



TEXAS A&M UNIVERSITY
Engineering



Texas A&M Engineering
Experiment Station

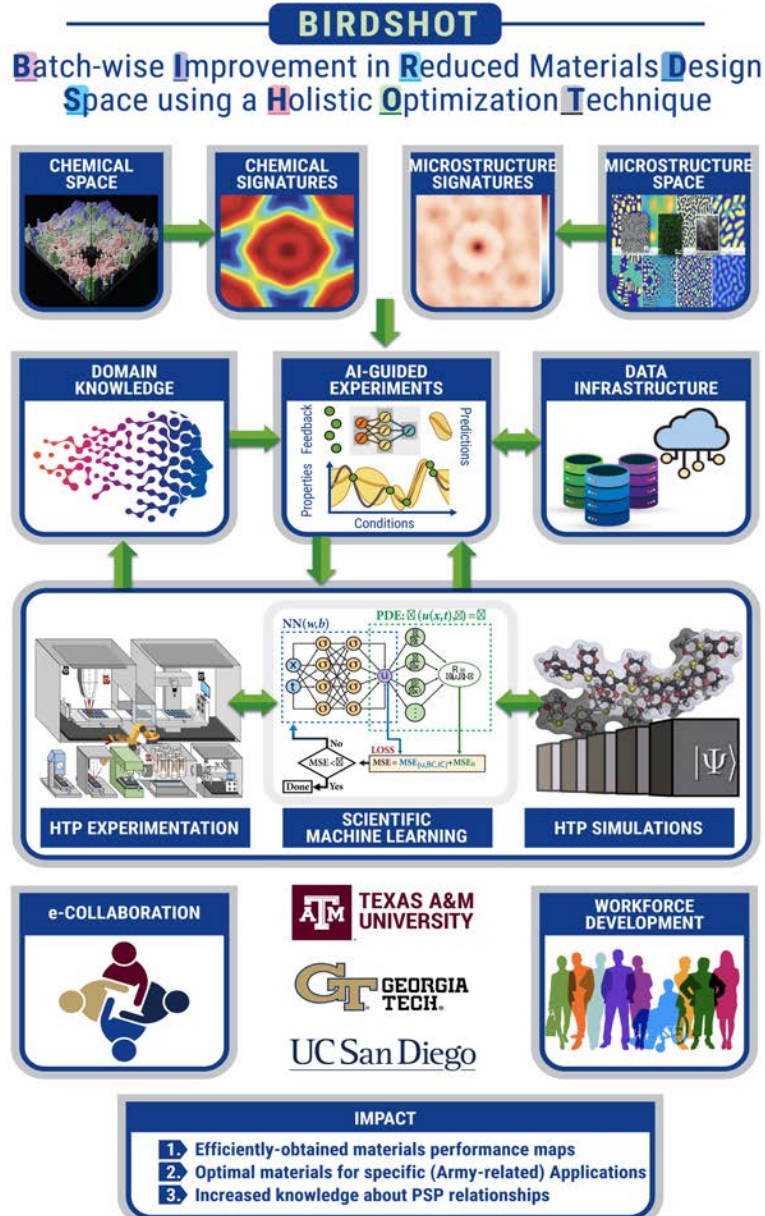
Batch-wise Improvement in Reduced Design Space using a Holistic Optimization Technique (BIRDSHOT)

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Ibrahim Karaman, Dimitris Lagoudas, Ankit Srivastava,
Doug Allaire



BIRDSHOT



Our **vision** is to develop an application- and materials-agnostic framework for the accelerated discovery of Army relevant-materials and materials systems.

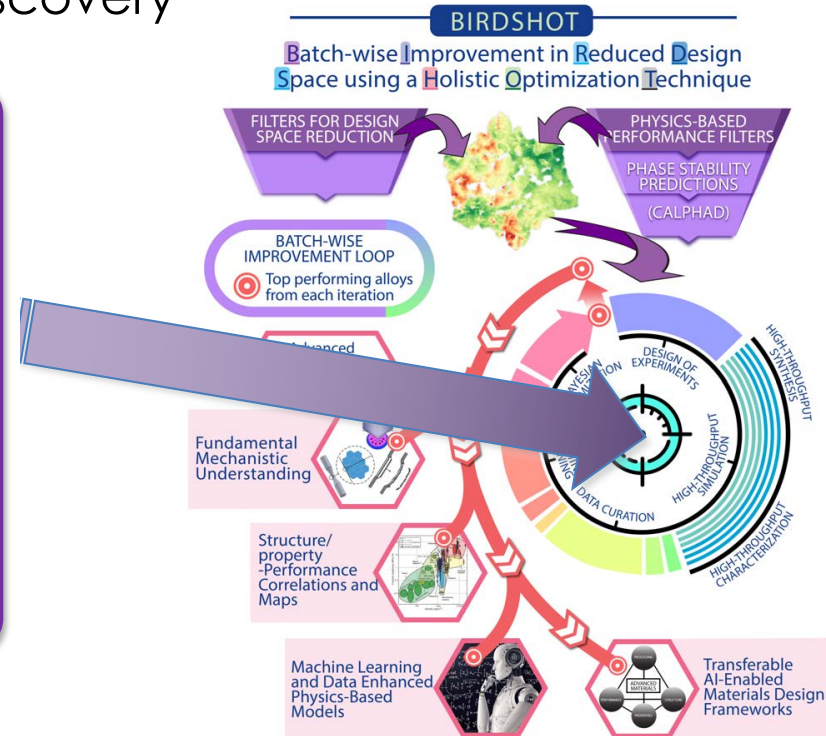
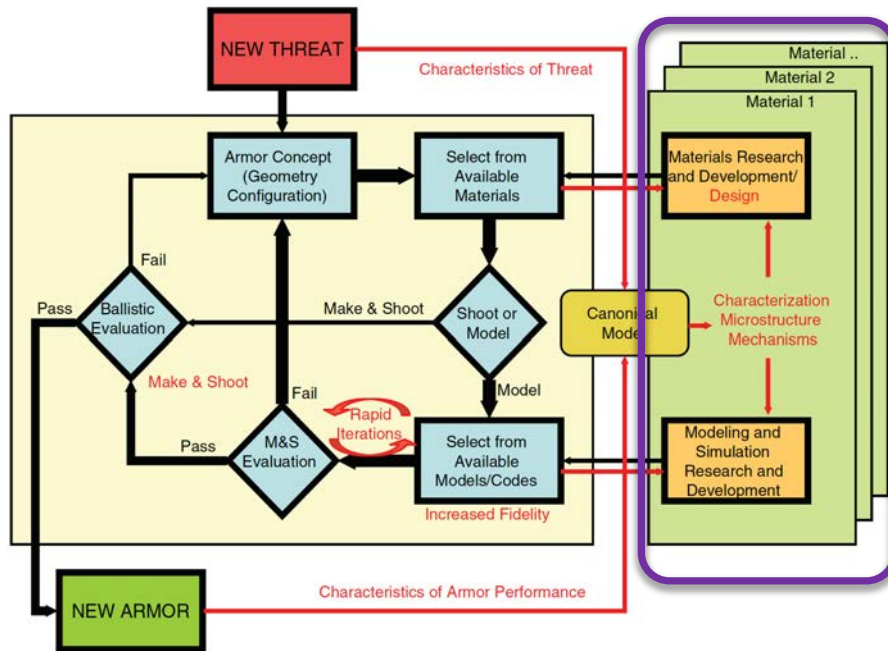
Our **mission** is to deploy integrated experimental-computational-Artificial Intelligence (AI)/Machine Learning (ML) platform for the accelerated discovery of advanced structural materials for Warfighter-relevant applications

