Materials Genome Initiative & Artificial Intelligence @ NIST

A. Gilad Kusne <u>aaron.kusne@nist.gov</u>

Welfare

Computational Tools

Materials Innovation

Infrastructure

Digital

Data

Next Generation

Workforce

Experimental

Tools

Hunger

Valional Security

James Warren, NIST MGI Director

National Institute of Standards & Technology

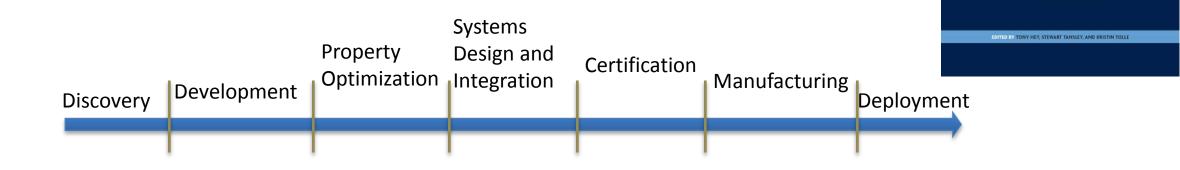
National Institute of Standards and Technology U.S. Department of Commerce

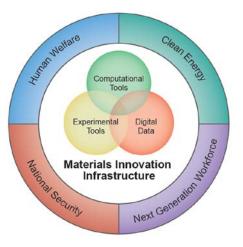
MGI + AI?

What is MGI?

- MGI Goal Accelerate materials development from Discovery to Deployment
- MGI Key part: Build data science infrastructure to Enable Data Science & in particular AI
- MGI Outcome Realizing the 4th Paradigm: Data-Intensive Scientific Discovery & Development

Make it easier for industry & academia to do materials data science.







FOURTH

PARADIGM

DATA-INTENSIVE SCIENTIFIC DISCOVERY

The

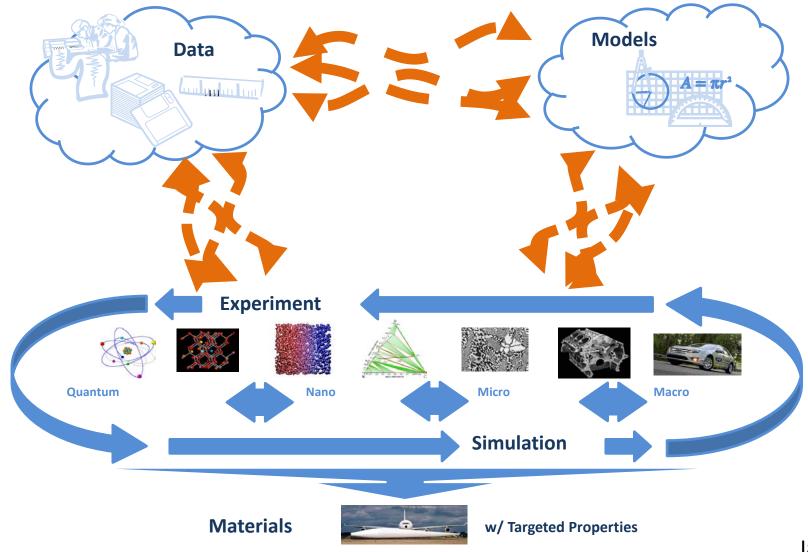
MGI + NIST

- MGI Subcommittee, Committee on Technology, National Science & Technology Council (First meeting 2012)
- Member Agencies (10): NIST, DOE, DOD, NSF, NASA, NIH, US Geological Survey, National Nuclear Security Administration, DARPA, and Office of Management and Budget
- National Institute of Standards & Technology
 - The US National Metrology Lab
 - Develop consensus standards to support international trade and commerce





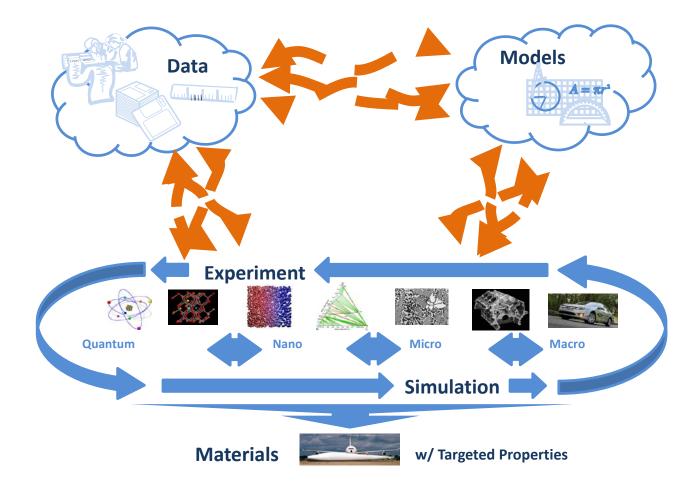
MGI: Facilitating Data Science



James Warren, NIST

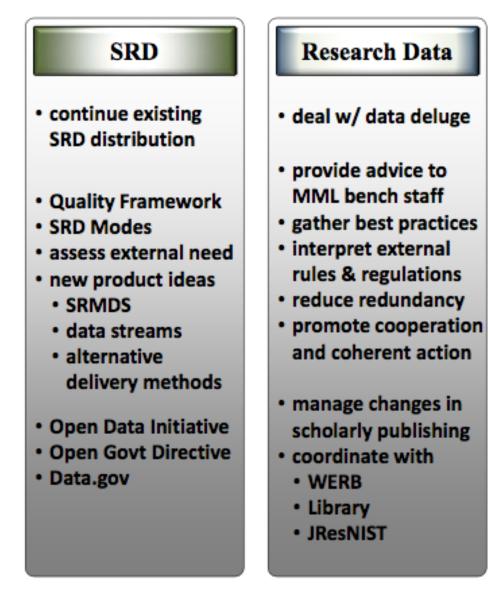
MGI: Facilitating Data Science

- Bank it: Data Ingestion & Repositories
- Share it: Standards for data & metadata
- Find it: Data Discovery
- Check it:
 - Curation
 - Uncertainty Quantification in Data / Models



