

# BEAST DB

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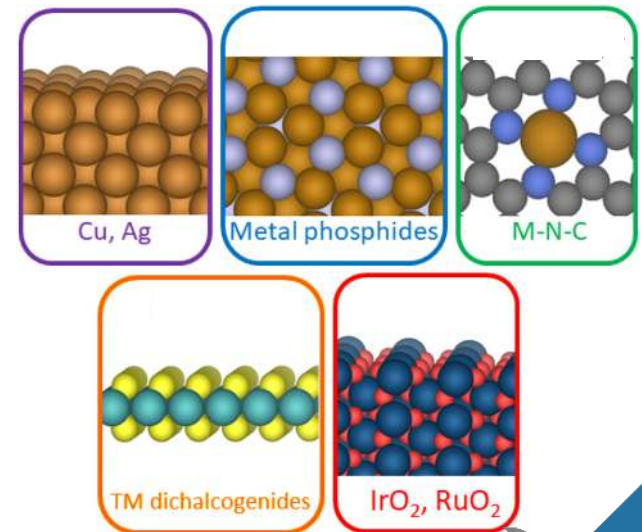
Derek Vigil-Fowler

1<sup>st</sup> Annual BEAST workshop

08/16/22

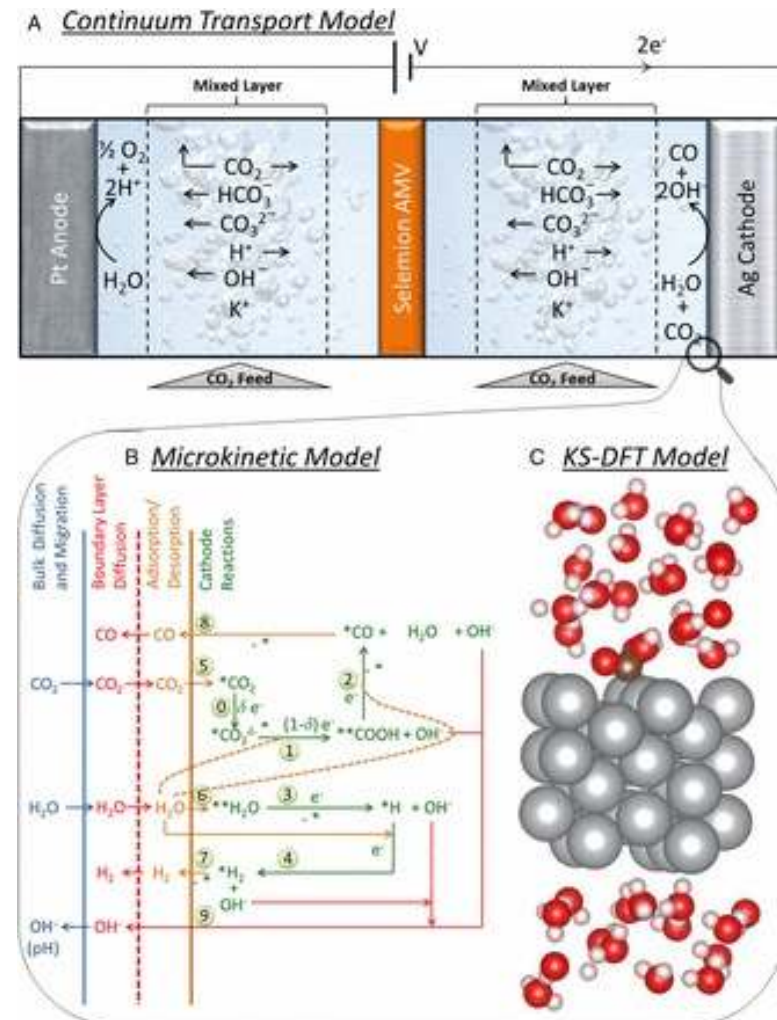


- Beyond-DFT Electrochemistry with Accelerated and Solvated Techniques Database
- Will have adsorption energies, other descriptors for range of common electrocatalysts, chemistries, use ML to obtain beyond-DFT accuracy



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# Electrochemistry is hard!



