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Bayesian Optimization in Automated Experiments

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FOR THE US DEPARTMENT OF ENERGY



Acknowledgements

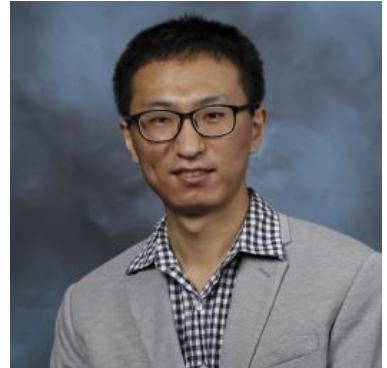


- Sergei Kalinin (UTK)
 - S. Jesse (ORNL)
 - P. Ganesh (ORNL)
 - Zijie Wu (ORNL)
- G. Duscher (UTK)
 - Many other students, postdocs, and staff at CNMS and ORNL

Sumner Harris



Yongtao Liu



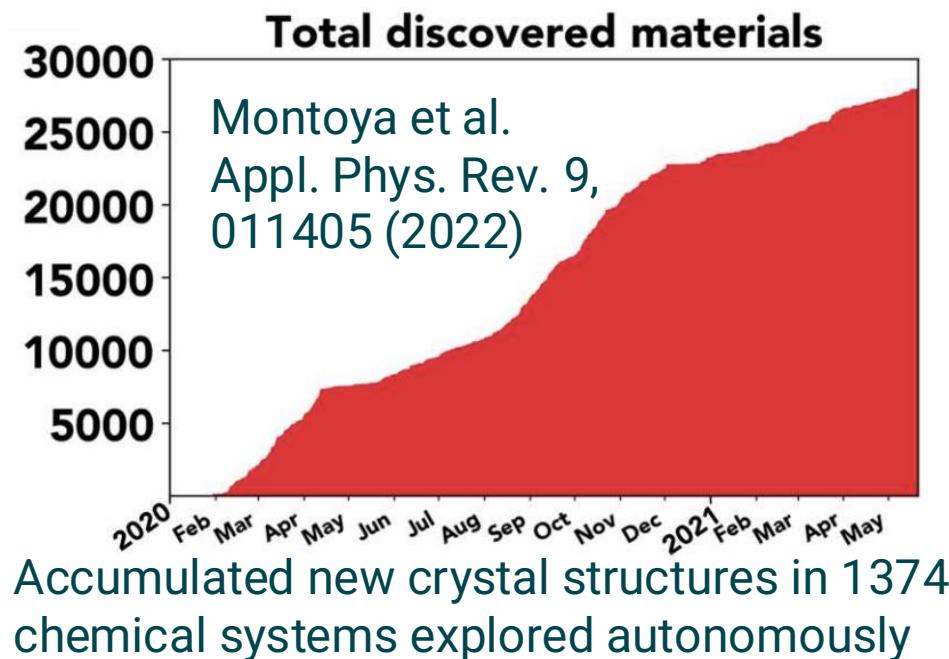
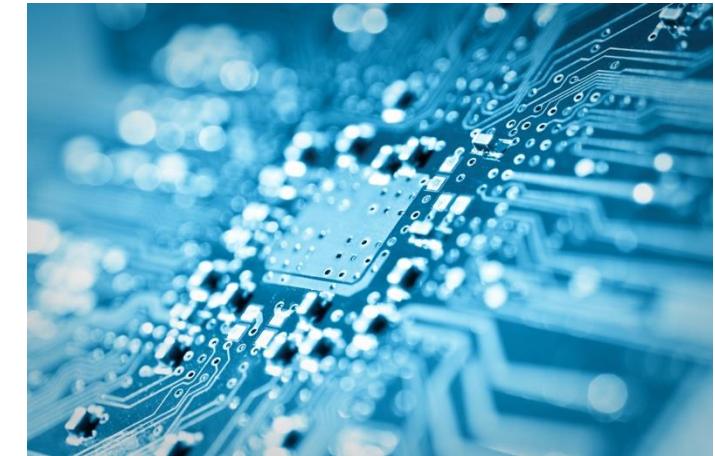
Ganesh
Narasimha



Soumendu
Bagchi



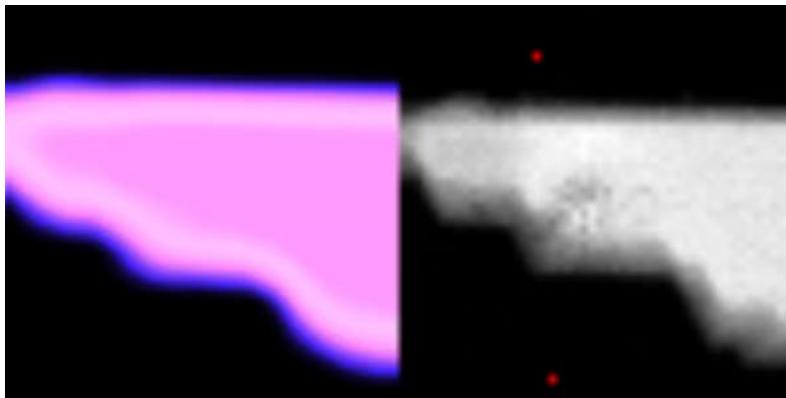
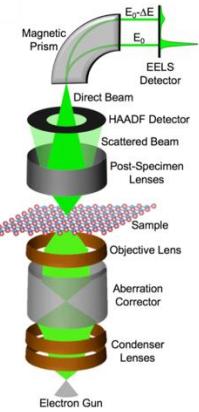
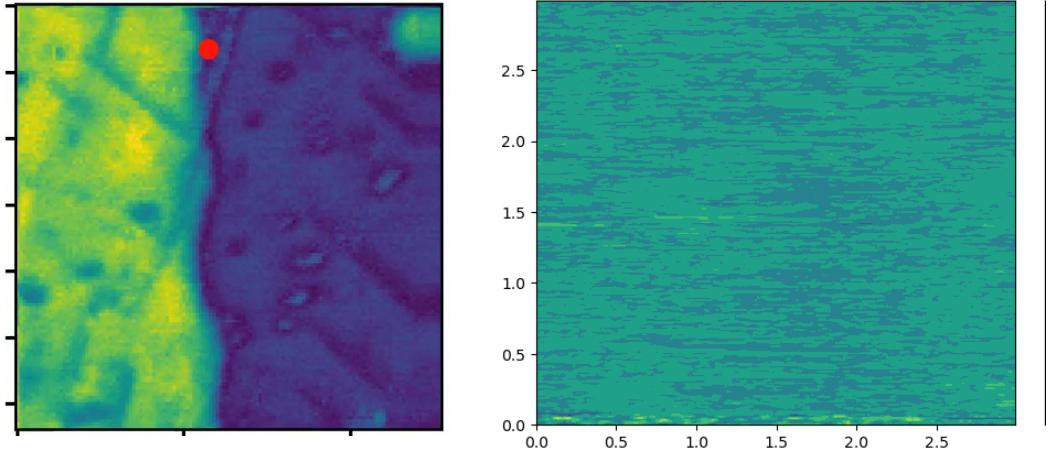
Today's materials challenges: autonomous labs?



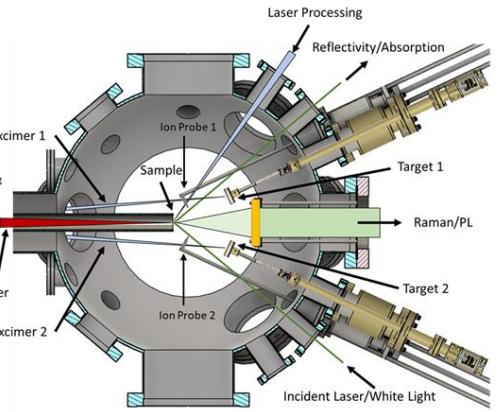
- Renewable energy, self-driving cars, transparent displays, new memory technologies, energy harvesting and generation
- Materials become more complex. We can predict many new materials. But we need to (a) synthesize them and (b) understand them, not just optimize for properties.

Outline

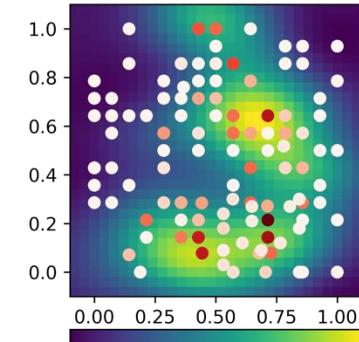
Autonomous Microscopy



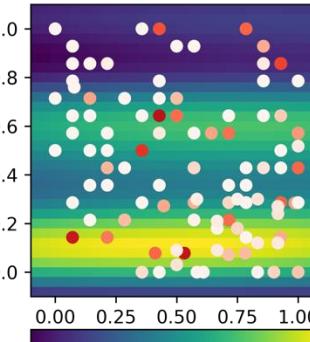
Autonomous Synthesis



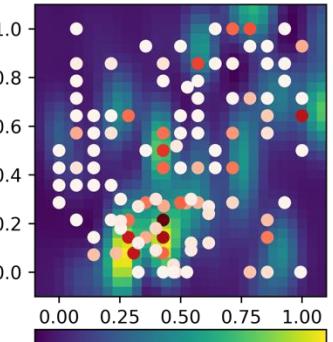
P vs T: Objective Mean



P vs e1: Objective Mean



P vs e2: Objective Mean



Automating SPM: AEcroscopy

Software Infrastructure



Welcome to AEcroscopy

Get Started

Get Started

Experiment

Experiments

```
Step 4. Do a BEPFM at the whole experiment area

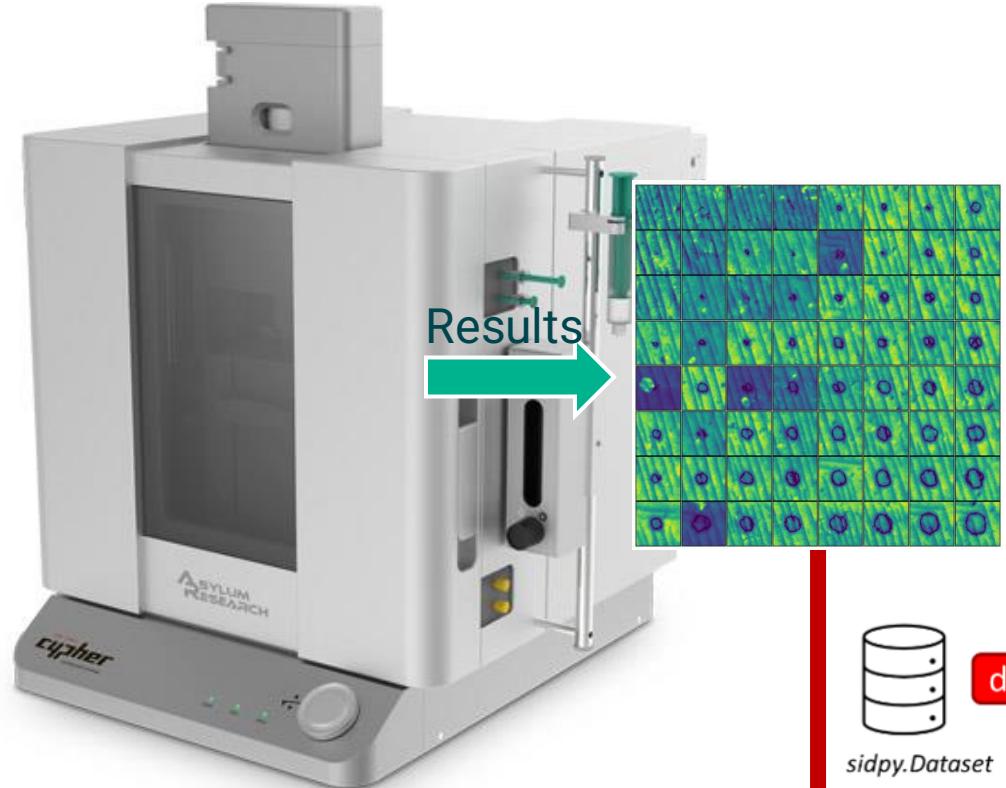
dset_pfm, dset_chns, dset_cs = newexp.raster_scan(raster_parms_dict = {"scan_pixel": 32, "scan_x_start": -1.0, "scan_y_start": -1.0, "scan_x_stop": 1.0, "scan_y_stop": 1.0}, file_name = "pfm_whole", ploton = False)

f, (ax1, ax2, ax3, ax4, ax5, ax6) = plt.subplots(1, 6, figsize = (30, 5), dpi = 100)
ax1.imshow(dset_pfm[:, :, 0])
ax2.imshow(dset_pfm[:, :, 1])
ax3.imshow(dset_pfm[:, :, 2])
ax4.imshow(dset_pfm[:, :, 3])
ax5.imshow(dset_chns[0, :, :])
ax6.imshow(dset_chns[1, :, :])
plt.show()
```

Y. Liu et al. Small Methods 2301740 (2024)

Deploy

Results



sidpy.Dataset

An ecosystem for microscopy data ingestion, analytics and visualization

pycroscopy
A general-purpose package for microscopy imaging and spectroscopy data analytics, including registration, image cleaning, unmixing, etc.

scifireaders
For ingesting a variety of microscopy files for output to sidpy dataset objects

pyusid
Python package for reading and visualizing our universal spectral imaging dataset format

pynsid
Python package for reading and visualizing our N-dimensional spectral imaging dataset format

sidpy
Python utilities for storing, visualizing and fitting Spectroscopic Imaging Data

bglib
Utilities to analyze, fit and visualize Band - Excitation and G - mode imaging data primarily for CNMS SPM Users

atomai
Deep learning toolkit for analysis of atomically resolved imaging and spectroscopy datasets

stemtools
Python based codes for analysis of 4D-STEM and aberration - corrected vanilla STEM datasets

pytemlib
Python tools for simulation, registration, analysis and visualization of TEM datasets

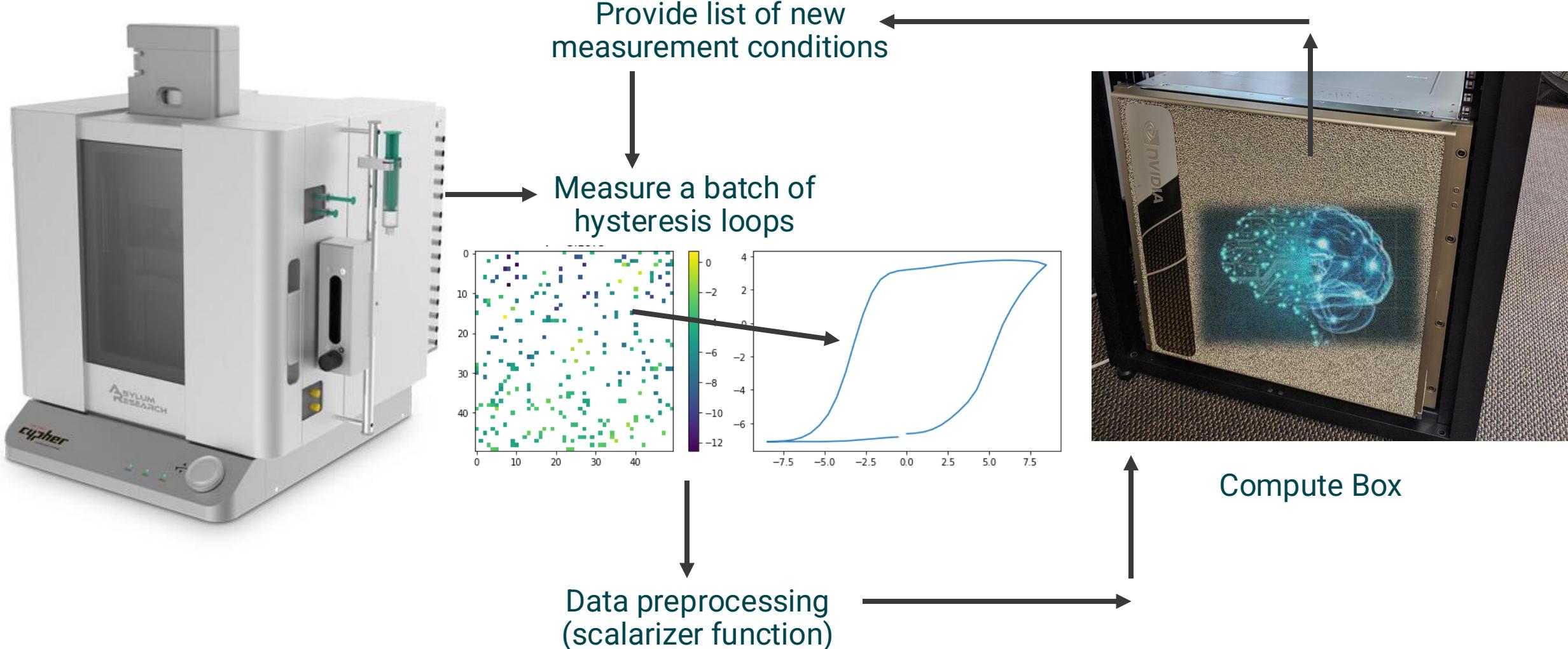
Y. Liu et al. Small Methods 2301740 (2024)

