

Interpretable ML Approaches for Novel Solid State Electrolyte Design

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Li batteries

Typical Li-ion batteries

- **cathode:** LiCoO_2 , LiFePO_4 , LiNiMnCoO_2 etc.
- **anode:** graphite
- **electrolyte:** $\text{LiPF}_6/\text{LiBF}_4/\text{LiClO}_4$ in dimethyl carbonate/diethyl carbonate (liquid)

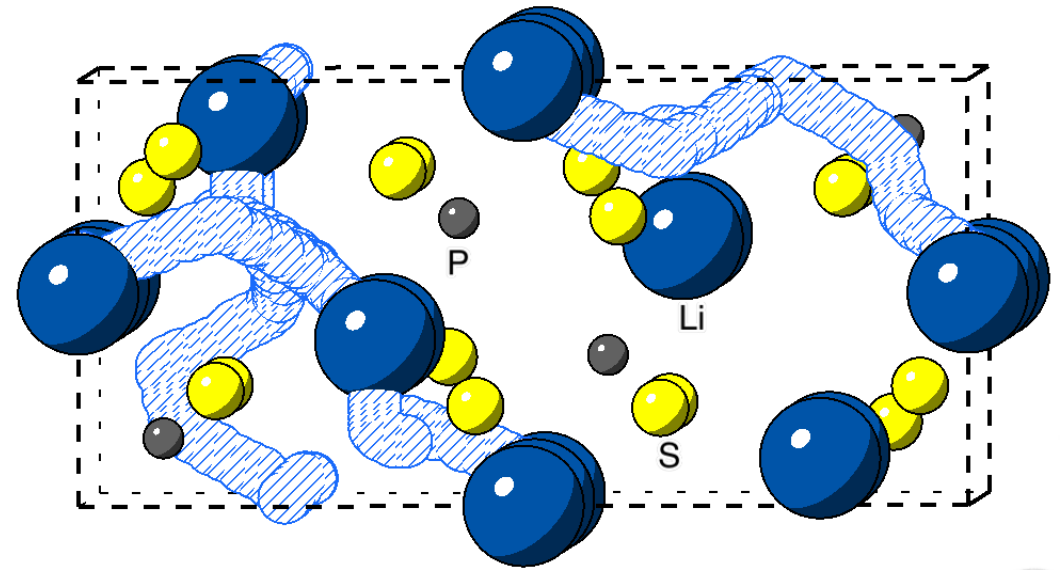
All solid-state batteries with Li anode – require solid electrolytes and anode coatings possessing:

- high ionic conductivity
- low electronic conductivity
- wide electrochemical window
- good stability against Li metal
- inertness to environmental elements like water and air

Methods

Current approaches to study ionic migration:

- experimental measurements
- ab-initio MD, NEB
- space topology analysis
- bond valence (BV) estimation



Percolation (3D) barriers

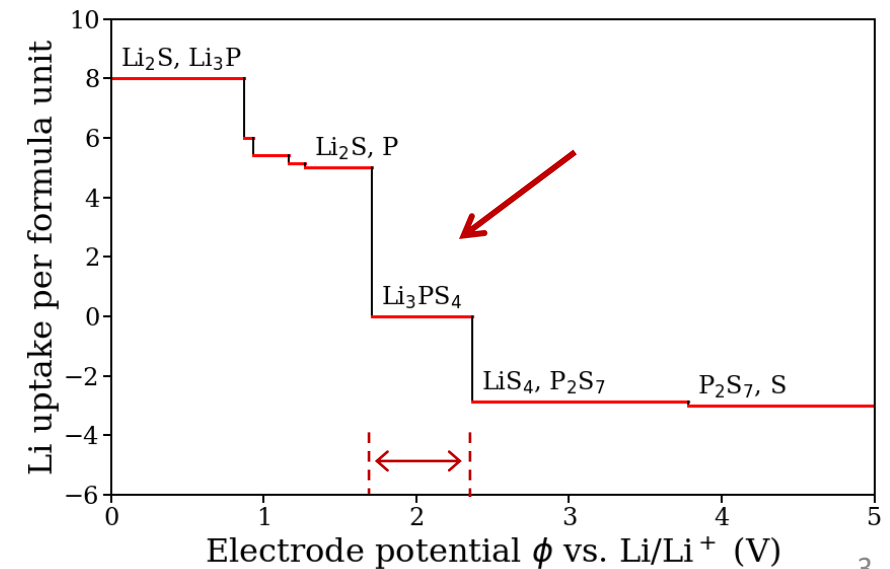
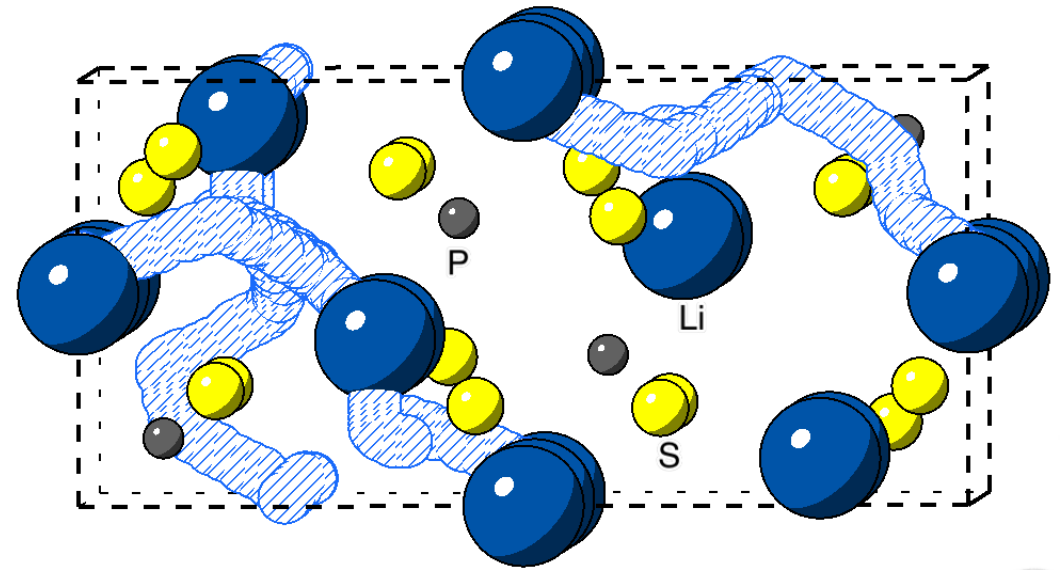
Methods

