

Derek Vigil-Fowler 2<sup>nd</sup> Annual BEAST workshop 08/18/23



 Beyond-DFT Electrochemistry with Accelerated and Solvated Techniques Database

 Will have adsorption energies, other descriptors for range of common electrocatalysts, chemistries



 Beyond-DFT Electrochemistry with Accelerated and Solvated Techniques Database
 A Continuum Transport Model

 Will have adsorption energies, other descriptors for range of common electrocatalysts, chemistries





# Electrochemistry is hard!



# Electrochemistry is hard!

• Diversity and dynamics



# Electrochemistry is hard!

- 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 spectator species
  - Electrolyte identity, concentration
  - pH
  - Applied potential
  - Kinetic and thermodynamic considerations
  - Transport/morphology

```
• ....
Nat. Comm. 8, 14621 (2017)
```



# Result: chemical intuition plays big role



## Result: chemical intuition plays big role

• Often unclear what governs choices



# Result: chemical intuition plays big role

- 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 K2SO4 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:

- SnO2 NPs on graphene oxide
- Potentials: --0.25 to -1.5 vs Ag/AgCl
- NaOH
- pH = 8.5 12 (alkaline conditions avoid SnO2 reduction)



# Experimental efforts on protocols



#### Suggested Testing Procedure for Round Robin Matrix

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

- Measure CV and EIS in  $H_2/N_2$  at BOT as specified.
- Flow O<sub>2</sub> on cathode. Wait until OCV is stable (e.g. 5 min).
- Measure activity in  $H_2/O_2$  as specified.
- Flow air on cathode. Wait until OCV is stable (e.g. 5 min).
- Measure pol curve in  $H_2$ /air as specified.
- Change T, RH, and P conditions for next test. Wait at least 30 min for equilibration.
- Measure pol curve in  $H_2$ /air at 250 kPa, 75% RH, 95 °C as specified.
- Flow N<sub>2</sub> 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 O<sub>2</sub> adsorbed on the catalyst, in order to have a CV shape "centered" around 0 current.
- Measure CV and EIS in H<sub>2</sub>/N<sub>2</sub> 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 N<sub>2</sub> purge delay). When finished (or asap after finishing) start to flow N<sub>2</sub> 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 N<sub>2</sub> 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 O<sub>2</sub> adsorbed on the catalyst, in order to have a CV shape "centered" around 0 current.
- Measure CV and EIS in  $H_2/N_2$  as described before.
- Flow O<sub>2</sub> on cathode. Wait until OCV is stable (e.g. 5 min).
- Measure activity in  $H_2/O_2$  as specified.
- Flow air on cathode. Wait until OCV is stable (e.g. 5 min).
- Measure pol curve in H<sub>2</sub>/air as described before.
- Flow air on cathode. Wait until OCV is stable (e.g. 5 min).





- 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



- 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
- Provide input for machine learning algorithms to get quantum mechanical accuracy at lower cost



- 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
- Provide input for machine learning algorithms to get quantum mechanical accuracy at lower cost
- Enable fair comparisons between electrochemical configurations across a diversity of conditions, e.g. electrolyte composition/concentration, pH, potential range

- 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
- Provide input for machine learning algorithms to get quantum mechanical accuracy at lower cost
- Enable fair comparisons between electrochemical configurations across a diversity of conditions, e.g. electrolyte composition/concentration, pH, potential range

# Materials databases



- Materials Project, NOMAD, OQMD, AFLOW, AiiDA
- Can quickly obtain various materials properties, e.g. relative stability, structure, and electronic structure, from a simple database query



- Materials Project, NOMAD, OQMD, AFLOW, AiiDA
- Can quickly obtain various materials properties, e.g. relative stability, structure, and electronic structure, from a simple database query





- Materials Project, NOMAD, OQMD, AFLOW, AiiDA
- Can quickly obtain various materials properties, e.g. relative stability, structure, and electronic structure, from a simple database query