Vasudevan et al. Advanced Theory and Simulations 6, 2300247 (2023)



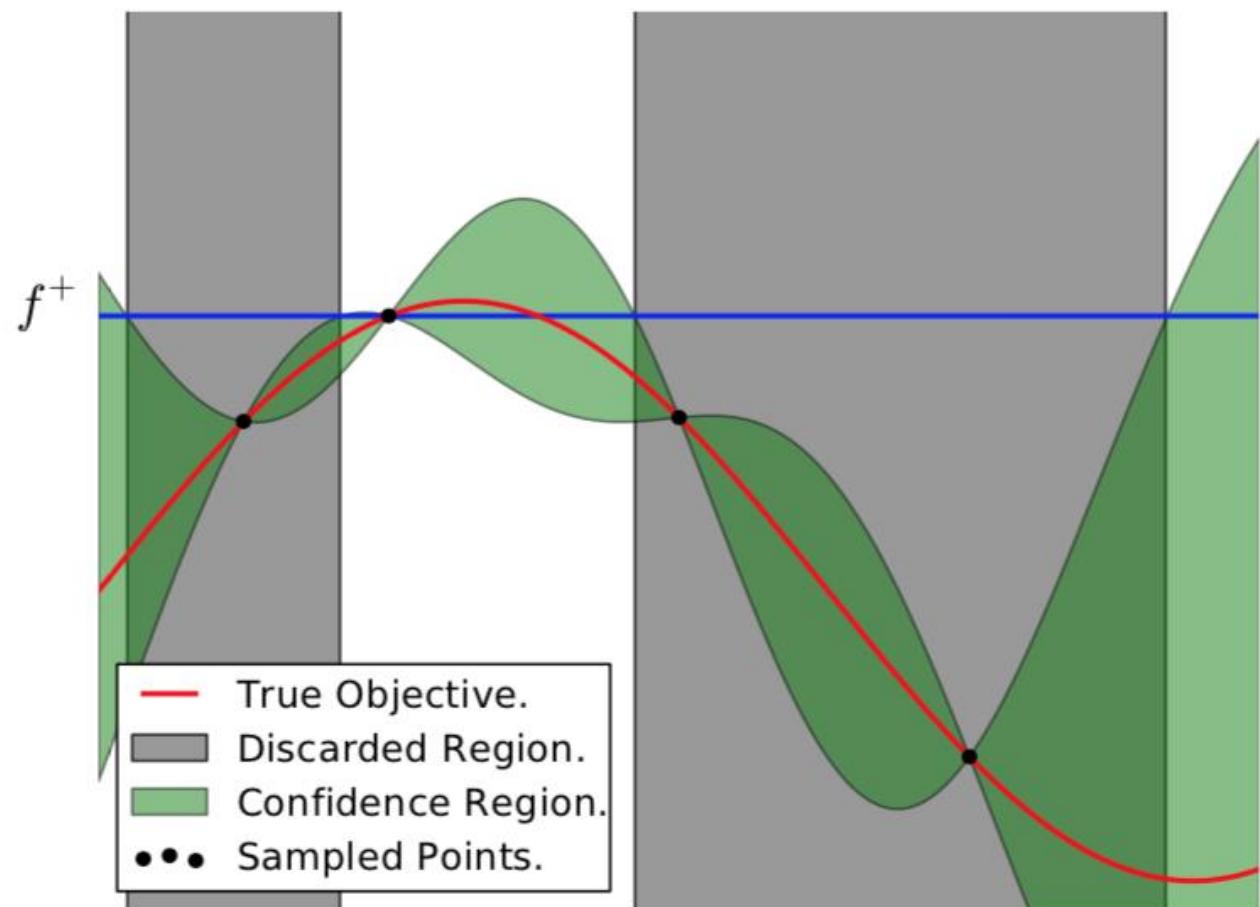
- Standardized data model
- In-built processing and viz utilities

Real-time automated SPM



- For long spectroscopies, measuring every pixel across a grid is not feasible. Bayesian optimization enables sampling only those points that will maximize a property of choice, enabling new experiments that would otherwise not be possible

Bayesian Optimization

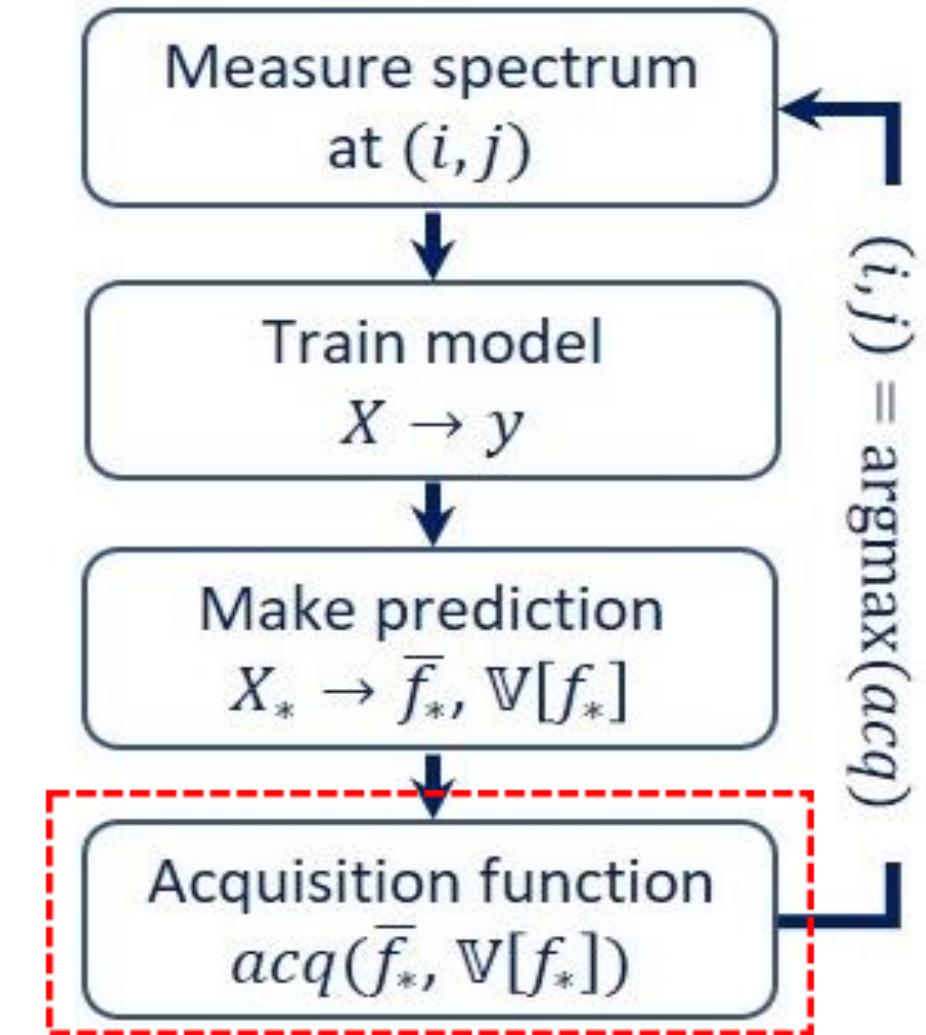
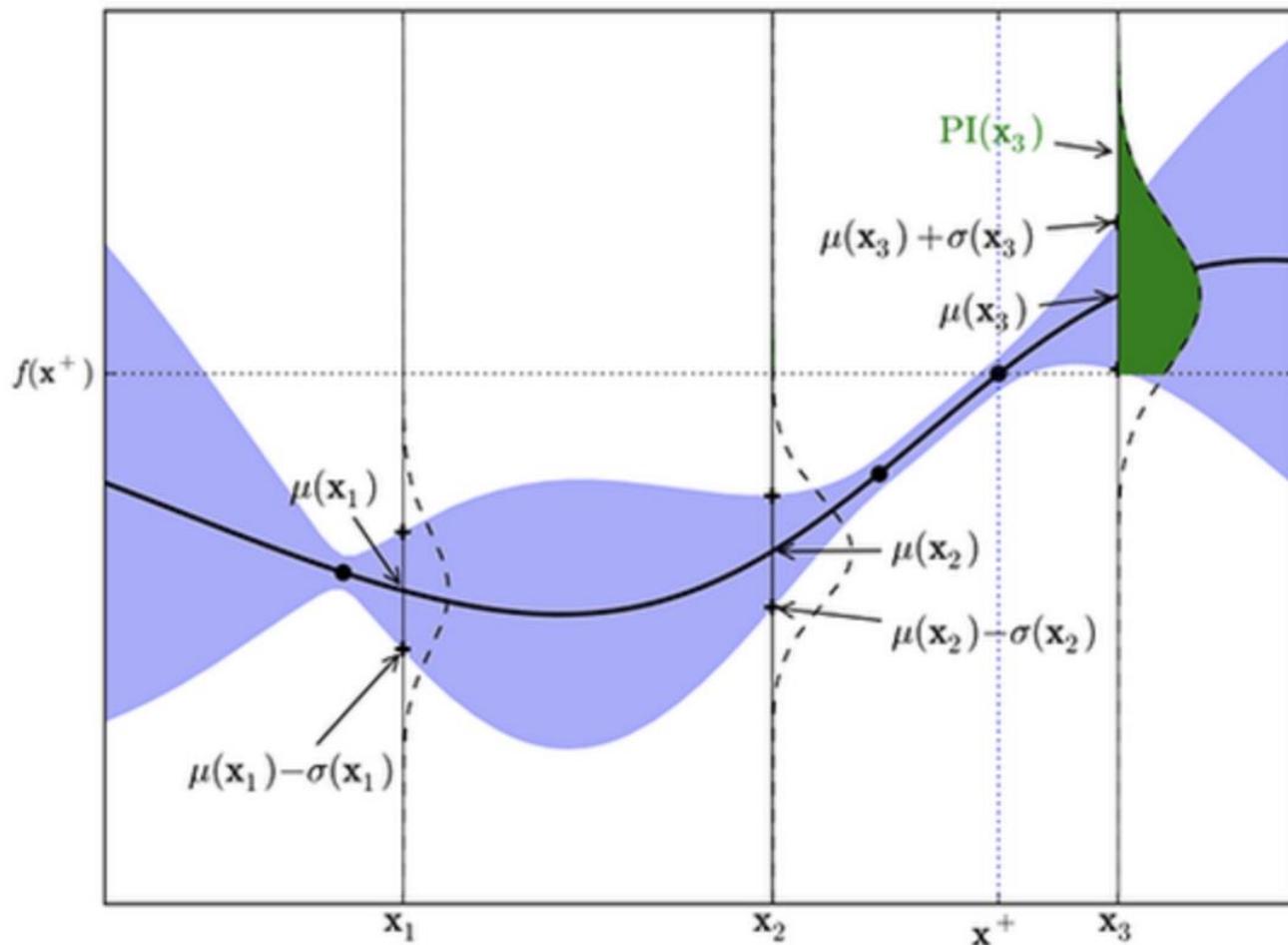


- We have some measurements in space X , and we want to maximize some property $f(X)$.
- Generalizes to higher dimensions
- Recently has become computationally tractable

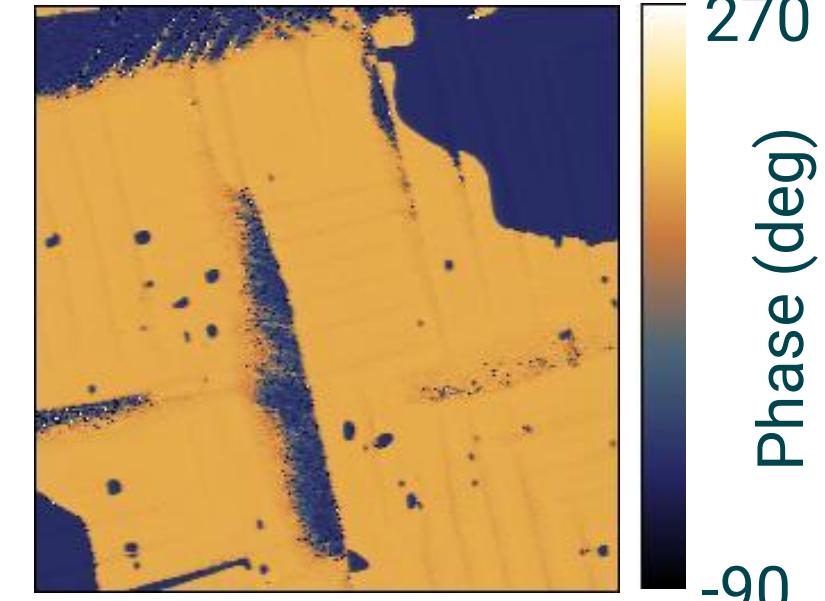
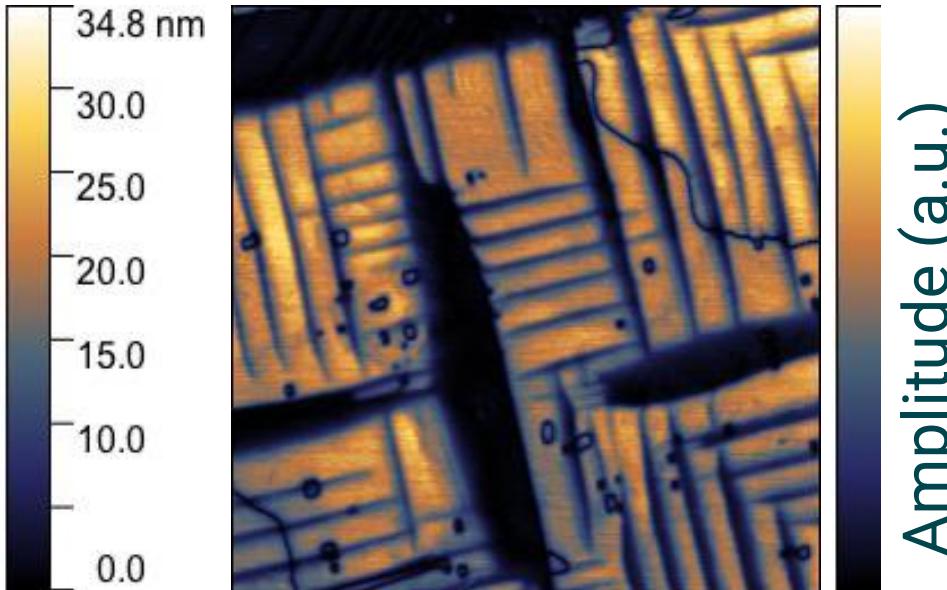
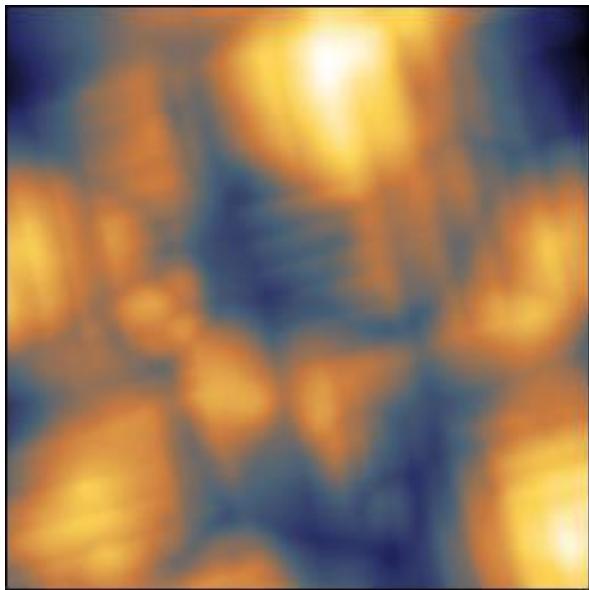
N. de Freitas et al., Taking the Human Out of the Loop: A Review of Bayesian Optimization , *Proceedings of the IEEE 104*, 148 (2015)

