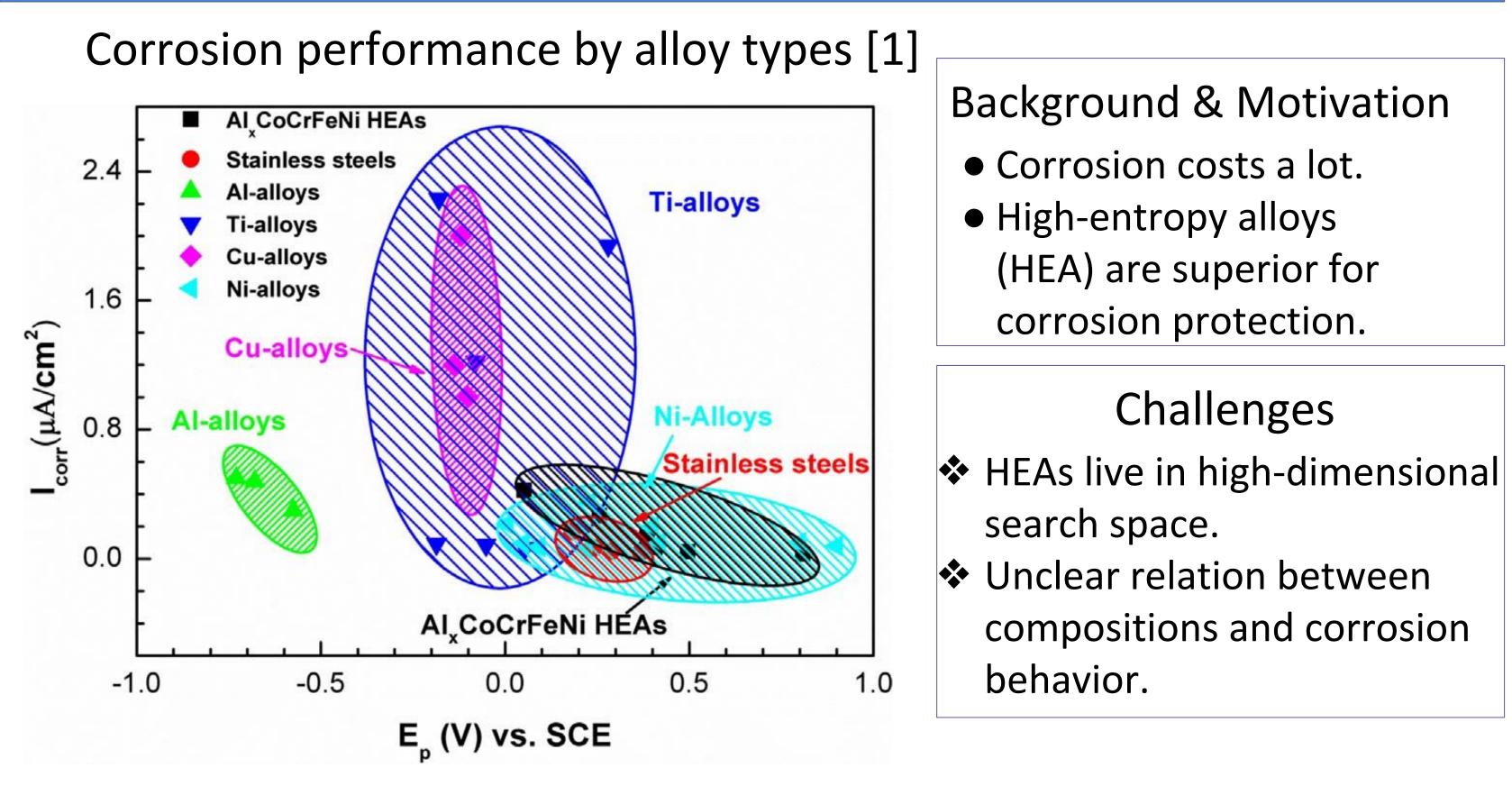
First-principles and Data-driven Discovery of High-entropy Alloys for Corrosion Protection



<u>Cheng Zeng</u>, Andrew Neils, Nathan Post, Jack Lesko The Roux Institute, Northeastern University, Portland, Maine, USA