James Warren, NIST

Office of Data and Informatics



- partner with ITL
- represent MML
 - NIST committees

Lead/Liaison

- NSTC & IWGs
- NIH, NSF, DOE
- other Fed Govt
- Research Data Alliance (RDA)
- data standards
- champion proposals
 - budget initiatives
 - IMS
 - inter-agency, RDA

Data Science
The 4 th paradigm?
will it stand next totheoretical
 experimental computational
Cloud

- Statistical Learning
- Big Data
- Knowledge Discovery
- very fast growing
- many new jobs
- new degrees/depts

NIST Center for Excellence in Advanced Materials

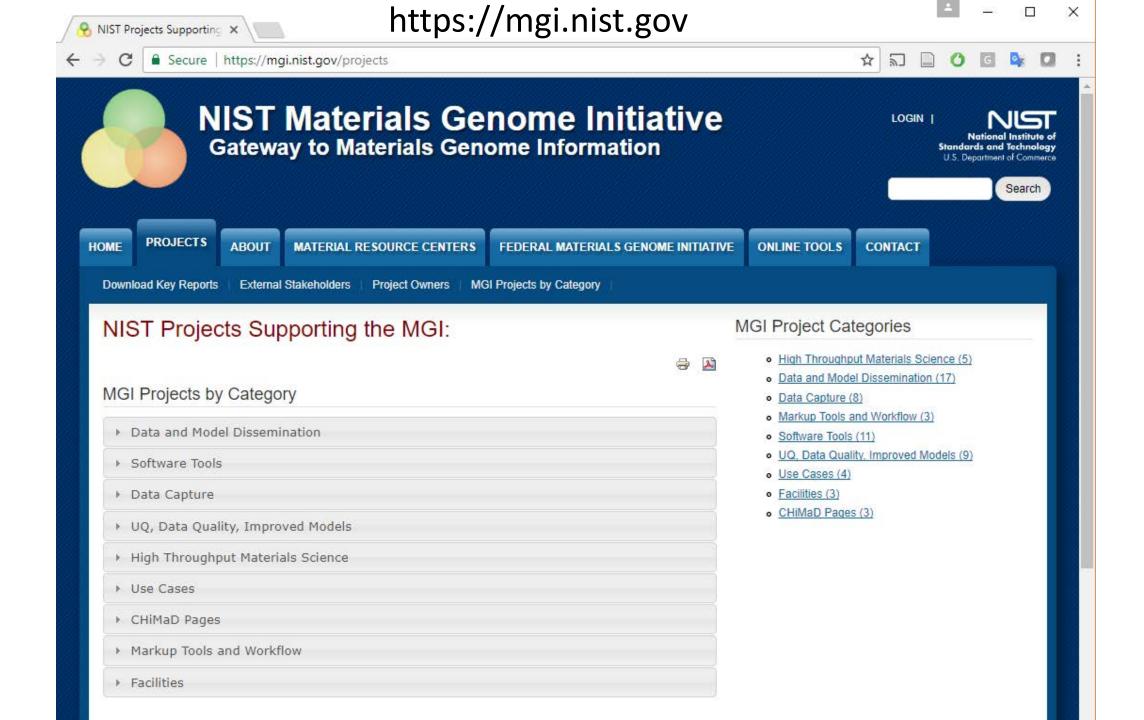
Center of Hierarchical Materials Design



Peter Voorhees, Gregory Olson | Begum Gulsoy Northwestern University Juan De Pablo | University of Chicago







MGI @ NIST

- MGI: Facilitating data science
 - Standards for data, metadata, & uncertainty
 - Repositories
 - Data Discovery
 - Uncertainty in Models
- MGI Examples / Prototypes
 - Force Field Calculations
 - Autonomous Phase Mapping

Repositories

• Bank it

https://materialsdata.nist.gov/

material	.sdata.nist.gov
IIST Repositories	
Communities in NIST Repositories	Search NIST Repositories
Select a community to browse its collections. [R] indicates an invitational community, [Z] indicates an archived community.	Go
ASM Structural Materials Data Demonstration Project Chemical Sciences	Advanced Search
CHiMaD Data Collections [R]	Browse
Community for Greenhouse Gases Computational File Repository	All of NIST Repositories
Experimental Data Repository	Communities & Collections By Issue Date
Genome in a Bottle	Authors
Heusler Phases: First Principles Simulations [R]	Titles Subjects
 ICME Approach to Development of Lightweight 3GAHSS Vehicle Assembly [R] 	and the second s
ICME of Carbon Fiber Composites for Lightweight Vehicles [R]	My Account
MGI Catalogs MICCoM Collections [R]	Login
NanoRelease [R]	
NIST/DOE-EERE Advanced Automotive Cast Magnesium Alloys [R]	Discover
NIST Thermodynamics and Kinetics Test Space [R]	Author
 Porous Metals and Ceramics: Freeze-casting under microgravity and terrestrial conditions 	Du, Y, (10) Bower, Allan F. (8) Butten Basianin B. (7)
RDA Demonstration Project: DT	C
 RVE fracture VUMAT for QP980 Customized DSpace reposito 	ry for materials
 State Variable Model for QP980 Synchrotron Studies of Slot Die Enables sharing of a variet 	v of data types
	y of uata types,
Thermal Conductivity of CVD D including text, images, an	d video

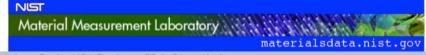
111 (13)

Platforms (9)

ALL CHEMICAL SYSTEMS (10)

In-Situ High-Throughput Synchrotron Diffraction Data of Multiple Principle Component Alloy Thin Films

Ruiz-Yi, Benjamin; Bunn, Jonathan K.; Stasak, Drew; Mehta, Apurva; Besser, Matthew; Kramer, Matthew J.;



NIST Repositories → Experimental Data Repository → Diffusion Data → View Item

Data Citation:		Searc
Campbell, Carelyn; Zhao, J-C; Henry, M.	E	
Examination of Ni-base superalloy diffu	sion couples containing multiphase regions	Se
(2014-04-02)		
http://hdl.handle.net/11256/22	Digital Identifier	Advan
	nology, Metallurgy Division, Gaithersburg, MD 20899-8555, USA	-
General Electric Company GE Global Research 1 E	lesearch Circle Niskavuna NY 12309 USA	Brow

Contact Email: carelyn.campell@nist.gov

Primary Publication Citation:

Materials Science and Engineering A 407 (2005) 135-146 http://dx.doi.org/10.1016/j.msea.2005.07.016 Related Work

Related Publications by Author:

Campbell CE, Boetttinger WJ, Kattner UR (2002) Development of a diffusion mobility database for Ni-base superalloys. Acta Mater 50:775-792 DOI: http://dx.doi.org/10.1016/S1359-6454(01)00383-4

Campbell CE, Zhao JC, Henry MF (2004) Comparison of experimental and simulated multicomponent Ni-base superalloy diffusion couples. J Phase Equil Dif 25 (1):6-15. DOI: http://dx.doi.org/10.1361/10549710417966

Abstract:

Four Ni-base superalloy diffusion couples with multiphase regions were studied. The diffusion couples contained single-phase (gamma), two phase(gamma +MC carbide) and three-phase (gamma + gamma prime+MC carbide) regions. Measured average composition profiles were in good agreement with the diffusion simulation predictions. The measured and predicted phase fraction profiles showed similar trends; however, there were some discrepancies in the predicted position of the gamma + gamma prime + MC/ gamma +MC boundary. Phase fraction profiles and optical metallography were used to determine the type and direction of the moving phase region boundaries.

Funding Agency & Award No.:

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This work was supported by the Defense Advanced Research Project Agency (DARPA) under the accelerated Insertion of Materials (AIM) Program (Grant number F33615-00-C-5215) with Dr. L. Christodoulou as the project manager and Dr. Rollie Dutton as the project monitor. The authors would like to express their appreciation to N. Saunders for the use of his thermodynamic database for Ni alloys and to Louis Advanced Research Project Materials (AIM) Program (Grant number F33615-00-C-5215) with Dr. L. Christodoulou as the project manager and Dr. Rollie Dutton as the project monitor. The authors would like to express their appreciation to N. Saunders for the use of his thermodynamic database for Ni alloys and to Louis Advanced Research Project Materials (AIM) Program (Grant New York (Grant New York)) and the project monitor.



Showing items related by title, author, creator and subject.

Further Studies on the Nickel-Aluminum System. I. The β-Ni2Al3 Phase Fields

Taylor, A; Doyle, N.J. (1972-01-31)

New lattice parameter and density results have been obtained for alloys in the fl-NiA1 and 6-Ni2A13 phase fields of the nickel-aluminum system. The lattice parameter of the fl-NiAI phase (CsCI-type) falls linearly from ...

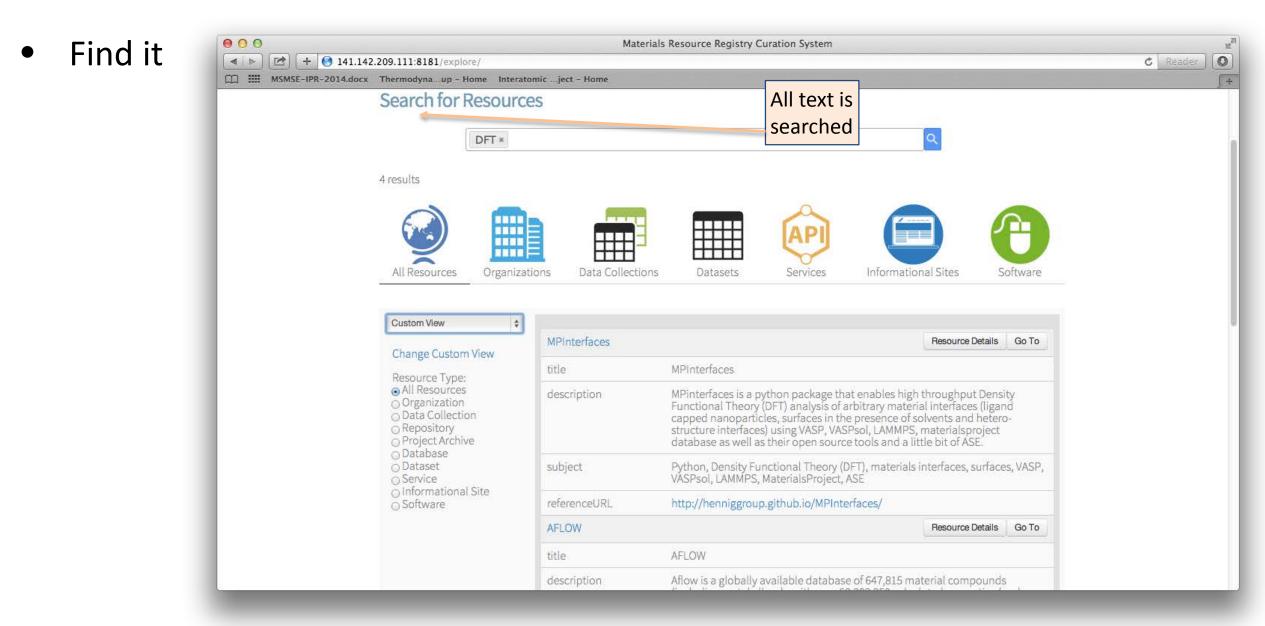
Elemental vacancy diffusion for fcc and hcp structures

Angsten, Thomas; Mayeshiba, Tam; Wu, Henry; Morgan, Dane (2014-08-08)

This work demonstrates how databases of diffusion-related properties can be developed from high-throughput ab initio calculations. The formation and migration energies for vacancies of all adequately stable pure elements ...

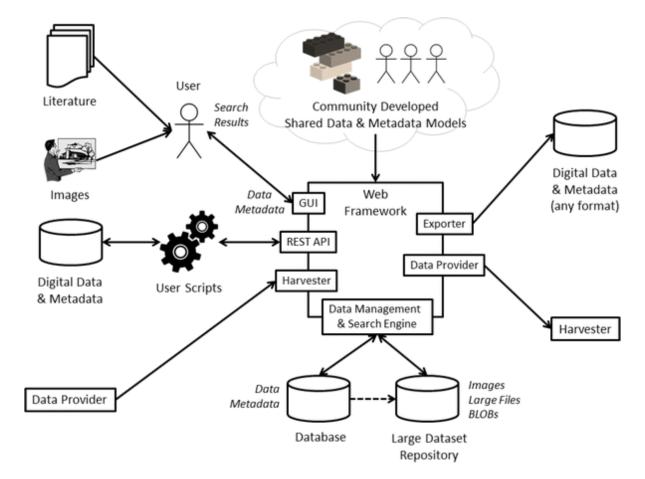
Data Discovery

Search for resources: Materials Resource Registry



Materials Data Curation System

- Bank it: "smart" data ingestion tools & repository
- Share it: tools to automatically convert data into and out of standard formats.
- Find it: search via Website or API
- Federated search



Dima (JOM 2016) Informatics Infrastructure for the Materials Genome Initiative.