Acquisition Functions

Probability of Improvement Acquisition Function



Spectroscopy on a ferroelectric film

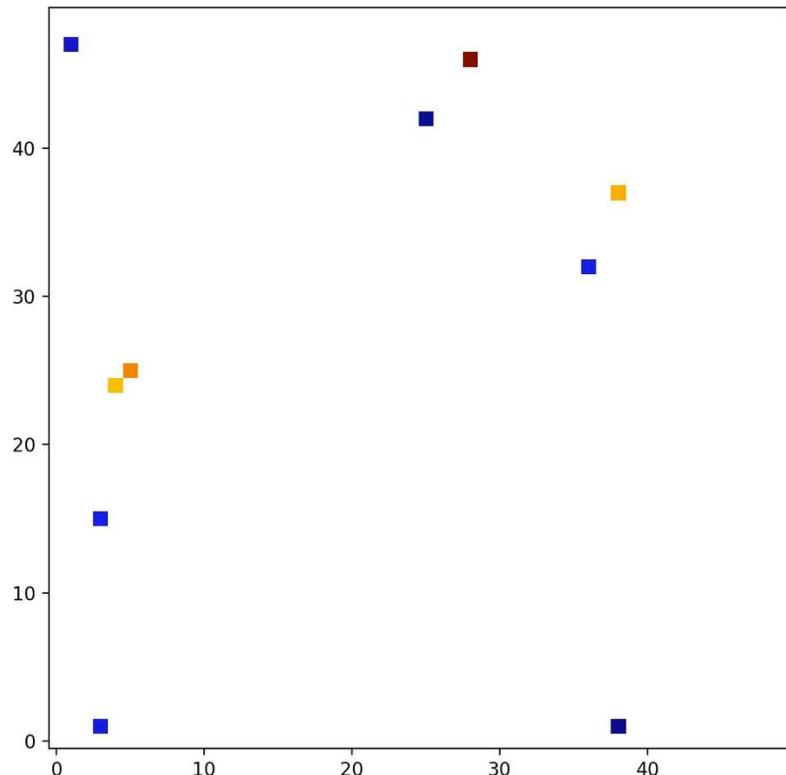


Can image the domain structure with the microscope -> 4 minutes

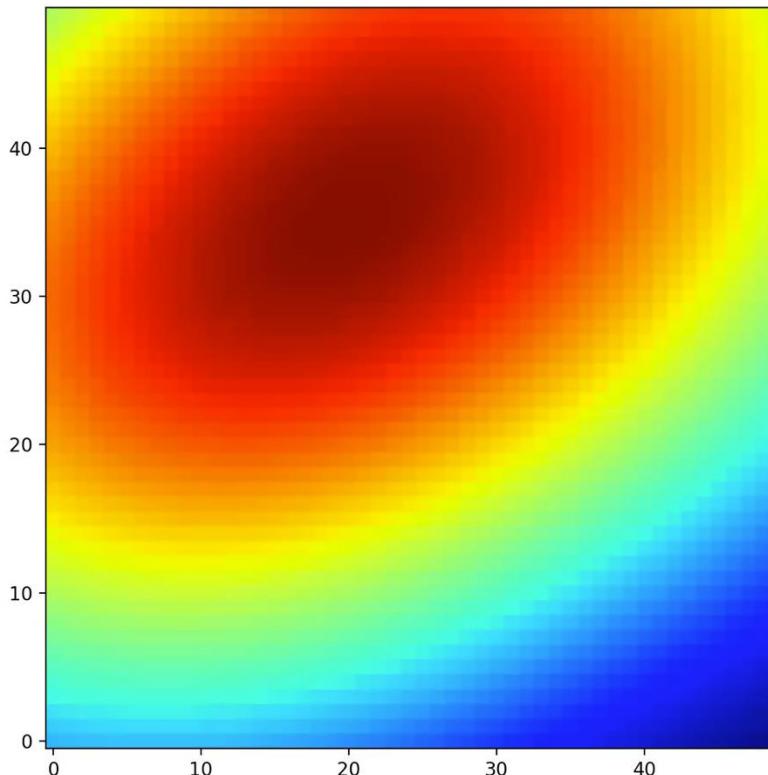
Spectroscopy – obtaining spectra pixel by pixel – can take 2-24 hours depending on type of measurement.

Automated Experiment example

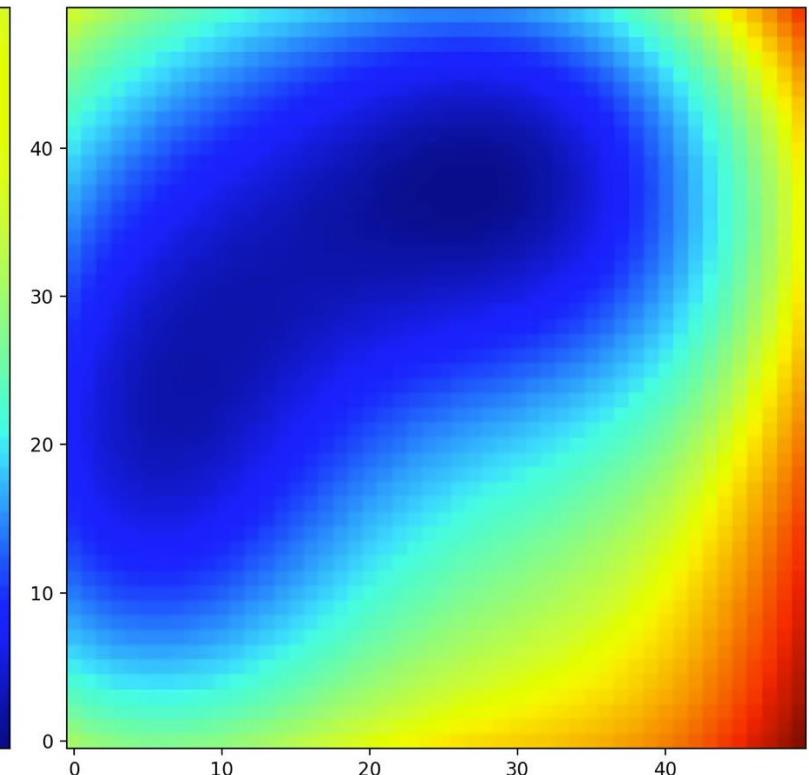
Measured Loop Areas



GP Prediction



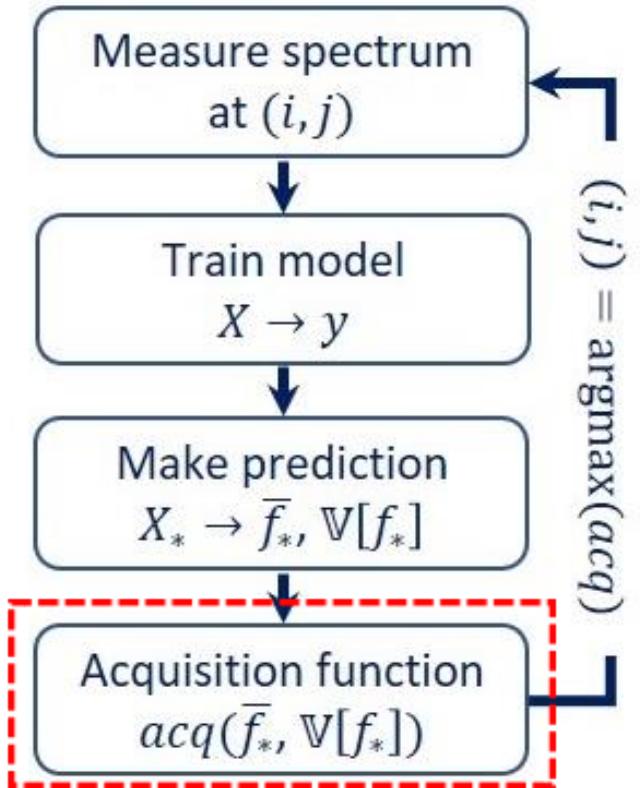
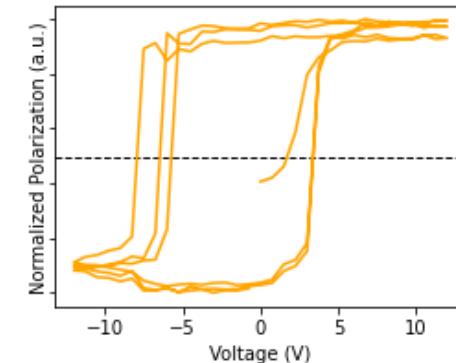
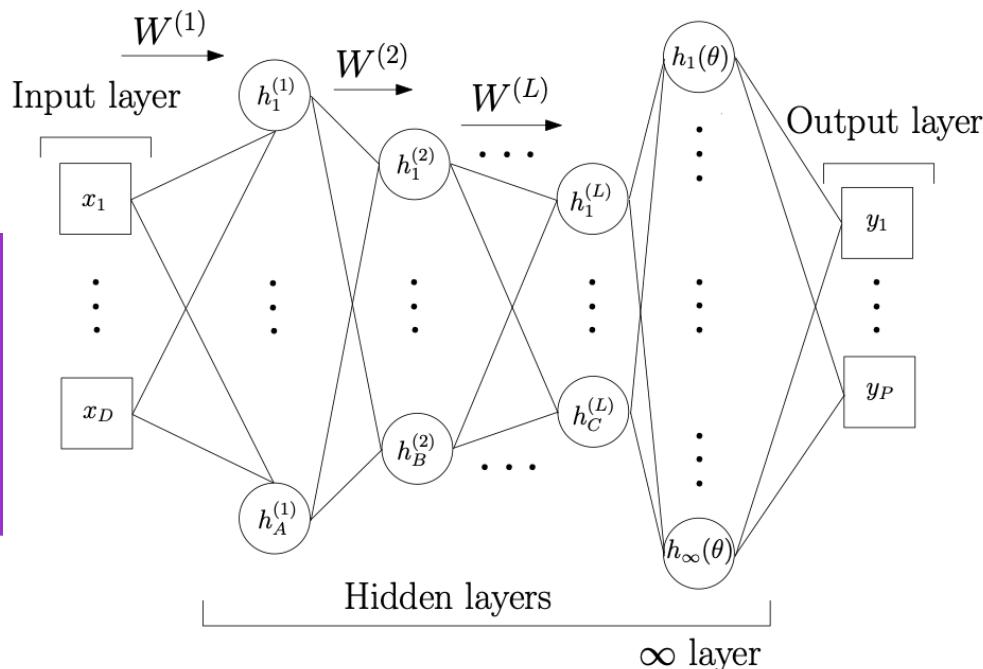
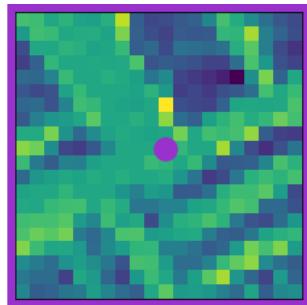
GP Uncertainty



R. Vasudevan et al., ACS Nano 15, 11253 (2021)

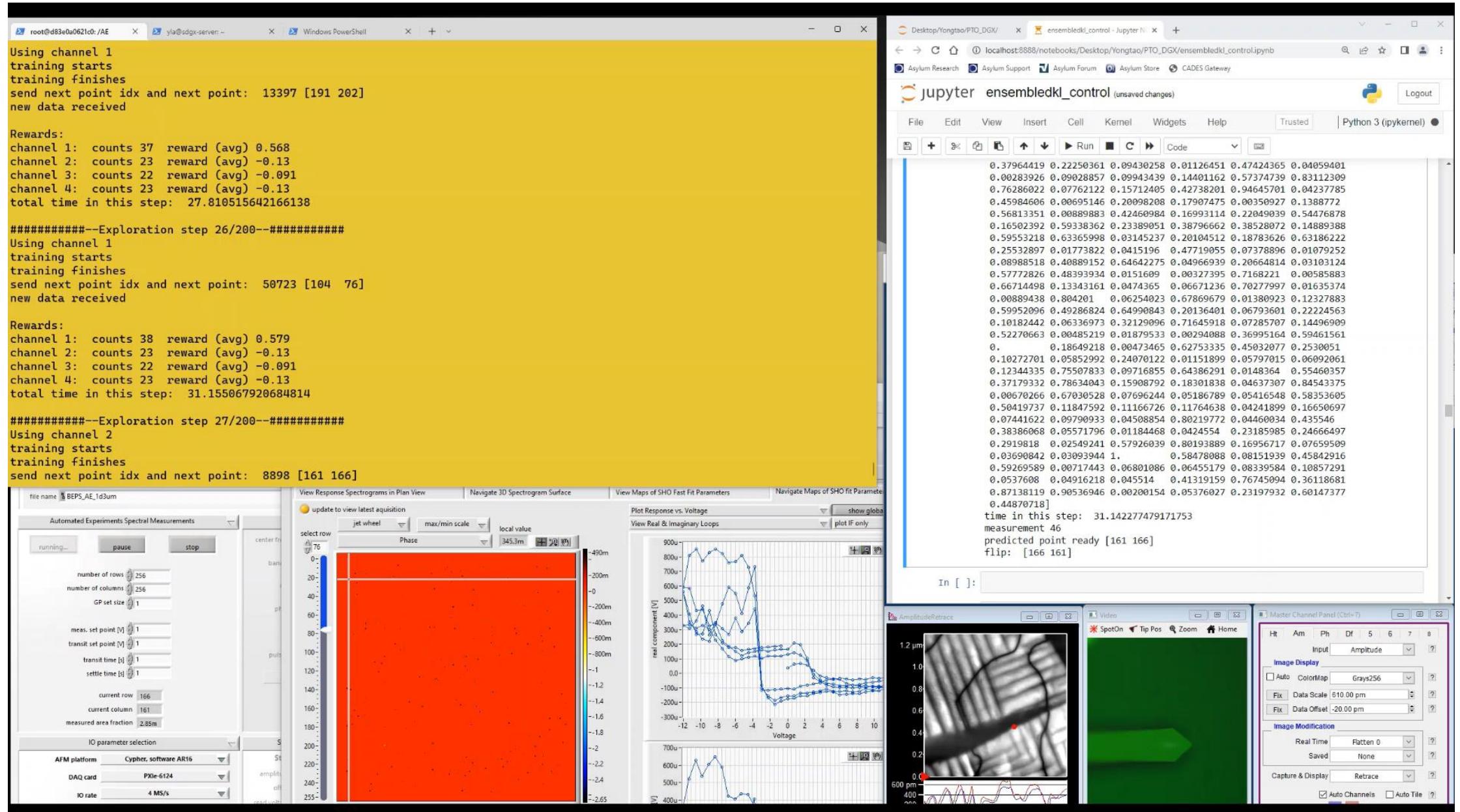
Deep Kernel Learning: More images, better kernels

