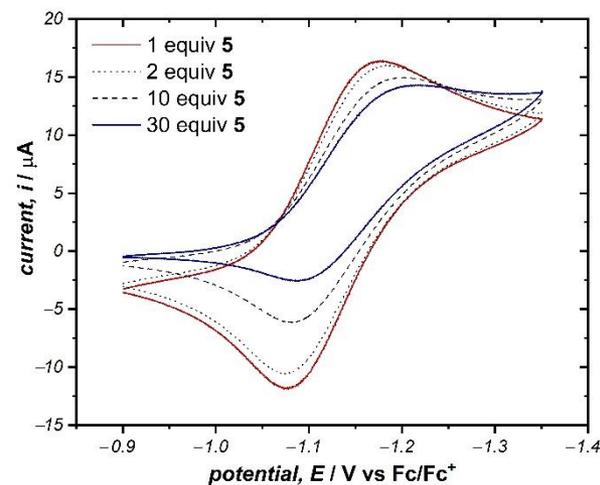
## case study 1: electrocatalysis



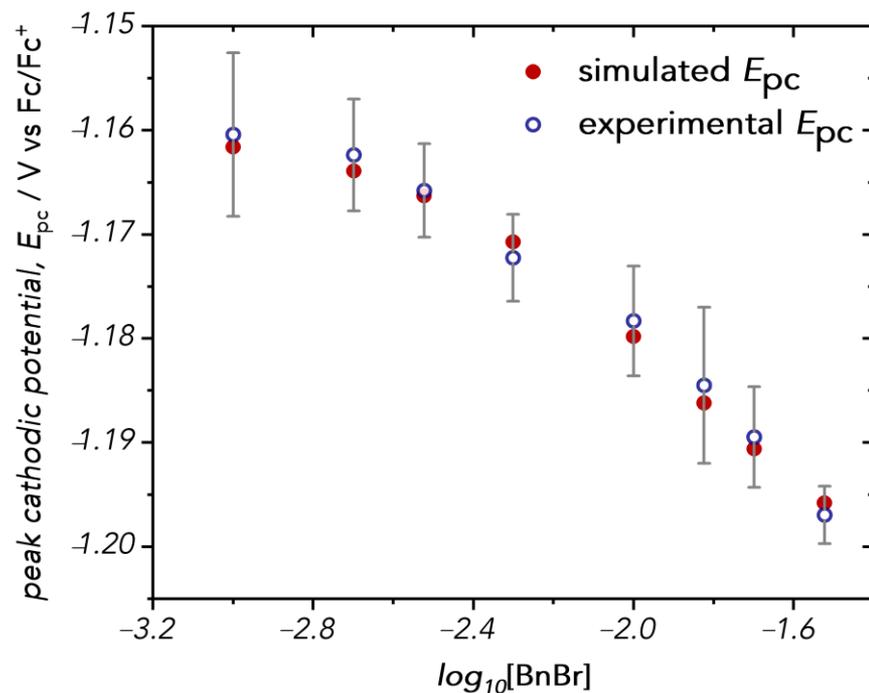
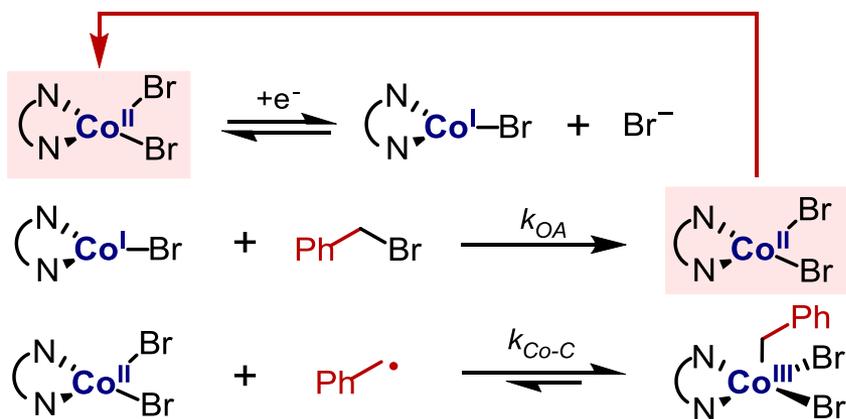
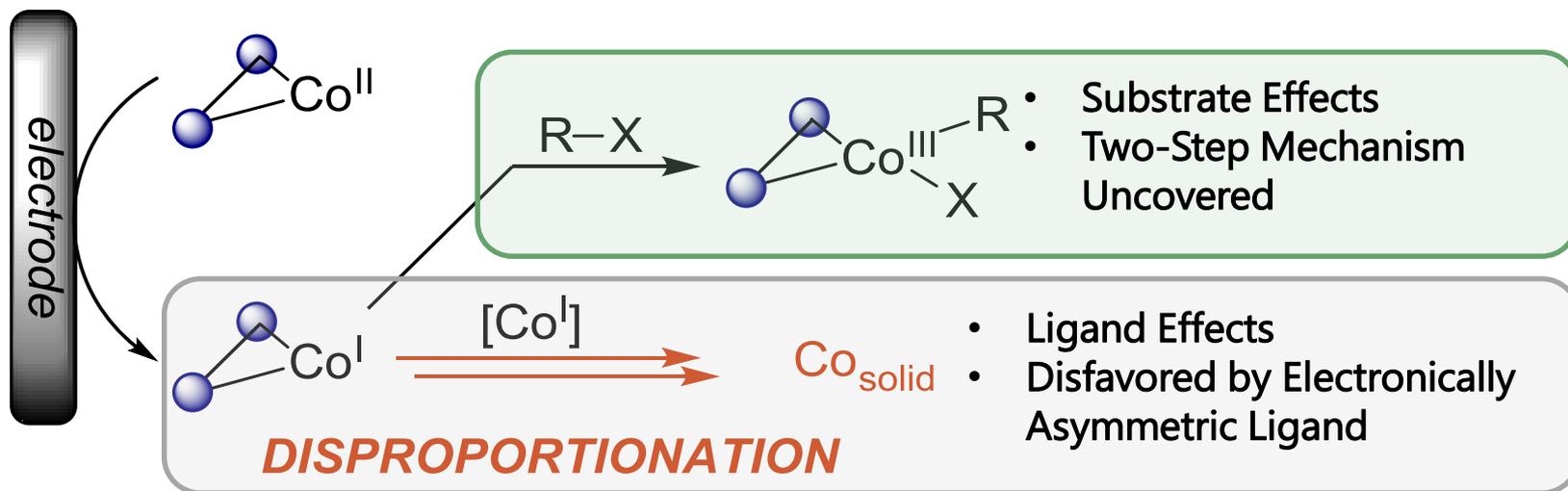
## case study 2: flow batteries