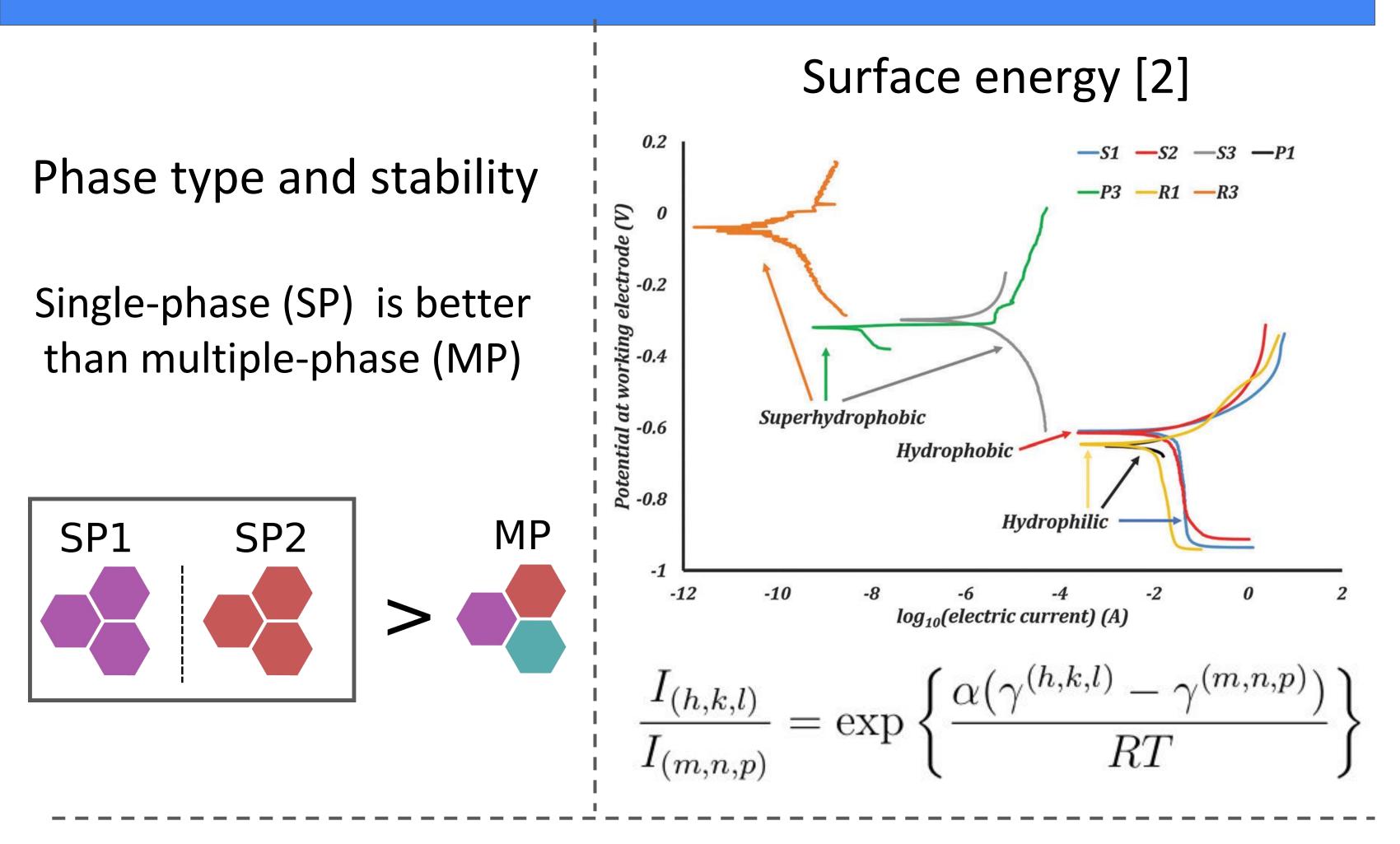


Introduction



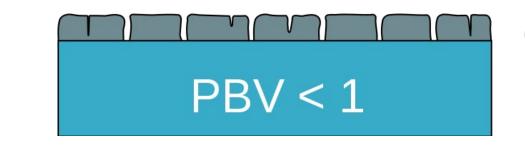
→ Machine learning accelerated search of corrosion-resistant HEAs