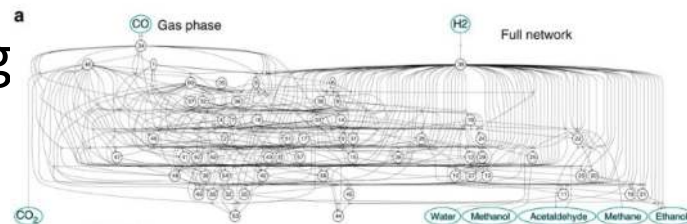
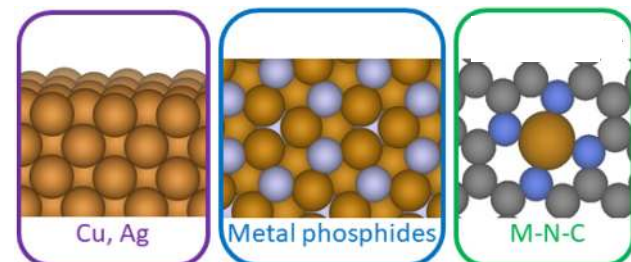
# Electrochemistry is hard!

- Diversity and dynamics



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- Diversity and dynamics
  - Combinatorial space of elements
  - Bulk vs reduced dimensional
  - Identity of active site, mechanism
  - Surface structure and reconstruction
  - Defects
  - Complex reaction pathways involving intermediates, spectator species
  - Electrolyte identity, concentration
  - pH
  - Applied potential
  - Kinetic and thermodynamic considerations
  - Transport/morphology
  - ....



~100 species

~200 reactions

>2,000 pathways



Result: chemical intuition plays big role



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- Often unclear what governs choices





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- Often unclear what governs choices
- Example: CO<sub>2</sub> reduction on Sn/SnO

*ACS Catal.* 2015, 5, 5, 3148–3156

## Conditions:

- Sn thin films;
- Potentials: –1 to –2.4 vs Ag/AgCl
- 0.1 M K<sub>2</sub>SO<sub>4</sub> electrolyte
- pH = 4.4

*ACS Catal.* 2017, 7, 7, 4822–4827

## Conditions:

- Metallic Sn foil; pretreatment removed excess oxide from the surface, leaving only a native oxide
- Potentials: –0.4 to –1.3 V vs. RHE
- 0.1 M KHCO<sub>3</sub> electrolyte
- pH = 6.8

*ACS Catal.* 2015, 5, 12, 7498–7502

## Conditions:

- SnO<sub>2</sub> NPs on graphene oxide
- Potentials: –0.25 to –1.5 vs Ag/AgCl
- NaOH
- pH = 8.5 – 12 (alkaline conditions avoid SnO<sub>2</sub> reduction)

credit: Carrie Farberow



# Experimental efforts on protocols



## Suggested Testing Procedure for Round Robin Matrix

### - Cell Assembly and Conditioning as specified. Test start.

- Measure CV and EIS in  $\text{H}_2/\text{N}_2$  at BOT as specified.
  - Flow  $\text{O}_2$  on cathode. Wait until OCV is stable (e.g. 5 min).
  - Measure activity in  $\text{H}_2/\text{O}_2$  as specified.
  - Flow air on cathode. Wait until OCV is stable (e.g. 5 min).
  - Measure pol curve in  $\text{H}_2/\text{air}$  as specified.
  - Change T, RH, and P conditions for next test. Wait at least 30 min for equilibration.
  - Measure pol curve in  $\text{H}_2/\text{air}$  at 250 kPa, 75% RH, 95 °C as specified.
  - Flow  $\text{N}_2$  on cathode and set back T = 80C, P=150 kPa, RH=100%. Wait until OCV decreases to ~0.1 V or for at least 20 min. If OCV does not decrease enough, reduce the residual  $\text{O}_2$  adsorbed on the catalyst, in order to have a CV shape “centered” around 0 current.
  - Measure CV and EIS in  $\text{H}_2/\text{N}_2$  at BOT again (CV and EIS may vary after measuring the first pol curve due to full hydration of CL and ionomer due to water generation).
  - Flow air on cathode. Wait until OCV is stable (e.g. 5 min).
- 
- **Start AST cycling up to 100 cycles** (should take ~10 min → helpful to set cathode  $\text{N}_2$  purge delay). When finished (or asap after finishing) start to flow  $\text{N}_2$  on cathode in case the test is going to be paused for long time (e.g. overnight) to not leave the cell under OCV conditions for too long.
  - Flow  $\text{N}_2$  on cathode. Wait until OCV decreases to ~0.1 V or for at least 20 min. If OCV does not decrease enough, reduce the residual  $\text{O}_2$  adsorbed on the catalyst, in order to have a CV shape “centered” around 0 current.
  - Measure CV and EIS in  $\text{H}_2/\text{N}_2$  as described before.
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  - Measure activity in  $\text{H}_2/\text{O}_2$  as specified.
  - Flow air on cathode. Wait until OCV is stable (e.g. 5 min).
  - Measure pol curve in  $\text{H}_2/\text{air}$  as described before.
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# Why build a computational electrochemistry database?