Deep Kernel Learning
(A.G. Wilson, 2015)



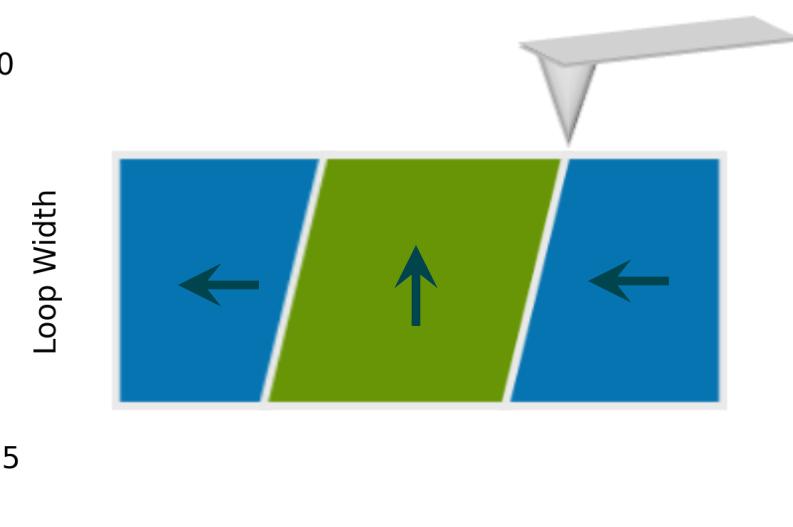
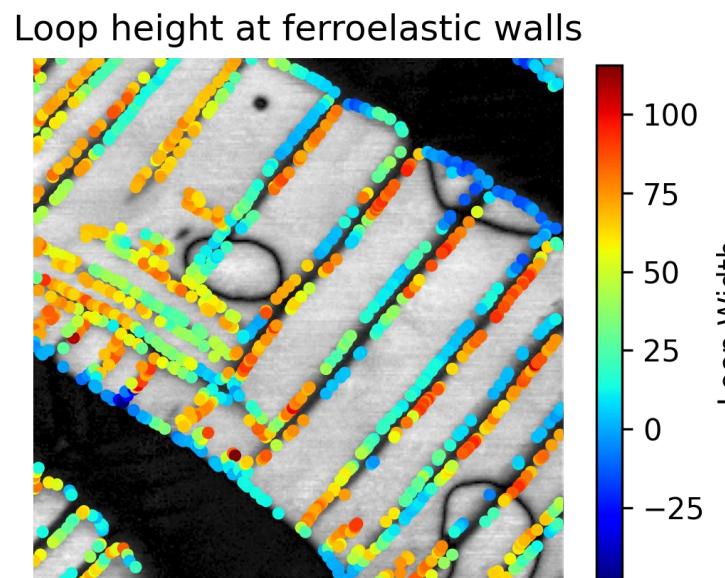
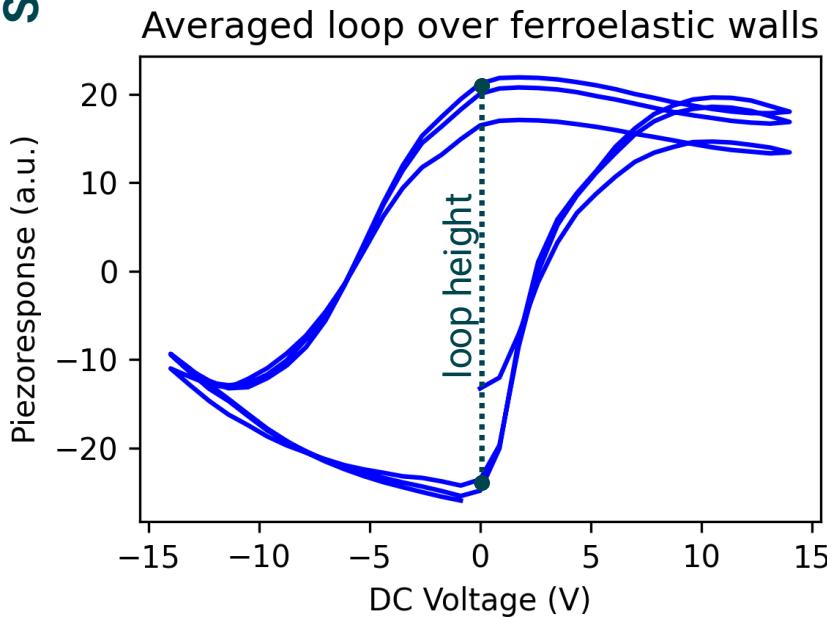
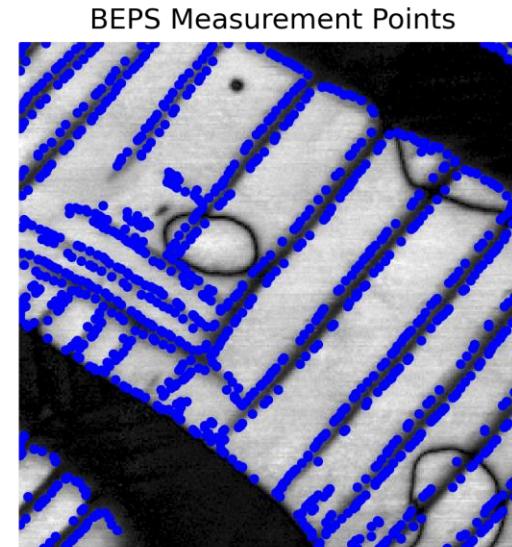
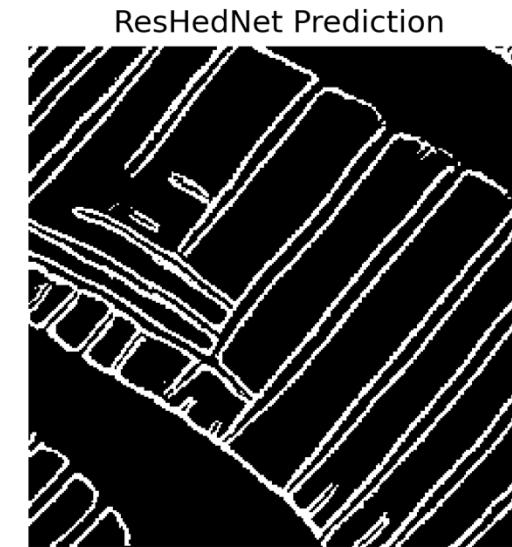
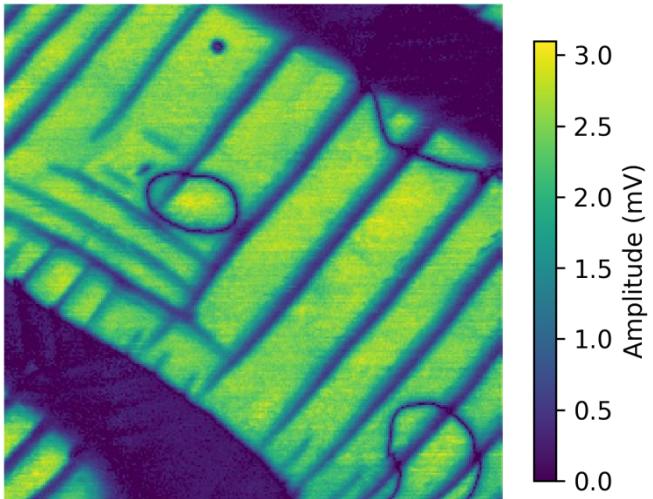
Combine a neural network with GP, learn parameters jointly

Liu, Yongtao, Kyle P. Kelley, Rama K. Vasudevan, Hiroshi Funakubo, Maxim A. Ziatdinov, and Sergei V. Kalinin. Nature Machine Intelligence 4, 4 (2022): 341-350.