Model Uncertainty

- (Check it)
- Molecular Dynamics
- Finite Element Analysis
- Thermodynamics (CALPHAD)
- etc.
- NIST Uncertainty Machine
 - Use probabilistic models to assess uncertainty – e.g. confidence, or credible intervals.

NIST Uncertainty Machin ×		*	-			×
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NIST Uncertainty Machine						
User's manual available here. Instructions :						
 Select the number of input quantities. Change the quantity names and update them if necessary. For each input quantity choose its distribution and its parameters. Choose the number of realizations. Write the definition of the output quantity in a valid R expression. Choose and set the correlations if necessary. Run the computation. 	onfiguration file here or click to upload	· , -				
Random number generator seed: 92						
Number of input quantities: 1 Names of input quantities:						
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x0 Gaussian (Mean, StdDev) ▼ 0	1					
Number of realizations of the output quantity:						
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Definition of output quantity (R expression):	. +					
Symmetrical coverage intervals						
Correlations						
Run the computation						
This software was developed at NSET. This software is not subject to copyright protection and is in the public domain. This software is an experimental system. NIST assumes no responsibility whatsoever for its use by other parties, and maken no guarantese, expressed or implied, about its quality, reliability, or any other characteristic. We would appreciate acknowledgement if the software is used. Version 1.3						



- Bank it
- Share it
- Find it
- Use it

Materials Data Facility

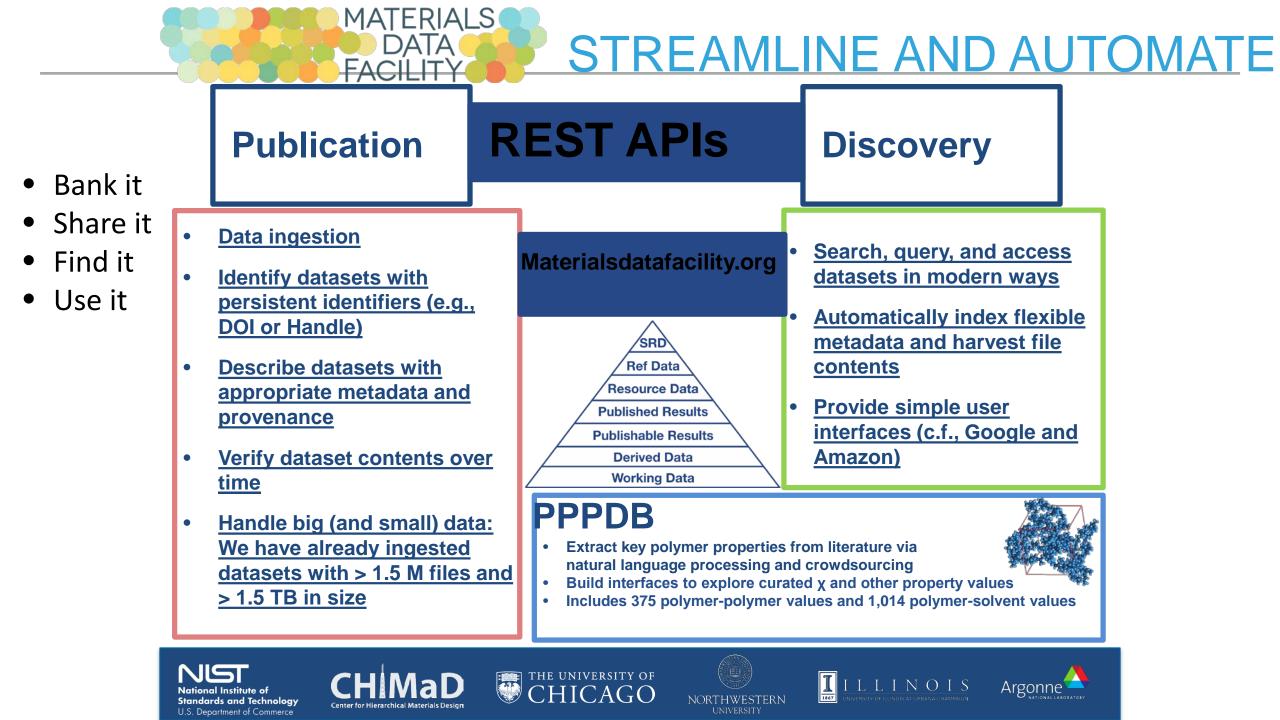
Streamlined and automated data sharing, discovery, access, and analysis

lan Foster (foster@uchicago.edu)^{1,2}, Ben Blaiszik^{1,2} (blaiszik@uchicago.edu), Jonathon Gaff¹, Logan Ward¹, Kyle Chard¹, Jim Pruyne¹, Rachana Ananthakrishnan¹, Steven Tuecke¹

Michael Ondrejcek³, Kenton McHenry³, John Towns³ University of Chicago¹, Argonne National Laboratory², University of Illinois at Urbana-Champaign³

materialsdatafacility.org globus.org





STREAMLINE AND AUTOMATE: FOUR KEY STEPS

- <u>Simplify data publication, regardless of size, type,</u> and location
- Automate data and metadata ingest, to enable capture of many valuable materials datasets
- Enable <u>unified search</u> of disparate materials data sources
- <u>Deploy APIs to foster community development</u>, <u>data creation, and data consumption</u>

Sharing Data and Tools

A New Model for Materials Genome Initiative - Driven Research: "High-throughput Experimental Materials Collaboratory (HTEMC)"