## future applications and thoughts



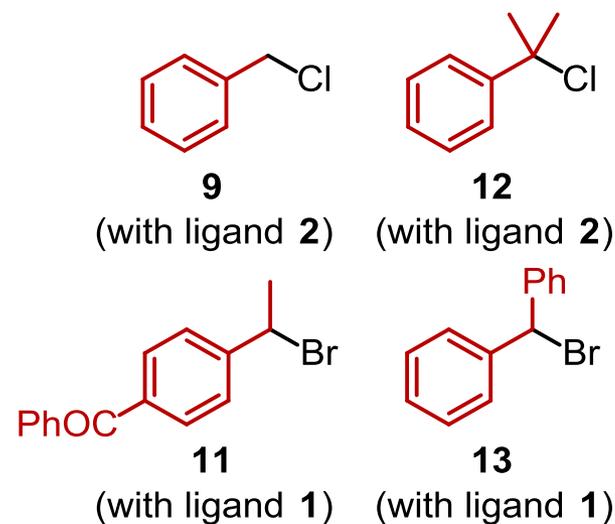
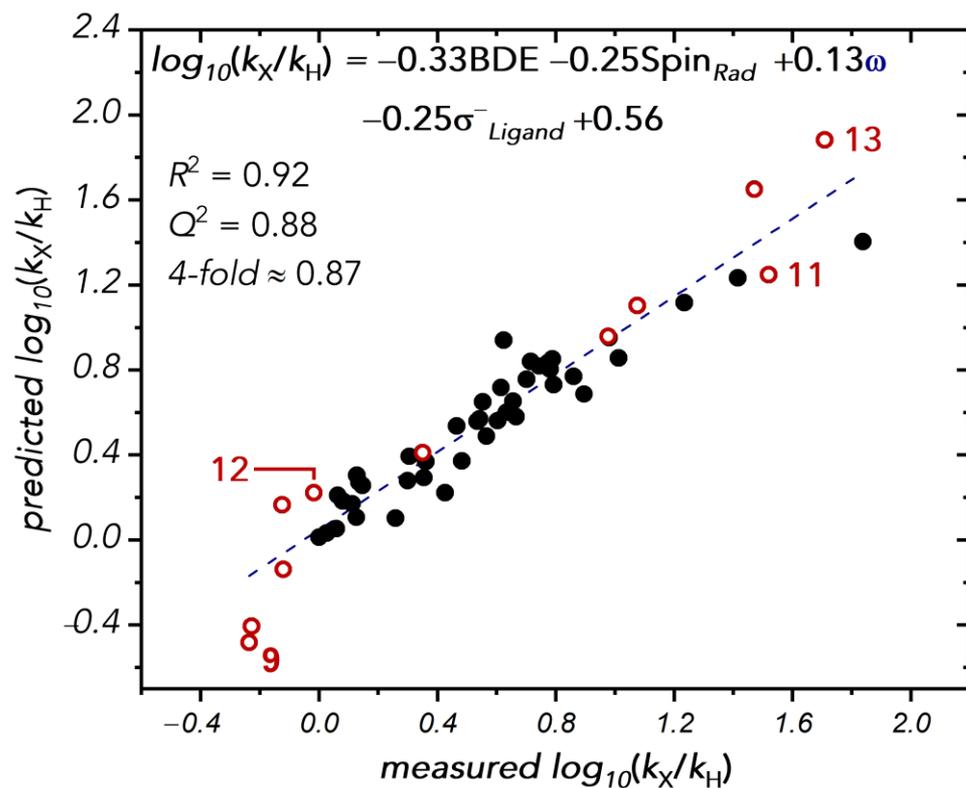
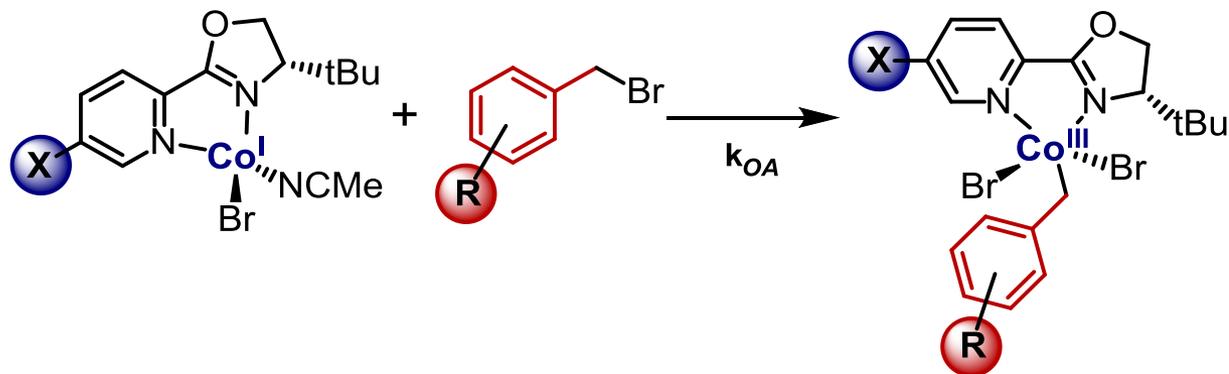
# Electroanalytical tools in organometallic electrocatalysis



Hickey, D. P.; Sandford, C.; Rhodes, Z.; Gensch, T.; Fries, L. R.; Sigman, M. S.; Minter, S. D. *J. Am. Chem. Soc.* **2019**, *141*, 1382.

