



Citrine Informatics

The data analytics platform for the physical world

Analyzing Large-Scale Data to Solve Applied Problems in Materials R&D

Bryce Meredig, Citrine Informatics

Artificial Intelligence Applied to Materials Discovery and Design

9 August 2017

“Centaur” Materials Science



Human and Machine > Human or Machine

Things Scientists Do With Data: Conventional View of Informatics

Collect

Process

Visualize

Search

Model

Optimize

Interpret &
Learn

Curate &
Evaluate

Machine Learning
Predicts Properties

Things Scientists Do With Data: Citrine's Vision

Machine Learning Will Be a Behind-the-Scenes Copilot for All of These

Collect

Process

Visualize

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Evaluate

Covered in today's talk

Citrine also working in these areas—ask me

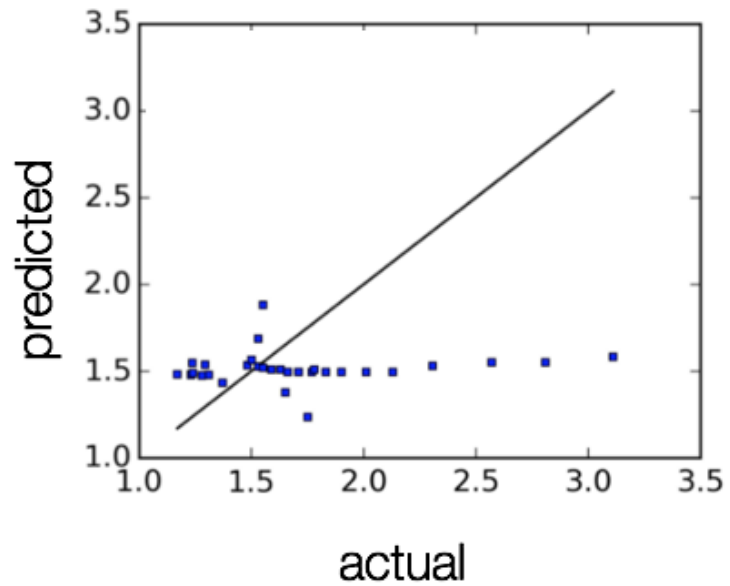
Citrine Has a Unique Business Model

- Open Citrination's data & infra available to everyone
 - Open data (one of world's largest collections of free materials data)
 - Open PIF data standard
 - Open-source lolo machine learning library
 - Open-source API tools and tutorials
- Enterprise Citrination users pay to leverage Open data while keeping internal data proprietary