BRDSHOT LEADS

- [Raymundo Arróyave](#), TAMU, (Alloy Design, Bayesian Materials Discovery)
- [George Pharr \(NAE\)](#), TAMU (High Strain Rate Deformation, HSR, HTP Nano-Indentation)
- [Ned Thomas \(NAE\)](#), TAMU (High Strain Rate Deformation, HSR, HTP LIPIT)
- [Surya Kalidindi](#), GTech, (Data-Driven Materials Design, ML+Physics Models for Materials Behavior)
- [Ken Vecchio](#), UCSD, (High-throughput Materials Synthesis)
- [Ibrahim Karaman](#), TAMU (Microstructure-Sensitive Materials Design, HTP Materials Synthesis)
- [Dimitris Lagoudas](#), TAMU, (Mechanics of Materials)
- [Ankit Srivastava](#), TAMU (Microstructure Mechanics, HSR Deformation Simulations, Bayesian Materials Discovery)
- Others: [Douglas Allaire](#), TAMU (Multi-Disciplinary Systems Design and Optimization)

BIRDSHOT'S VISION

Accelerated, Goal-Oriented Materials Discovery



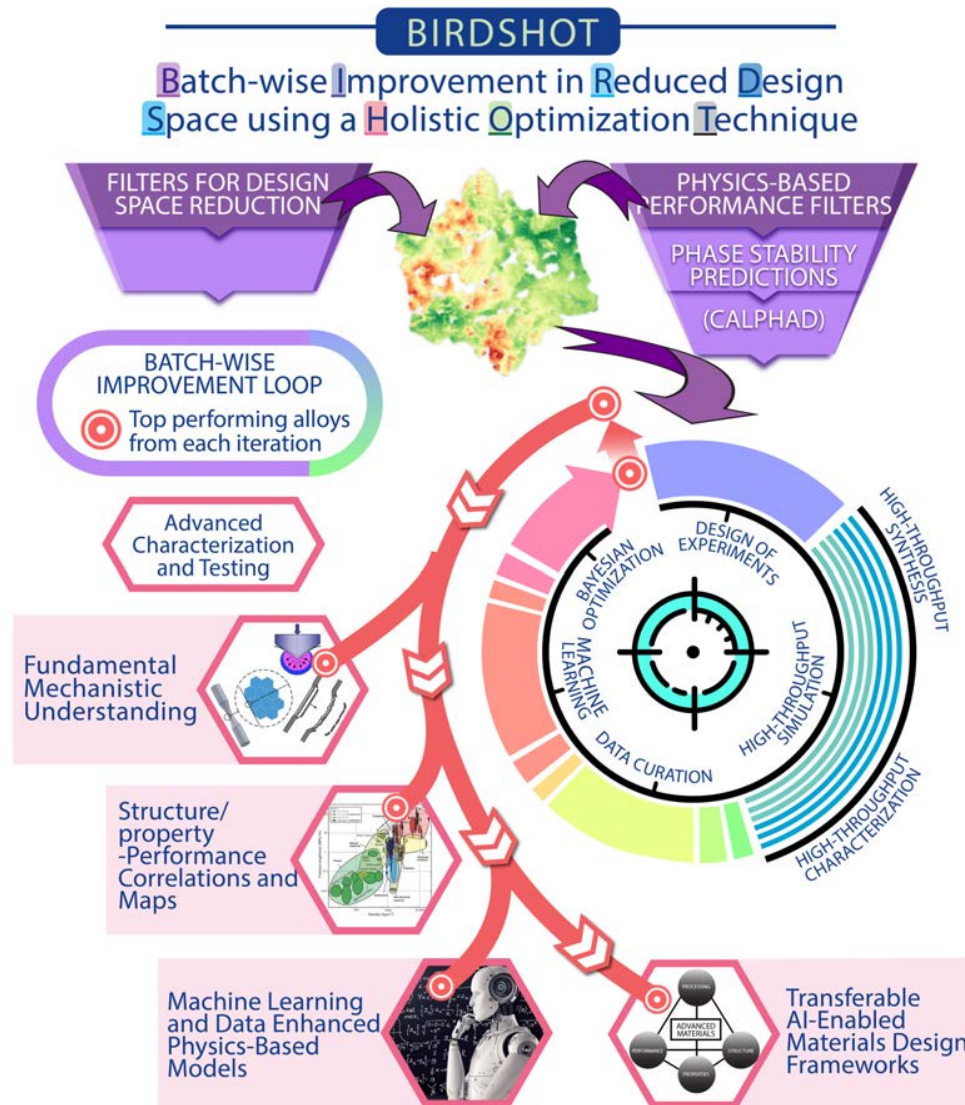
For Agile War Fighter Technology Development