> Zachary T. Trautt¹, Andriy Zakutayev², Martin L. Green¹, John Perkins²

¹National Institute of Standards and Technology (NIST) ²National Renewable Energy Laboratory (NREL)

martin.green@nist.gov

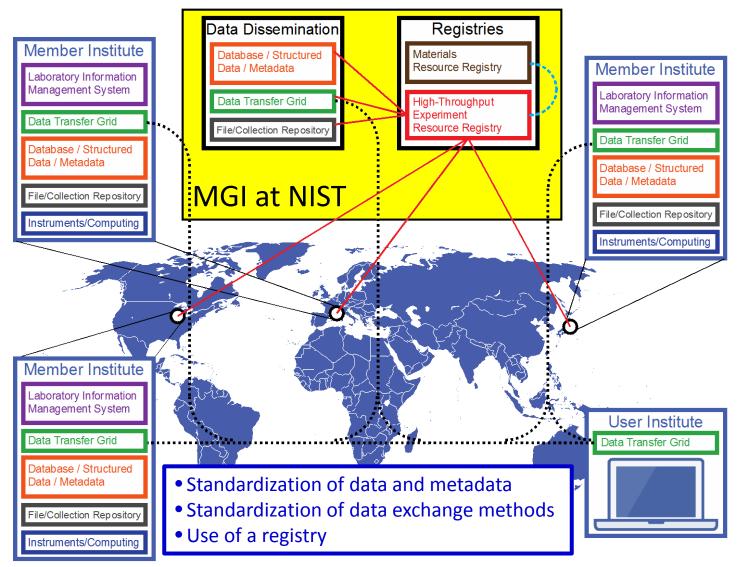
Collaboratory

Collaboratory: a 1989 neologism (William A. Wulf, Computer Scientist at University of Virginia):

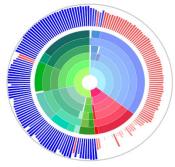
"...defined by...a '<u>center without walls</u>,' in which the nation's researchers can perform their research without regard to physical location, interacting with colleagues, accessing instrumentation, sharing data and computational resources, accessing information in digital libraries."

- The HTEMC would consist of:
 - An integrated, delocalized network of high-throughput synthesis and characterization tools
 - A best-in-class materials data management platform, consisting of NIST (and other) software

Platform Integration Model



Education



Annual Machine Learning for Materials Research: Bootcamp and Workshop

University of Maryland Host:

https://nanocenter.umd.edu/events/mlmr/

- TBD (~June / July) Dates:
- Location: University of Maryland, College Park, MD

The event will introduce materials researchers from industry, national laboratories, and academia to machine learning theory and tools for rapid materials data analysis.

Bootcamp

Three days of lectures and hands-on exercises covering a range of data analysis topics from data pre-processing through advanced machine learning analysis techniques. Example topics include:

- Identifying important features in complex/high dimensional data
- Visualizing high dimensional data to facilitate user analysis.
- Identifying the fabrication 'descriptors' that best predict variance in functional properties.
- Quantifying similarities between materials using complex/high dimensional data

The **hands-on exercises** will demonstrate practical use of machine learning tools on real materials data. Attendees will learn to analyze a range of data types from scalar properties such as material hardness to high dimensional spectra and micrographs.

Workshop

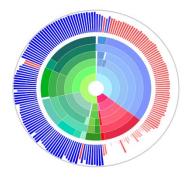
Talks by top researchers in the field as well as open discussions in which attendees can discuss their data analysis needs with experts.

UNIVERSITY

MARYLAND STANFORD OAK RIDGE JOHNS HOPKINS

National Laboratory

UNIVERSITY



Annual Machine Learning for Materials Research: Bootcamp and Workshop

https://nanocenter.umd.edu/events/mlmr/

TUE 6/28	THEORY, DATA, ALGORITHMS WED 6/29	THEORY & ALGORITHMS THU 6/30	Technology Materials Measurement Science Division	Technology Information Technology Laboratory
Filtering: Noise Smoothing Background Subtraction Feature Extraction Cross-correlation Wavelets Edges Closed Boundaries Shapes	Data Handling Cross Validation Prediction Algorithms Regularized Least Squared Support Vector Machines Neural Networks Decision Trees & Ensemble Learning Genetic Programming	Theory Similarity Measures Latent Variable Analysis Spectral Unmixing Matrix Factorization Clustering	Alexei Belianinov Oak Ridge National Laboratory Center for Nanophase Materials Sciences	Tim MuellerJohn HopkinsUniversityDepartment ofMaterials Science &EngineeringStefano ErmonStanford UniversityDepartment ofComputer ScienceComputer ScienceLchiro Takeuchi
MACHINE LI	EARNING FOR MATERIALS RESEARCH: WO	RKSHOP		University of Maryland, College Park Department of

NGT UNIVERSITY OF STANFORD OAK RIDGE JOHNS HOPKINS UNIVERSITY DIVINIVERSITY DATIONAL LABORATORY JOHNS HOPKINS

MGI Examples

- Force Field Calculations (Logan Ward, Northwestern Univ)
- Autonomous Phase Mapping

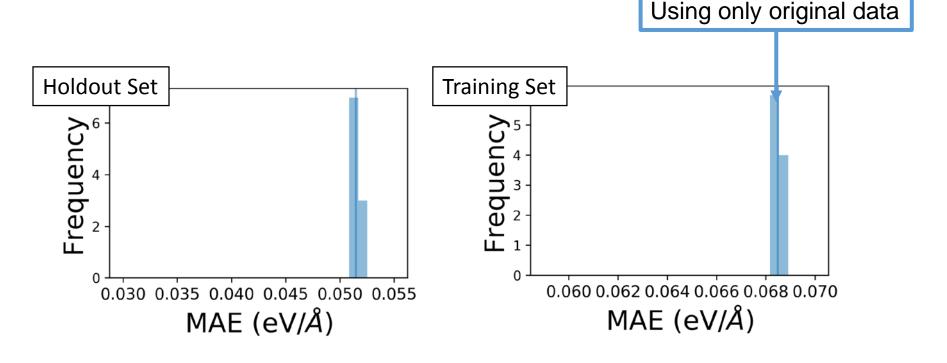
Building a machine learning model using MDF

Example: Building force-field potentials from different datasets

Data resources: 3 DFT datasets with Aluminum data

1 dataset from <u>khazana.uconn.edu</u>, 2 datasets from <u>materialsdata.nist.gov</u>

Result: Improved performance by integrating data sources



MAE – Mean absolute error

Method: Botu et al. JPCC. (2017)