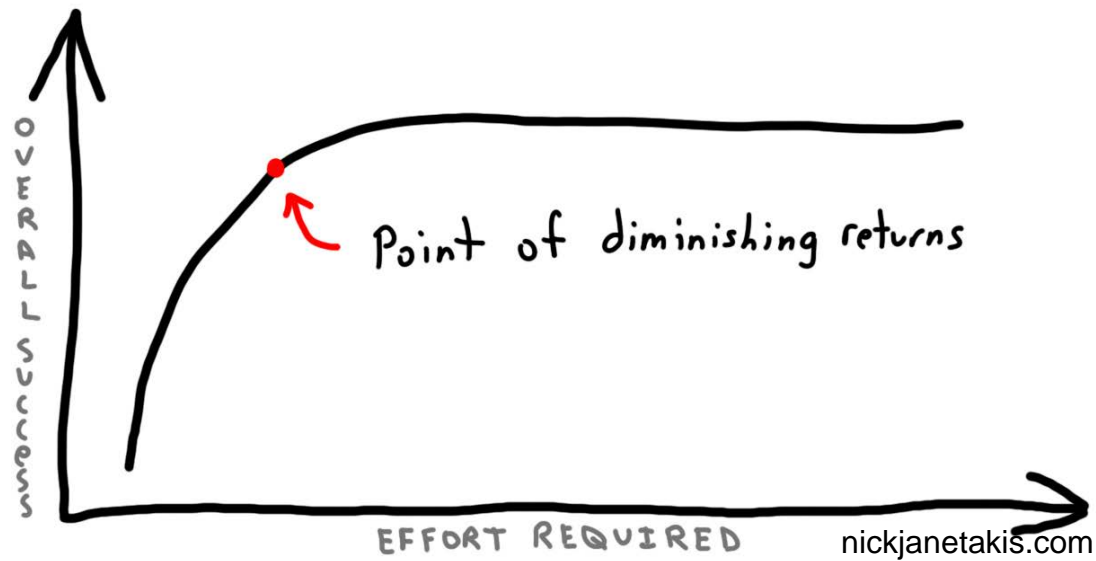
Industrial Applications & Research

Industrial Case Study #1

Isolated dataset too small
for machine learning

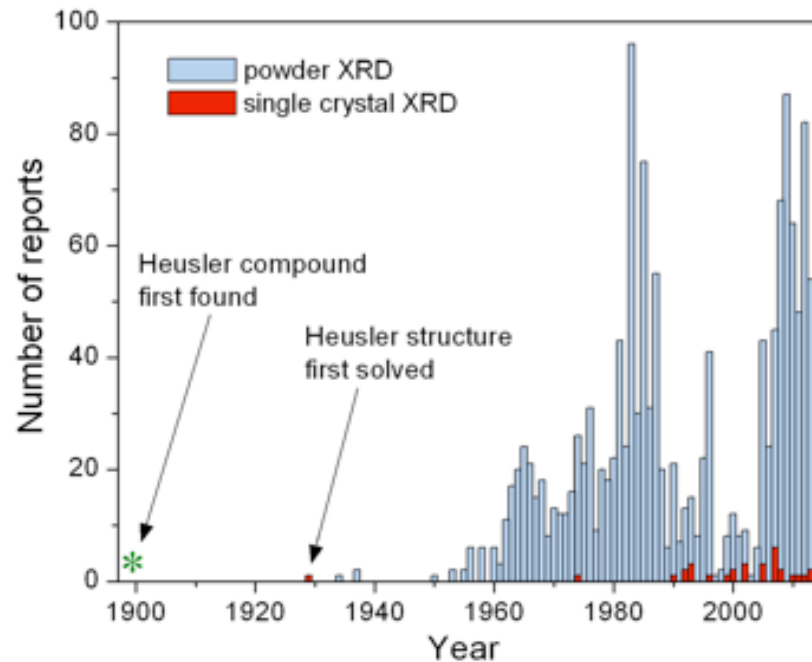


Industrial Case Study #2

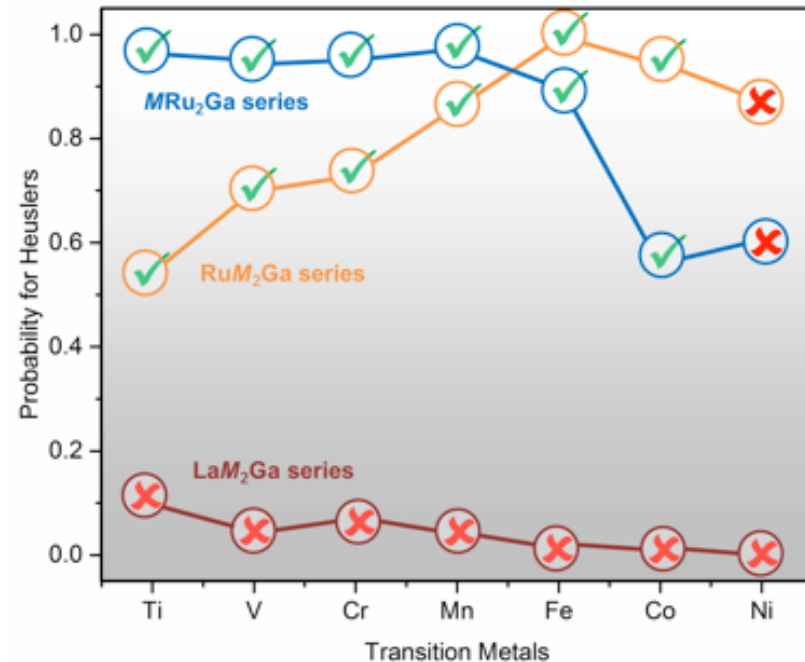


Machine learning helped save a customer >\$30m on materials characterization by identifying the point of diminishing returns