BIRDSHOT CAPABILITIES PORTFOLIO

- ARMY+ARL Partners
 - Identify Army Requirements & Responsive R&D
 - Inform and Collaborate in Research and Transitioning
- TAMU+GTECH+UCSD:
 - Beyond SOA High-Throughput Synthesis of Advanced Army-relevant Materials
 - World-unique HTP Characterization of Materials' Response under *EXTREME CONDITIONS*
 - Best-in Class AI/ML Enabled Materials Discovery/Design Frameworks
 - Highly Integrated Multi-Scale Modeling Capabilities
 - Efficient Integrated Center-wide Data Management Tools
- **INDUSTRY PARTNERS:**
 - Provide Needed Core Competencies in Scale-up and Commercialization
 - Collaborate in Research
 - Co-invest in the Center

The BIRDSHOT Way



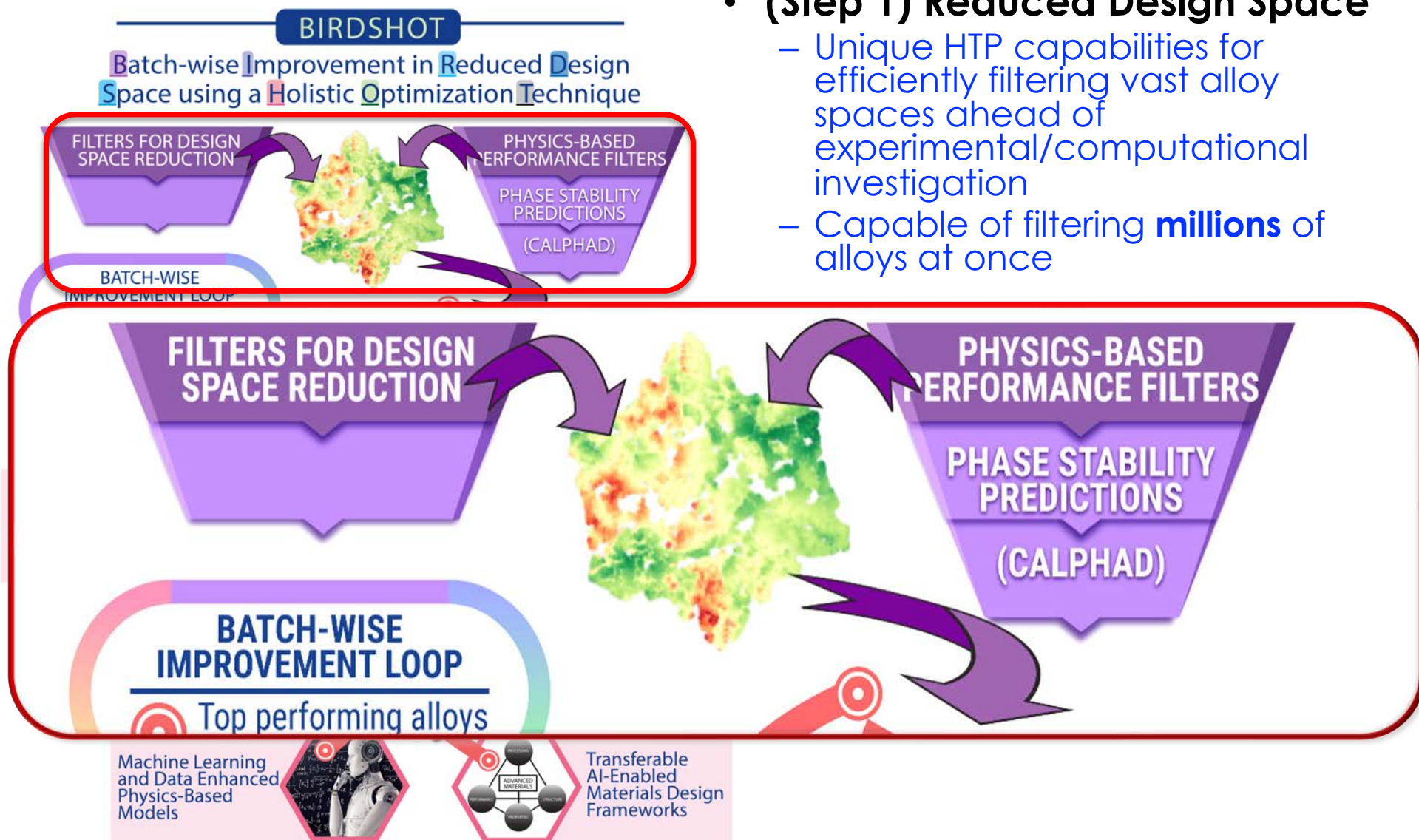
BIRDSHOT Approach:

- **Step 1:** Filter Alloy/Materials Space
- **Step 2:** HTP Synthesis
- **Step 3:** HTP Characterization (Extreme Conditions)
- **Step 4:** HTP Simulations
- **Step 5:** Optimal Learning of Physics of HSR Deformation
- **Step 6:** Deploy Multi-Information Source Batch Bayesian Optimization