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- Quick access to structures, energies, properties of catalysts for researchers working on catalysts in database (or related)
  - Increases ability to quickly get started with confidence, speeds catalyst discovery
  - Properties: give fundamental understanding of what's driving observed catalytic activity and selectivity



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# Materials databases



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- Can quickly obtain various materials properties, e.g. relative stability, structure, and electronic structure, from a simple database query




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1

H



by Elements

Mo-S

×

search

2

He

3

Li

4

Be

5

B

6

C

7

N

8

O

9

F

10

Ne

11

Na

12

Mg

13

Al

14

Si

15

P

16

S

17

Cl

18

Ar

19

K

20

Ca

21

Sc

22

Ti

23

V

24

Cr

25

Mn

26

Fe

27

Co

28

Ni

29

Cu

30

Zn

31

Ga

32

Ge

33

As

34

Se

35

Br

36

Kr

37

Rb

38

Sr

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Y

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Zr

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Nb

42

Mo

43

Tc

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Ru

45

Rh

46

Pd

47

Ag

48

Cd

49

In

50

Sn

51

Sb

52

Te

53

I

54

Xe

55

Cs

56

Ba

57-71

La-Lu

72

Hf

73

Ta

74

W

75

Re

76

Os

77

Ir

78

Pt

79

Au

80

Hg

81

Tl

82

Pb

83

Bi

84

Po

85

At

86

Rn

87

Fr

88

Ra

89-103

Ac-Lr

104

Rf

105

Db

106

Sg

107

Bh

108

Hs

109

Mt

110

Ds

111

Rg

112

Cn

57

La

58

Ce

59

Pr

60

Nd

61

Pm

62

Sm

63

Eu

64

Gd

65

Tb

66

Dy

67

Ho

68

Er

69

Tm

70

Yb

71

Lu

89

Ac

90

Th

91

Pa

92

U

93

Np

94

Pu

95

Am

96

Cm

97

Bk

98

Cf

99

Es

100

Fm

101

Md

102

No

103

Lr



# Materials databases

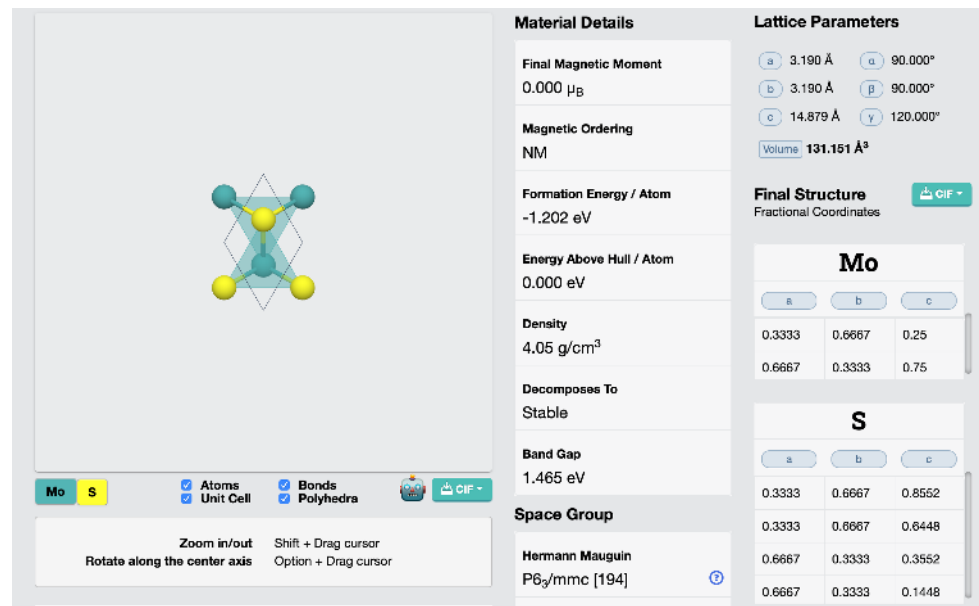
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Materials Id	Formula	Spacegroup	Formation Energy (eV)	E Above Hull (eV)	Band Gap (eV)	Volume	Nsites	Density (gm/cc)	
mp-2815	MoS <sub>2</sub>	P6 <sub>3</sub> /mmc	-1.202	0	1.465	131.151	6	4.053	<input type="checkbox"/>
mp-1434	MoS <sub>2</sub>	R3m	-1.201	0	1.578	62.649	3	4.243	<input type="checkbox"/>
mp-1027525	MoS <sub>2</sub>	P $\bar{3}$ m1	-1.201	0.001	1.491	350.447	12	3.034	<input type="checkbox"/>
mp-1025874	MoS <sub>2</sub>	P $\bar{6}$ m2	-1.201	0.001	1.509	284.872	9	2.799	<input type="checkbox"/>
mp-1023939	MoS <sub>2</sub>	P $\bar{3}$ m1	-1.2	0.001	1.554	219.296	6	2.424	<input type="checkbox"/>
mp-1018809	MoS <sub>2</sub>	P6 <sub>3</sub> /mmc	-1.2	0.001	1.336	123.452	6	4.306	<input type="checkbox"/>