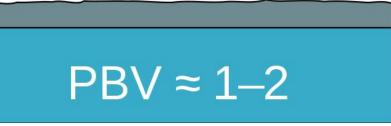
Three factors influencing corrosion

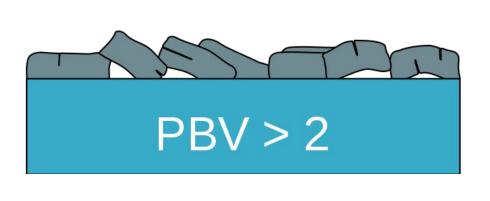


Pilling-Bedworth Ratio (PBR) for oxidation of alloys [3]

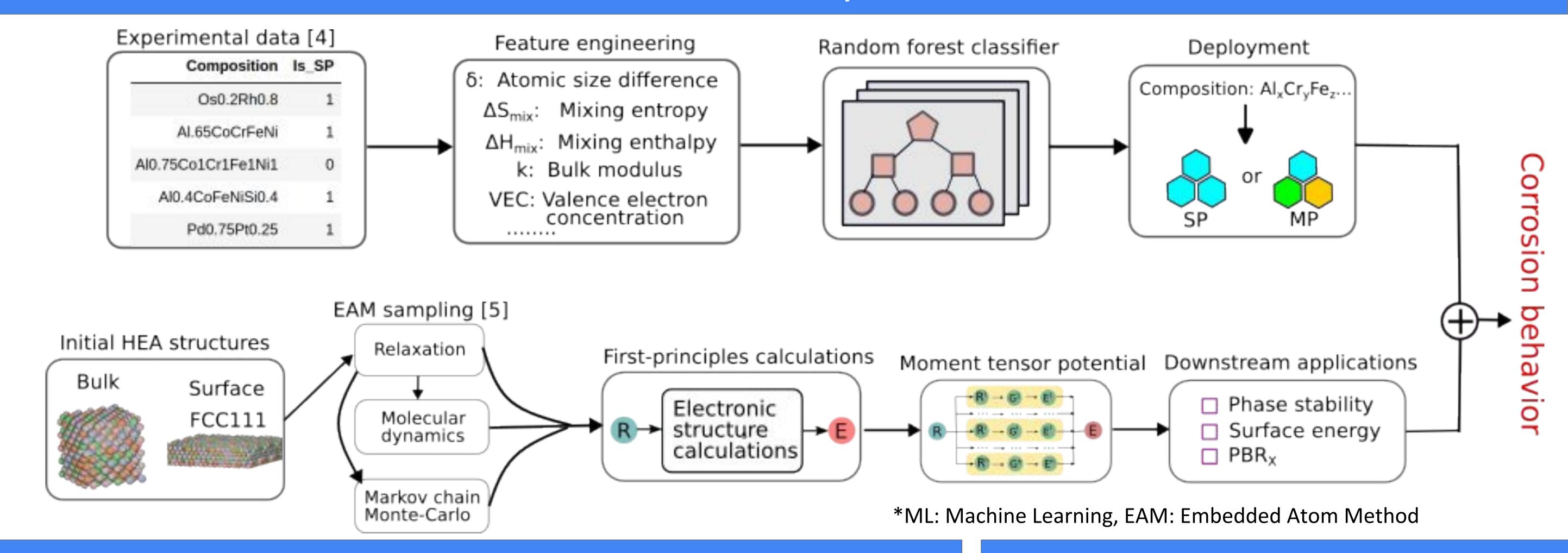
$$PBR_{\text{alloy}} = \frac{\text{Volume of a mole of B}_{x}O_{y}}{\text{Volume of x moles of B in alloy}}$$