Data-Driven Methods Give >10x Yield Boost

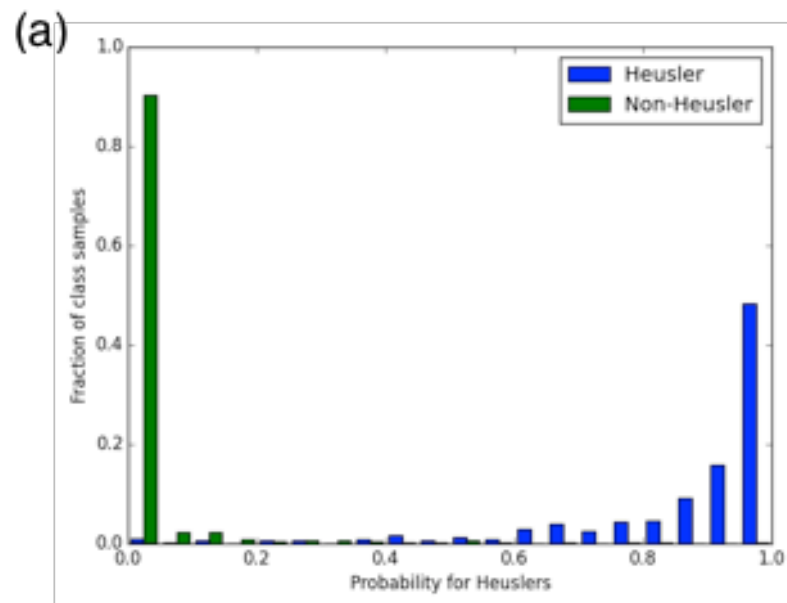


Scientific community discovers ~50 Heuslers/year

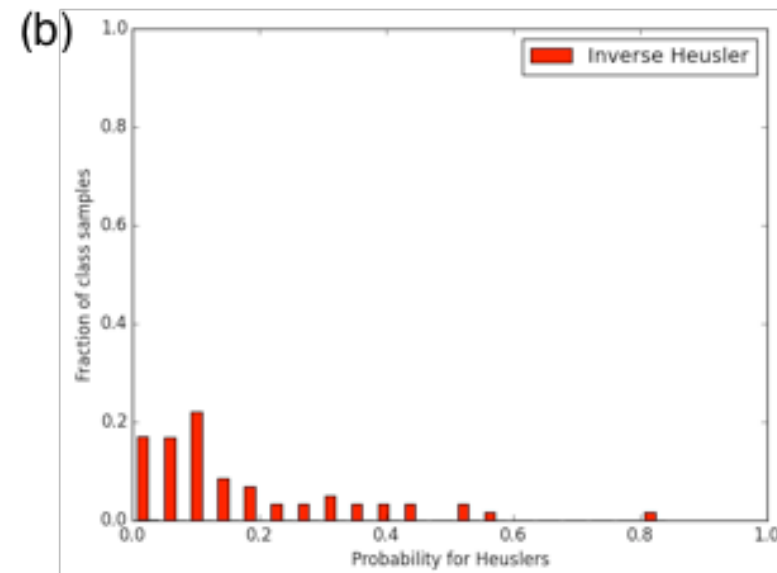


Our collaborators made 12 in one paper

Models Discriminate Similar Structures

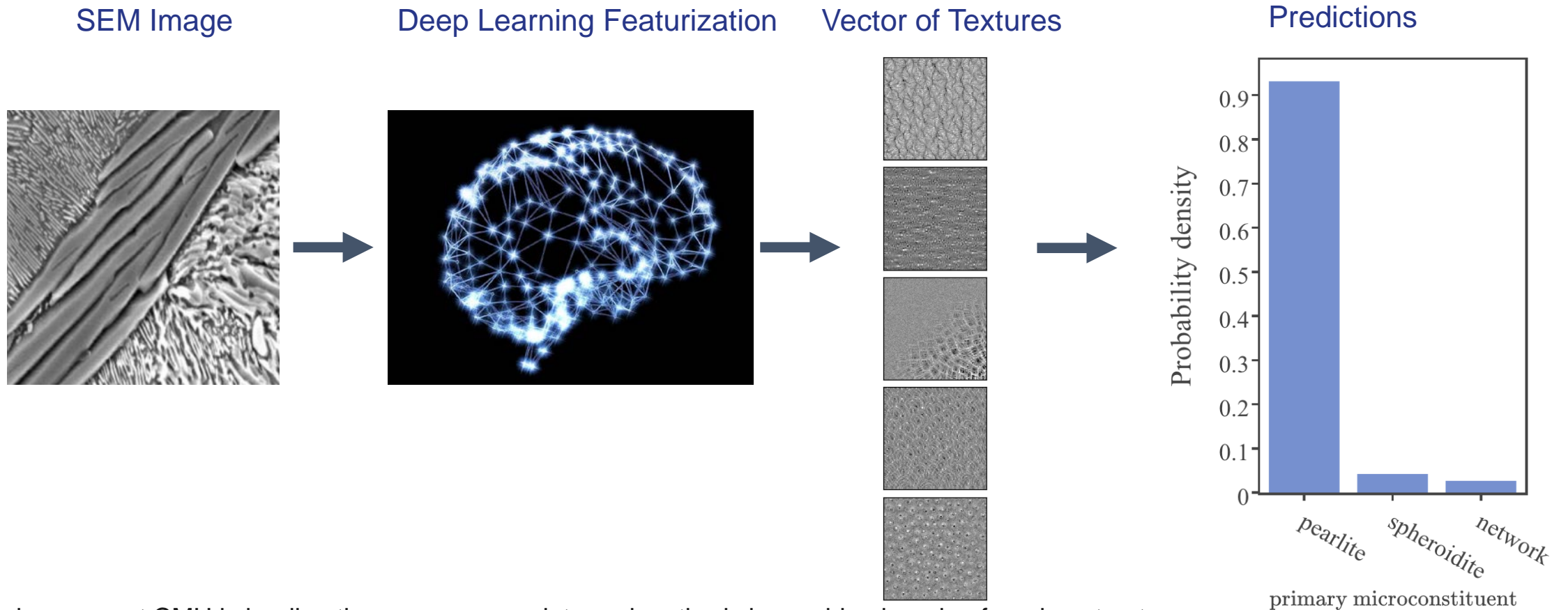


Heusler vs other



Heusler vs
inverse

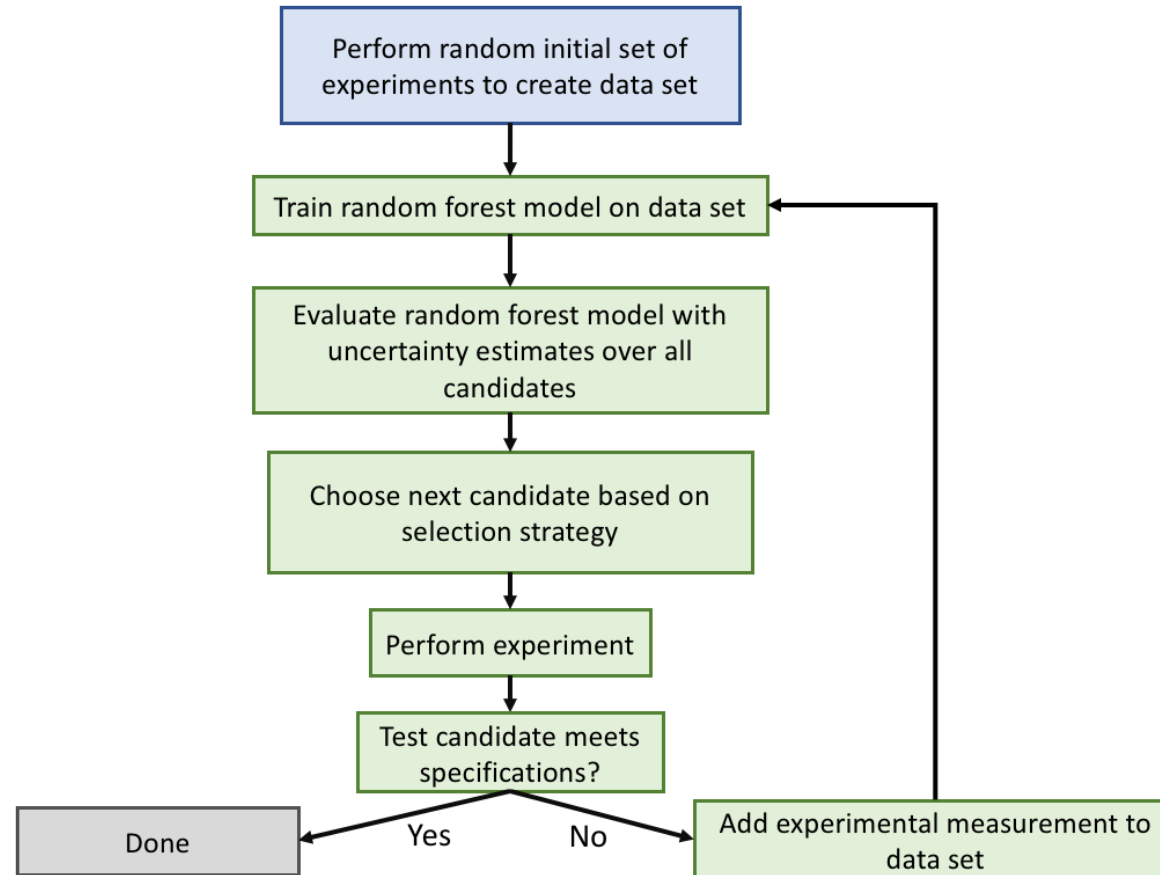
Deep Learning for Microstructure Featurization