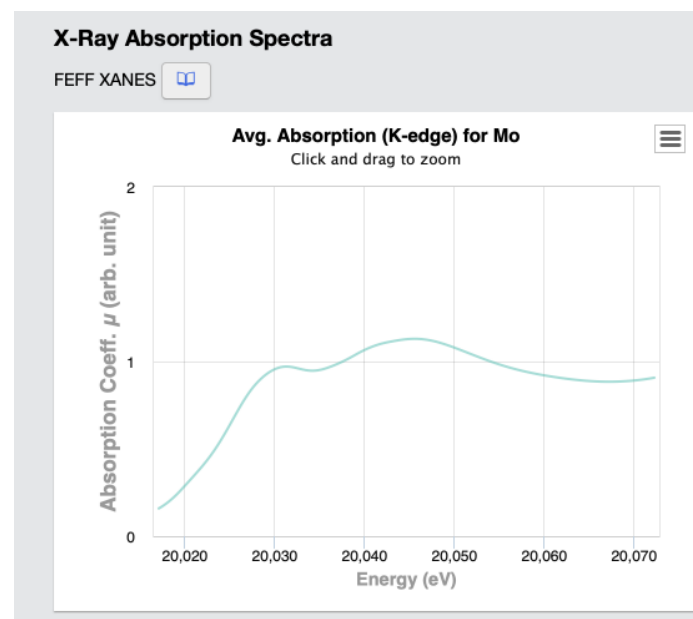
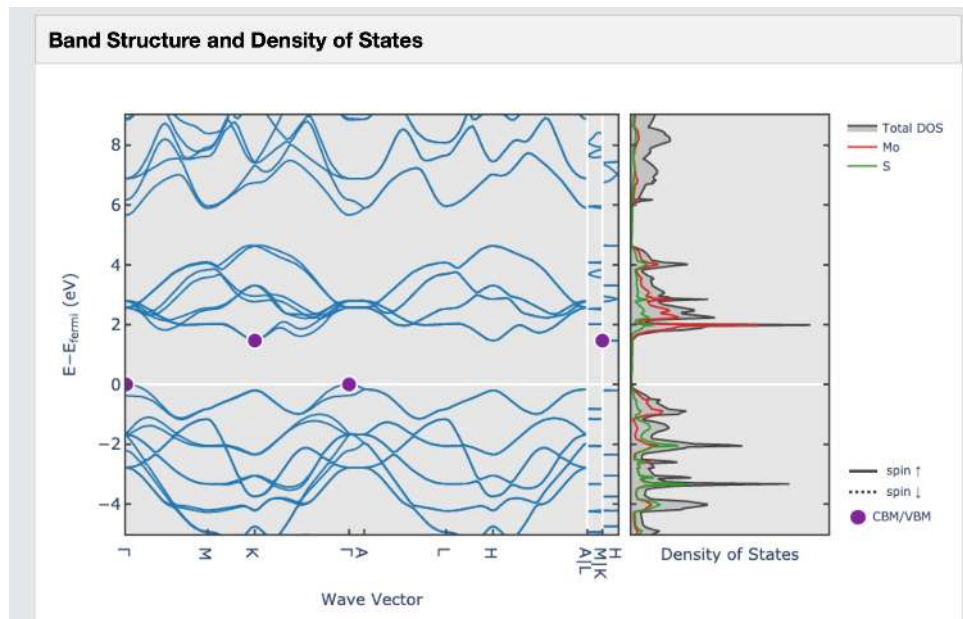
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# Existing catalysis databases: Open Catalyst Project