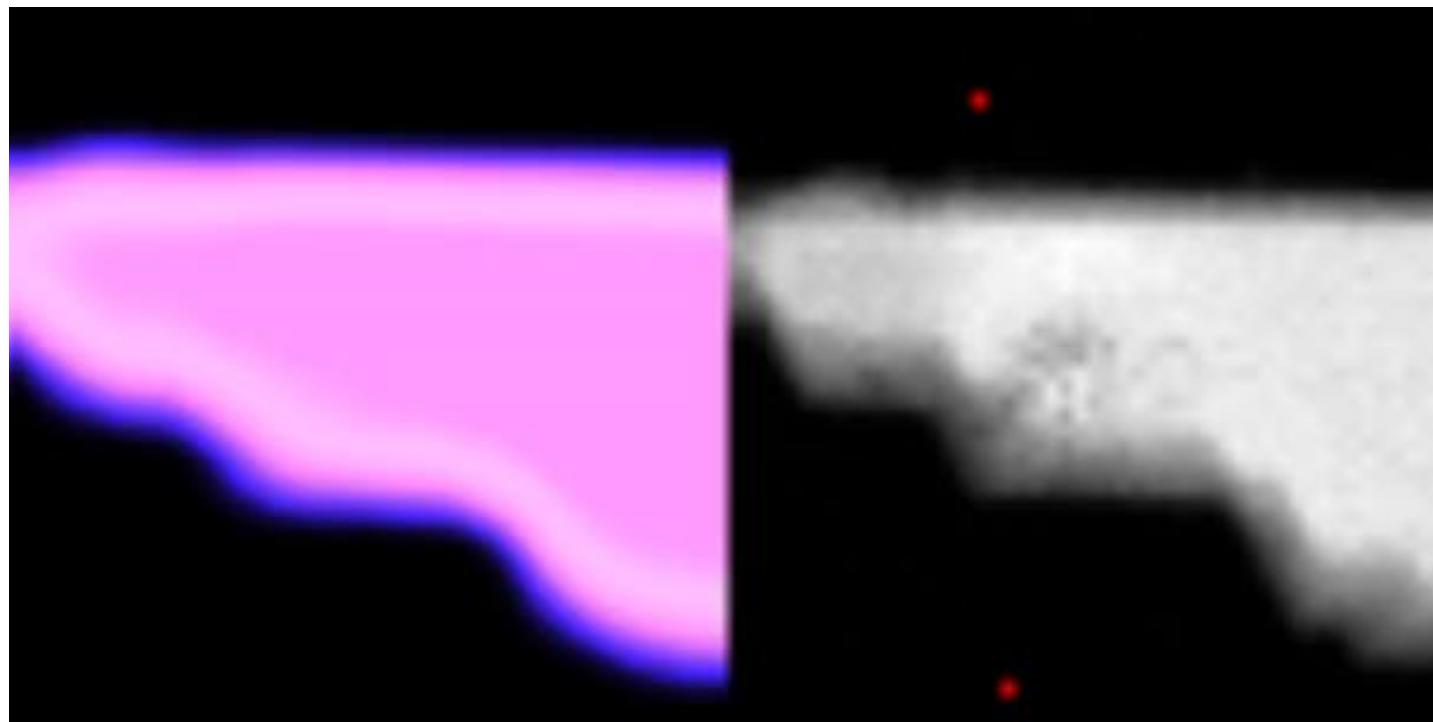


Automated SPM—Objects of Interest

Slide by Yongtao Liu ORNL



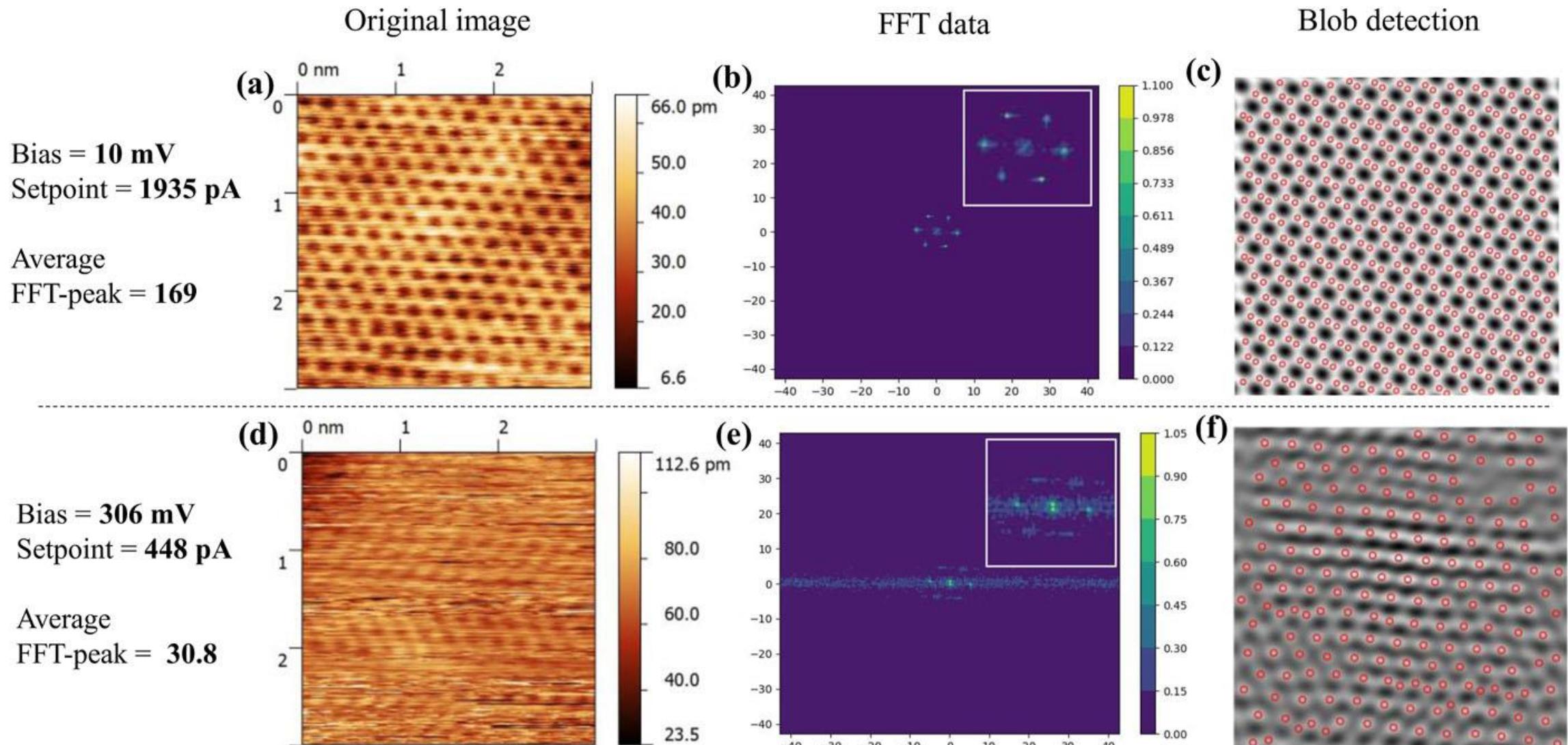
STEM Bayesian Optimization



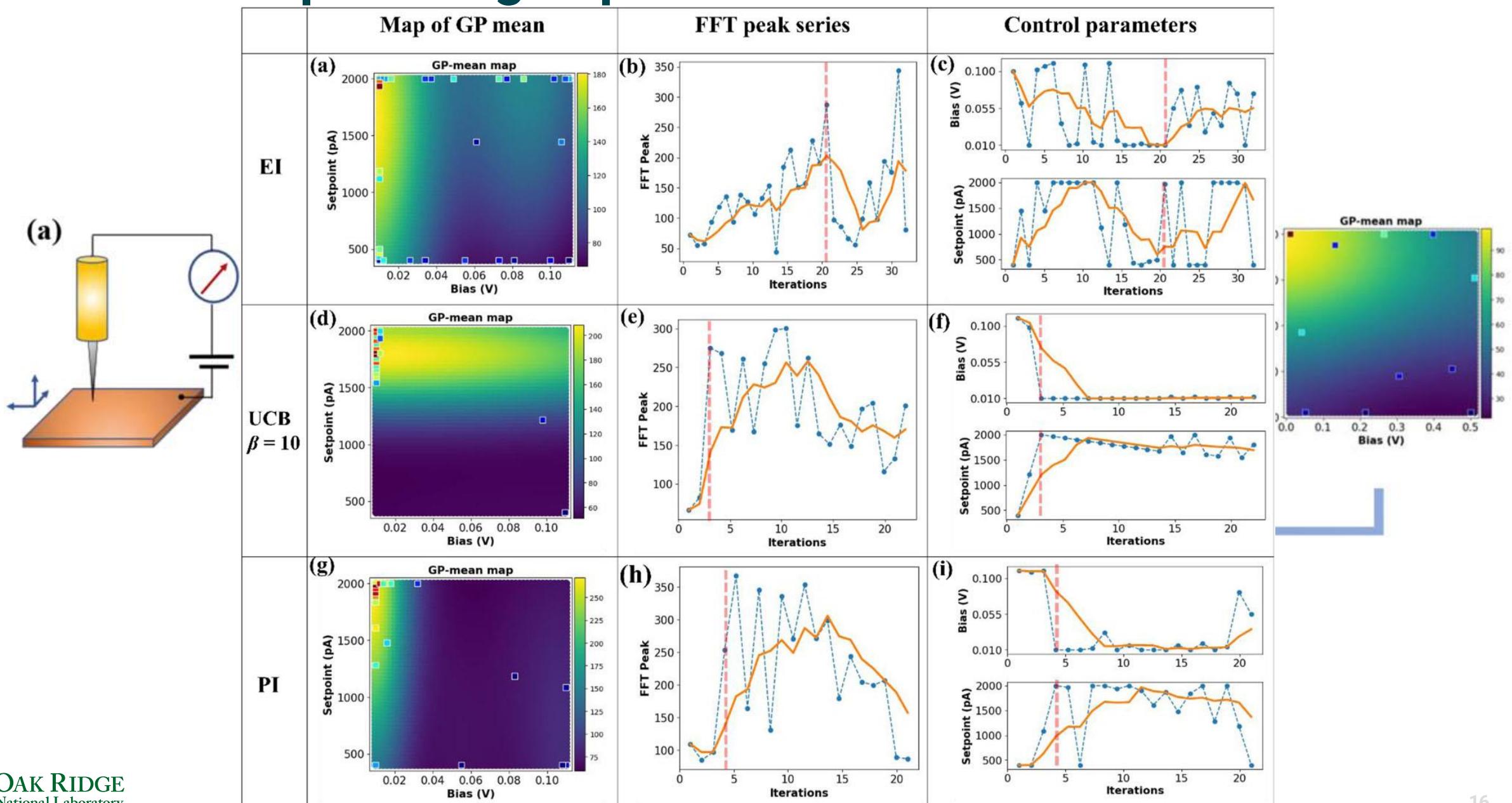
- Bulk and edge plasmons in MnSP₃ investigated via deep kernel active learning
- Optimize for ratio of peaks to find where edge plasmon is strongest
- Automated structure-property relationship determination

K. Roccapriore et al., Adv. Sci. 2203422 (2022)

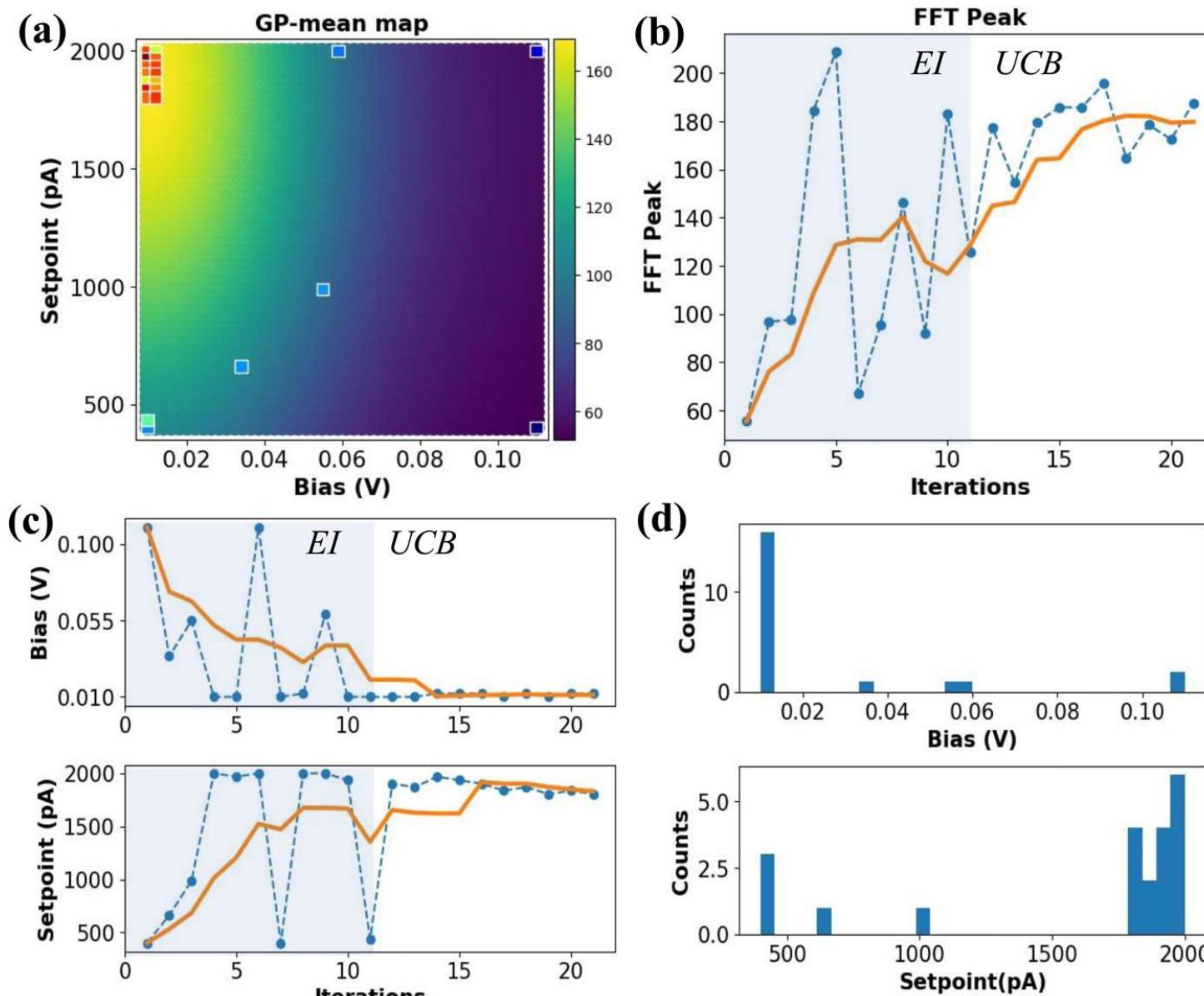
Another example: Image optimization in STM



Another example: Image optimization in STM



Another example: Image optimization in STM



Beyond Simple Bayesian Optimization

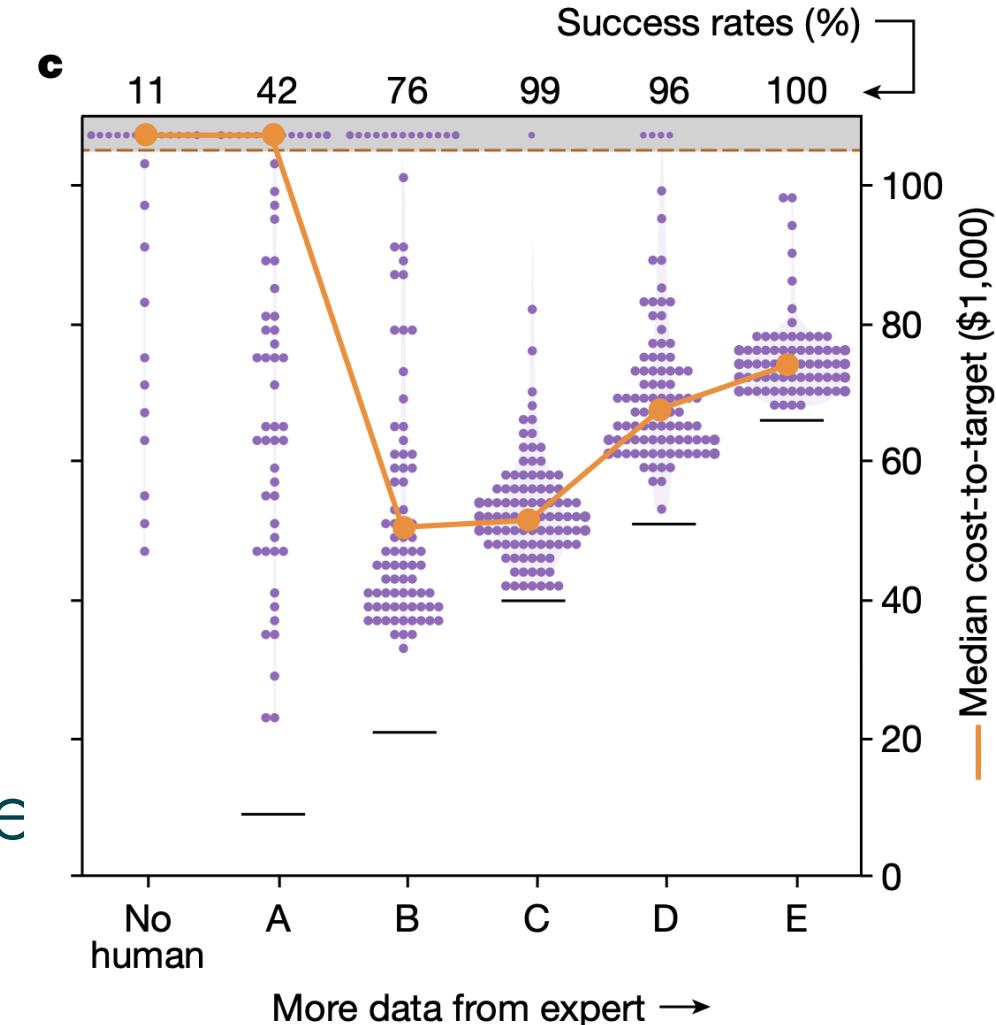
- There is a significant issue with traditional BO based methods
 - We need a scalarizer function to be known *apriori*
- Two solutions
 - Use recommender system to learn the scalarizer
 - Use the notion of curiosity and optimize for it

Algorithms: Human in the Loop

- Human-AI systems work better together than either alone
- Prior knowledge injection can be used to shape targets, reduce wastage, can be informed by simulations
- Increase AI alignment, monitor autonomous progress. Develop better metrics for monitoring autonomous experiments, and better methods for human input