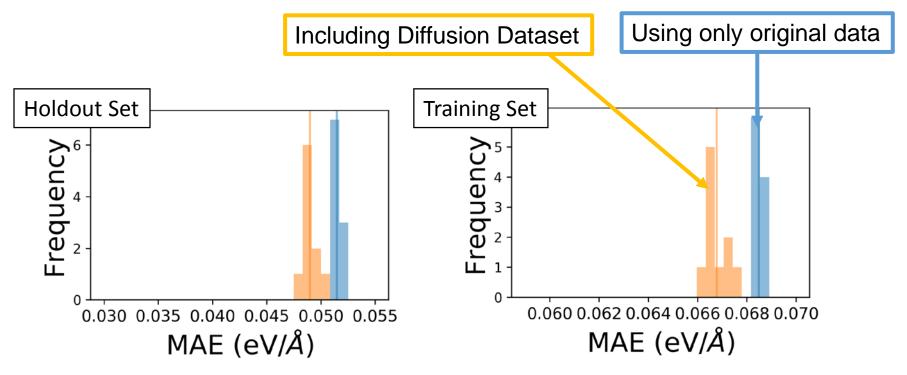
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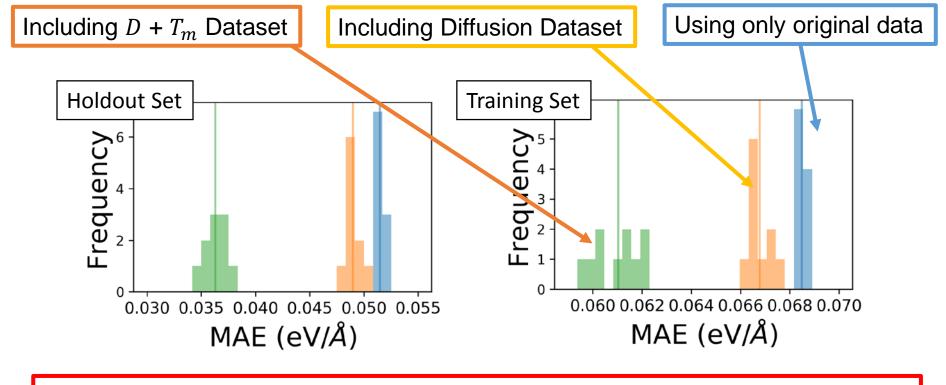
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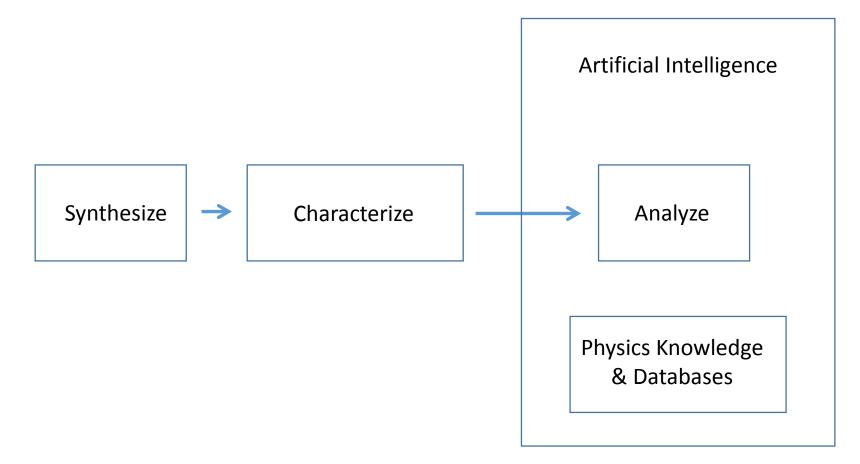
Result: Improved performance by integrating data sources



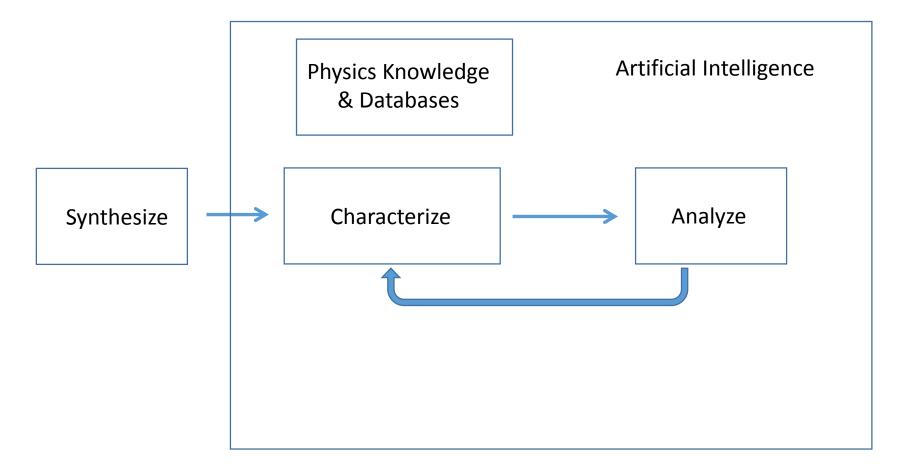
Better performance in original application: No new DFT calculations

Method: Botu et al. JPCC. (2017)





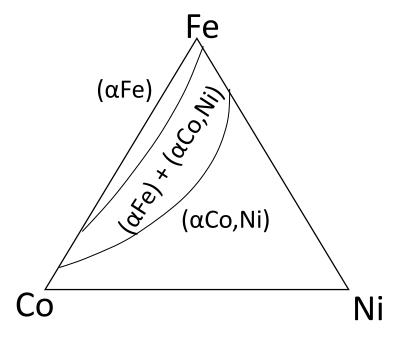
Autonomous Metrology



Using AI to Identify Structural Phase Maps

Structural Phase Map

- Structure as a function of fabrication parameters (e.g. composition, temperature, pressure, etc.)
- Use map to predict structure of new materials.
- Structure is good predictor of important properties.

