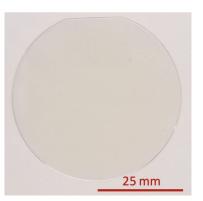
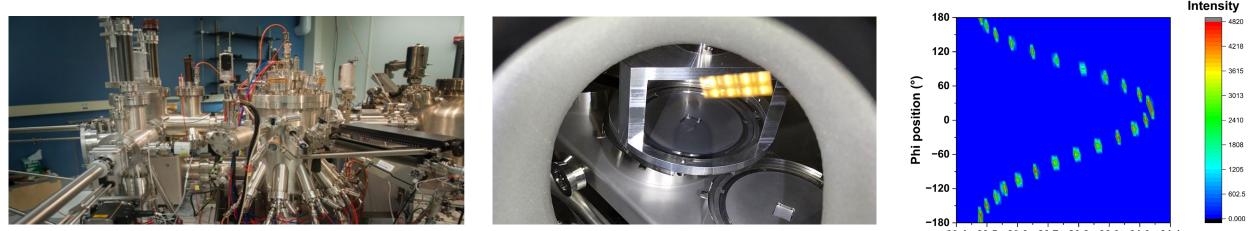


Data Science Activities in the 2DCC-MIP



Joan Redwing, Anthony Richardella, Konrad Hilse, Kevin Dressler, Wesley Reinhart, Nitin Samarth, Vincent Crespi 2D Crystal Consortium (2DCC), Pennsylvania State University



20.4 20.5 20.6 20.7 20.8 20.9 21.0 21.1 Omega position (°)



2D Crystal Consortium NSF Materials Innovation Platform

User Facilities

Thin Films and in situ Characterization

• MBE, MOCVD and CVD/epi graphene

Bulk Crystal Growth

• CVT, Flux growth, Bridgman, Float Zone

Theory, Simulation and Data Science

- DFT, ReaxFF-based MD, Phase-field
- LiST database

In-House Expertise



A national user facility focused on advancing the synthesis of 2D layered chalcogenides

Exotic Superconductor High Mobility Topological FeSe Insulator **Withh** Bi₂Se InSe 2-D Layered Chalcogenides Magnetic Weyl Semimetal Vallev WSe, Polarization MoTe Metal-Insulator Transition

User Program



For more information: www.2dccmip.org

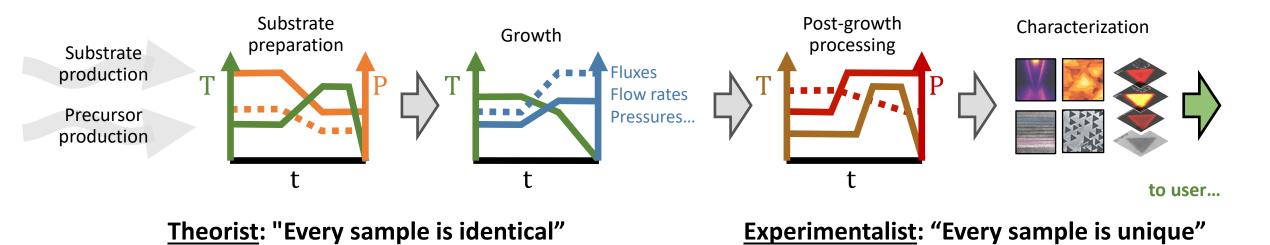
Funded in 2016, renewed in 2021

In synthesis, every sample has a history...



2D Crystal Consortium NSF Materials Innovation Platform

• Series of processes in time with parameters and uncertainties at every step.



• Important to capture the histories, especially the differences, across samples as well as "failed" experiments.

Lifetime Sample Tracking - LiST



• Infrastructure for the capture, curation, and analysis of materials growth and characterization data

Chalcoge

- Sample growth and characterization data > 16,000 bulk and thin film samples
- Growth recipes/parameters imported directly from the synthesis tool
- Automated pipelines to collect data wherever possible