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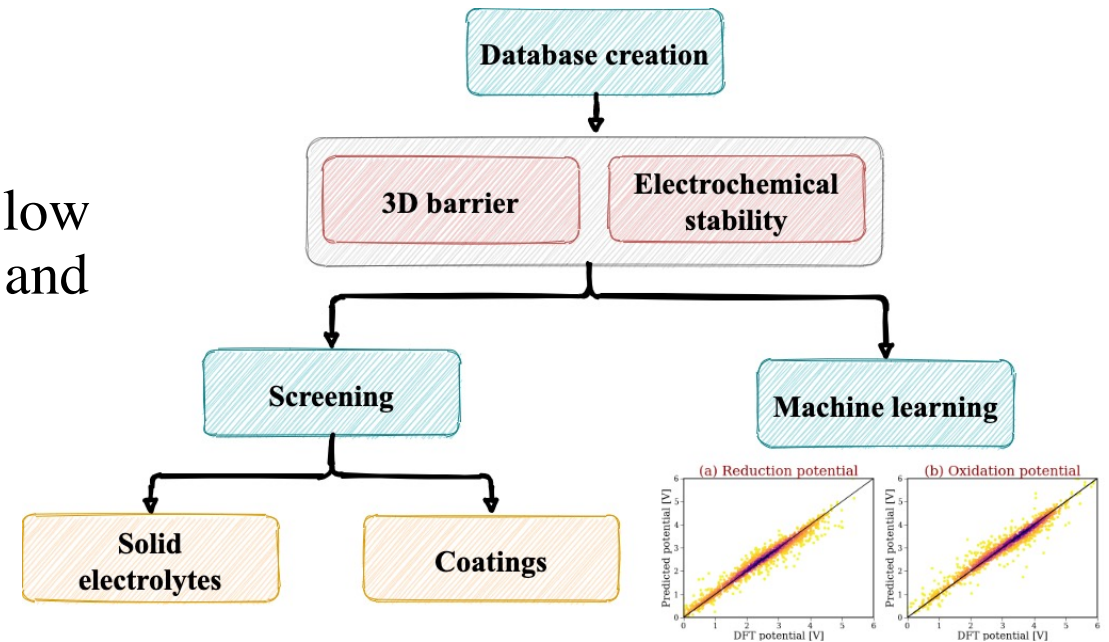
To compute electrochemical stability windows:

- Grand potential phase diagram analysis



Our approach

- Generate a database of battery-related material properties
- Screen through the database for candidates with low Li^+ migration barriers and good thermodynamic and electrochemical stabilities
- Train machine learning (ML) models to predict migration barriers and oxidation and reduction potentials
- Explain individual predictions and provide model-level interpretation of feature importance