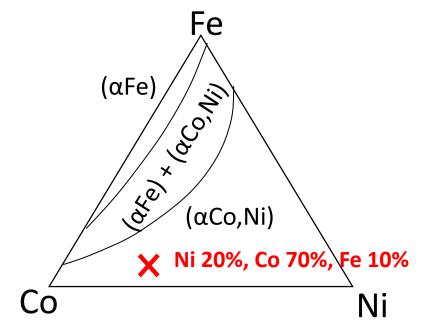


Phase Equilibria in Iron Ternary Alloys (1988) #60

Structural Phase Mapping: Edisonian Approach

Traditional / Edisonian Approach:

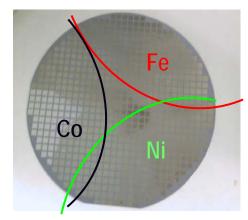
- Fabricate sample
- Measure structure
- Point placed on phase diagram
- Repeat
- This process takes years.

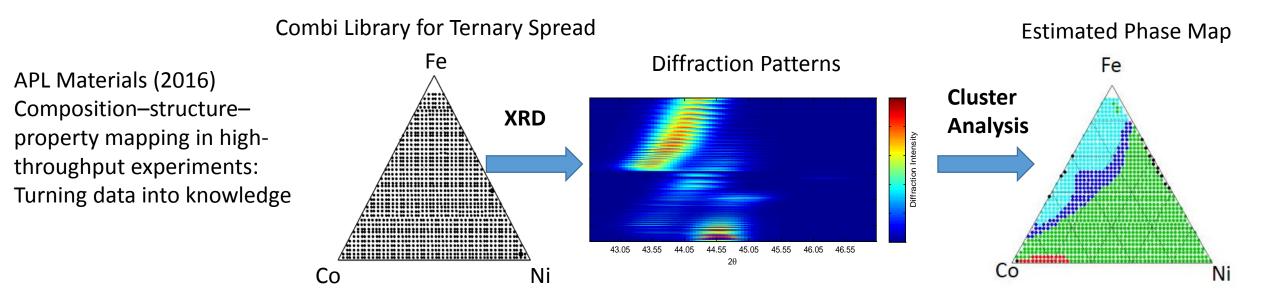


Phase Equilibria in Iron Ternary Alloys (1988) #60

Phase Mapping: High-Throughput Approach

- Fabricate hundreds-thousands of samples -> HiTp Synthesis
- Measure all samples -> HiTp Characterization
- Rapid phase mapping -> Machine Learning





Phase Mapping: High-Throughput Approach

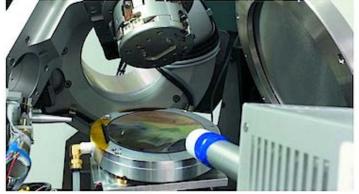
- Measurement is a time / resource sink
- For wafer of 500+ samples:
- In Lab: Takes weeks-months
- Synchrotron: Takes 5+ Hours (Every second counts)



Mn-Ni-Ge library 535 samples



Bruker D8 30 Minutes per sample 2 weeks!



Stanford Synchrotron Radiation Lightsource 30 seconds per sample 4.5 hours

Autonomous Metrology: Motivation

Why use AI to just analyze data? Put it on control of the equipment!

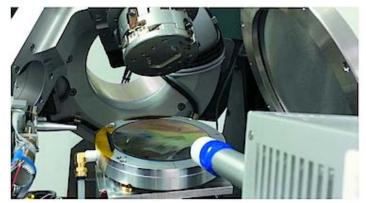
Instead of measuring all the samples, measure only the ones that count -> AI for optimal experiment design

- Minimum measurements -> Maximum knowledge
- Save on worker hours and instrument time.
- Start it up and let it run.
- Minimize human bias: experiment design, execution, data analysis
- Replaced with traceable algorithmic bias
- Democratize Science
 - Simplify equipment use
 - Collaboratory

Mn-Ni-Ge library 535 samples



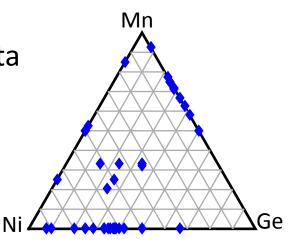
Bruker D8 30 Minutes per sample 2 weeks!



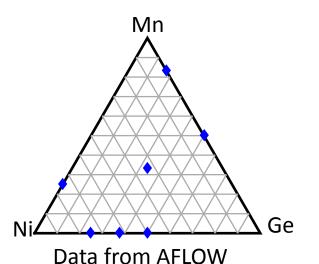
Stanford Synchrotron Radiation Lightsource 30 seconds per sample 4.5 hours

Autonomous Phase Mapping: MGI + AI

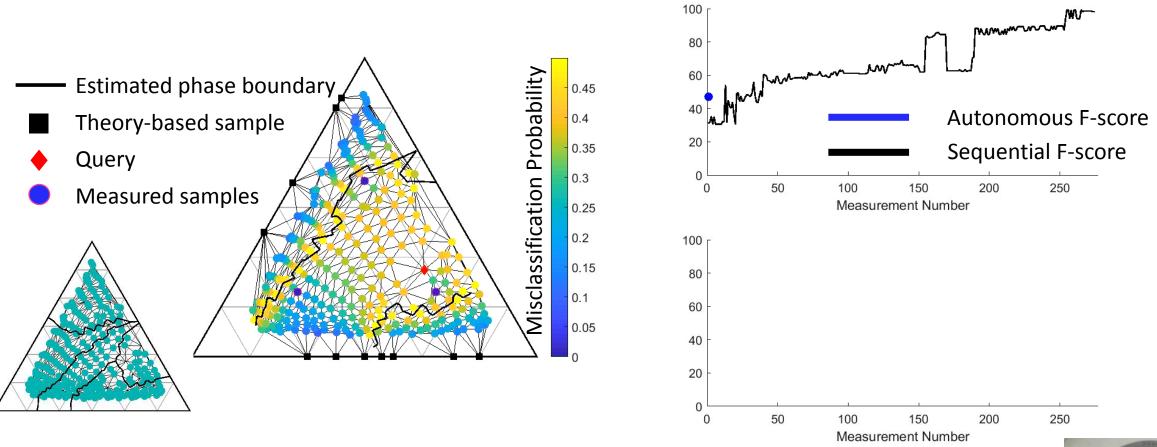
- For <u>Optimal Experiment Design</u>, AI needs access to prior data + physics theory
- Al Interface with Databases
 - Import pertinent data and metadata
 - AFLOW (DFT), Inorganic Crystal Structure Database (Experimental)
- Theory built in (e.g. Gibbs Phase Rule, X-ray diffraction)
 - Constraint Programming
 - Access to physics modeling software
- Al Interface with Equipment
 - X-ray diffraction systems
 - Bruker D-8, SLAC HiTp X-ray diffraction system
 - Data ingestion tools
- Automatic data storage, MDCS standards