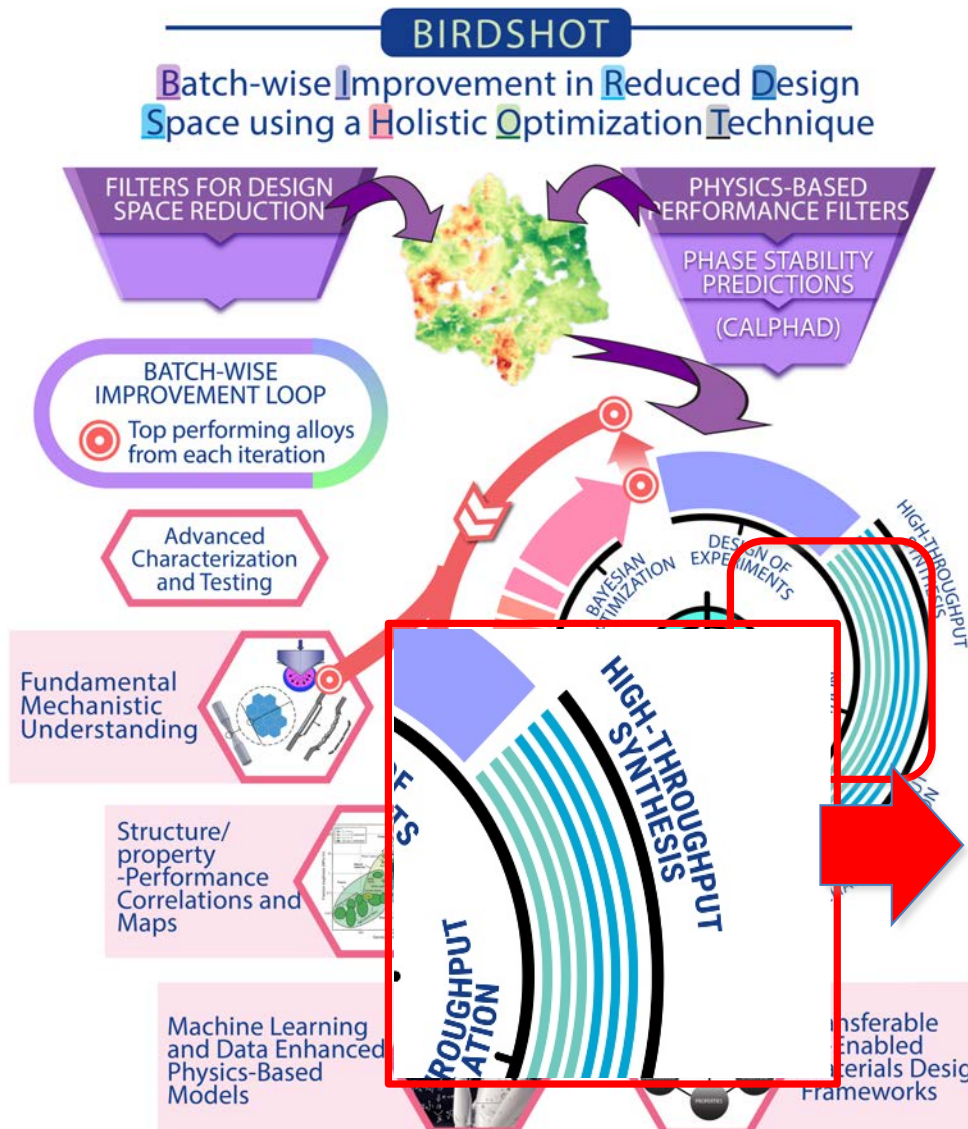
HTP Screening (Arroyave)

• (Step 1) Reduced Design Space

- Unique HTP capabilities for efficiently filtering vast alloy spaces ahead of experimental/computational investigation
- Capable of filtering **millions** of alloys at once



HTP Synthesis (Vecchio, Karaman)