Screening results

Electrolytes

3D barrier < 0.5 eV

Anode coatings

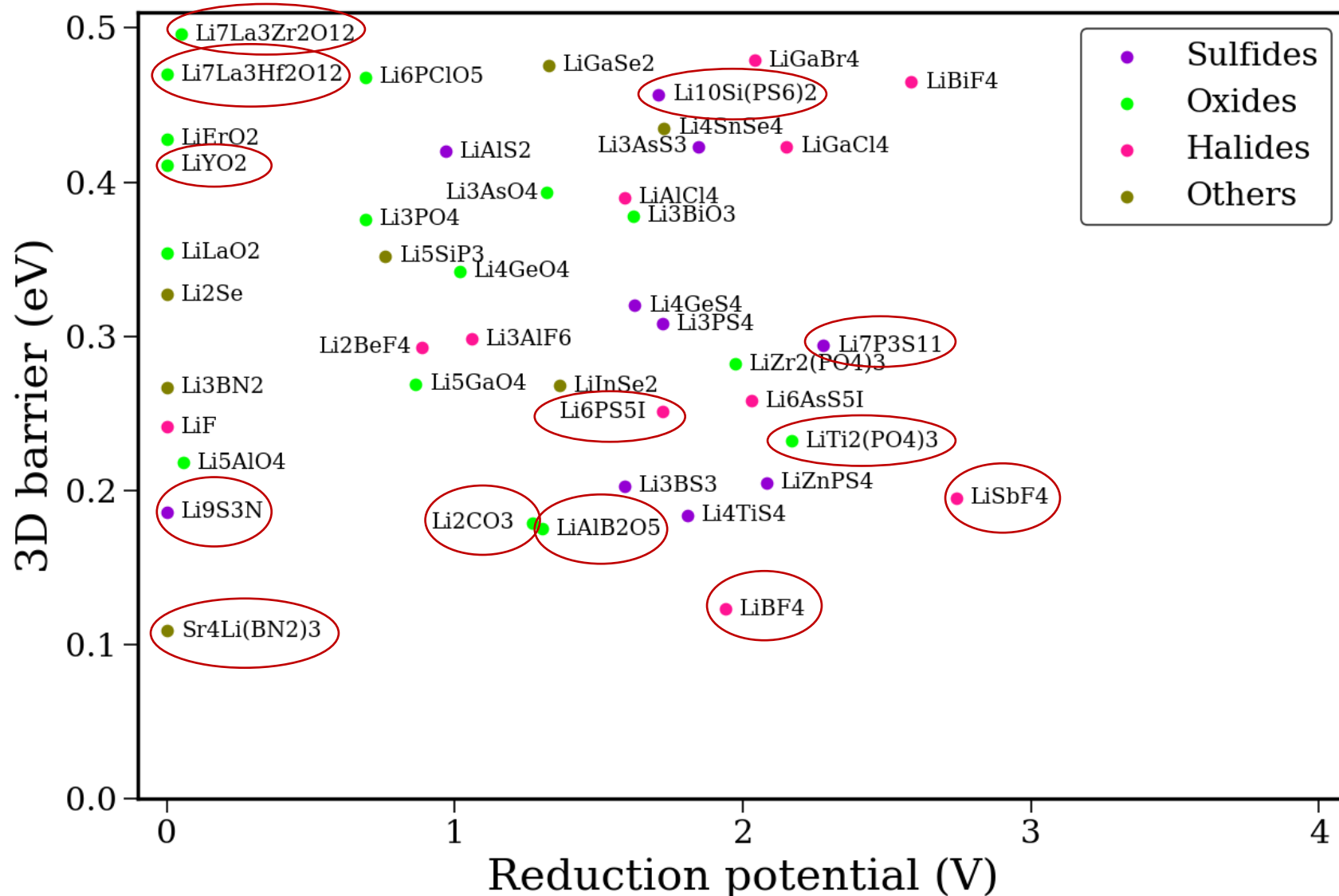
3D barrier < 1 eV

Reduction potential = 0 V

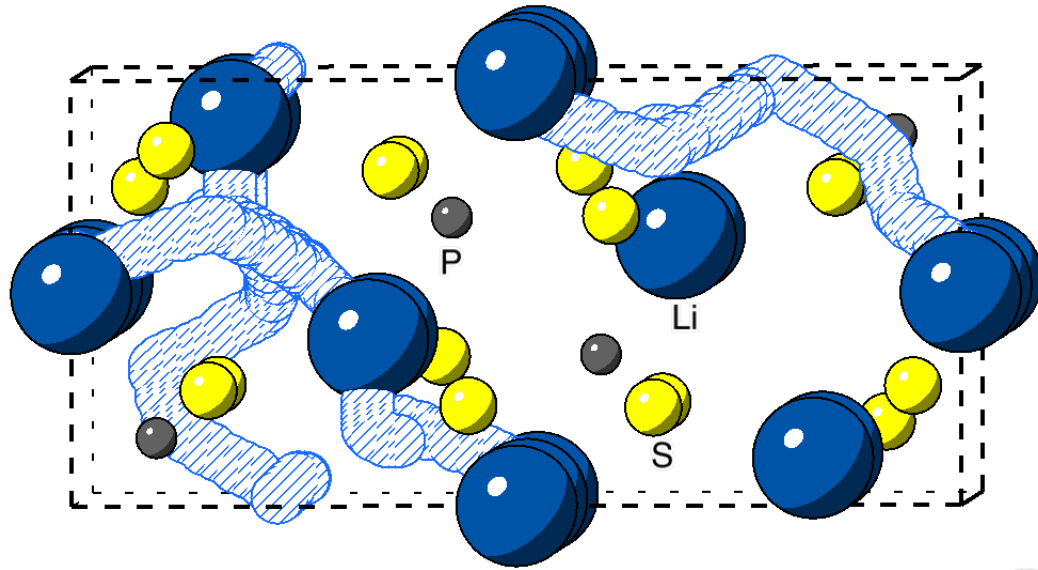
Stability window > 1 V

* $E_{\text{hull}} < 30 \text{ meV}$

* $E_g > 1 \text{ eV}$



ML Features: 3D barriers



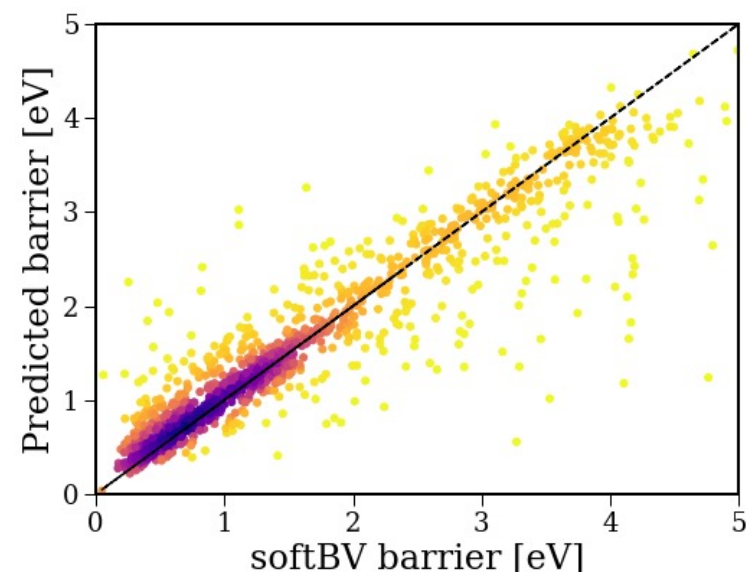
Sendek, Yang, Cubuk, et al., *Energy Environ. Sci.* **10**, 306-320 (2017)
Ward, Agrawal, Choudhary, et al., *npj Comput. Mater.* **2**, 16028 (2016)

No.	Feature	Acronym
1.	<i>Li atomic fraction</i>	Li
2.	<i>Mean Li neighbor count</i>	LNC
3.	<i>Mean Li-Li bonds per Li</i>	LLB
4.	<i>Mean Sublattice neighbor count</i>	SNC
5.	<i>Mean Sublattice bond ionicity</i>	SBI
6.	<i>Mean Electronegativity of sublattice</i>	ENS
7.	<i>Mean Li-Li separation distance</i>	LLSD
8.	<i>Mean Li-anion separation distance</i>	LASD
9.	<i>Mean Anion-anion separation distance</i>	AASD
10.	<i>Mean neighbor distance variation</i>	NDV
11.	<i>Mean ordering parameter shell 1</i>	OP_1
12.	<i>Mean ordering parameter shell 2</i>	OP_2
13.	<i>Mean ordering parameter shell 3</i>	OP_3
14.	<i>Diameter of largest free sphere</i>	DLFS
15.	<i>Mean Straight Line Path Width</i>	SLPW
16.	<i>Sublattice packing fraction</i>	SPF
17.	<i>Max packing efficiency</i>	MPE
18.	<i>XRD principal component 1</i>	XRD_1
19.	<i>XRD principal component 2</i>	XRD_2
20.	<i>XRD principal component 3</i>	XRD_3
21.	<i>XRD principal component 4</i>	XRD_4
22.	<i>XRD principal component 5</i>	XRD_5

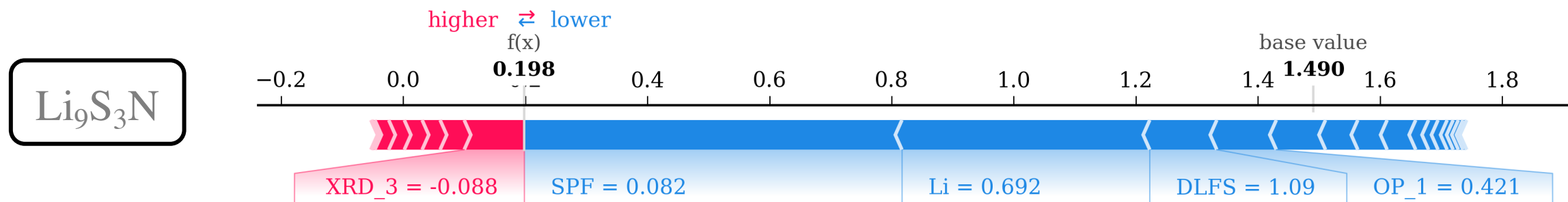
ML Results: 3D barriers

Features + Model	R^2	vector length
Current work + RF	0.84	22
Current work + GB	0.86	22
Sendek model features + GB	0.76	20
Coulomb matrix + GB	0.72	200
Powder X-ray diffraction pattern + GB	0.70	128