Materials Id 🍦	Formula 🍦	Spacegroup 🖕	Formation Energy (eV)	E Above Hull_ (eV)	Band Gap (eV)	Volume 🍦	Nsites 🖕	Density (gm/cc)	ø
mp-2815	MoS <sub>2</sub>	P6 <sub>3</sub> /mmc	-1.202	0	1.465	131.151	6	4.053	
mp-1434	MoS <sub>2</sub>	R3m	-1.201	0	1.578	62.649	3	4.243	
mp- 1027525	$MoS_2$	P3m1	-1.201	0.001	1.491	350.447	12	3.034	
mp- 1025874	$MoS_2$	P6m2	-1.201	0.001	1.509	284.872	9	2.799	
mp- 1023939	$MoS_2$	P3m1	-1.2	0.001	1.554	219.296	6	2.424	
mp- 1018809	$MoS_2$	P6 <sub>3</sub> /mmc	-1.2	0.001	1.336	123.452	6	4.306	

https://materialsproject.org/

- Materials Project, NOMAD, OQMD, AFLOW, AiiDA
- Can quickly obtain various materials properties, e.g. relative stability, structure, and electronic structure, from a simple database query





https://materialsproject.org/

#### Materials databases

- Materials Project, NOMAD, OQMD, AFLOW, AiiDA
- Can quickly obtain various materials properties, e.g. relative stability, structure, and electronic structure, from a simple database query





https://materialsproject.org/

- 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
- Provide input for machine learning algorithms to get quantum mechanical accuracy at lower cost
- Enable fair comparisons between electrochemical configurations across a diversity of conditions, e.g. electrolyte composition/concentration, pH, potential range

# Existing catalysis databases: Open Catalyst Project



# Existing catalysis databases: Open Catalyst Project

FACEBOOK Al 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, but so-so metadata and data standardization
  - Good post-processing tools (pourbaix diagrams, volcano plots, etc.)
  - No treatment of applied potential/solvent
  - Not based on promising catalysts

## Existing catalysis databases: Summary

- Catalysis Hub (Stanford), Open Catalyst Project (CMU/Facebook), Catalyst Property Database (NREL)
- 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







 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 firstprinciples electrochemistry

- 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)



**Fig. 14**. Promising electrocatalysts and chemistries proposed as a starting point for our electrochemical database, BEAST DB.



- 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



**Fig. 14**. Promising electrocatalysts and chemistries proposed as a starting point for our electrochemical database, BEAST DB.



• BEAST dataset contains 80 unique bulk compositions, 120 surface facets, over 3000 adsorbate calculations



- BEAST dataset contains 80 unique bulk compositions, 120 surface facets, over 3000 adsorbate calculations
- **Chemistries:** HER, OER, CO2R, NRR, ORR, partial methane oxidization reaction (pMOR) to methanol
- Materials classes: d-block metals, metal oxides, 2D chalcogenides, single-atom alloys (SAAs), 2D metalnitrogencarbon surfaces (MNCs), and multinary Chevrel phase (CP) chalcogenides
- Properties: adsorption energies, converged structure geometries, Δ electrons, orbital-projected density of states (pDOS), surface-adsorbate pDOS overlap, Bader charge distributions



- BEAST dataset contains 80 unique bulk compositions, 120 surface facets, over 3000 adsorbate calculations
- **Chemistries:** HER, OER, CO2R, NRR, ORR, partial methane oxidization reaction (pMOR) to methanol
- Materials classes: d-block metals, metal oxides, 2D chalcogenides, single-atom alloys (SAAs), 2D metalnitrogencarbon surfaces (MNCs), and multinary Chevrel phase (CP) chalcogenides
- Properties: adsorption energies, converged structure geometries, Δ electrons, orbital-projected density of states (pDOS), surface-adsorbate pDOS overlap, Bader charge distributions
- BEAST DB backend is close to being completed and UI is currently being implemented