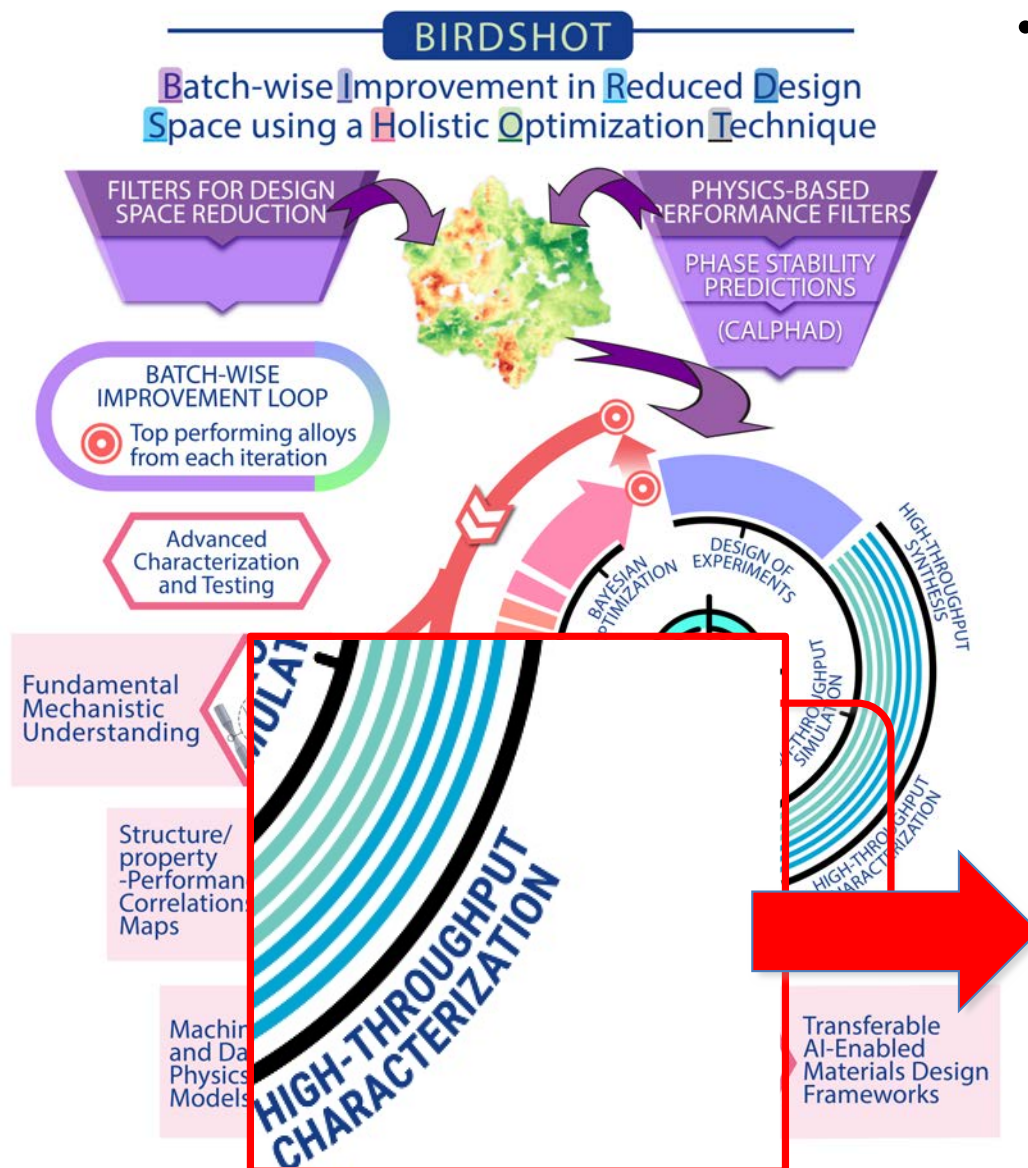
• (Step 2) HTP Synthesis

- Highly integrated, beyond SOA HTP synthesis and preparation platform
- (DED-based Alloy Prototyping)