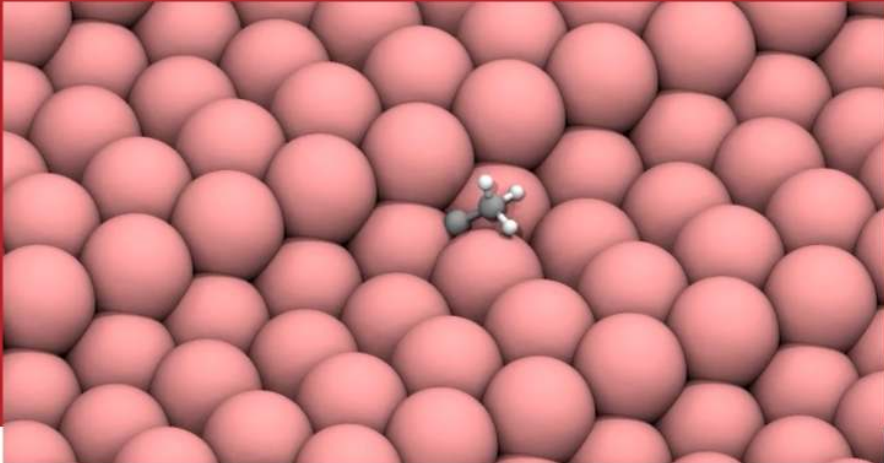
# Existing catalysis databases: Open Catalyst Project

FACEBOOK AI Carnegie Mellon University

Home Leaderboard Dataset Challenge Discuss

## Open Catalyst Project

Using AI to model and discover new catalysts to address the energy challenges posed by climate change.



# Existing catalysis databases: Open Catalyst Project

- Team: Facebook, Carnegie Mellon
- Goal/philosophy: use machine learning to replace DFT relaxations that find adsorbed states of molecules on catalysts to speed up catalyst screening and discovery
- Points of interest
  - Big data, but not lowest energy states
  - No UI since meant for ML
  - No treatment of applied potential/solvent
  - Not based on promising catalysts



# Existing catalysis databases: Catalyst Property Database

Catalyst Property Database



# Existing catalysis databases: Catalyst Property Database

- Team: ChemCatBio EMN, NREL
- Goal: (1) reduce time searching literature for previously computed catalytic pathways by providing data in a central, searchable location, (2) enable accelerated discovery of catalyst descriptors, property correlations
- Points of interest
  - Less data in initial set, but labeled if lowest energy states
  - Excellent UI, metadata
  - No treatment of applied potential/solvent
  - Not based on promising catalysts



# Existing catalysis databases: Catalysis Hub



# Existing catalysis databases: Catalysis Hub

- Team: SUNCAT, Stanford
- Goal: (1) provide fully self-contained data for predicting experimental observations from electronic structure calculations (primary), (2) starting point for training and developing machine-learning based approaches accelerating quantum chemical simulations (secondary)
- Points of interest
  - Moderate data
  - Good UI
  - Good post-processing tools (pourbaix diagrams, volcano plots, etc.)
  - No treatment of applied potential/solvent
  - Not based on promising catalysts



# Existing catalysis databases: Summary

- Don't target promising catalysts, but do broader search
- Less complete than materials databases because calculations are more expensive, catalysts are more diverse than materials
- Fewer properties, e.g. PDOS, bond orders, than materials databases
- Simpler or no APIs
  - Specifying catalytic reactions harder than specifying materials