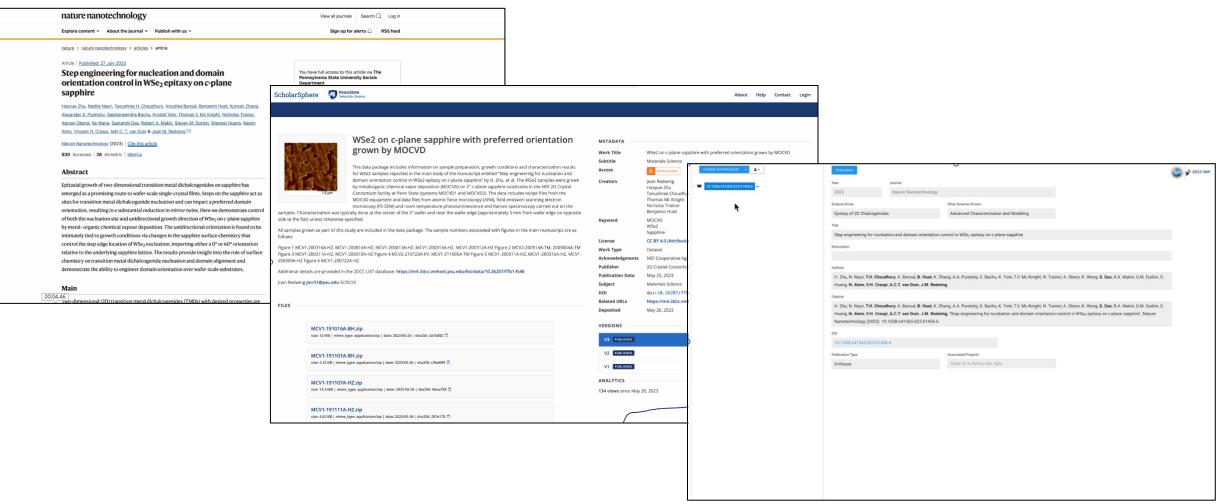
348 301 301 301 301 301 301 301 301	► S0026 ▼ — Proposal	Sample Activity Notes Processing type Synthesis Created by Mikhail Chubarov	Visibility User Date 12/03/2018		
	MCV1-181213A-MC MCV1-181213A-MC	Instrument MCV1 - MOCVD1 Favorites Select a Fav * Precursors	D D	Material MoS2	* Q
	 MOCVD (12/03/2018) Raman (12/03/2018) AFM (12/04/2018) Split (12/17/2018) Raman (12/17/2018) Samples older than 14 days 	Precusors Mo(CO)6 I: W(CO)6 (diluted II: W(CO)6 DET H2S H2Se	Yes	Temperature [°C] 10	Тетр [K] 283.
	 Samples older than 14 days Recent samples (14 days) 		[sec] [°C] 17 1000	ature Pressure [Torr] 50 50	Metal Injector [sccm] 1000 1000

- Available to 2DCC-MIP users to view their own projects and access data on their samples.
- Researchers can obtain direct access to LiST data via API, through a Data Request.
- Public access to metadata on all (non-proprietary) LiST samples through the 2DCC website.
- Data Packages connected to data DOIs support publication and broader data dissemination.

Data Packages



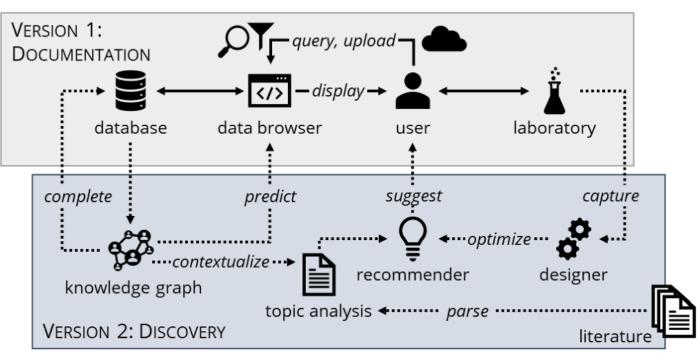
Paper links to data archived in Penn State ScholarSphere, which links to LiST



SE DATAPACKAGE 🚽 💄 🚽								
🗢 🖕 Publ	ic Data Publications Projects						2DCC-MIP	с. С.
Materials Search in Title, DOI and	Available Data x Q Any	Synthesis Techniques	*	Available Characterization Data	Ŧ	RESET SEARCH CRITERIA	SEARCH	
Show 10 entries		÷	2DCC Data DOI	Project	Publication DOI	🔶 🛛 Available Data	🔷 Туре	Å.
Young Modulus				I_ReaxFF_2D_Toolbox		Theory Data	Snapshot	
WSe2 on c-plane sapphire	with preferred orientation grown by MOCVD		10.26207/f7b1-fs46		10.1038/s41565-023-01456-6	87 Samples	Snapshot - Published	
Wafer-scale MOCVD TMD f	ilms used for 3D Monolithic Integration		10.26207/khwb-rr73			38 Samples	Snapshot - Published	
Structures of defect pairs				I_SIM_BN_MoS2_1	10.1103/PhysRevB.99.155430	Theory Data	Snapshot	
Potatoe Stamp Concept				I_ReaxFF_2D_Toolbox	10.1021/acs.jpcc.8b02991	Theory Data	Snapshot	
MoSe2-WSe2 in-plane hete	rostructures for exciton confinement					21 Samples	Snapshot - Published	
InSe on 3 Inch Si(111) Wafe	er-Scale Synthesis with Combinatorial Growth Approach by MBE		10.26207/qakv-p610			13 Samples	Snapshot - Published	
Showing 1 to 7 of 7 entries							Previous 1	Next