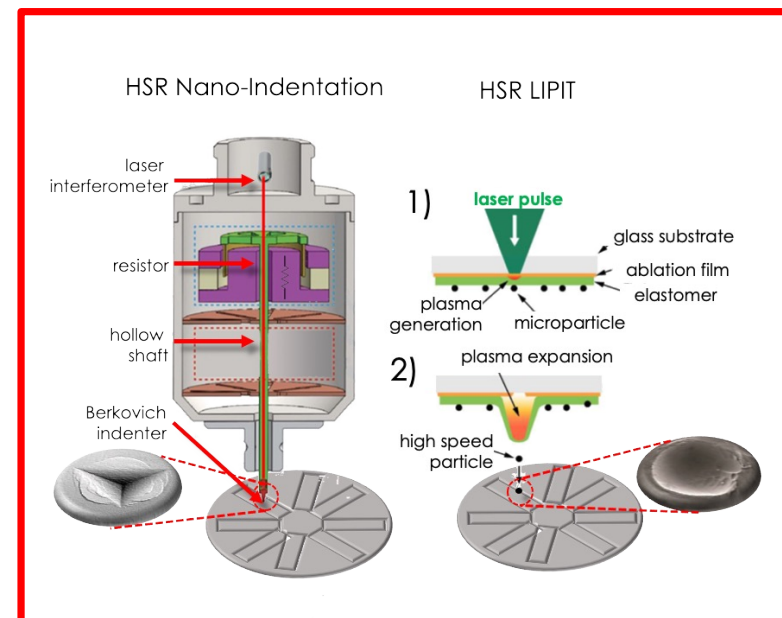
HT-READ



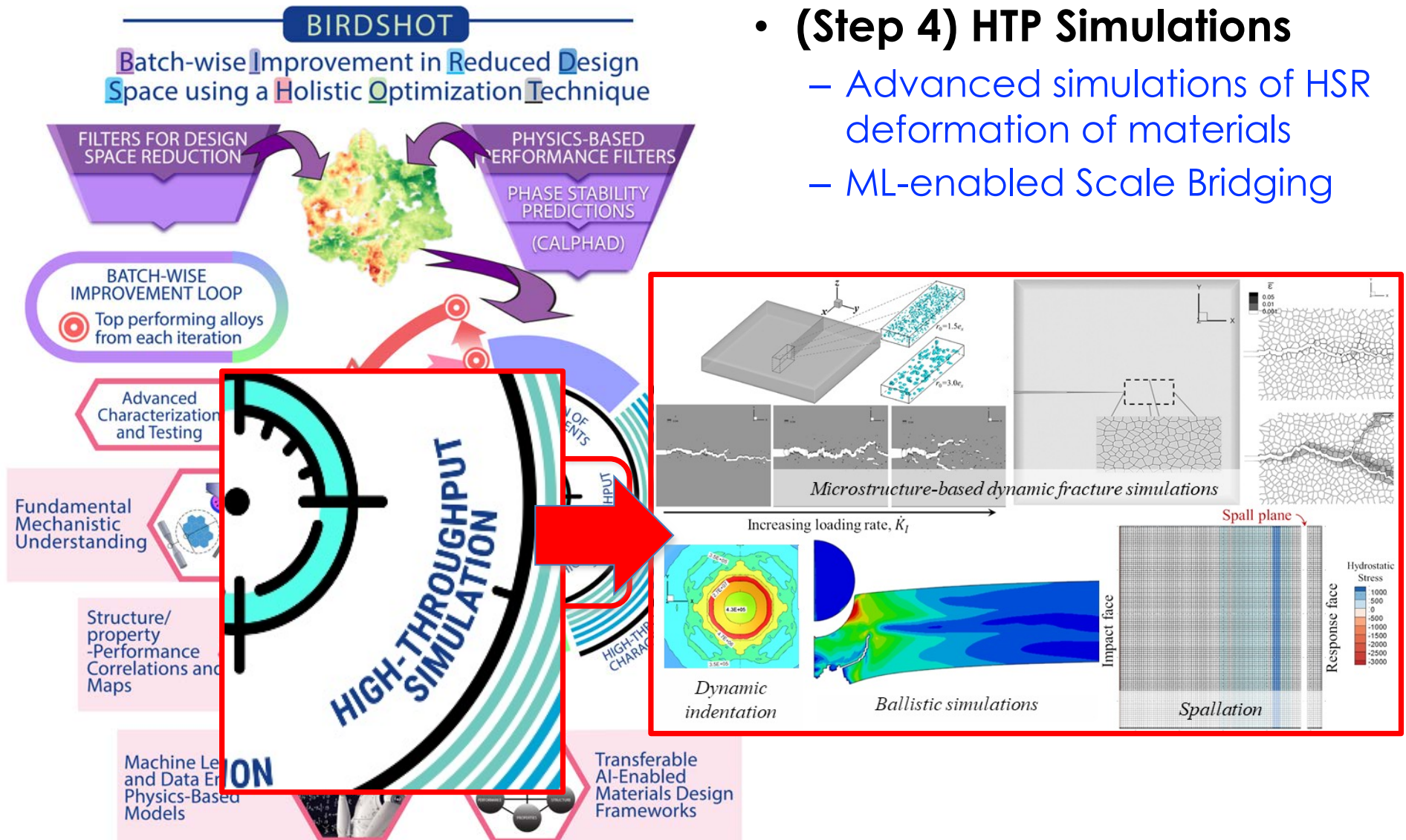
HTP Characterization (Pharr, Thomas)



- **(Step 3) HTP Characterization**
 - HTP nano indentation at high-strain rates and temperatures (Pharr)
 - HTP Laser Induced Particle Impact Testing (LIPIT) (Thomas)
 - Strain Rates: 10^3 - 10^8 /s
 - Other extreme conditions (i.e. high temperature, oxidation, etc.)



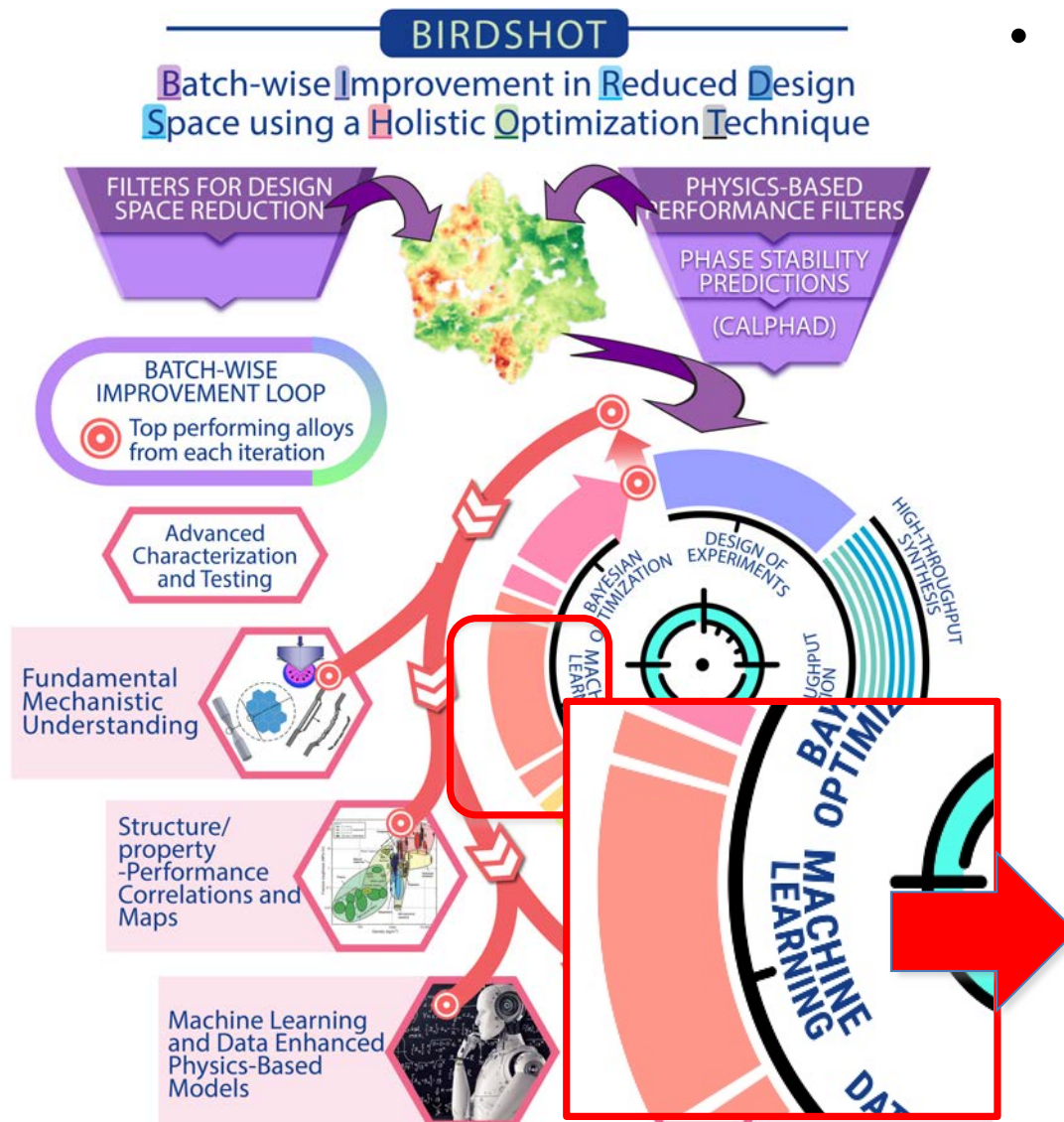
HTP Simulations (Srivastava)