Sandford, C.; Fries, L. R.; Ball, T.; Minter, S. D. Sigman, M. S. *J. Am. Chem. Soc.* **2019**, *141*, ASAP

# Electroanalytical tools enable data science



# Final thoughts and data science in organic chemistry

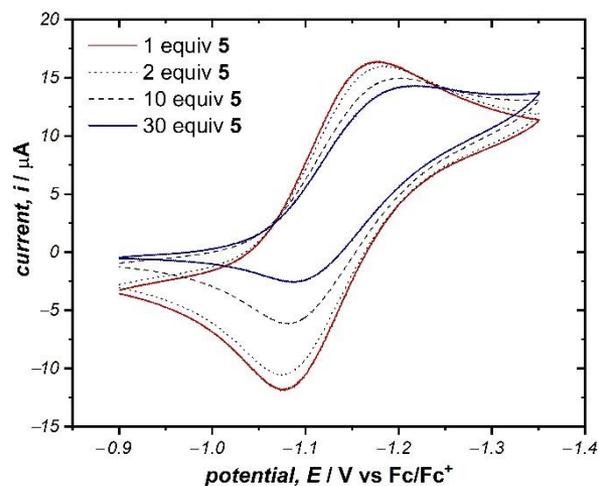
## possible applications

- structure function relationships
- synthetic route planning
- reaction optimization protocols
- autonomous reaction optimization
- novel reaction prediction
- feature predictions