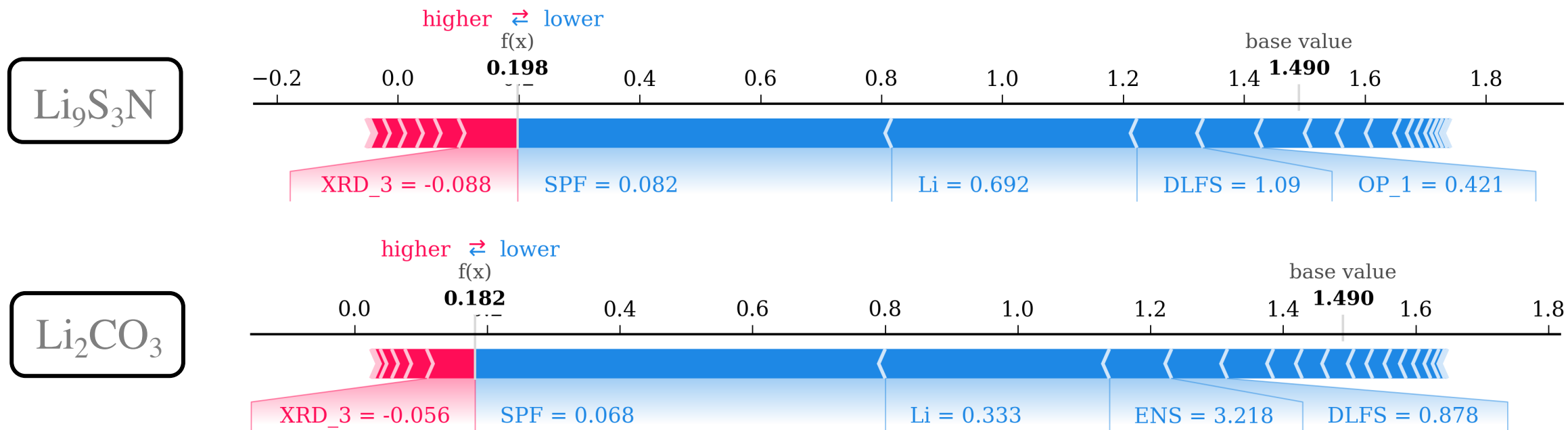
GB model predictions



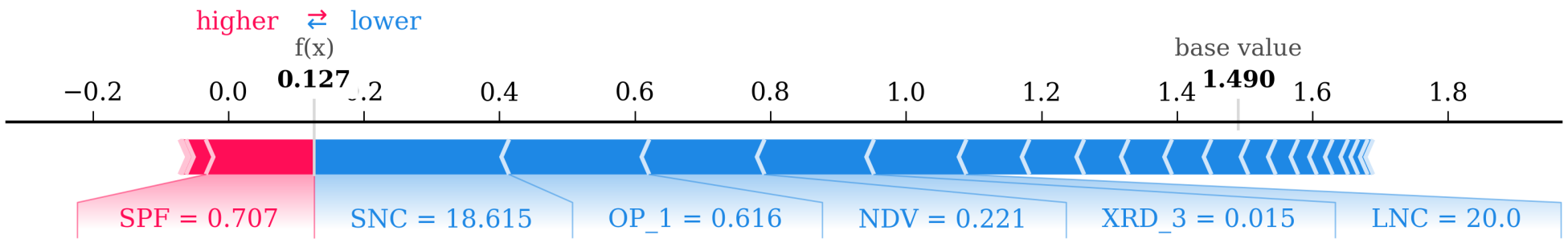
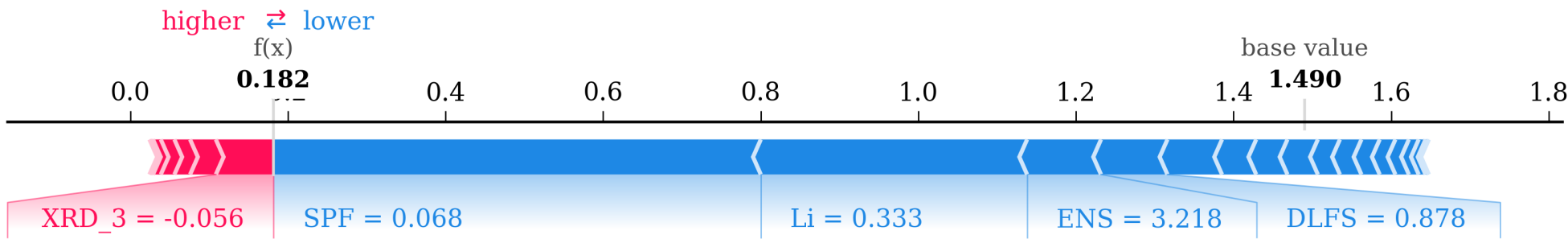
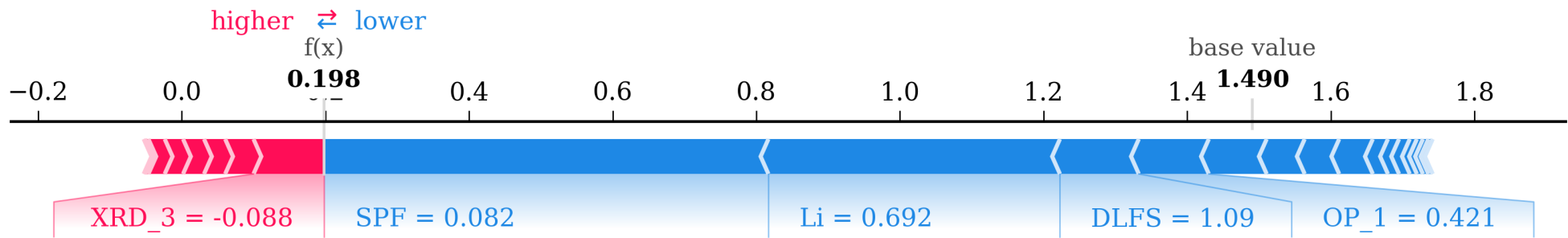
Shapley Additive Explanations (SHAP)



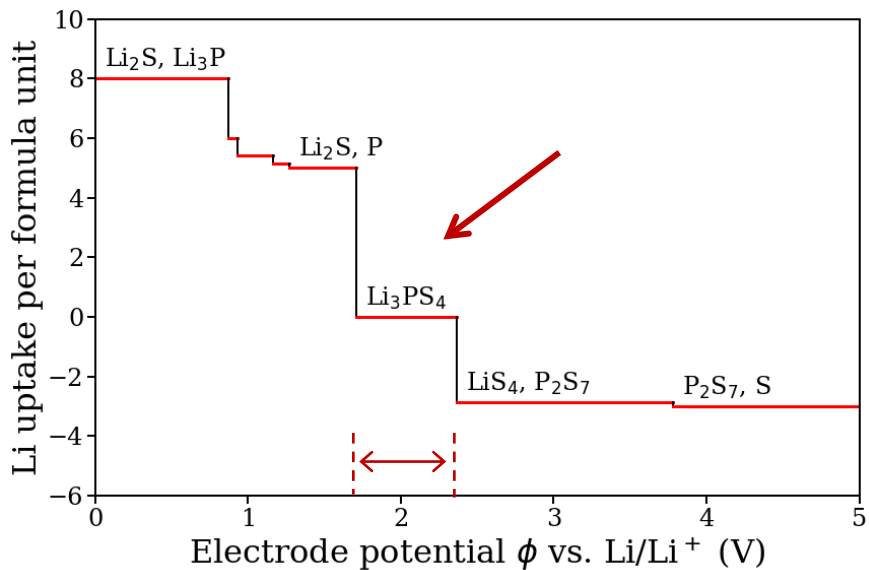
Shapley Additive Explanations (SHAP)



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ML Features: electrochemical stability

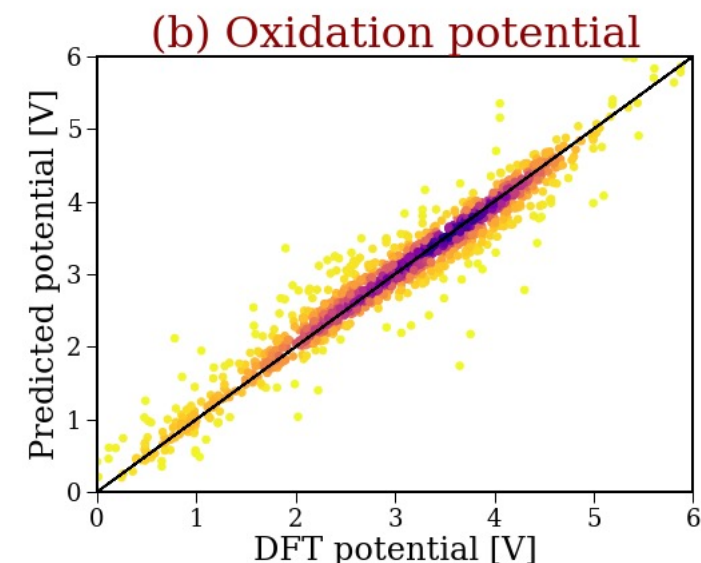
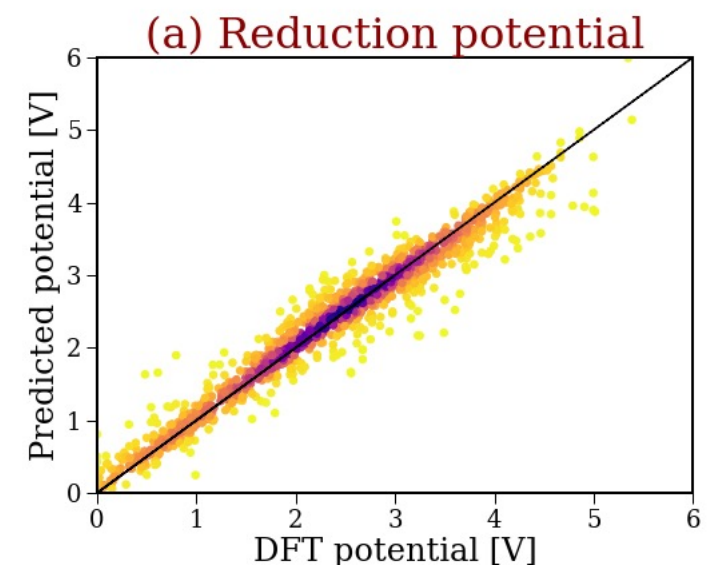