2DCC-MIP LIST 2.0: From Data Store to Knowledge Graph



1.0: Documentation↓2.0: Discovery

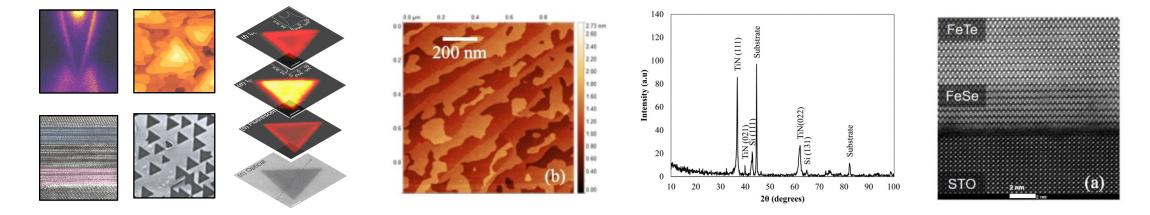
LiST 1.0 is a **traditional database** whose consistent schema are straightforward to query, synthesize, and maintain, but it can only map explicit relationships between data.

List 2.0's **knowledge graph** will contain both a data store and an ontology describing the relationships between entities and will be able to infer relationships not explicitly provided.



Why should materials researchers care about computer vision?

2DCC-MIP



- In the data science sense, "images" are any data with regular spatial structure. Images thus are an abundant data modality for 2DCC.
- Each image contains more data than other common modalities like text or scalars.
- Humans under-utilize image data (in science) as we can't study them pixel-by-pixel.

Thus, computer vision will be a key component of materials informatics.





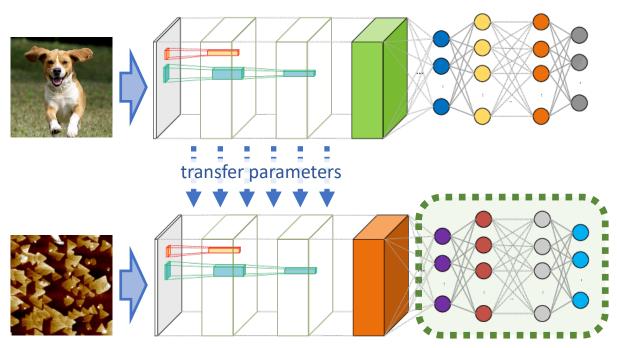
Pretrained Convolutional Neural Networks

Convolutional Neural Networks learn abstractions for patterns in large image collections, such as classifying "dog" versus "cat". They can have billions of learned parameters and leverage the internet for data.

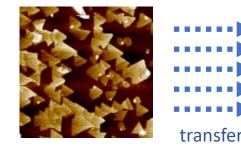
Transfer learning can retrain just a few of these weights to **specialize this highly trained classifier to a new domain** that has a more modest image collection.

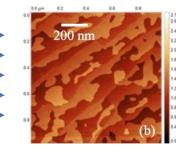
More recently, we have also been leveraging "feature extraction" with pretrained networks to evaluate patterns in micrographs without any network retraining.

Transfer learning can leverage pattern recognition developed in one (non-materials) context into new (materials research) contexts, and also between different materials datasets (e.g. MOCVD \rightarrow MBE).