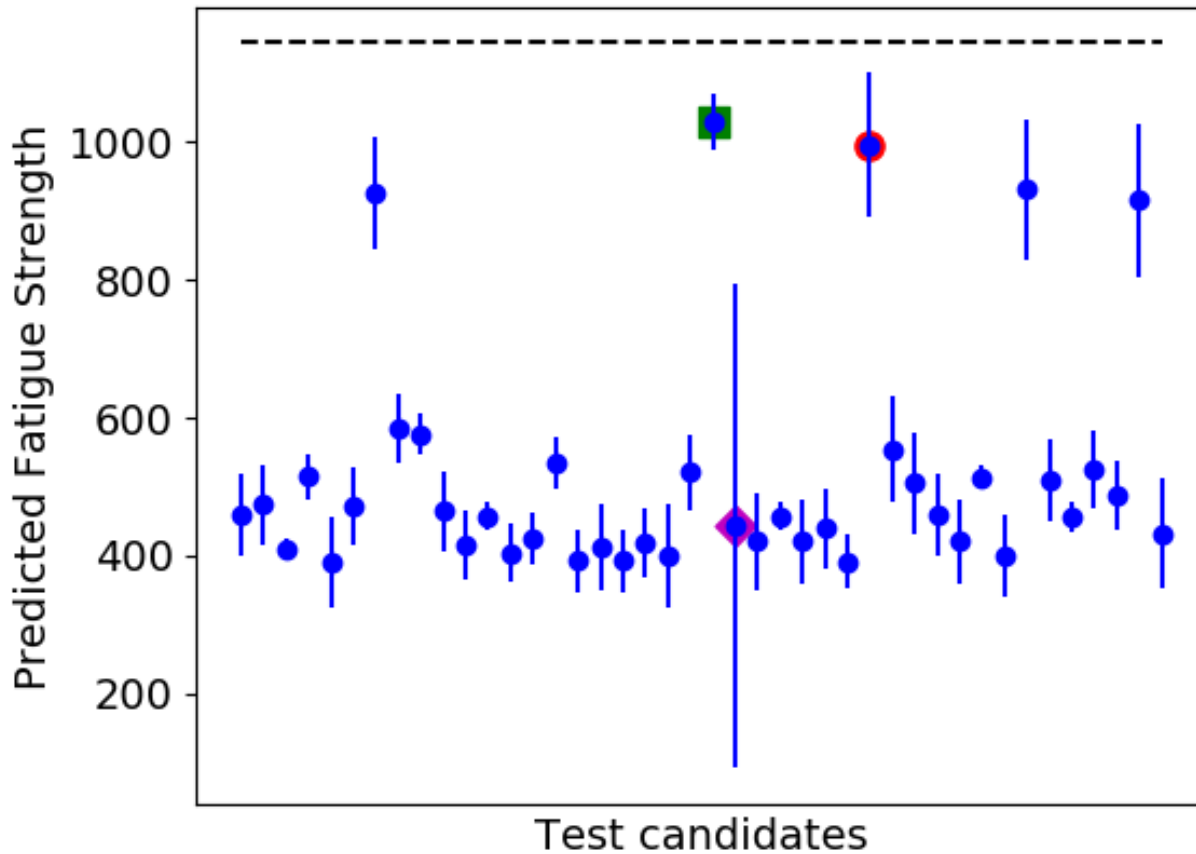
The Holm group at CMU is leading the way on open data and methods in machine learning for microstructure; see e.g. DeCost et al., UHCSDB: UltraHigh Carbon Steel Micrograph DataBase, *IMMI* (2017).

Emerging Methods to Accelerate Materials Discovery

Forest with Uncertainty Estimates for Learning Sequentially (FUELS)



Candidate Selection Strategy



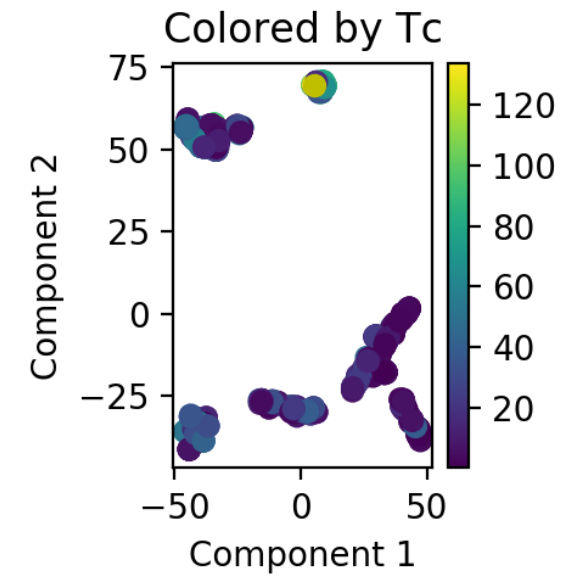
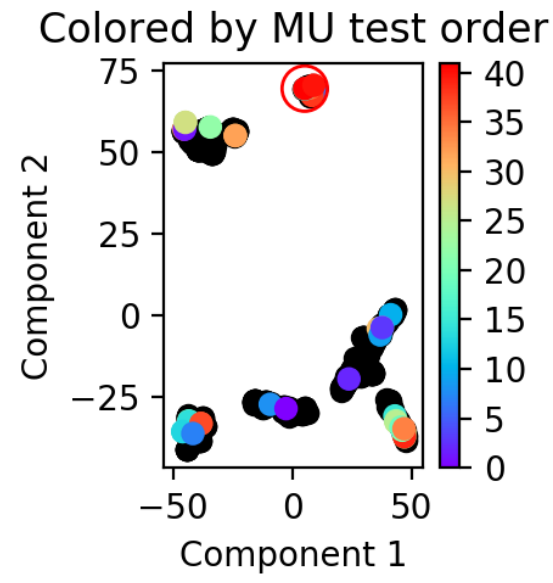
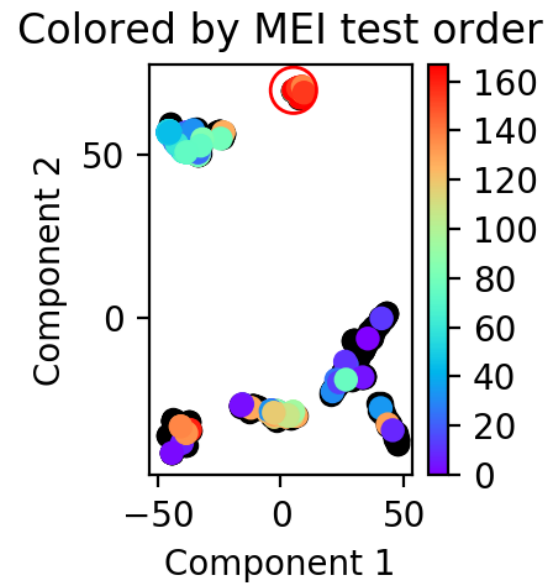
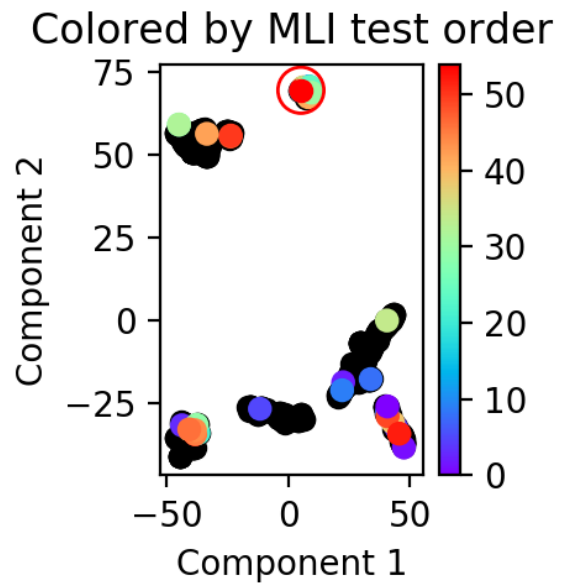
Strategies:

- Maximum Likelihood of Improvement (MLI)
- Maximum Expected Improvement (MEI)
- Maximum Uncertainty (MU)

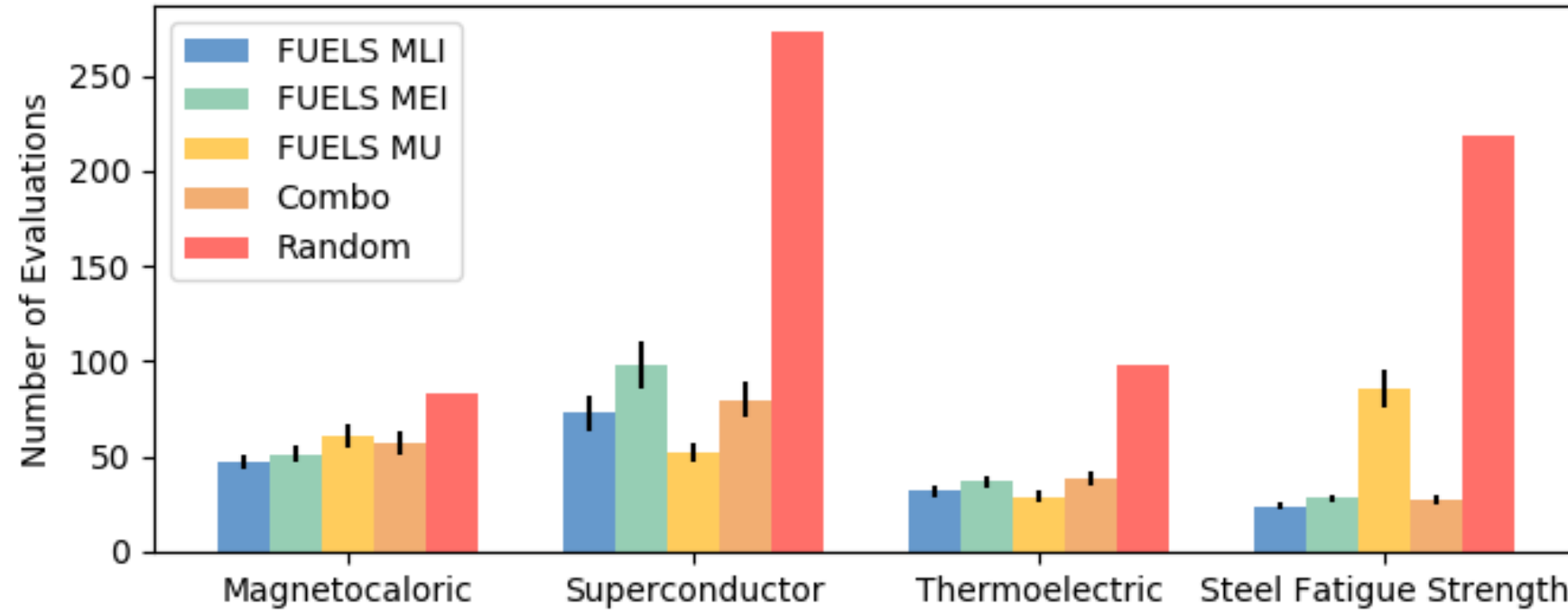
Test Cases

- Four materials problems
 1. Magnetocalorics (maximize magnetic deformation)
 2. Superconduction (maximize critical temperature)
 3. Thermoelectrics (maximize ZT figure of merit)
 4. Steel Fatigue Strength (maximize fatigue strength)
- Five candidate selection strategies:
 1. Maximum Expected Improvement
 2. Maximum Likelihood of Improvement
 3. Maximum Uncertainty
 4. COMBO Bayesian Optimization (Ueno et al. 2016)
 5. Random guessing
- Inputs: 20-60 features based on composition and processing
- Goal: Find optimal candidate after fewest number of “measurements”