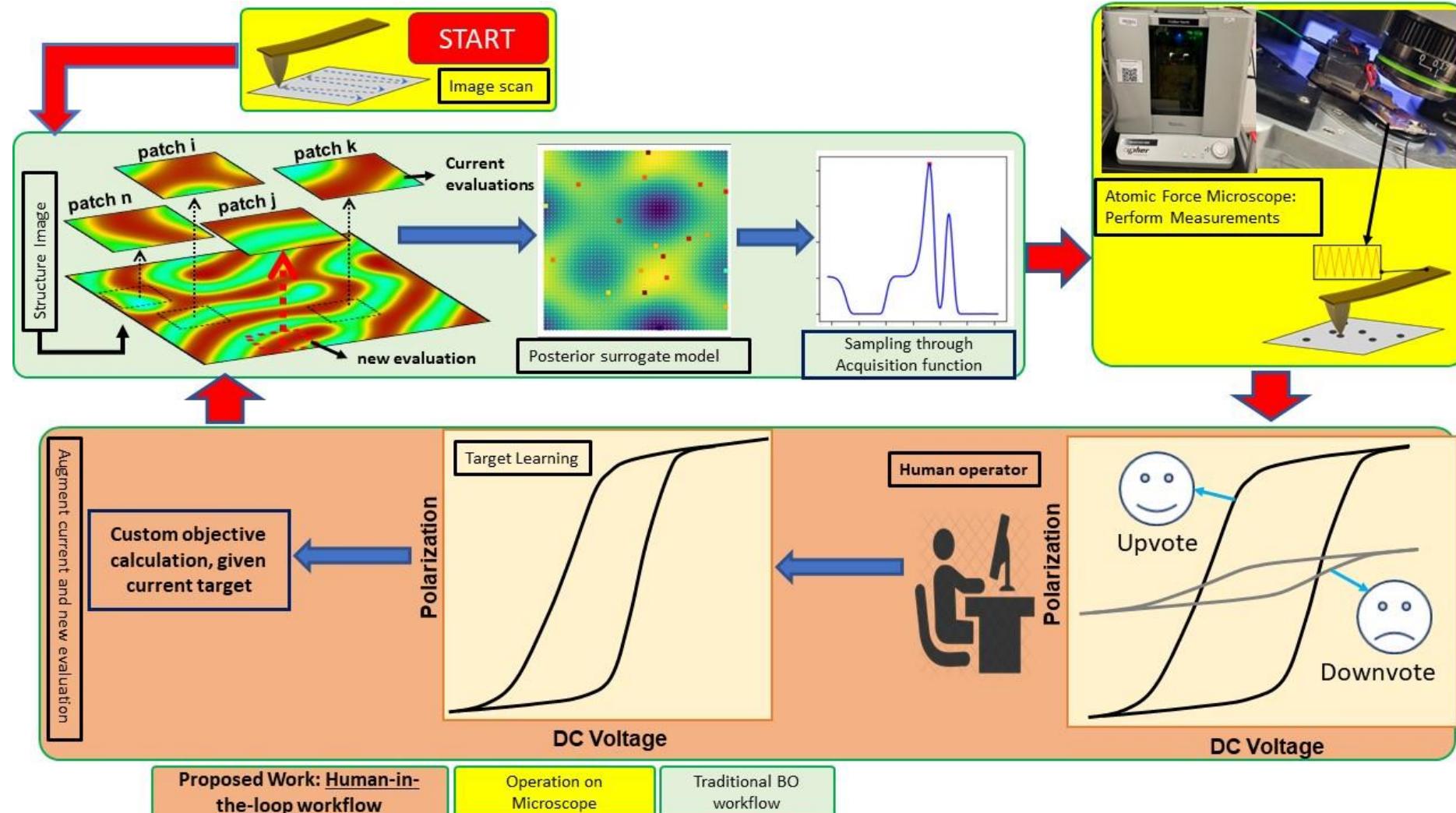
Article

Human–machine collaboration for improving semiconductor process development



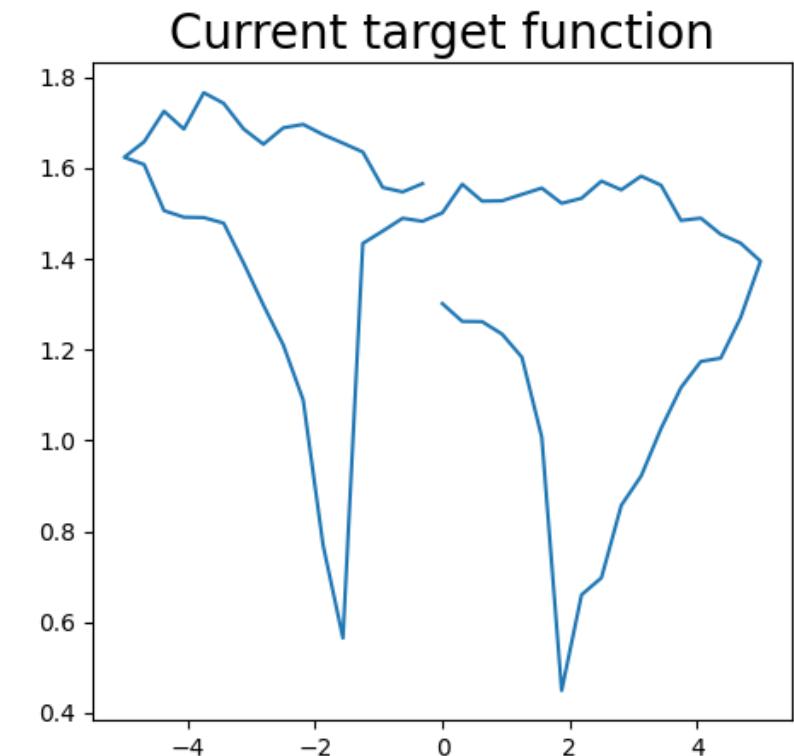
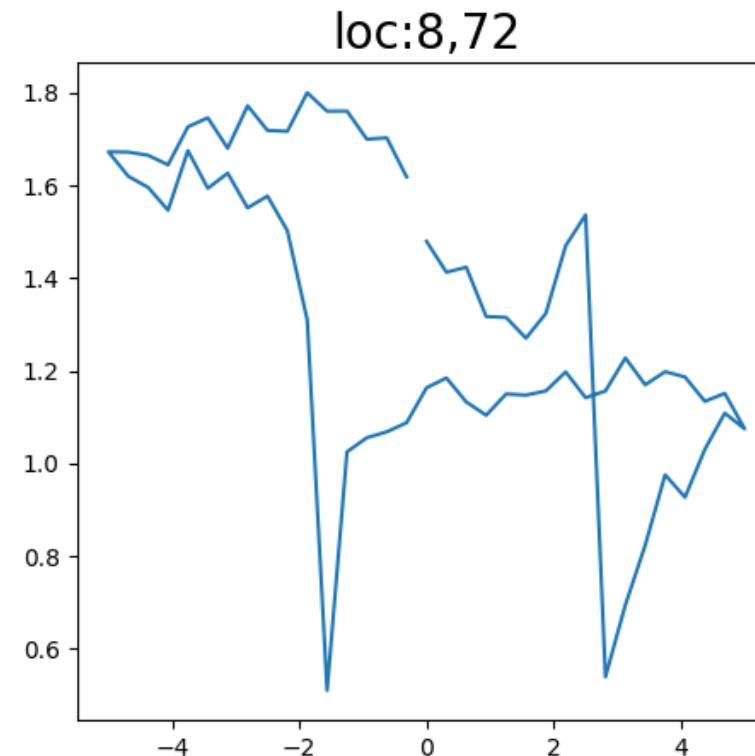
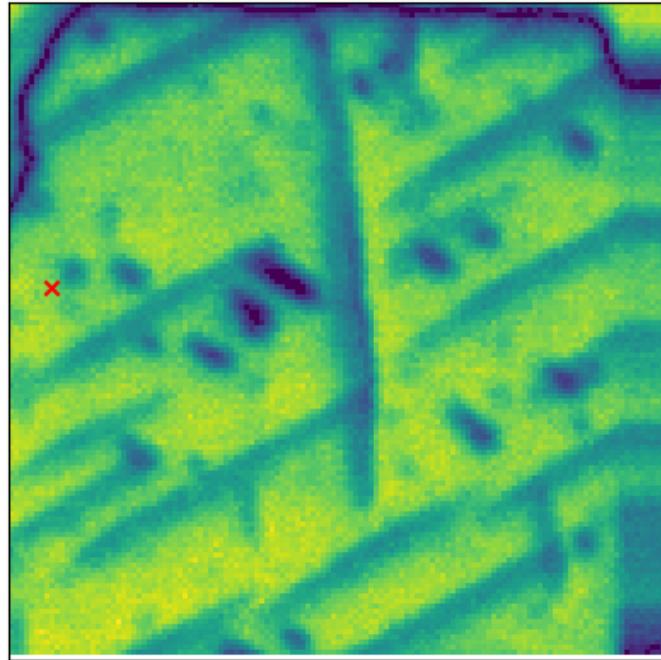
Kanarik et al. Nature 616, 707 (2023)

Learning what to optimize: reccomender systems



A. Biswas et al. npj Comp. Mater. 10, 29 (2024)

Spectral Recommender: When no Target will suffice



User gets to rate spectra (in this case 15 spectra were rated)

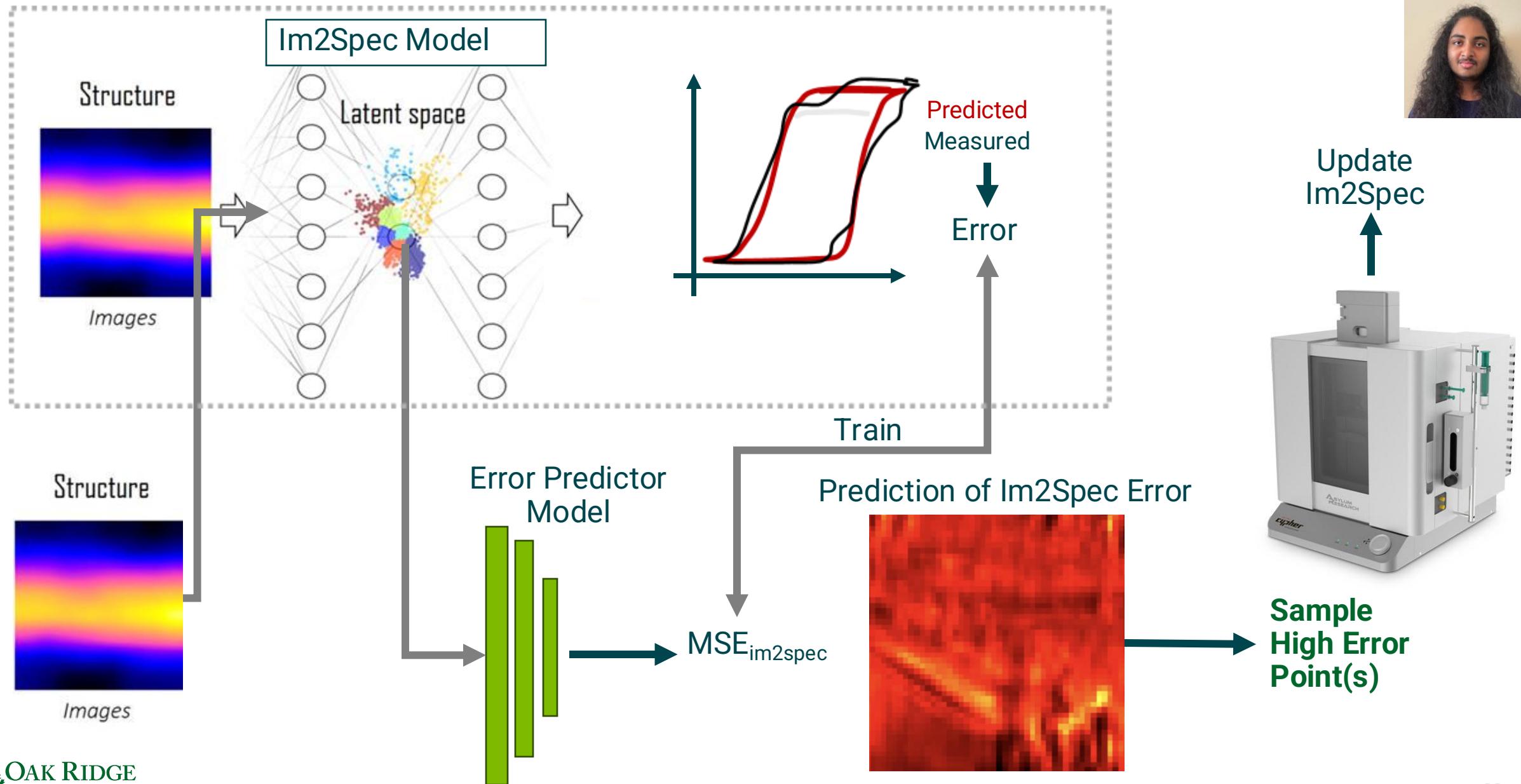
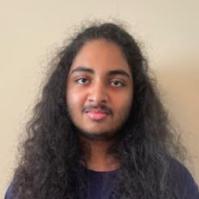
Sample by J. C. Yang (NCKU/Taiwan)

Spectral Recommender system

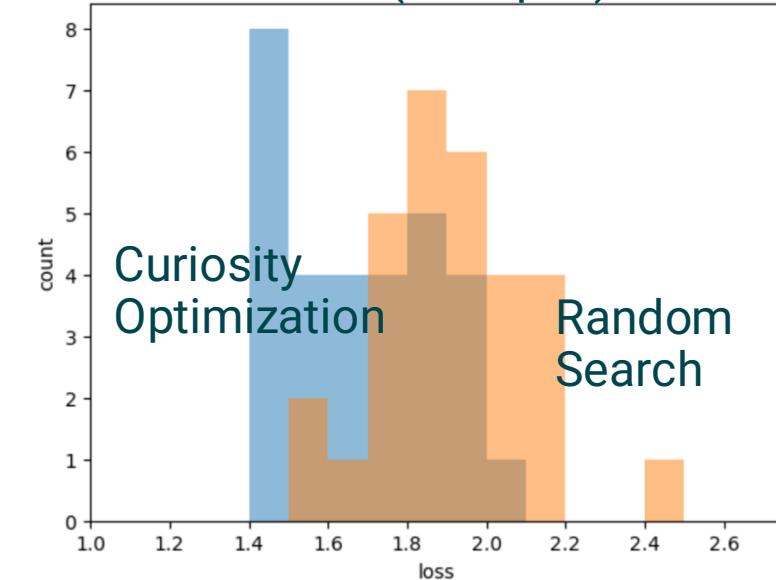
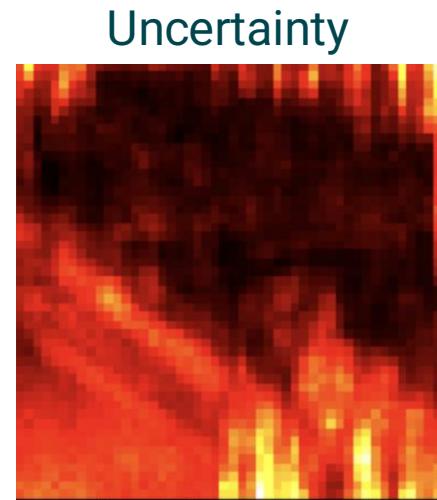
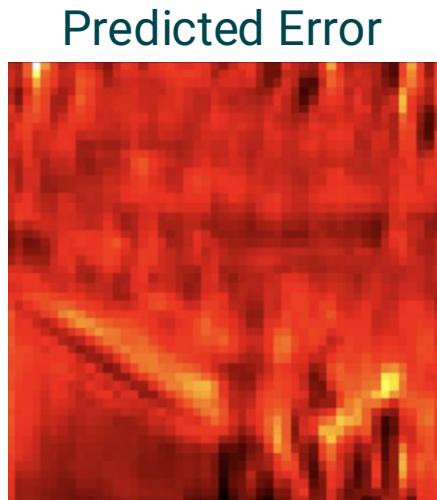
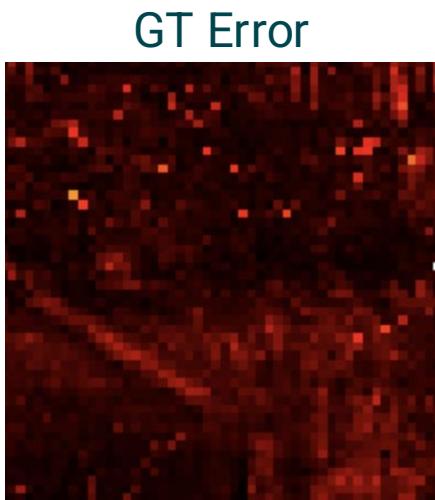
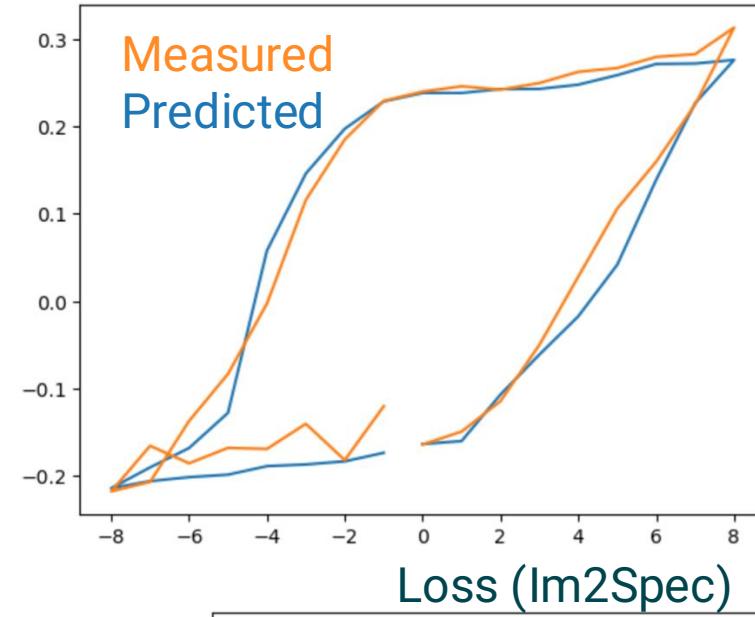
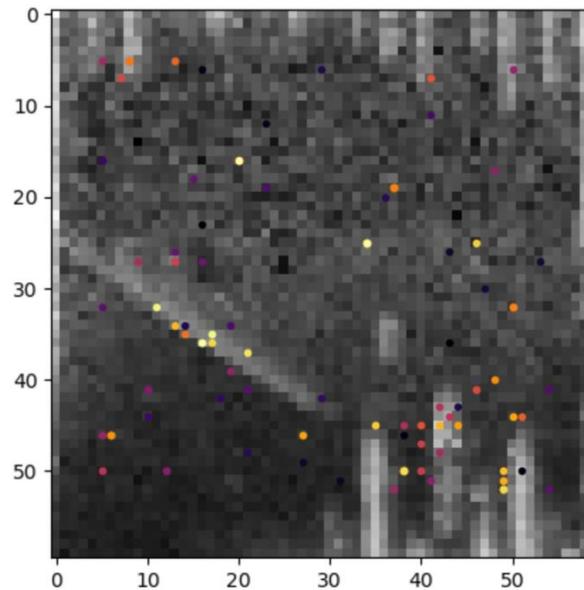
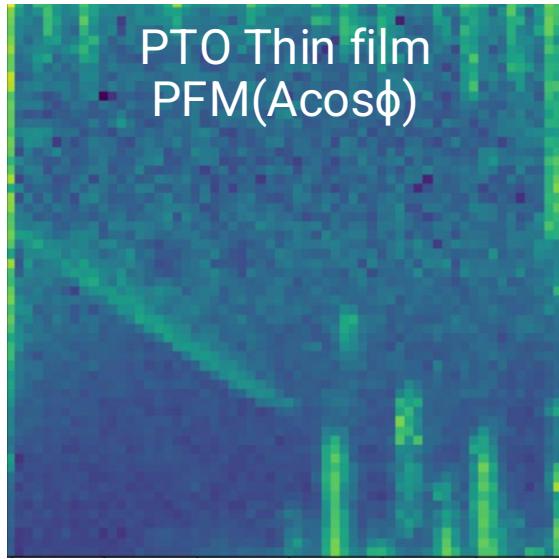