Composition-weighted element properties	Statistics
—— standard features ——	
Atomic number	Mean
Electronegativity	Maximum
Valence d-electrons	Range
Unfilled d-electrons	
Unfilled p-electrons	
Band gap	
Magnetic moment	
Melting Temperature	
—— new oxidation state features ——	
oxidation state – min. oxidation state	
max. oxidation state – oxidation state	
(oxidation state – min. oxidation state) * E _{neg}	
(max. oxidation state – oxidation state) * E _{neg}	

ML results: electrochemical stability

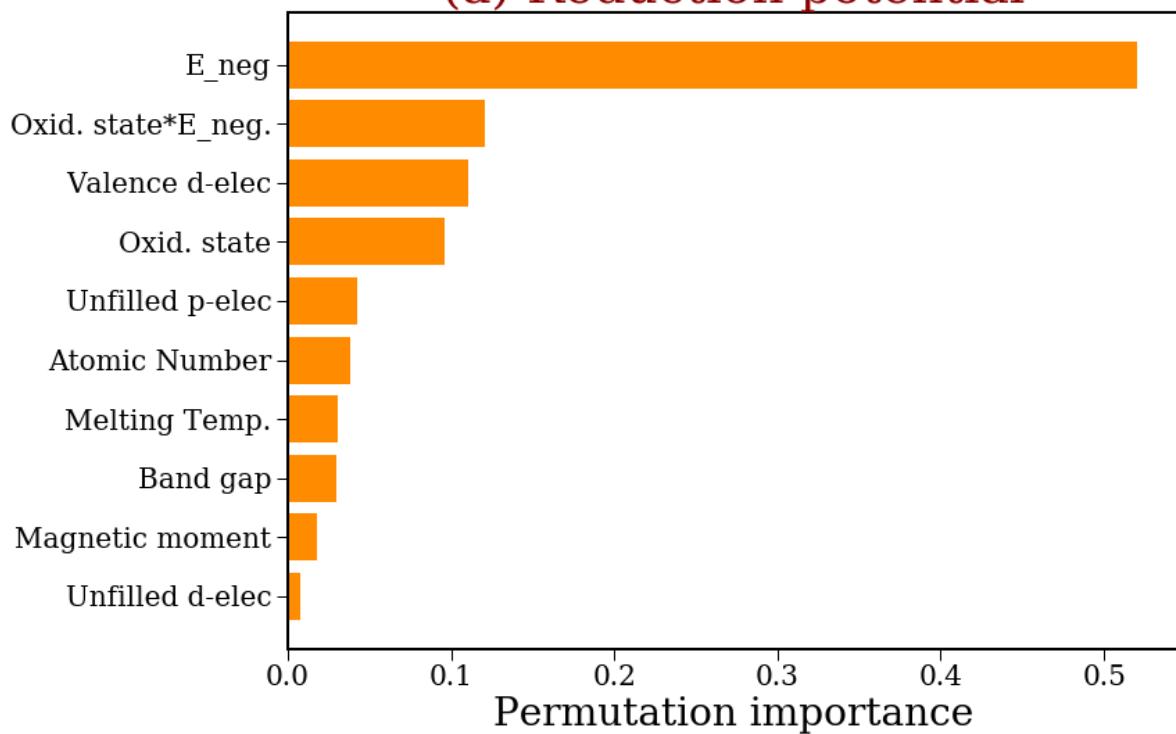
Features + Model	reduction potential	oxidation potential	vector length
Current work + RF	0.93	0.91	28
Current work + GB	0.95	0.92	28
Roost + neural network	0.92	0.92	64
Magpie element features + GB	0.89	0.84	132
Element fractions + GB	0.87	0.87	103

GB model predictions



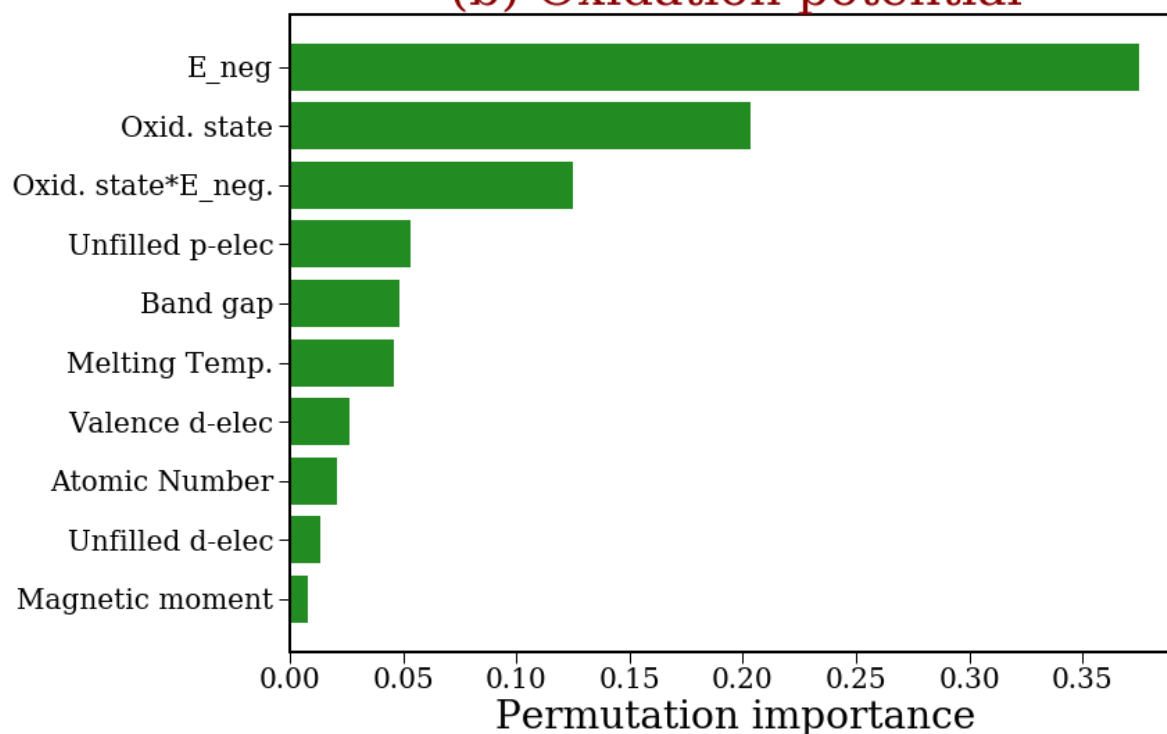
Permutation Feature Importance (PFI): electrochemical stability