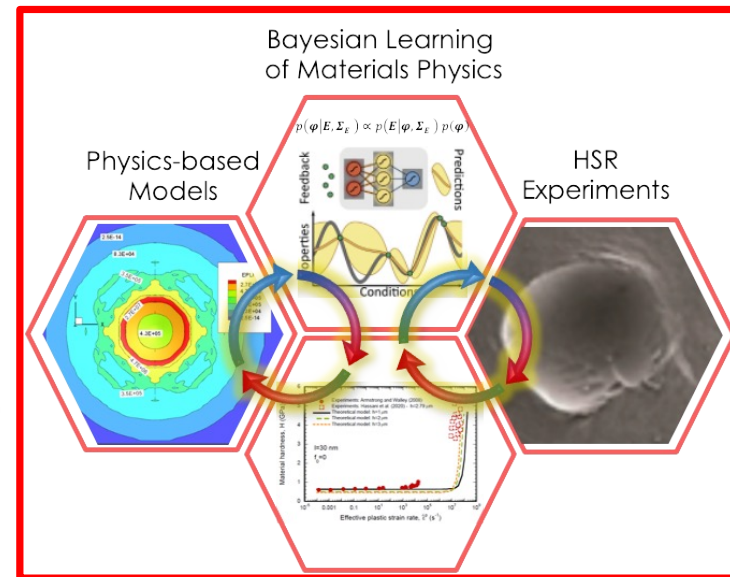
• (Step 4) HTP Simulations

- Advanced simulations of HSR deformation of materials
- ML-enabled Scale Bridging

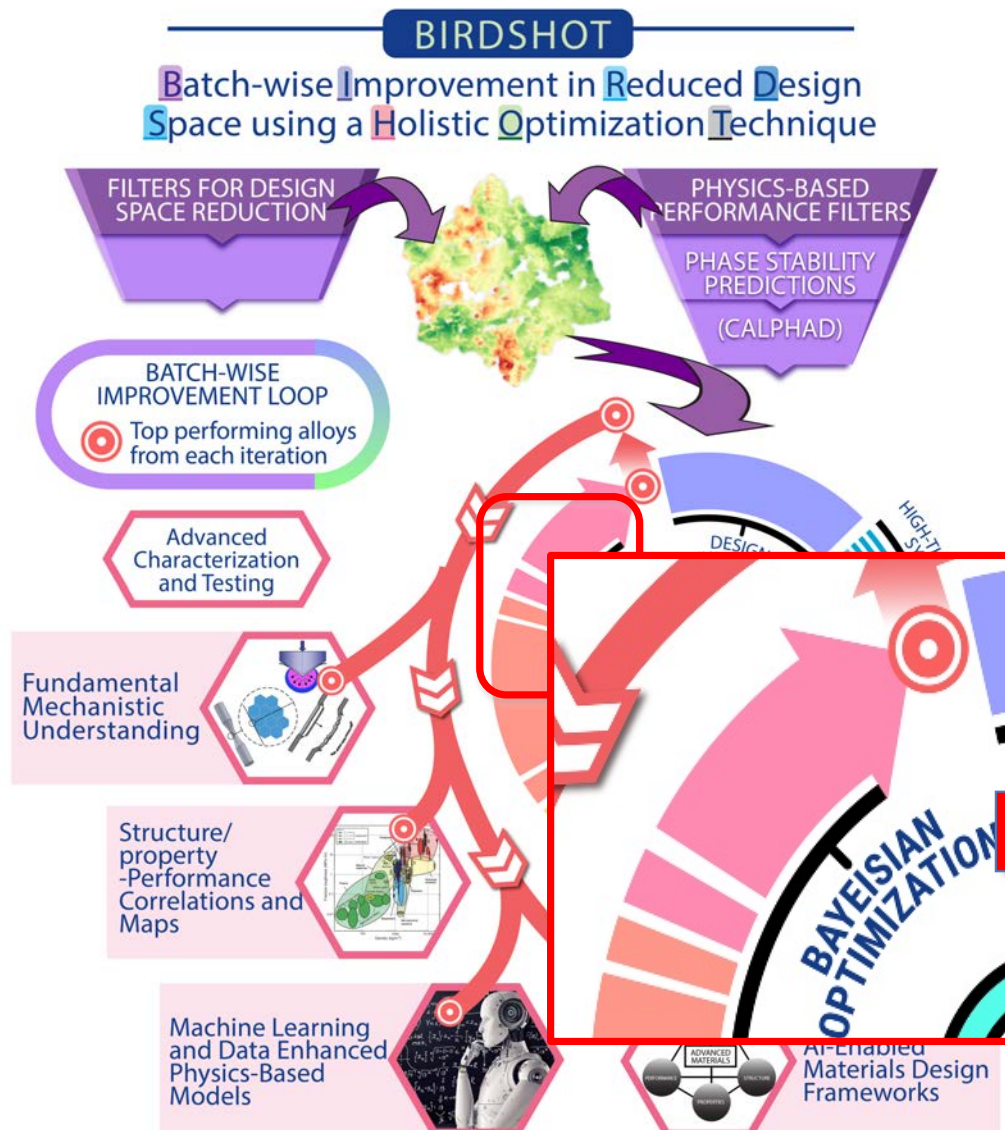
Optimal Learning (Srivastava, Kalidindi, Arroyave, Allaire)



