

“Opening the “Black Box”: An Experimentally-Validated Explainable Machine Learning Framework for Materials Design and Discovery”

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Introduction / Motivation

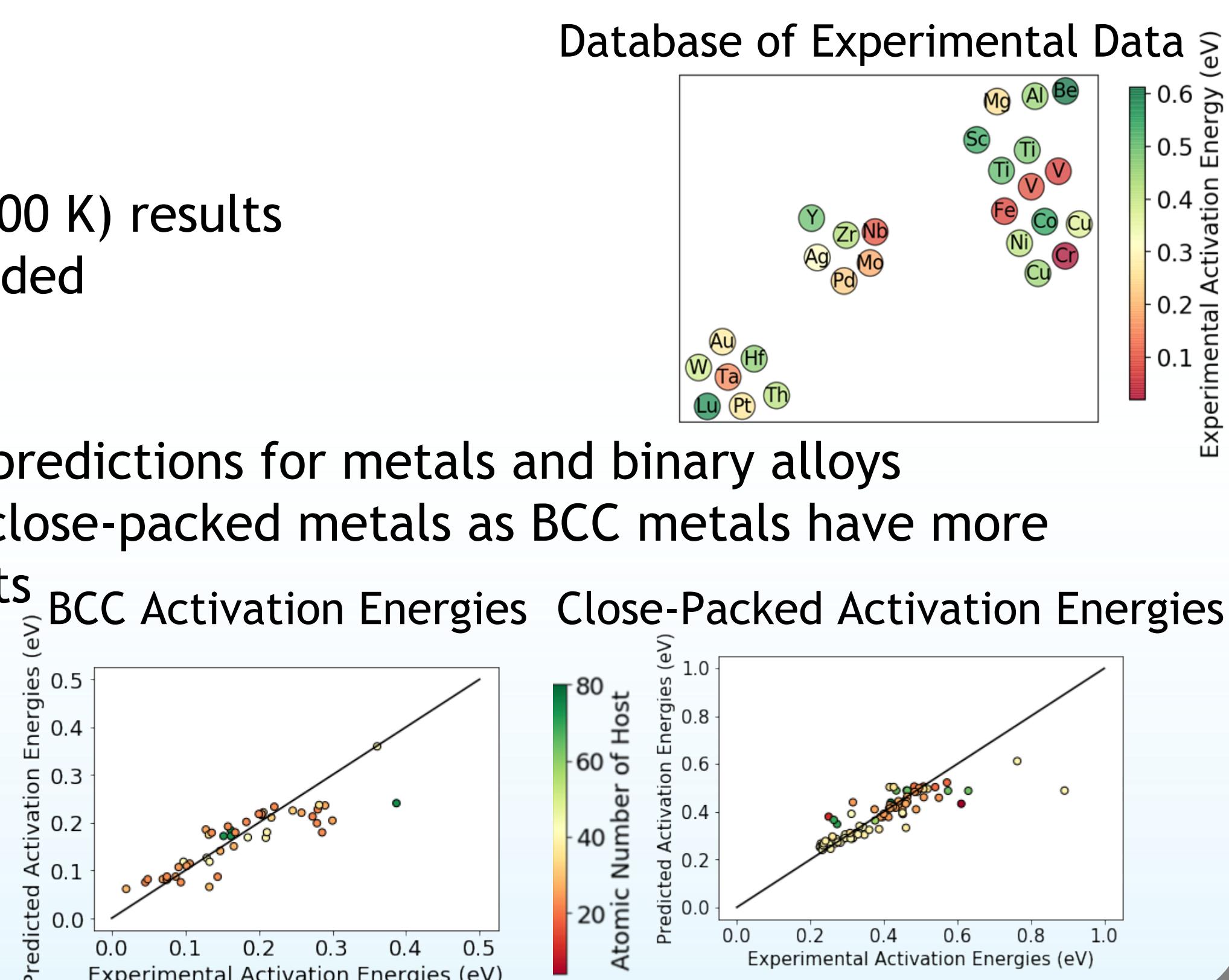
- Materials that diffuse hydrogen slowly are useful for storing hydrogen. Conversely, materials that diffuse hydrogen quickly are important for use in hydrogen **fuel cells**.
- Hydrogen’s small mass results in intrinsically quantum mechanical effects, namely a large contribution to diffusion from zero-point vibrational energy.
- Previously, machine learning models have successfully been used to predict diffusion in metals [1, 2].
- Most machine learning models are a ‘black box,’ but we want to enable **expert-guided extrapolation** beyond our dataset by revealing relationships between metal properties and hydrogen diffusion.
- Our findings can therefore be expanded beyond the metals and alloys in our dataset.

Approach

- Feature selection: 196 total features**
 - Previous researchers [1] have used the Wolverton group **MAGPIE** features database [3] to predict vacancy-based diffusion in metals. This database includes a variety of characteristics such as atomic data, crystal structure, electrical properties, and elastic constants.
 - We further added features from theoretical models of diffusion, which were previously used successfully in a machine learning model for C, O, and B interstitial diffusion in metals [3].
 - Electrical thermal conductivity** is correlated with the solubility activation energy of hydrogen [4].
- Model selection: ElasticNET**
 - Linear model which combines properties of LASSO and ridge regression
 - Cuts down the number of features and keeps coefficients small
 - Very similar to normal least-squares linear regression, but is more stable against overfitting
 - Explainable:** coefficients for the features give us an idea of their relative importance
 - Helps us generate a physical understanding for why properties may be important in hydrogen diffusivity

Current Status/ Results (If any)

- Gathered a database of experimental hydrogen diffusion data, including data collected at Sandia:
 - 50 metals
 - 88 binary random alloys
 - Contains only high temperature (>300 K) results
 - All three isotopes of hydrogen included
- Hydrogen diffusion activation energy predictions for metals and binary alloys
- Fit two separate models for BCC and close-packed metals as BCC metals have more prominent quantum mechanical effects



Challenges

- Large number of features and relatively **small amount of data** (especially by machine learning standards)
- Limits the types of models that can be used since S more flexible and accurate models learn ‘too well’, so they can’t generalize to new data
- Hydrogen-metal interactions are more difficult to predict due to their **highly quantum-mechanical** nature.
- Previous models, which focused on larger interstitials, cannot simply be applied here.

Next Steps/ Future Work

- Compare predictions from the model to new experimental/density functional theory results

Predicted Hydrogen Diffusion in Pd Binary Alloys

A scatter plot showing 'Activation Energies (eV)' on the y-axis versus 'Element A' on the x-axis. The x-axis includes Ti, Zn, Al, Cu, Nb, and V. The y-axis ranges from 0.3 to 0.5 eV. Data points are colored according to the 'Atomic Fraction of Element A' on the right, with a color scale from red (0) to green (1). A diagonal line of unity is shown.

- Expand the model to work with more complicated random alloys such as high-entropy alloys