(a) Reduction potential



GB model

(b) Oxidation potential



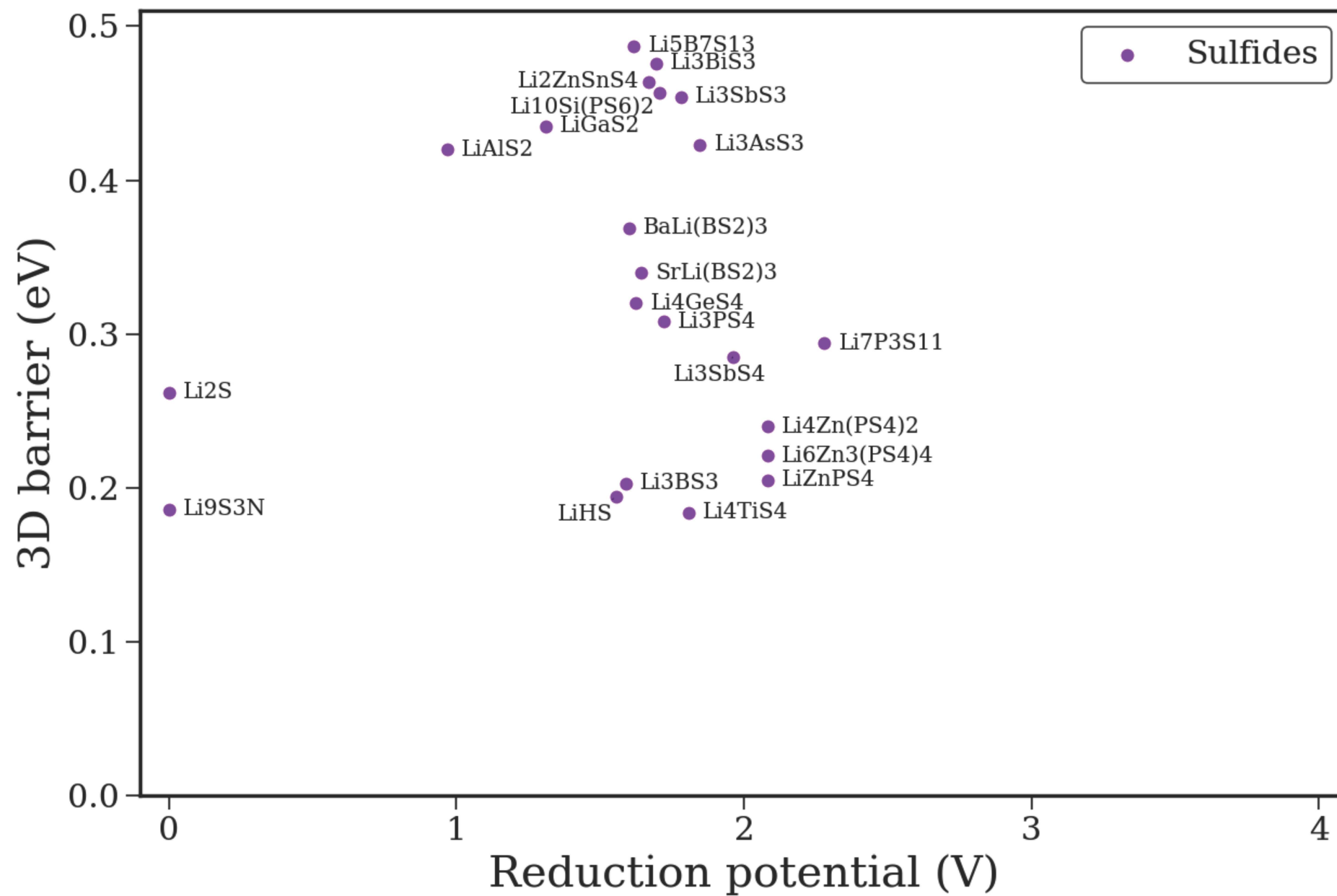
GB model

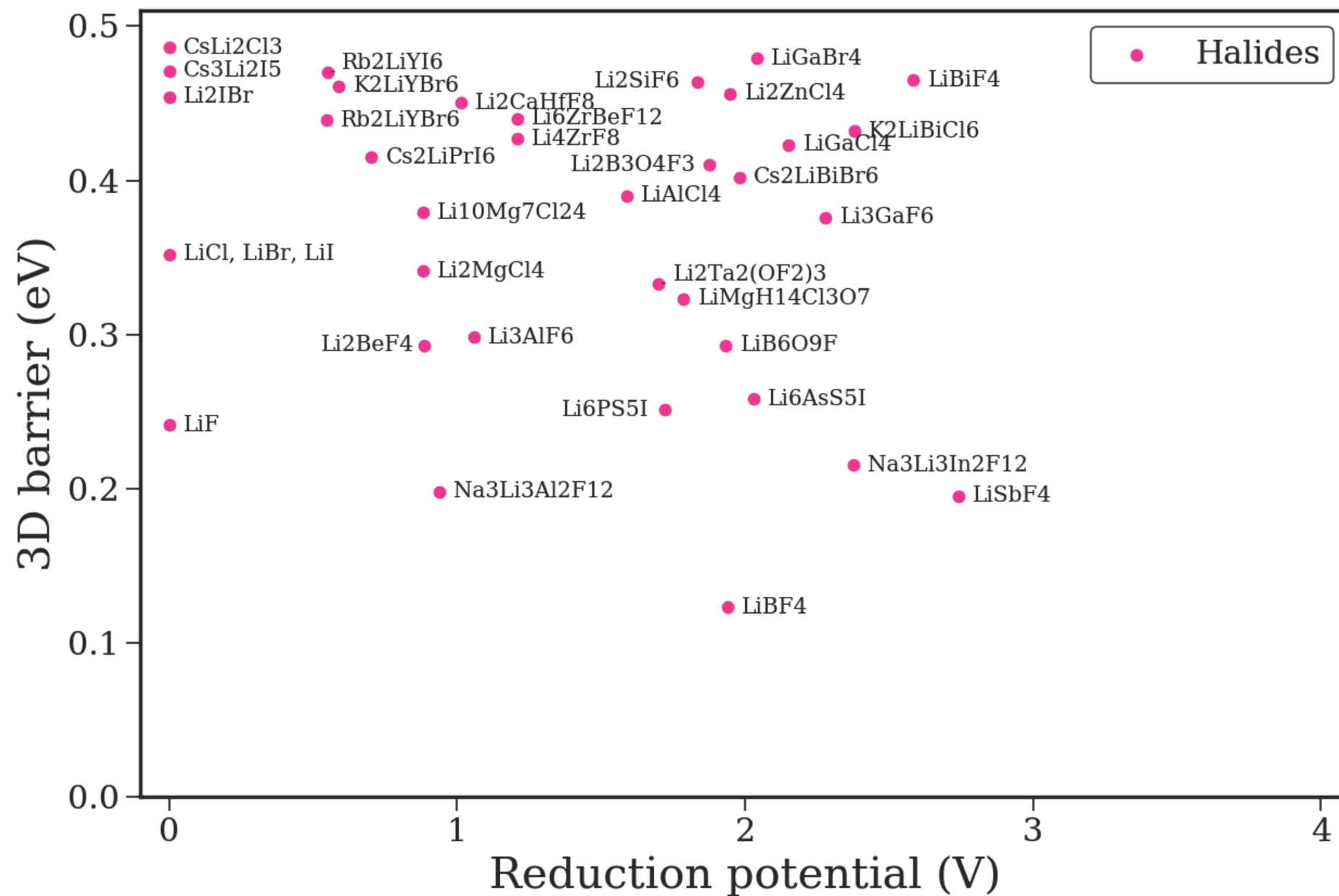
Summary

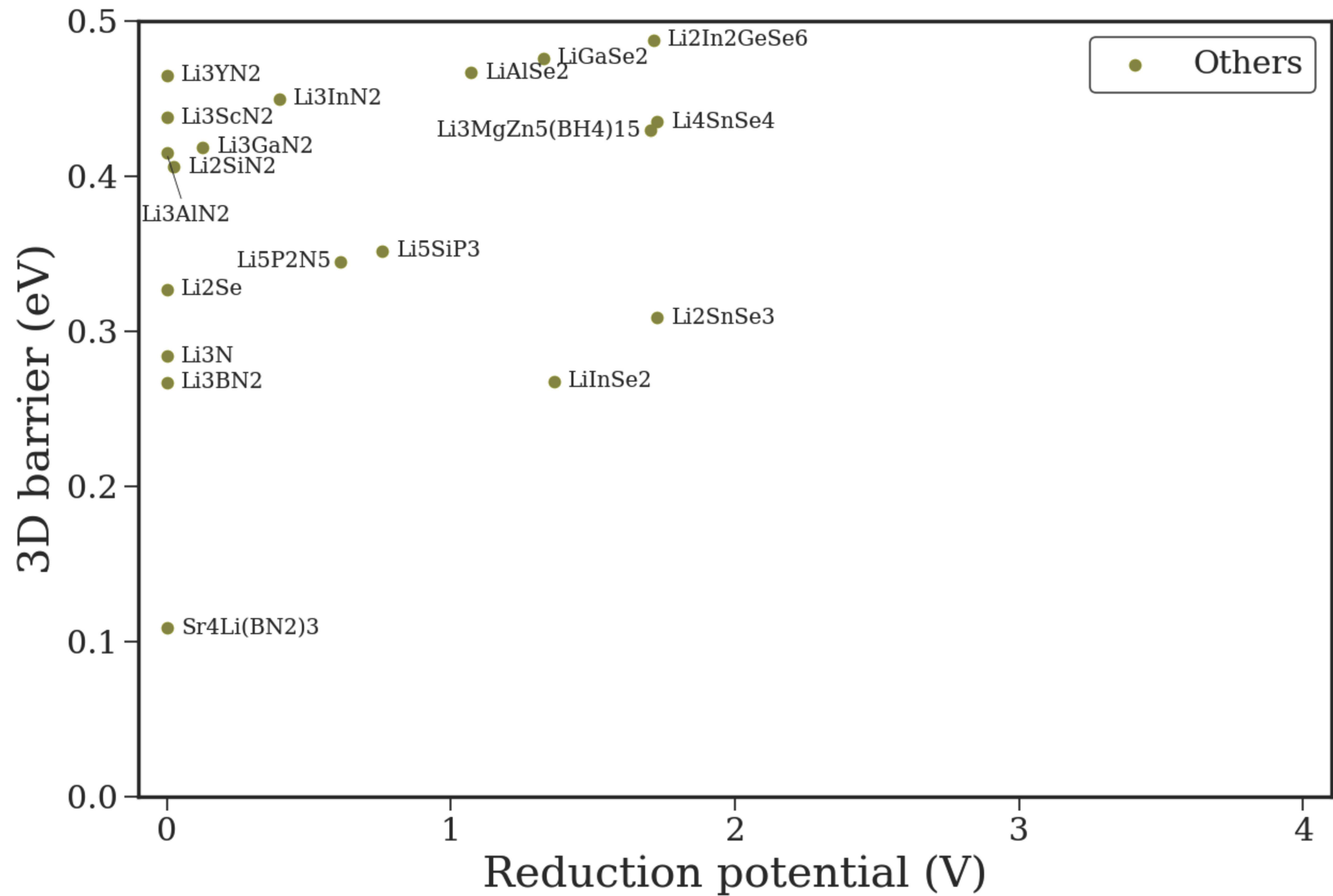
- We developed a materials informatics approach to explore and identify candidates for solid electrolytes and anode coatings in all solid-state Li metal batteries
- Generated a database of battery-related material properties
- Screened through the database to identify over 200 candidates with low Li⁺ migration barriers and good thermodynamic and electrochemical stabilities (Li₉S₃N, LiAlB₂O₅, LiBF₄, LiSbF₄, Sr₄Li(BN₂)₃, LiYO₂, Li₇La₃Hf₂O₁₂, etc.)
- Trained machine learning (ML) models to predict migration barriers and oxidation and reduction potentials
- Explained individual predictions from screening and ML model, provided model-level interpretation of feature importance

Thank you

Back-up slides







Screening results: Li anode coatings