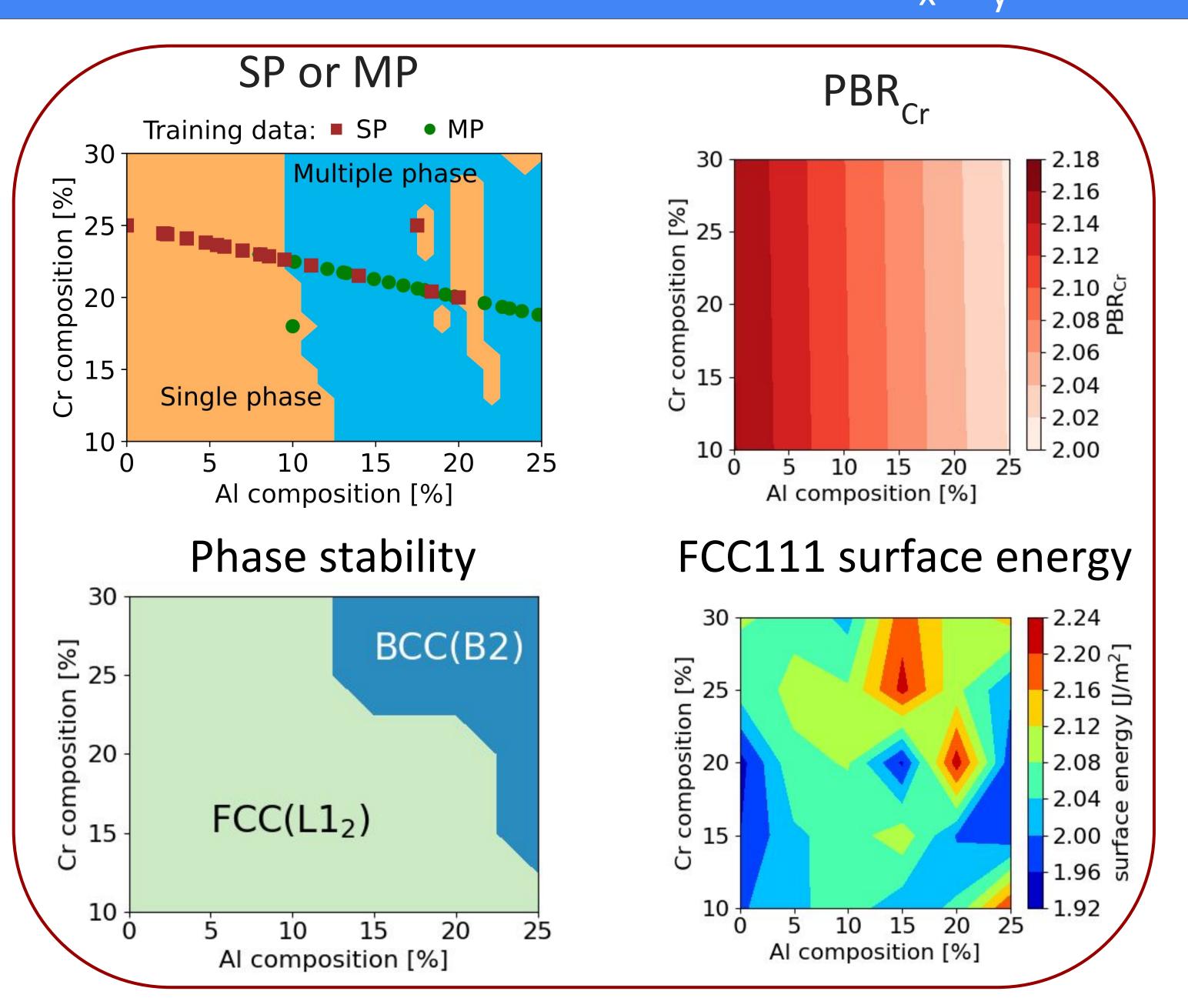




Workflow for ML-enabled discovery of corrosion-resistant HEA



Synergistic effects of Al and Cr for Al Cr, FeNiCo



- Al is the critical element and Cr is the associated element.
- Low Al and Cr compositions tend to show single phase, FCC structure, high PBR_{Cr} (>2) and low FCC111 surface energy.
- The best combo is around (Al, Cr)=(0, 15-18%).

Conclusions

- A framework combining first-principles calculations and data-driven models to evaluate corrosion performance of HEAs is developed.
- Corrosion behavior is gauged in terms of SP formability, PBR and surface energy.
- SP formability is predicted by random forest classifier and the other properties are quantified by moment tensor potential.
- For Al_xCr_yFeNiCo, the best Al and Cr composition ranges are around 0% and 15-18%.

References

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