Lemley, Bazrafkan, and Corcoran (2017) MAICS





Leveraging computer vision advances for materials

Recent examples of transfer learning:

2DCC-MIP

Monolayer coverage of WSe₂

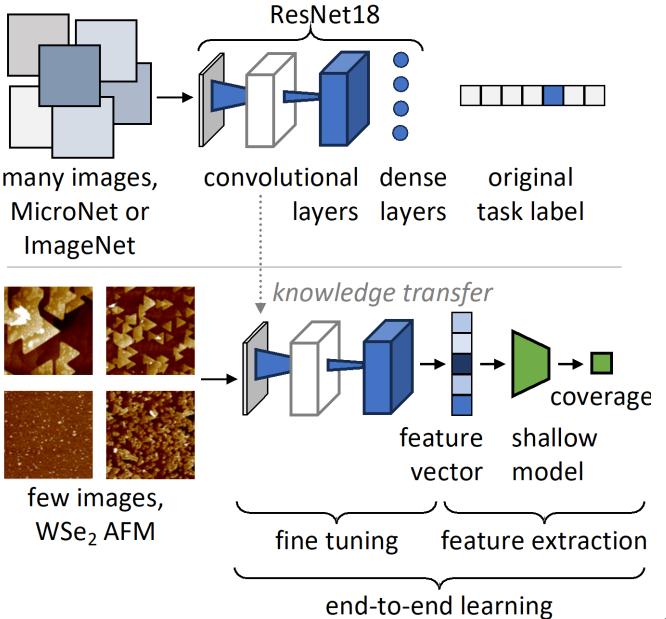
We perform systematic testing of different ML methods for estimating a scalar quantity from 221 AFM. Top-performing models have $R^2 = 0.98$. I.A. Moses, C. Wu, W.F. Reinhart, Materials Today Advances, 2024, 22, 100438.

Classification of MoS₂ growth conditions

We investigate many different classification methods to retroactively "predict" the growth conditions from 262 AFM. Best $R^2 = 0.70$.

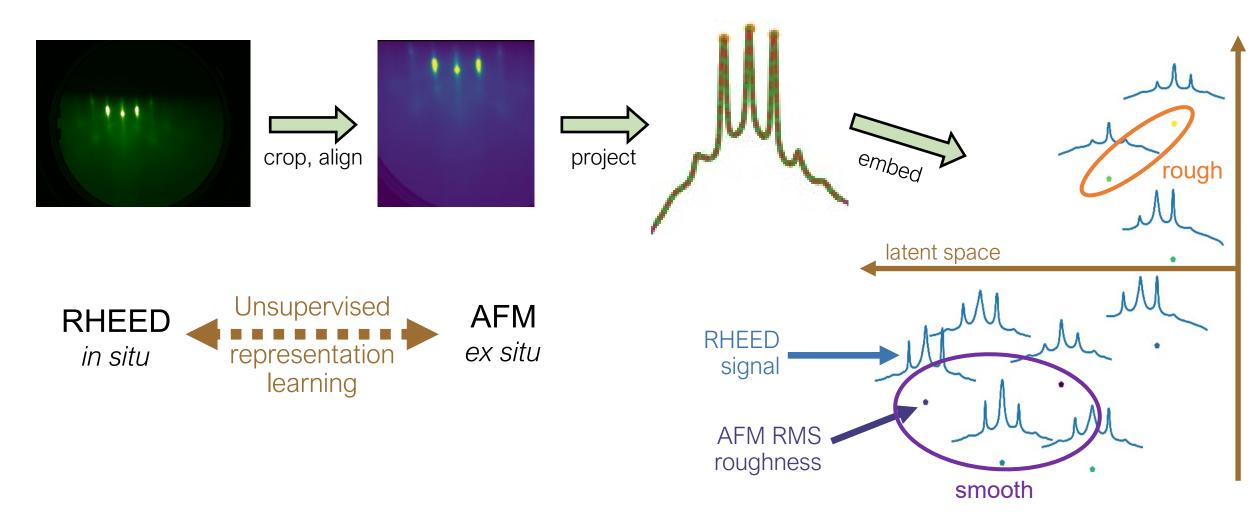
I.A. Moses, W.F. Reinhart, Materials Characterization, 2024, 209, 113701.

This appears to be an effective strategy for producing accurate models with few data.



Reflection high-energy electron diffraction (RHEED)