- **(Step 5) ML-Physics Coupled Models**
 - Bayesian approaches for accelerated learning of physics of HSR deformation
 - Enabled by Physics-Constrained Fast-Acting ML Surrogate Models



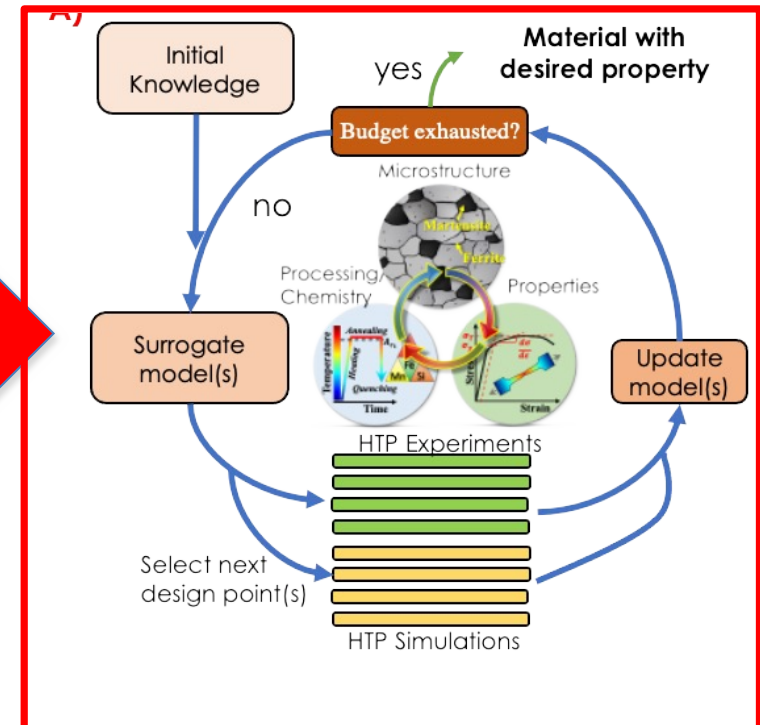
Bayesian Optimization (Srivastava, Allaire, Arroyave)



• (Step 6) Bayesian Optimization

– BO Capabilities:

- Sparse data sets
- Multi-Information Source
- Multi-Objective, Multi-Constraints
- Batch (to account for parallel experiments)
- Microstructure Aware



Workforce Development

Computational Materials
Science Summer School:

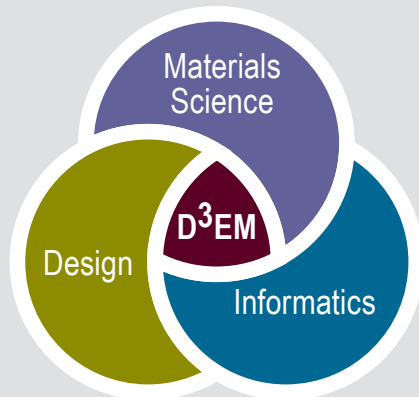


D³EM Program:

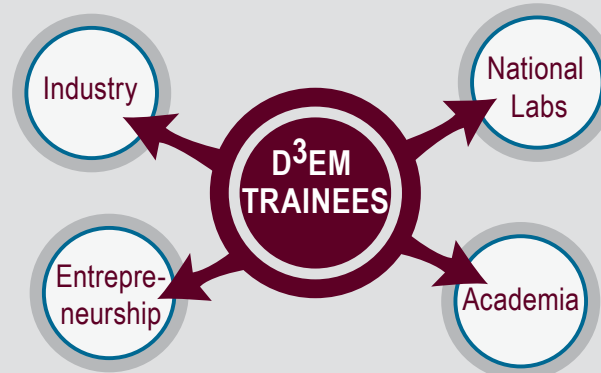
SIX DEPARTMENTS • THREE DISCIPLINES • ONE VISION

Building a collaborative framework for the accelerated development of materials through materials science, informatics, and engineering design.

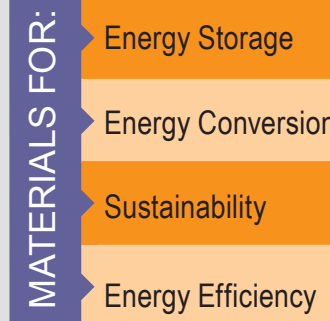
TRANSCEND DISCIPLINES



LAUNCH SUCCESSFUL CAREERS



IMPACT ENERGY
TECHNOLOGY & SYSTEMS





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Our Vision: An Autonomous Materials Research & Development Platform


INTUITIVE HUMAN-FRIENDLY INTERFACES



CLOUD-BASED DATA MANAGEMENT



HUMAN-IN-THE-LOOP AI-ENABLED DISCOVERY



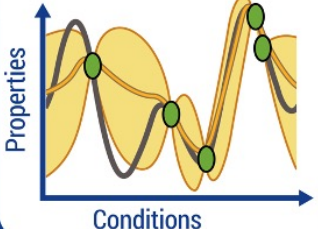
AI-BASED CONTROL



AUTOMATED EXPERIMENTATION PLATFORMS

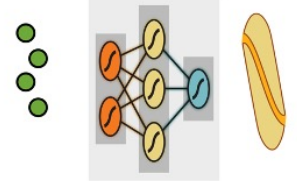


AI-AIDED EXPERIMENT PLANNING

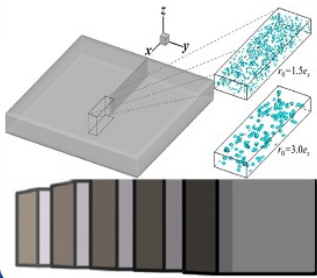


SCIENTIFIC MACHINE LEARNING

$F=ma$



HIGH-PERFORMANCE COMPUTING





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THANKS!