Home Web A	Application	API	User Guide			
Search Ma	aterials					
Select adsorbat	te v					
Select catalyst						
+ Add criterion						
+ Add criterion						
					*Results i	n Beast DB Standard 🕕
Unique ID	Plot E	Adsorbate	Reference Species	Canonical Eads(eV)	Gads(eV)	Oxidation State
					First Previou	is 123 Next Last



lome Web	Application	API U	ser Guide			
Search M	aterials	5				
Select adsorba	ite 🗸	)				
Select catalys	с v					
+ Add criterion		, ,				
Select criterio	ı v	)				
Unique ID	>	]				
	>				*Results	in Beast DB Standard 🕦
Facet						A 11 -2 AL 1
Facet Reference Speci	es >	Adsorbate	Reference Species	Canonical Eads(eV)	Gads(eV)	Oxidation State

First Previous 1 2 3 Next Last



lome Web /	Application	API U	ser Guide			
Search Ma	aterials					
н	~ )					
Zn	~					
+ Add criterion						
		j.			*Results	in Beast DB Standard 🕻
	Plot E	Adsorbate	Reference Species	Canonical Eads(eV)	*Results Gads(eV)	in Beast DB Standard 🕻 Oxidation State
+ Add criterion	Plot E	Adsorbate H	Reference Species	Canonical Eads(eV) -0.4		
+ Add criterion Unique ID	Plot E				Gads(eV)	Oxidation State
+ Add criterion Unique ID 123445	Plot E	н	H2	-0.4	Gads(eV) 0.12	Oxidation State

First Previous 1 2 3 Next Last



Home Web Application API User Guide

Catalyst -	FeN4@G-bulk	•	Calculation settings
Facet -	001	•	
Adsorbate -	H, O2, OH	•	Solvation method -

ID	Plot ads. energ y	Plot Struct.	Adsorbate	Reference species	Canonical Eads (eV)	Gads (eV) # V vs SHE	Oxid. St. # V vs SHE
1155			1H	H3O+-H2O	-0.40	0.13	+0.68
1158			102	02	-1.02	-0.50	-0.21
1161			10Н	OH-	-1.23	-1.63	-0.34



Fe

ò

2





Home Web Application API U

Disclaimers and Legal

Using the Web Application

#### User Guide

#### About BEAST

Searching

Using the API

Searching

Visualizations

Uploading Data

**Downloading Data** 

Visualizations

Uploading Data

Downloading Data

#### About BEAST

Computational modeling of electrochemistry is limited in accuracy by

 the lack of a universal framework that efficiently treats arbitrary electrolytes, solvents and applied potentials with sufficient detail and fidelity to realistically and accurately model electrochemical systems, and
 the deficiencies of density functional theory (DFT), the primary computational tool for reaction modeling, in describing charge transfer and reaction barriers. Accurate reaction barriers are crucial for connecting predictions to measured rates of chemical reactions, and quantum chemical techniques that may be accurate enough are not yet practicable for heterogeneous and electrocatalyst systems involving solid-liquid interfaces.

Funded by the DoE Computational Chemical Sciences program under DE-SC0022247 starting October 2021, the BEAST collaboration will address both challenges above by developing accurate and efficient exascaleready solvated beyond-DFT methods.

The first ingredient in these methods are accurate atomic-scale electrolyte solvation models that capture the equilibrium effect of electrolyte in a single electronic structure calculation.

The second ingredient is the incorporation of GW many-body perturbation theory and the <u>random phase</u> approximation (RPA) total energy, which are accurate methods beyond DFT, into solvated and grandcanonical techniques to make them practicable for electrochemistry including solvation and bias effects.

Finally, in addition to optimizing these combined techniques for exascale computing, we will also make them more widely applicable using machine learning (ML) approaches trained to a beyond-DFT electrochemical database to make RPA-quality predictions at DFT cost.



#### BEAST DB: community involvement

• Want contributions from researchers in the electrocatalysis community, like YOU



#### BEAST DB: community involvement

- Want contributions from researchers in the electrocatalysis community, like YOU
- Planning on having public workshop in the next year to solicit ideas further development of BEAST DB



### BEAST DB: community involvement

- Want contributions from researchers in the electrocatalysis community, like YOU
- Planning on having public workshop in the next year 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