Another alternative: “Curiosity” optimization

Adi Vatsavai
UNC

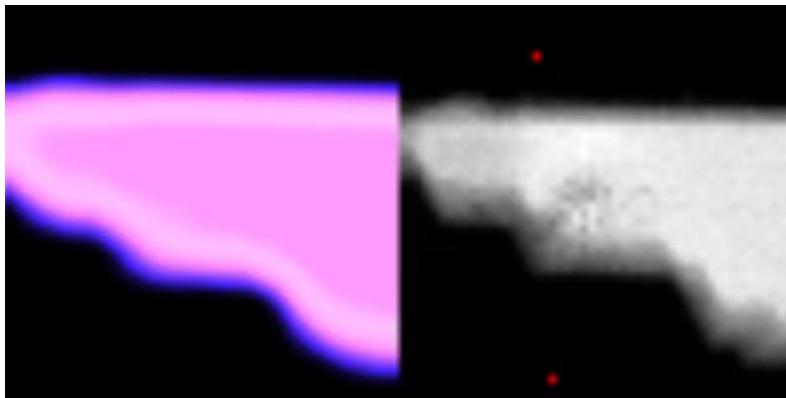
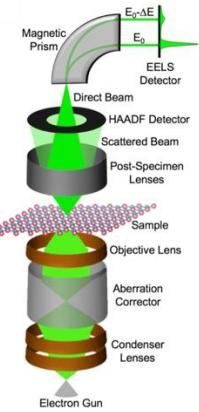
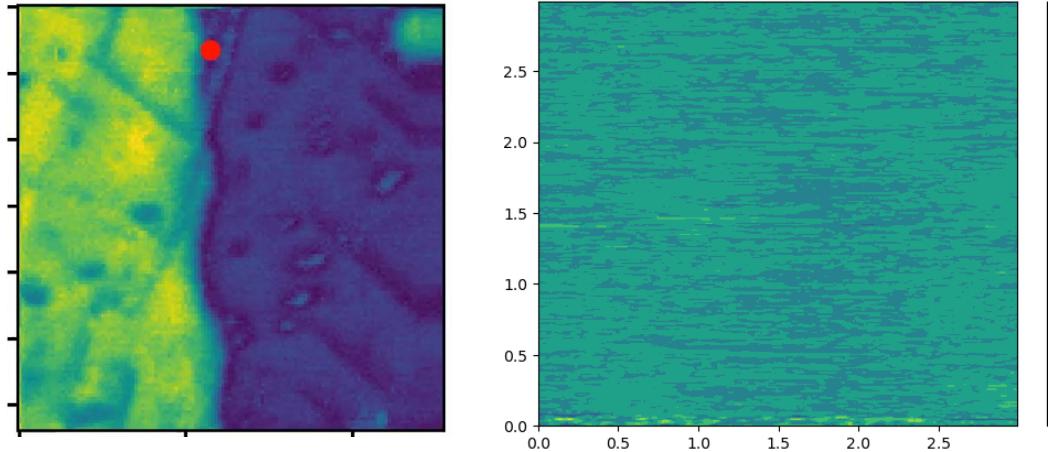


Error prediction model enables efficient sampling!

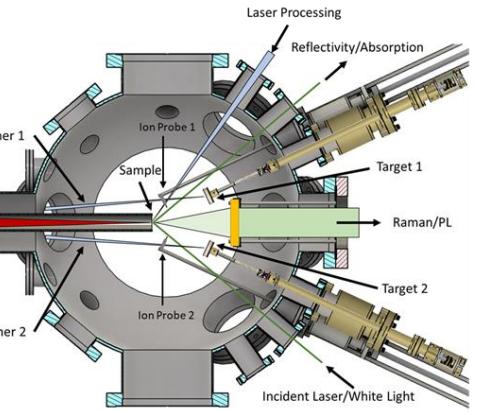


Outline

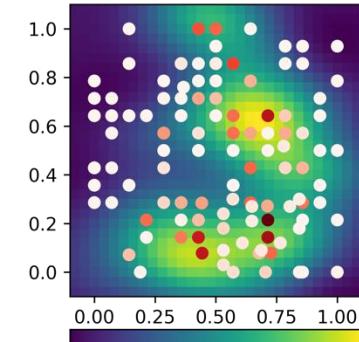
Autonomous Microscopy



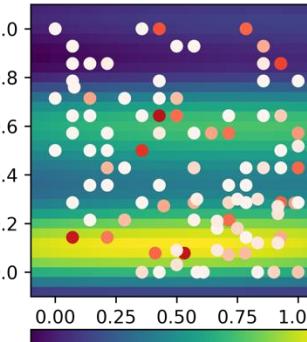
Autonomous Synthesis



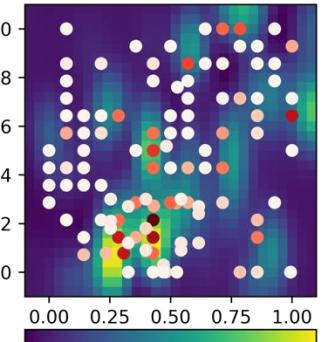
P vs T: Objective Mean



P vs e1: Objective Mean

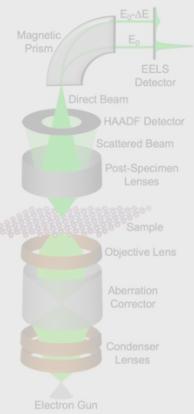
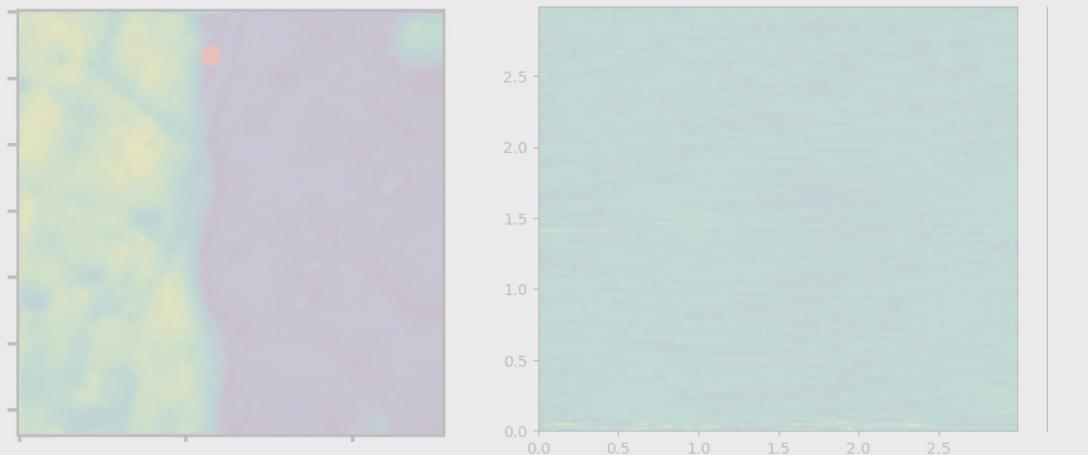


P vs e2: Objective Mean

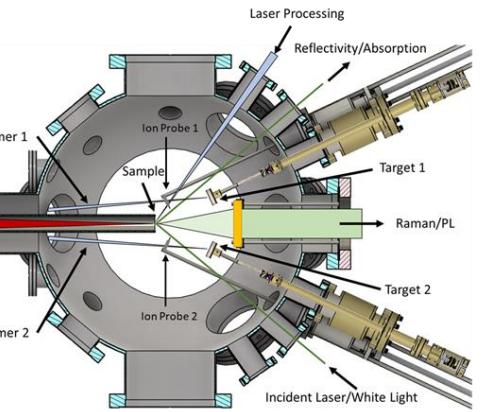


Outline

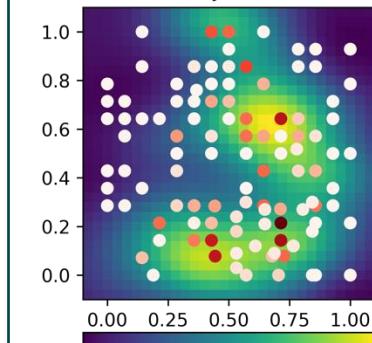
Autonomous Microscopy



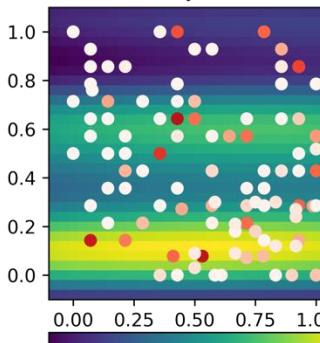
Autonomous Synthesis



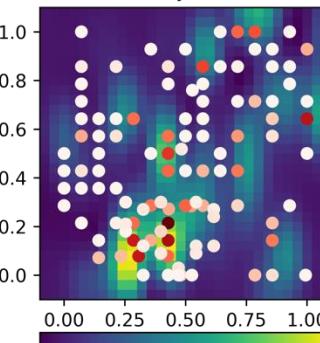
P vs T: Objective Mean



P vs e1: Objective Mean



P vs e2: Objective Mean



Autonomous Pulsed Laser Deposition

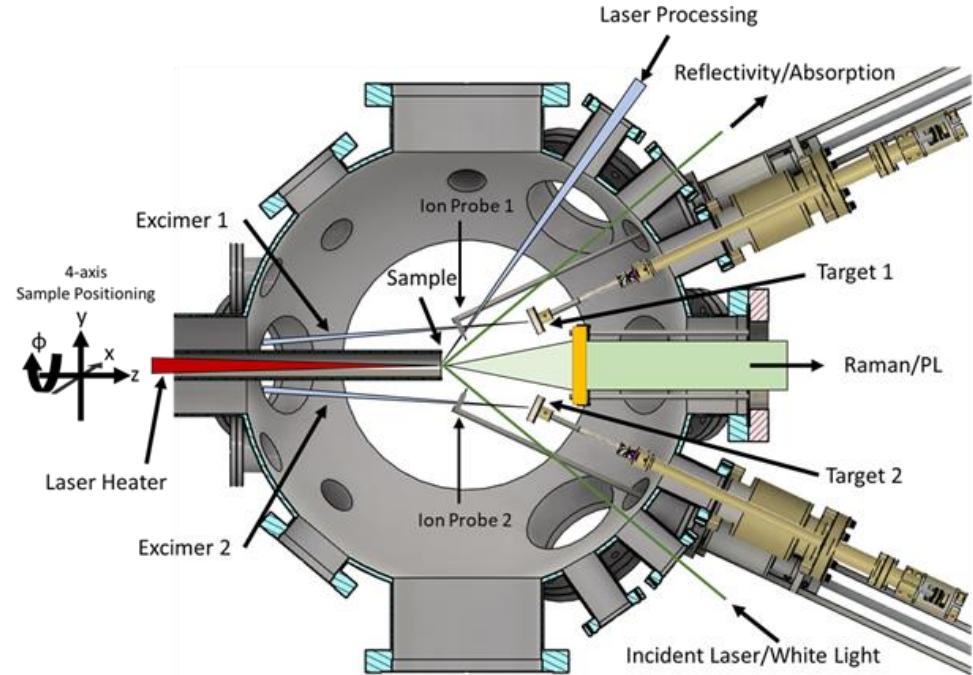
- ✓ Full process automation
- ✓ Automated material characterizations

- PLD Chamber Design

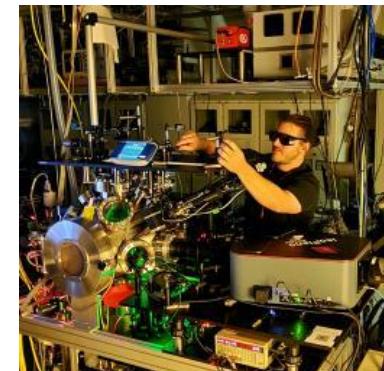
- Two PLD targets enable **simultaneous deposition** of different materials – tune stoichiometry of deposition
- **Plasma diagnostics:** ICCD Imaging, ion probe, gated plume spectroscopy.
- **Sample diagnostics/characterization:** Raman, PL, laser reflectivity, white light absorbance.
- **Laser Processing:** x,y nanosecond excimer laser processing of the sample

- Full automation of chamber processes

- Allows in-person and **remote/programmatic** control of all PLD processes and diagnostics via Python-> **enables machine autonomy and seamless integration with ML libraries**
- **Automated control** of: excimer laser energy, spot size, pulse number, and rep rate; background gas pressure, flow rates, mix of 2 gases; processing laser energy, pulses, rep rate, sample position; etc...



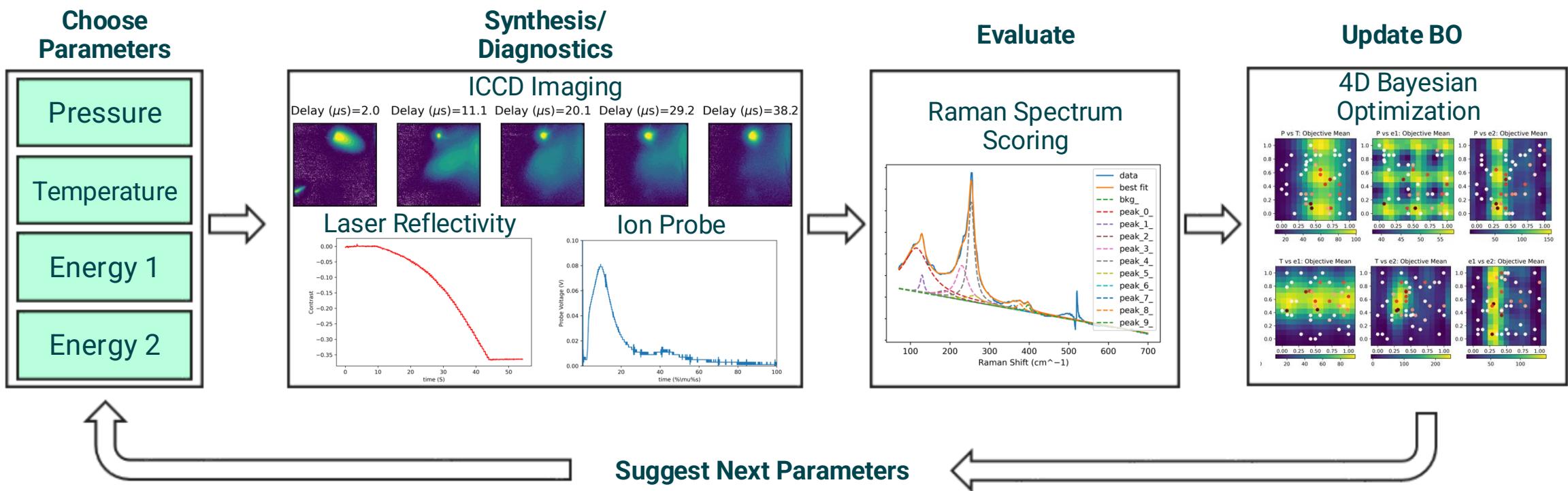
Sumner Harris



Autonomous synthesis of WSe₂

Goal: Autonomously search a broad parameter space to identify good growth conditions for ultrathin (<3 monolayers) WSe₂ by PLD.