Visualizing the Optimization Path



Benchmark Results

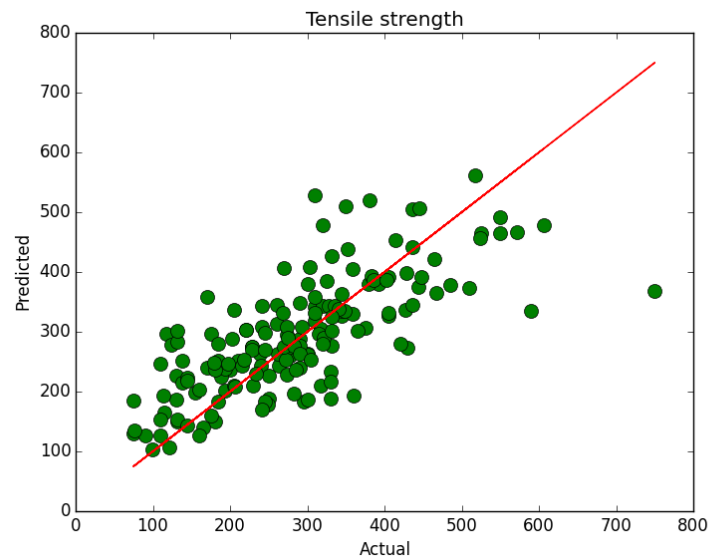


Integrating Known Physics in ML

Collaboration with CompuTherm to demonstrate benefits of CALPHAD data in training ML to predict Al alloy mech properties

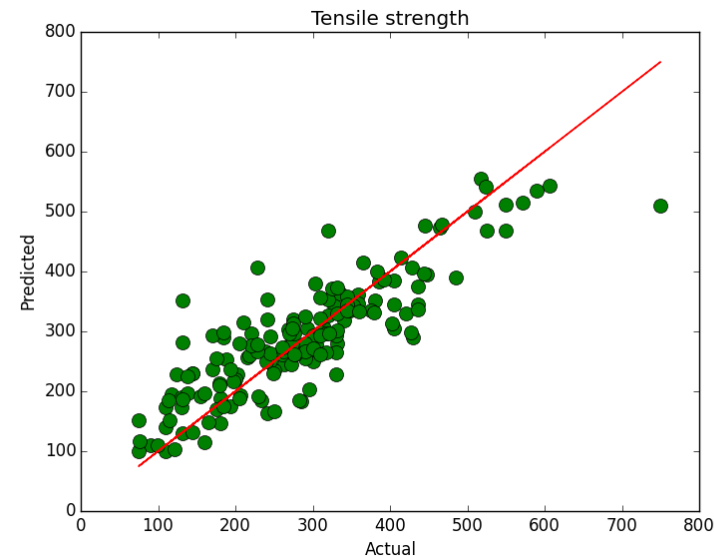
ML without CALPHAD

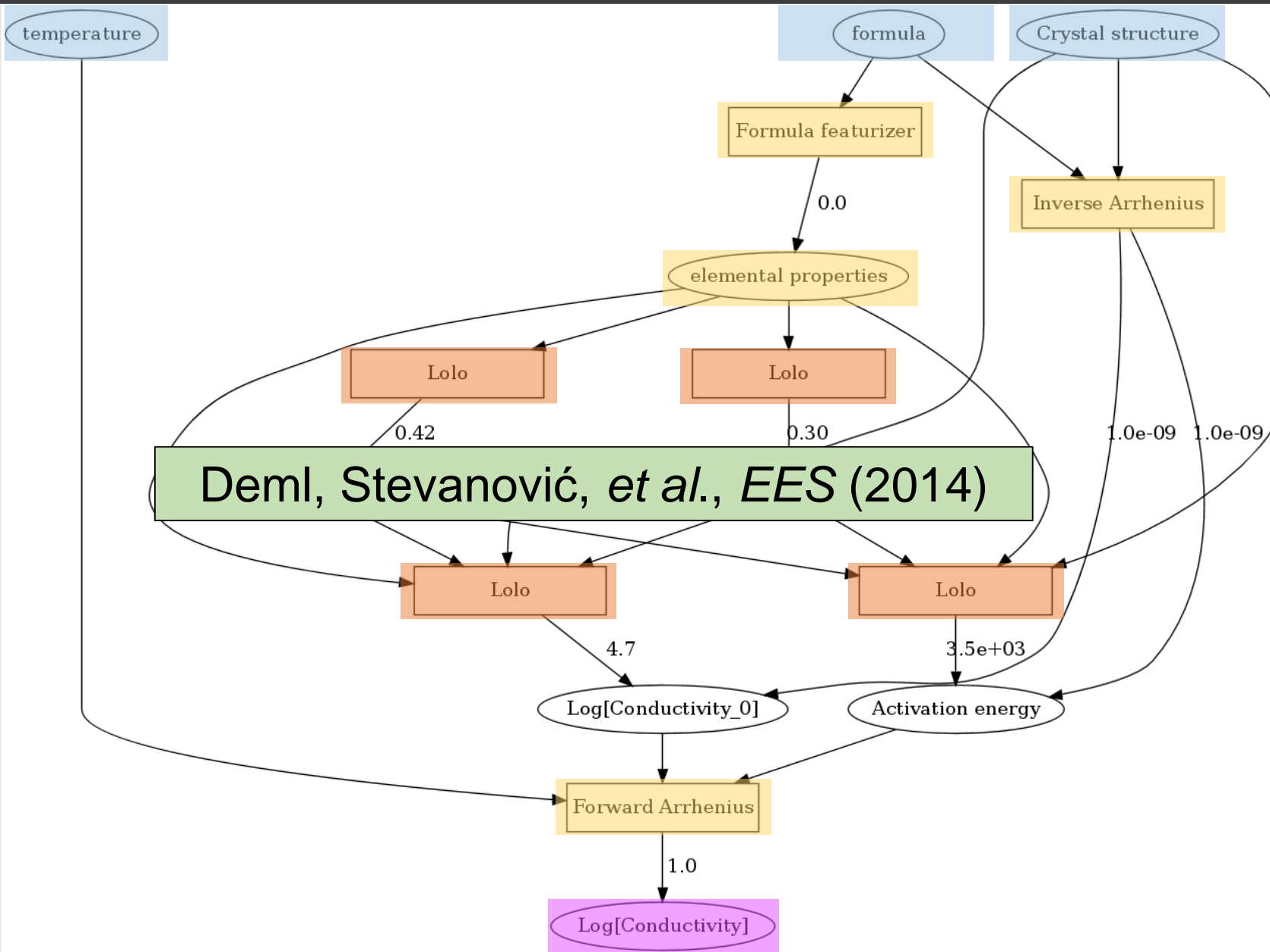
RMSE = 82 MPa



ML with CALPHAD

RMSE = 61 MPa





Experimental measurement (data)