TABLE S1: Compounds identified as promising candidates for coatings on Li metal anode. [Reduction potential (*vs.* Li) = 0 V, stability window > 1 V, 3D barrier < 1 eV, $E_{hull} < 30$ meV, $E_g > 1$ eV]

No.	mp_id	Formula	3D barrier (eV)	electrochemical window (V)
1.	mp-9723	Sr4Li(BN ₂) ₃	0.109	1.39
2.	mp-1960	Li ₂ O	0.259	2.90
3.	mp-1153	Li ₂ S	0.262	2.13
4.	mp-2286	Li ₂ Se	0.327	1.89
5.	mp-1185319	LiCl	0.349	4.25
6.	mp-976280	LiBr	0.350	3.14
7.	mp-570935	LiI	0.352	2.47
8.	mp-756544	LiLaO ₂	0.354	2.90
9.	mp-7020	LiYO ₂	0.411	2.92
10.	mp-752922	Li ₈ HfO ₆	0.419	2.90
11.	mp-10970	LiErO ₂	0.428	3.00
12.	mp-1222669	Li ₂ IBr	0.454	2.47
13.	mp-1198622	Li ₇ La ₃ Hf ₂ O ₁₂	0.470	3.02
14.	mp-1181918	Cs ₃ Li ₂ I ₅	0.471	2.35
15.	mp-1190687	CsLi ₂ Cl ₃	0.486	4.25
16.	mp-1185301	LiF	0.536	6.36
17.	mp-1080534	Cs ₂ Li ₃ I ₅	0.544	2.35
18.	mp-28237	RbLiBr ₂	0.590	3.14
19.	mp-1190087	CsLiI ₂	0.601	2.35
20.	mp-1184020	CsLi ₃ I ₄	0.668	2.35
21.	mp-28243	RbLiCl ₂	0.703	4.25
22.	mp-606680	CsLi ₂ Br ₃	0.774	2.96
23.	mp-569055	CsLi ₂ I ₃	0.817	2.35
24.	mp-770805	Li ₆ Hf ₂ O ₇	0.845	3.22
25.	mp-23057	CsLiBr ₂	0.882	2.96
26.	mp-9610	Li ₂ CN ₂	0.982	2.12