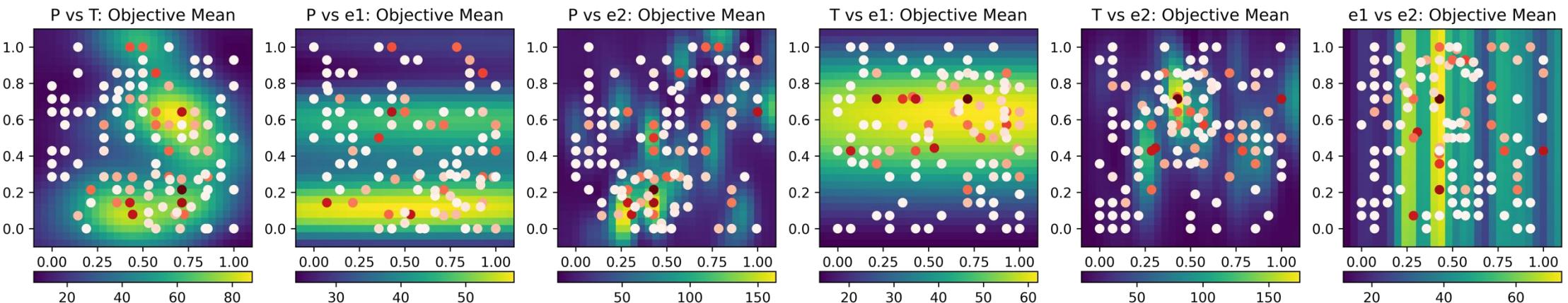
- 4D Bayesian optimization to search for optimal Raman “Score”
- Co-deposition PLD, general Workflow:



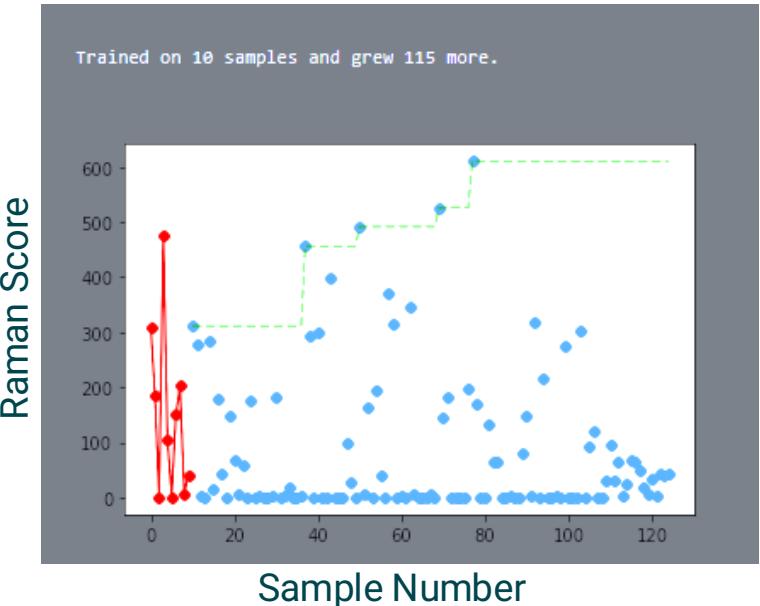
Autonomous synthesis of WSe₂

Started with 10 initial samples that were previously grown, autonomously grew 115 more with Bayesian optimization.

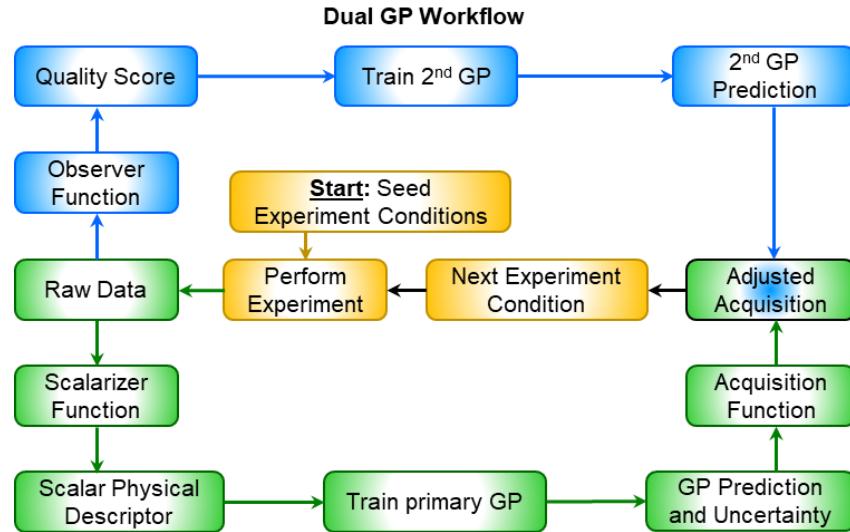
- Result after 115 samples (0.25% of space explored)
 - Showing averaged **surrogate function** projected into each 2D parameter plane
 - Seems **insensitive to WSe₂ laser energy**
 - Se laser energy seems critical -> **Needs Se compensation**
 - Potential identification of multiple growth regimes



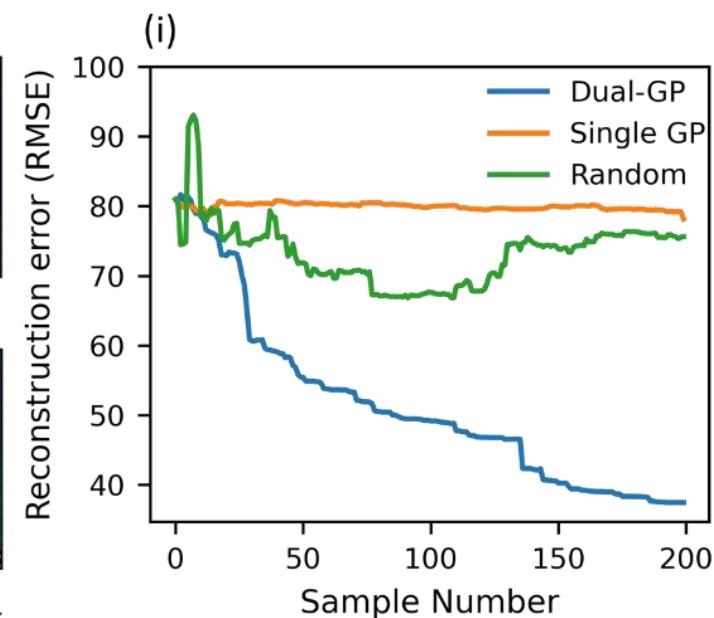
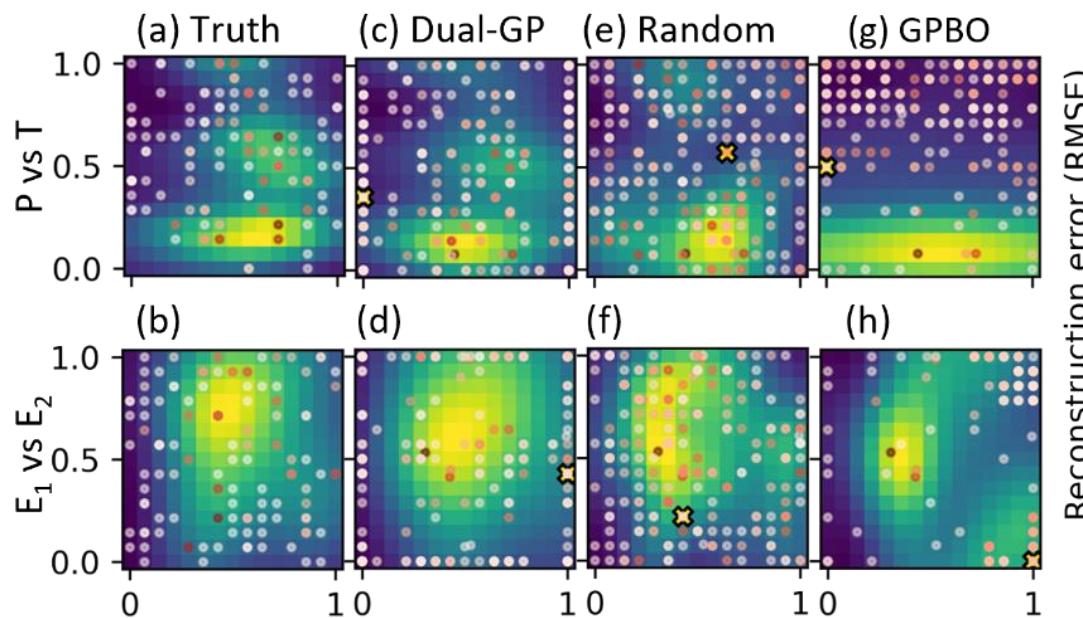
Colormap of predicted Raman spectrum score projected into each 2D plane.



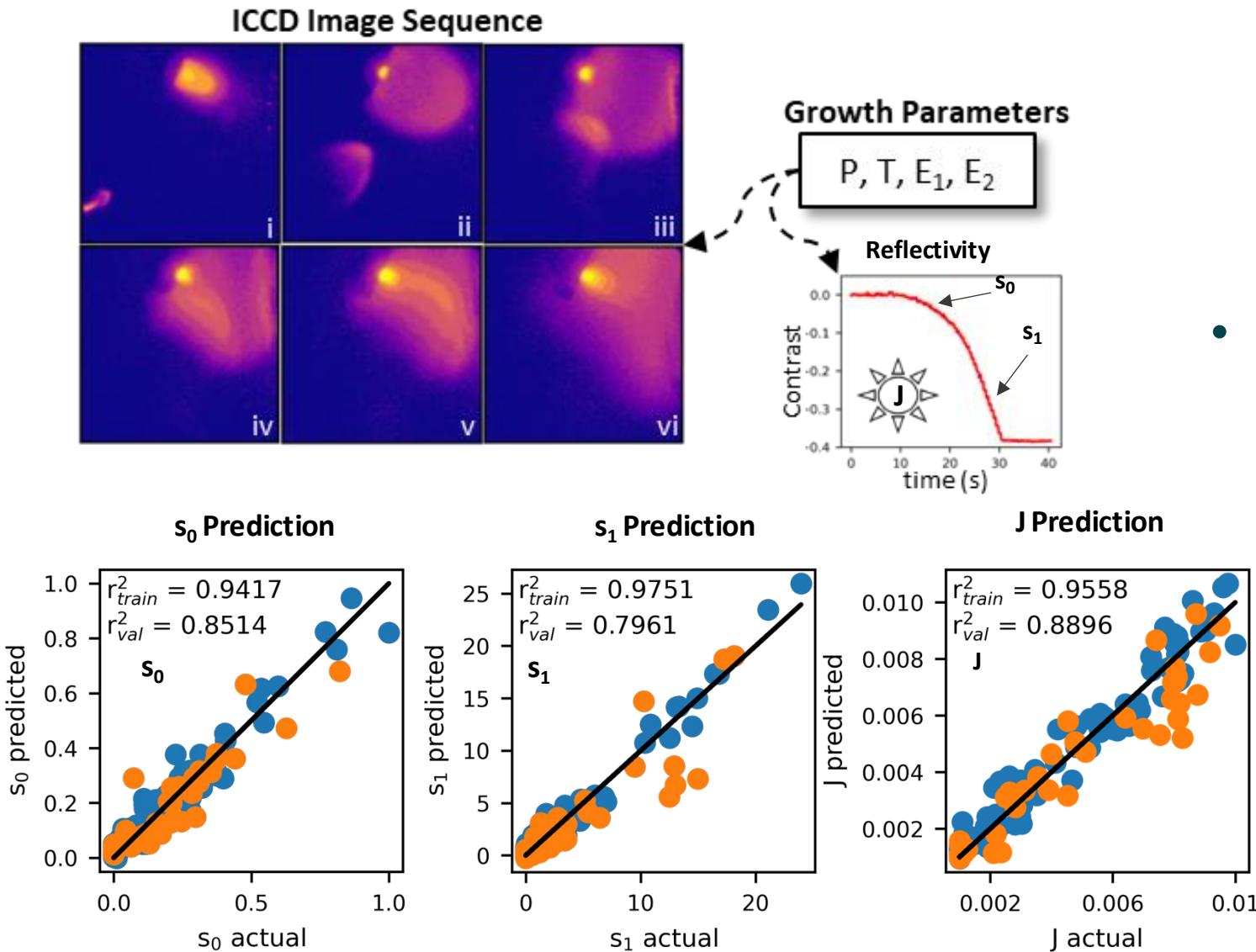
Dual GP method to reduce ‘bad’ samples



- One of the problems is that samples are wasted if the quality of the spectra is not sufficient for the scalarizer
- A dual GP method is proposed to alleviate this, that forces exploration only in areas where the quality of the score is sufficiently high



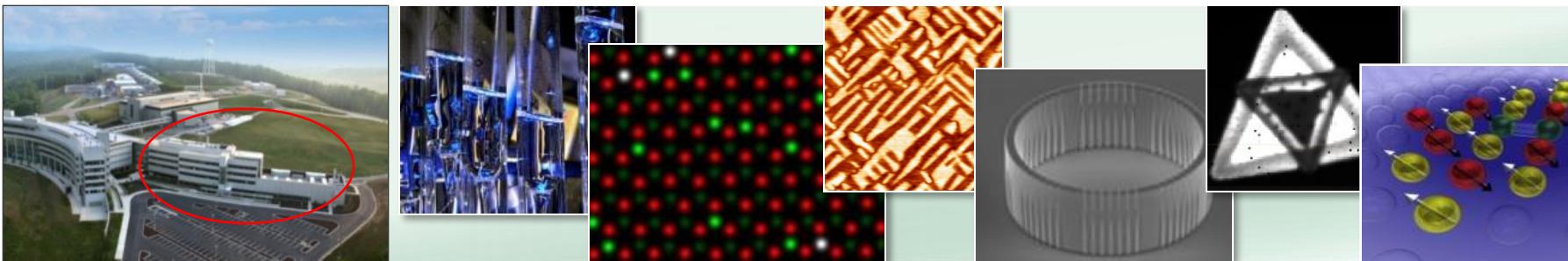
In-situ plume imaging



- By imaging the PLD plume, we can predict values of pressure, temperature, and laser fluences
- We can also estimate parameters of a kinetic model!

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Beyond Bayesian Optimization

Simulations and human experts can enable more efficient learning