Data from ICSD



Autonomous Phase Mapping

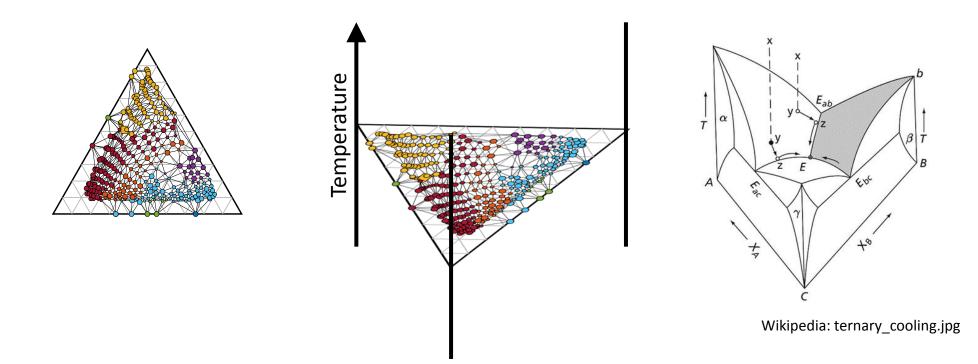


AI is controlling X-ray diffraction systems at SLAC & in the lab!



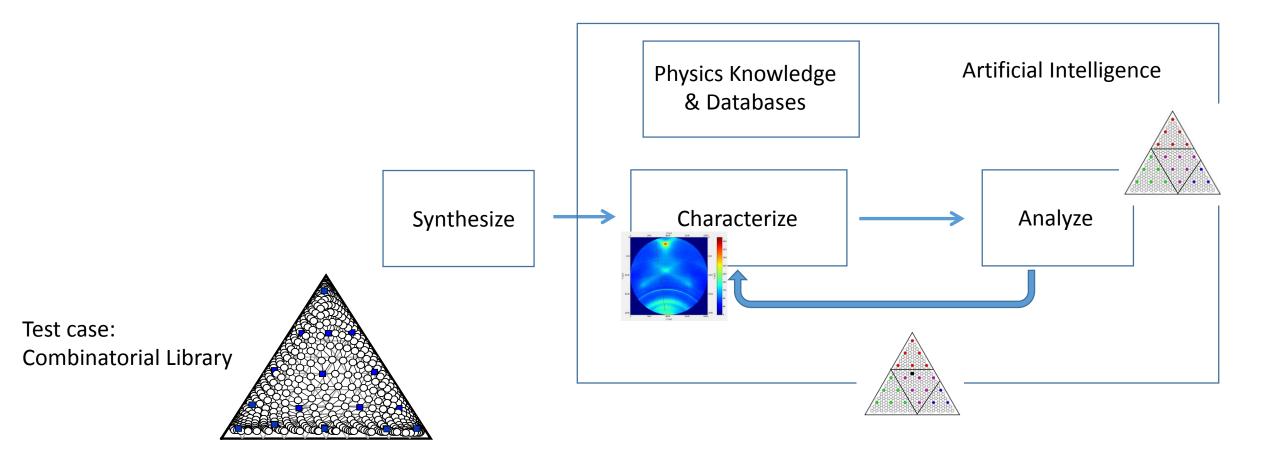
Autonomous Temperature Phase Mapping

- Developing 2 systems for autonomous composition & temperature phase mapping.
- Minimum measurements for maximum knowledge.



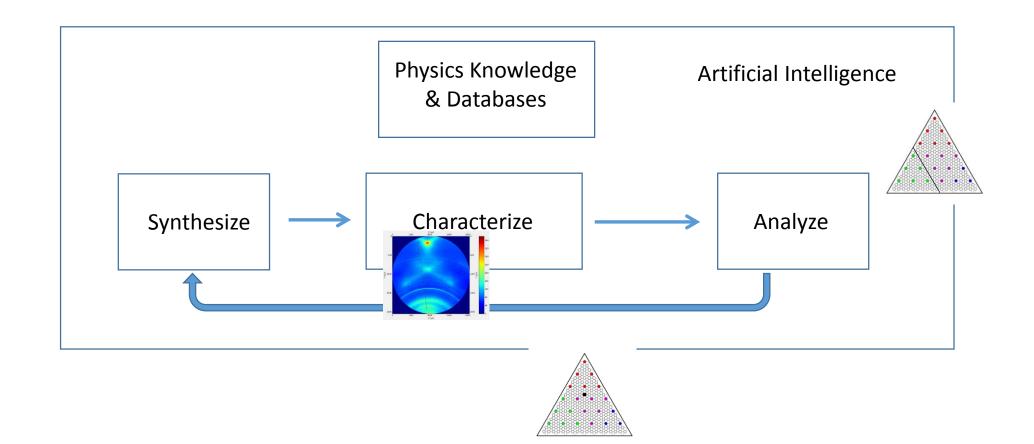
Autonomous Metrology

• Past: Al is given a pool of samples (100s-1,000s).



Autonomous Materials Science

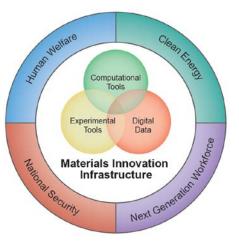
• Current: Place AI in control of Synthesis.



MGI + AI: Contacts

- MGI Jim Warren (MGI Director), james.warren@nist.gov
- Materials Data Curation System Zach Trautt, <u>zachary.trautt@nist.gov</u>
- Materials Data Facility Ian Foster, <u>foster@uchicago.edu</u>
- Materials Resource Registry Chandler Becker, <u>chandler.becker@nist.gov</u>
- Collaboratory Martin Green, <u>martin.green@nist.gov</u>
- Autonomous Metrology / Lab A. Gilad Kusne, <u>aaron.kusne@nist.gov</u>

Questions?





The FOURTH PARADIGM

DATA-INTENSIVE SCIENTIFIC DISCOVERY

ITED BY TONY HEY, STEWART TANSLEY, AND KRISTIN TOLLE