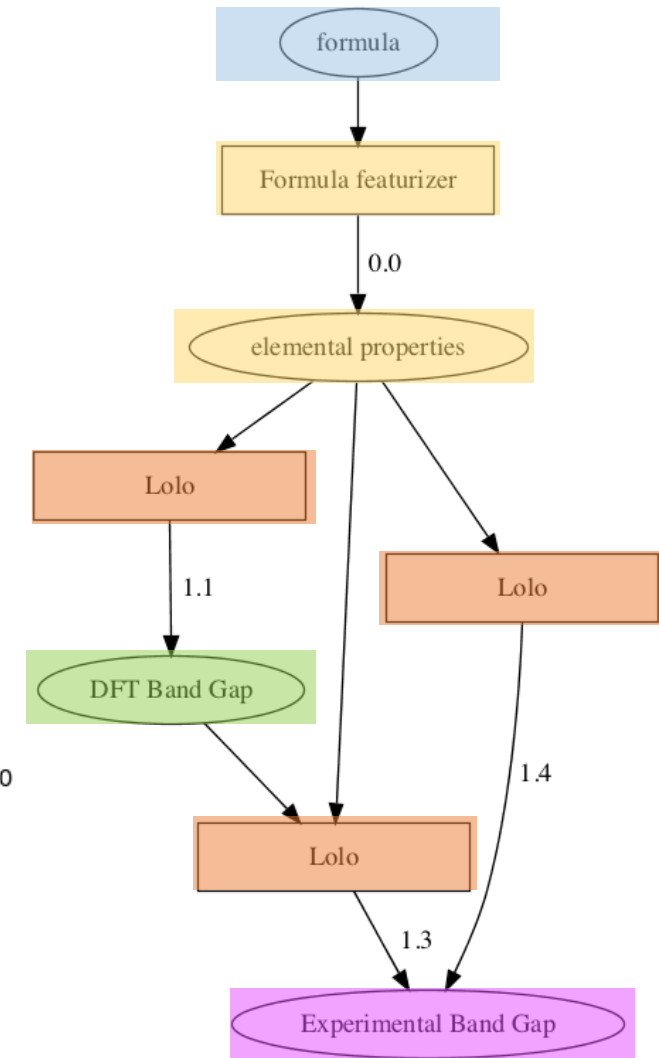
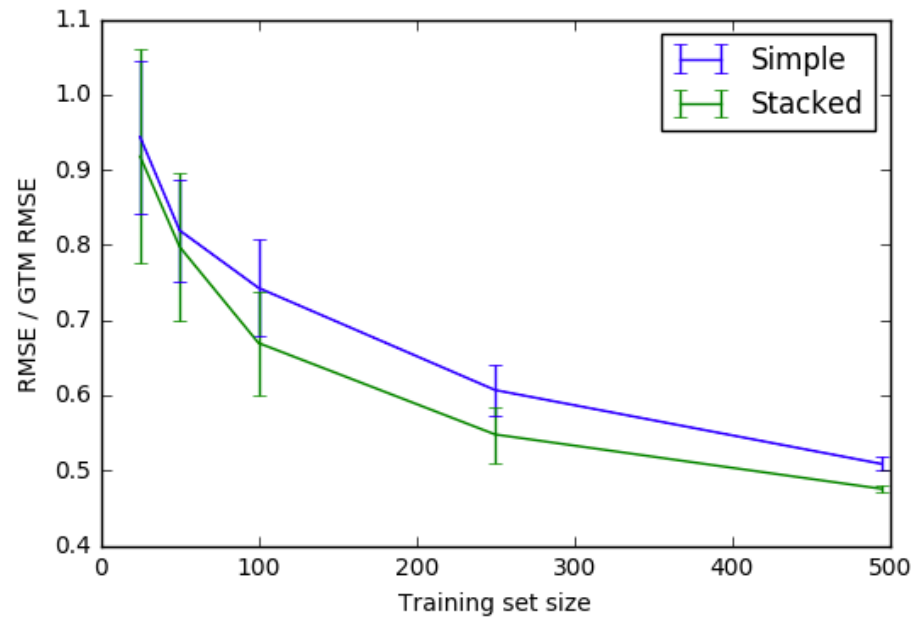
Experimental inputs

Computational data

Theory and known relationships

Machine learning glue

Using even small number (~2k) calculations from Materials Project as a node on the relation graph reduces error in band gap model