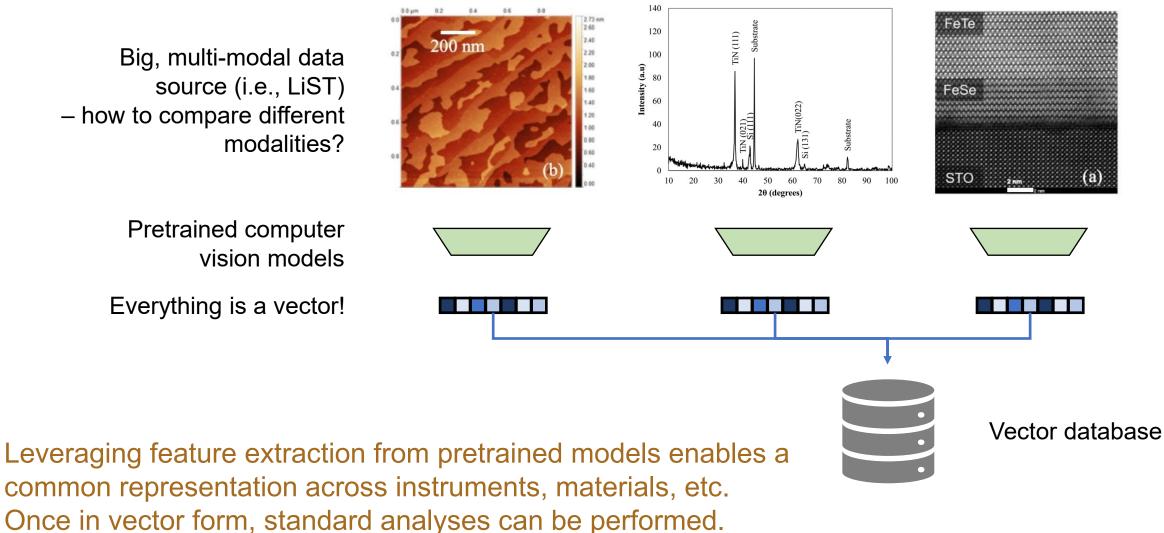




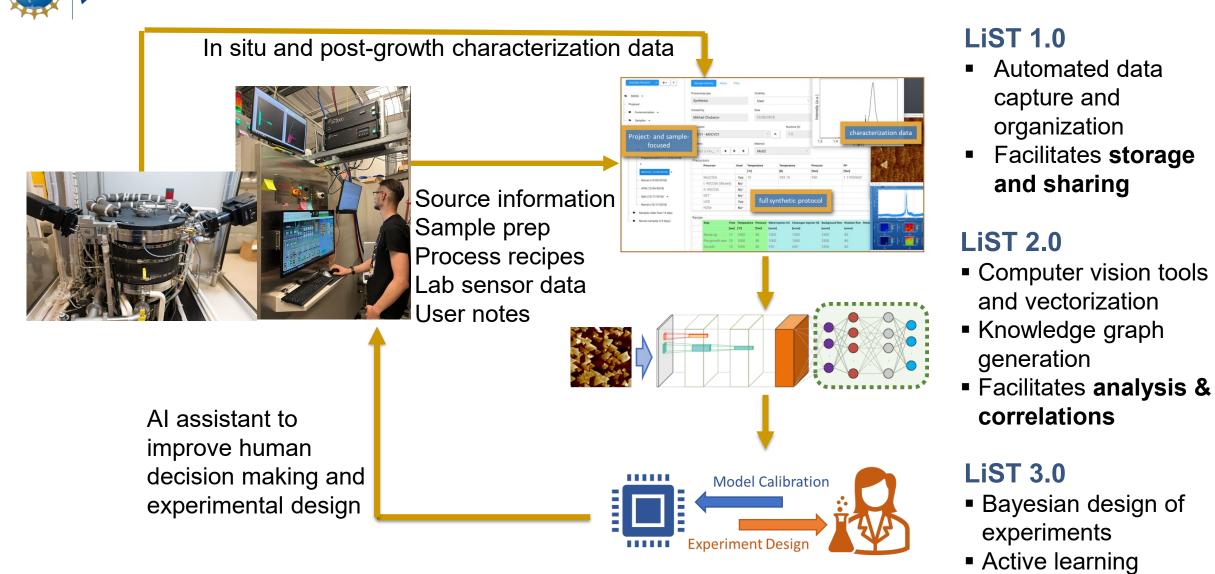
Correlating signals between instruments unlocks new predictive capabilities, especially if *in situ* measurements acquired during growth can predict *ex situ* ones measuring growth outcomes.



Vector database for multi-modal data



2DCC-MIP Advancing 2D materials synthesis through data science



 Facilitates human-Al collaboration

2DCC Data Science Team





LiST 1.0





Konrad Hilse Full Stack Dev

Kevin Dressler Operations Manager



Vin Crespi r Theory, Simulation, Data Science Facility Lead



Wes Reinhart Data Science Lead



Isaiah Moses Postdoctoral Scholar



Tool Integration

Anthony Richardella MBE Research Prof