Permutation Feature Importance: 3D barriers

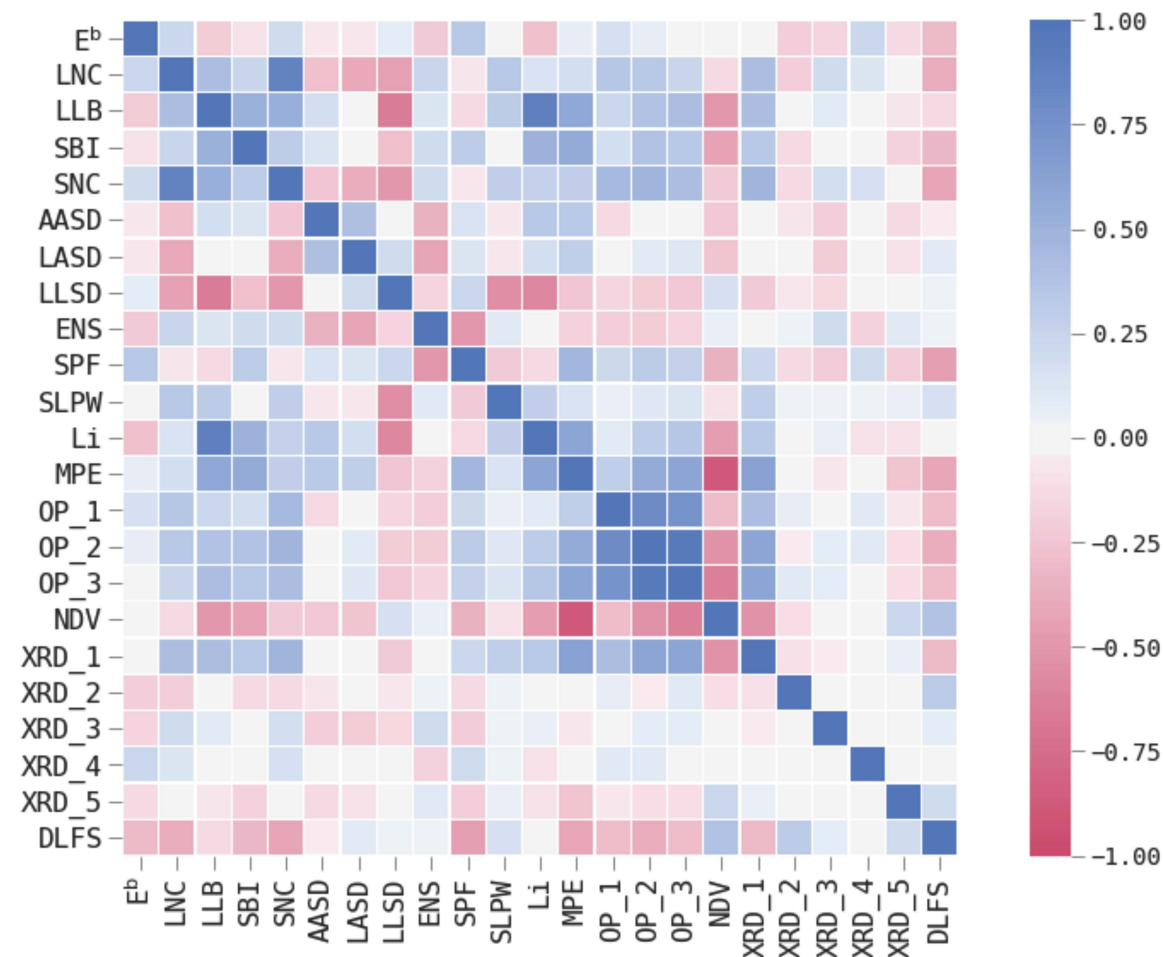
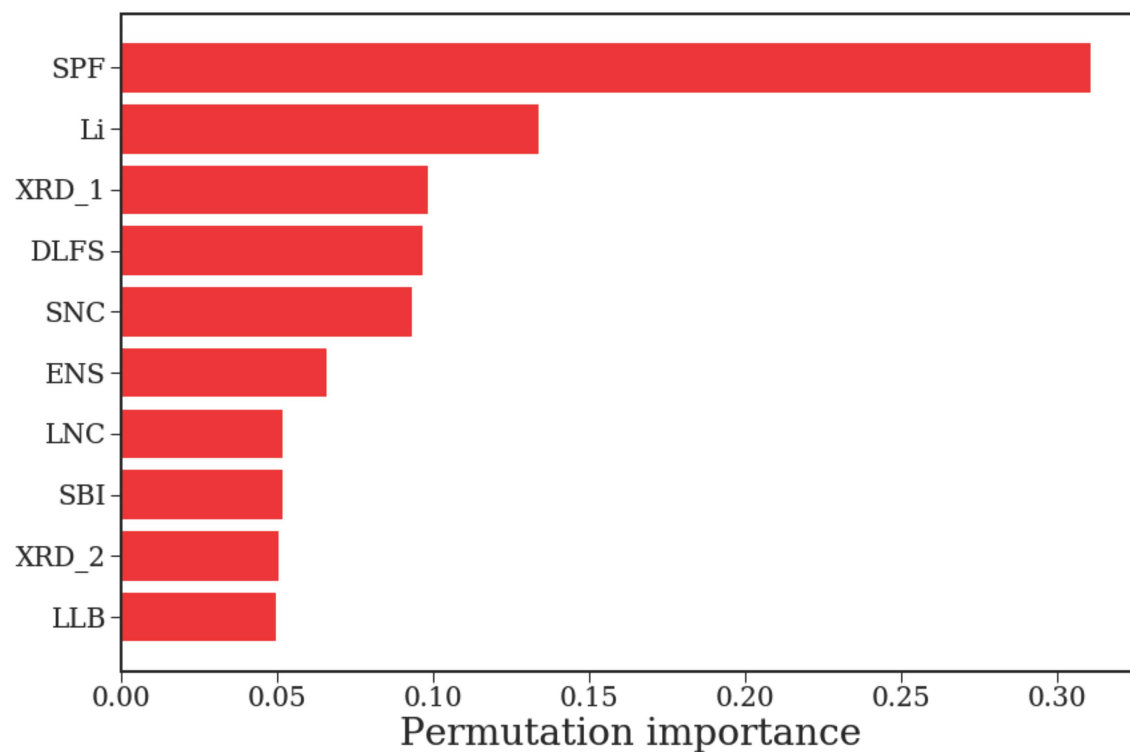


TABLE IV: Li compounds identified as possible superionic conductors by the Sendek model [59] are arranged in increasing order of their softBV 3D barriers. Where calculated barriers are missing, ML predictions are used instead. The rightmost column indicates whether the compound was predicted to have an ionic conductivity $> 10^{-4}$ S/cm based on high temperature DFT-MD simulations by Sendek *et al.* [60].

No.	mp_id	Formula	3D barrier (eV)	DFT-MD predicted ionic conductivity $> 10^{-4}$ S/cm
1.	mp-558219	SrLi(BS ₂) ₃	0.340	x
2.	mp-532413	Li ₅ B ₇ S ₁₃	0.487	yes
3.	mp-643069	Li ₂ HfO	0.519	yes
4.	mp-7744	LiSO ₃ F	0.529	yes
5.	mp-569782	Sr ₂ LiCBr ₃ N ₂	0.548	marginal
6.	mp-676109	Li ₃ InCl ₆	0.595	yes
7.	mp-676361	LiErCl ₆	0.664	yes
8.	mp-22905	LiCl	0.735	x
9.	mp-559238	CsLi ₂ BS ₃	0.780	yes
10.	mp-29410	Li ₂ B ₂ S ₅	0.972 ^d	yes
11.	mp-34477	LiSmS ₂	0.977	x
12.	mp-8430	KLiS	1.720 ^d	x
13.	mp-8751	RbLiS	1.727 ^d	x
14.	mp-554076	BaLiBS ₃	2.035	x
15.	mp-866665	LiMgB ₃ (H ₉ N) ₂	2.330 ^d	yes
16.	mp-19896	Li ₂ GePbS ₄	2.835	x
17.	mp-561095	LiH ₃ O ₃ Ge ₂ (O ₄ F) ₂	3.259	x
18.	mp-15791	LiErS ₂	4.698 ^d	x
19.	mp-15790	LiHoS ₂	4.749 ^d	x
20.	mp-15789	LiDyS ₂	4.872	x
21.	mp-15797	LiErSe ₂	4.884	marginal

^d ML prediction

Sendek model