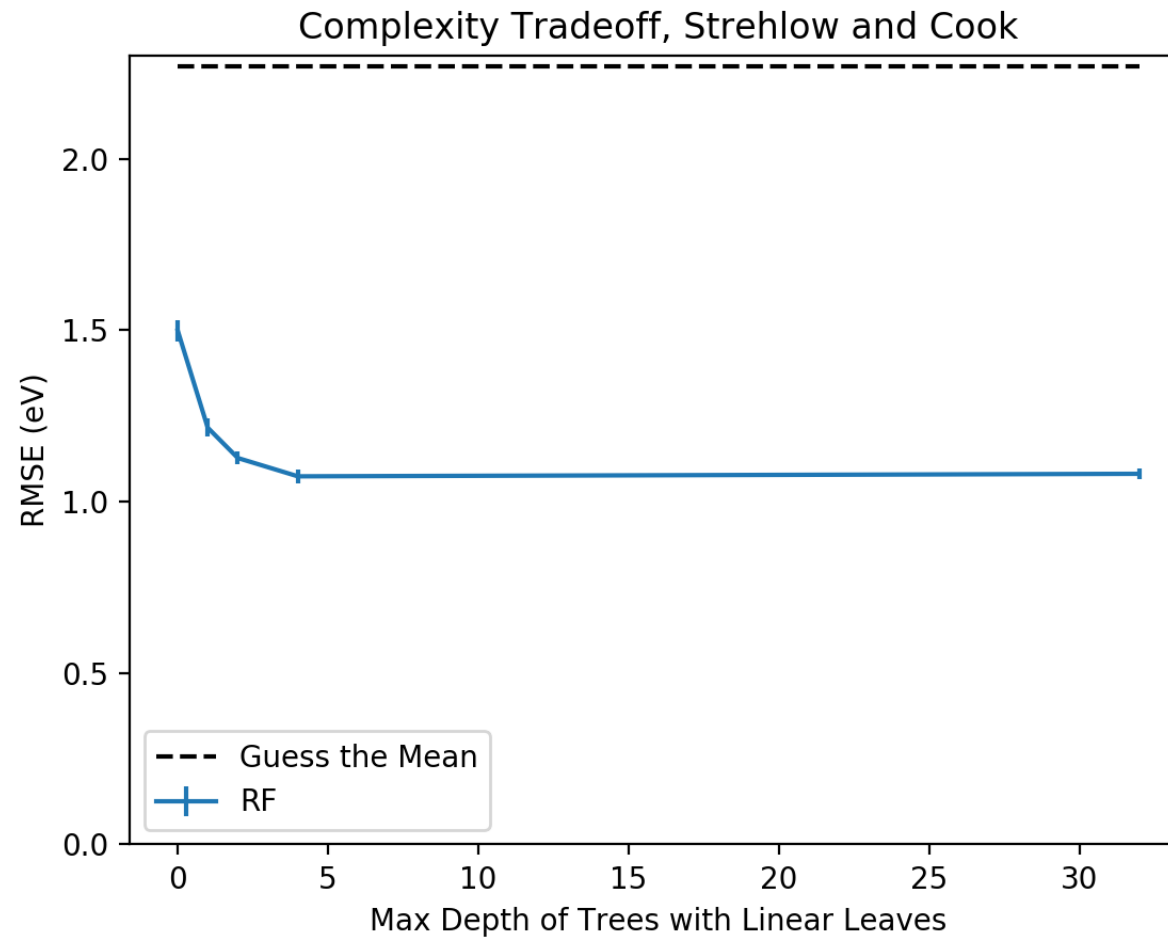


Barriers to Materials Discovery Nirvana

Democratized (free, easy-to-use) infrastructure, data, ML

Education for physical scientists in machine learning

Physical Interpretability vs. Accuracy





UW-Madison MSE

@UWMadisonMSE

Follow



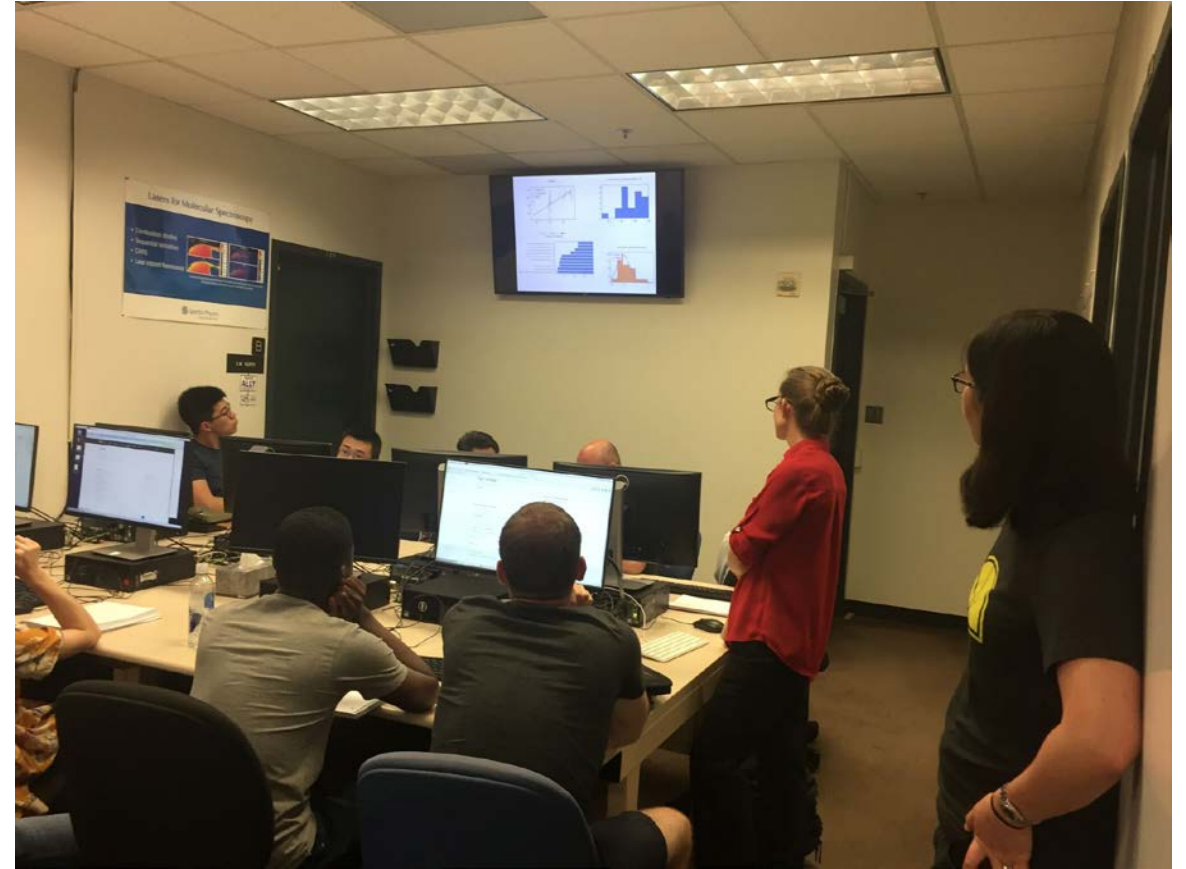
We are excited to announce that department undergrad Vaness Meschke has won the [@Citrine_io](https://www.citrine.io) NextGen Fellowship!
skunkworks.engr.wisc.edu/vaness-meschke

...

9:54 AM - 13 Jun 2017

4 Retweets 4 Likes





2017 Summer School on Computational Materials Science Across Scales, Texas A&M

Summary

Machine learning has significantly accelerated materials discovery across a variety of application areas

In our experience, lack of tools and education prevent such acceleration from becoming ubiquitous

We strive to give materials scientists **both the platform and knowledge** to accelerate their work with machine learning