# BEAST DB

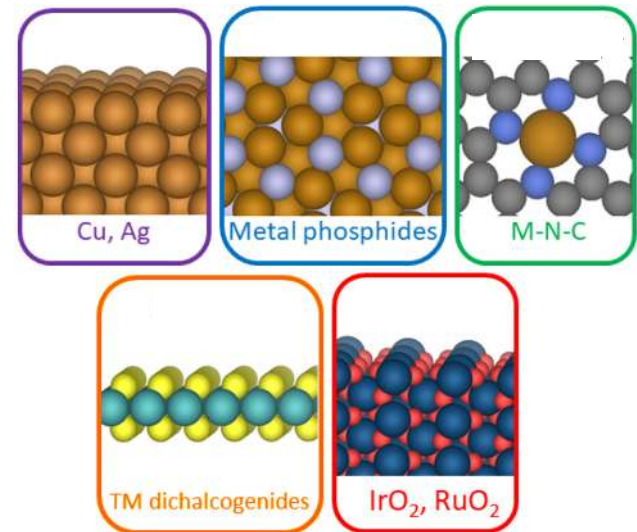




- Thrust 1: develop next generation of electrochemical solvation models with detailed double layer structure
- Thrust 2: beyond-DFT electrochemistry at exascale
- Thrust 3: apply techniques to electrocatalytic systems, forming BEAST-DB database for first-principles electrochemistry



- Reaction energetics, and electrolyte and electronic properties (e.g. PDOS)
- Start with most promising facets, electrolytes, electrolyte concentrations, and potential ranges for chosen catalysts
- Use ML to obtain beyond-DFT accuracy



# BEAST DB “demonstration”



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- Search feature similar to Catalyst Property Database, Catalysis Hub



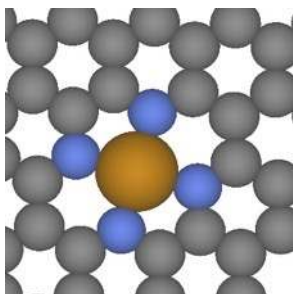
# BEAST DB “demonstration”

- Fe-N-C


0 V 1 V

Potential: 

Electrolyte: ☒ H<sub>2</sub>SO<sub>4</sub> ☐ HClO<sub>4</sub> ☐ HCl ☐ NaF

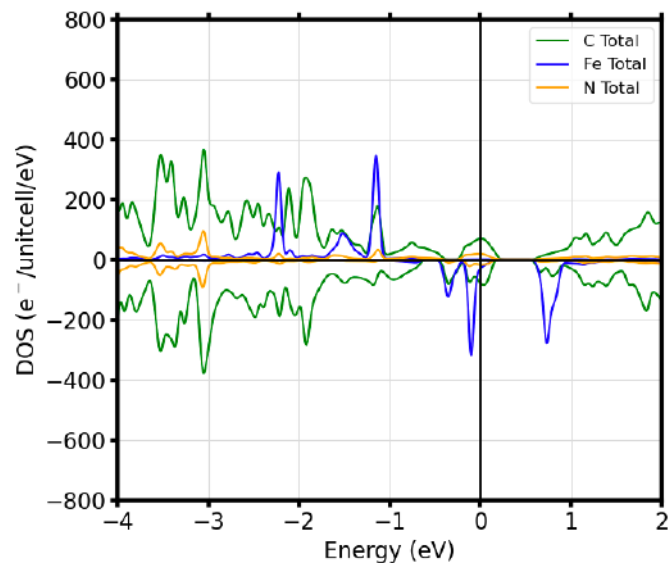


10<sup>-2</sup> M 10 M

Concentration:   
0.5

Total energy: -11526.2912 eV

AtomType	TotalNetCharge
C	3.676
N	-0.970
Fe	2.736



# BEAST DB “demonstration”

- Fe-N-C

0 V

1 V

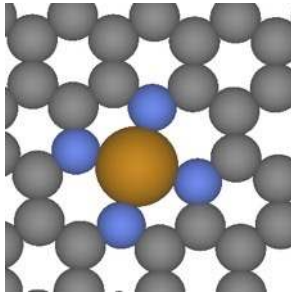
Potential:



Concentration:  $10^{-2}$  M 10 M

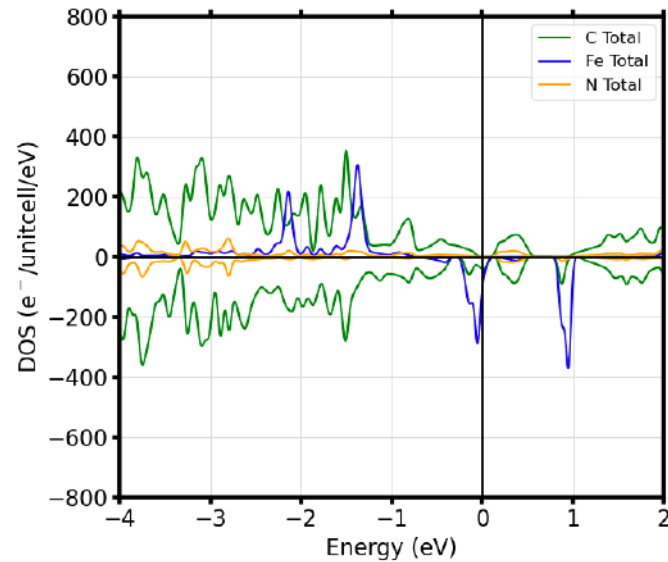
0.5

Electrolyte: ☒ H<sub>2</sub>SO<sub>4</sub> ☐ HClO<sub>4</sub> ☐ HCL ☐ NaF



Total energy: -11275.8951 eV

AtomType	TotalNetCharge
C	4.992
N	-0.778
Fe	2.841



# BEAST DB

- Team: NREL, CU, RPI, LBNL, U of S. Carolina
- Goal: (1) provide insight into how changes in electrochemical conditions lead to observed activity and selectivity, (2) give beyond-DFT accuracy for reaction energetics and electronic structuring using ML
- Points of interest
  - Allow variation of electrolyte, applied potential and easy comparison of variations with these knobs
  - Variety of electronic descriptors (PDOS, Bader charges, bond orders, wavefunction localization), electrolyte descriptors for rationalizing changes in behavior with different conditions
  - Base catalyst models on which are already promising
  - Beyond-DFT accuracy for reaction energetics (planned)
  - Smaller range of catalysts (targeted)



# BEAST DB: current status





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- BEAST dataset contains 80 unique bulk compositions, 120 surface facets, over 3000 adsorbate calculations
- Chemistries: HER, OER, CO<sub>2</sub>R, NRR, ORR, partial methane oxidization reaction (pMOR) to methanol.

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- Chemistries: HER, OER, CO<sub>2</sub>R, NRR, ORR, partial methane oxidization reaction (pMOR) to methanol.
- Materials classes: d-block metals, metal oxides, 2D chalcogenides, single-atom alloys (SAAs), 2D metal-nitrogen-carbon surfaces (MNCs), and multinary Chevrel phase (CP) chalcogenides.
- Properties: adsorption energies, converged structure geometries,  $\Delta$  electrons, orbital-projected density of states (pDOS), surface-adsorbate pDOS overlap, Bader charge distributions.



# BEAST DB: current status

- BEAST DB backend and UI under construction in upcoming year

Beyond-DFT Electrochemistry with Accelerated and Solvated Techniques

Home News Publications Thrust 1 Thrust 2 Thrust 3 BEAST DB

Catalyst  Search criteria

Facet  Search criteria

Adsorbate  Search criteria

DOI  Search criteria

Overall reaction overall  Search criteria

Calculation settings

Solvation method

GCDFT Potential

ID	Plot ads. energy	Plot Struct.	Adsorbate	Reference species	Canonical Eads (eV)	Gads (eV) # V vs SHE	Oxid. St. # V vs SHE
bd-####	<input checked="" type="checkbox"/>	<input type="checkbox"/>	1H	H3O+H2O	-0.40	0.13	+0.68
bd-####	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	1O	1/2 O2	-1.02	-0.50	-0.21
bd-####	<input type="checkbox"/>	<input type="checkbox"/>	1CO+1OH	1CO+1OH	-1.23	-1.63	-0.34

Applied potential ☒ V vs SHE ☐ V vs RHE

Density of states

E - E<sub>F</sub> (eV)

Export structure

3D visualization of the catalyst structure (catalyst, adsorbate, and solvent molecules) in a box.

Plot of G<sub>ads</sub> (eV) vs Applied potential (V vs SHE) for 1H (blue) and 1O (orange).



# BEAST DB: community involvement



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- Planning on having public workshop in the next 1-2 years to solicit ideas further development of BEAST DB



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- Want contributions from researchers in the electrocatalysis community, like YOU
- Planning on having public workshop in the next 1-2 years to solicit ideas further development of BEAST DB
- BEAST team has developed uniform set of computational parameters for database that will be required and checked for community upload



# BEAST DB