## the issues

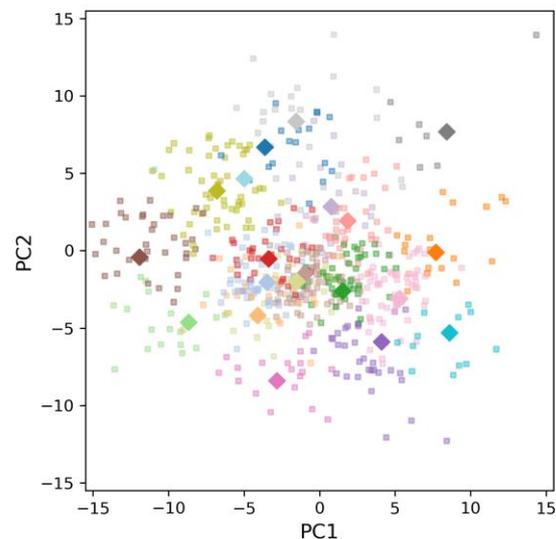
- data quality & quantity
- data bias
- feature selection
- not trained in data science
- AI versus ML versus data science
- OVERHYPED!

## Data starved for data science



- electroanalytic tools are data rich
- kinetics, thermodynamics, etc.

## Design of data sets



- use molecular features
- clustering to statistically orient data

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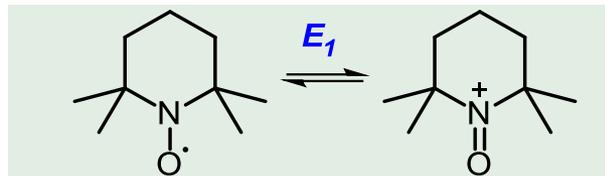
**Active Collaborators**  
 Alán Aspuru-Guzik (Toronto)  
 Mark Biscoe (CCNY)  
 Christophe Copéret (ETH)  
 Miquel Costas (iQCC)  
 Huw Davies (Emory)  
 Abigail Doyle (Princeton)  
 Justin Du Bois (Stanford)  
 Jason Hein (UBC)  
 Todd Hyster (Princeton)  
 Eric Jacobsen (Harvard)  
 Song Lin (Cornell)  
 Neal Mankad (UIC)  
 Scott Miller (Yale)  
**Shelley Minteer (Utah)**  
 Olaf Wiest (Norte Dame)  
 Rob Paton (CSU)  
 Robert Phipps (Cambridge)  
 Sarah Reisman (Caltech)  
**Melanie Sanford (Michigan)**  
 Corinna Schindler (Michigan)  
**Dean Toste (UC Berkeley)**

**Financial Support**

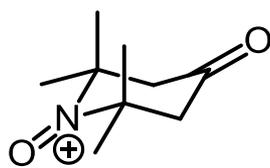
**NSF (CHE-1925607 – C-CAS)**  
**NSF (CHE-1763436)**  
 NIH (NIGMS, GM121383 with Toste/Miller)  
 NIH (NIGMS, GM63540)  
**DOE (JCSER) with Minteer/Sanford**  
**ARO (MURI) with Shelley Minteer**  
 NSF (CHE-1205646 – NSF CCHF)  
 Merck Research Labs, Millipore Sigma  
 Novartis (NIBR), Pfizer, Genentech



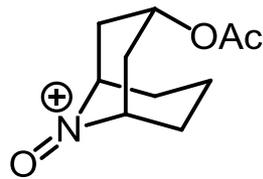
# Mechanistic insight



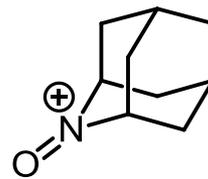
Geometric Stabilization



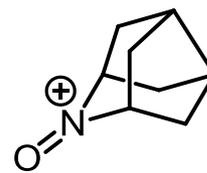
$E_{a1} = 0.67$



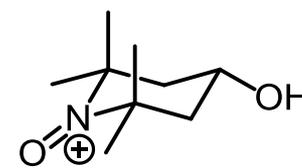
$E_{a1} = 0.62$



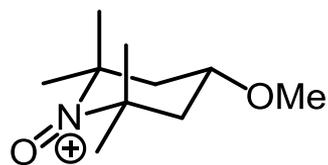
$E_{a1} = 0.51$



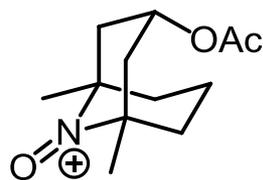
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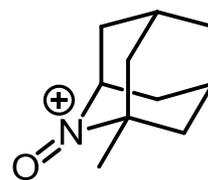
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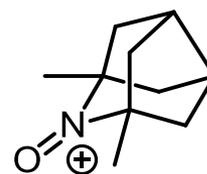
$E_{a1} = 0.62$



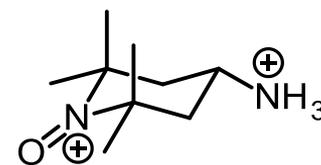
$E_{a1} = 0.51$



$E_{a1} = 0.43$



$E_{a1} = 0.37$



$E_{a1} = 0.67$

Coulombic Repulsion