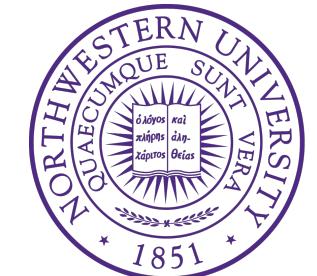


# Artificial Intelligence for Accelerating Materials Science and Engineering: *Leveraging GNNs, LLMs, XAI, Nanocombinatorics, and more*



Northwestern  
University

Ankit Agrawal  
Research Professor

Department of Electrical and Computer Engineering,  
Northwestern University



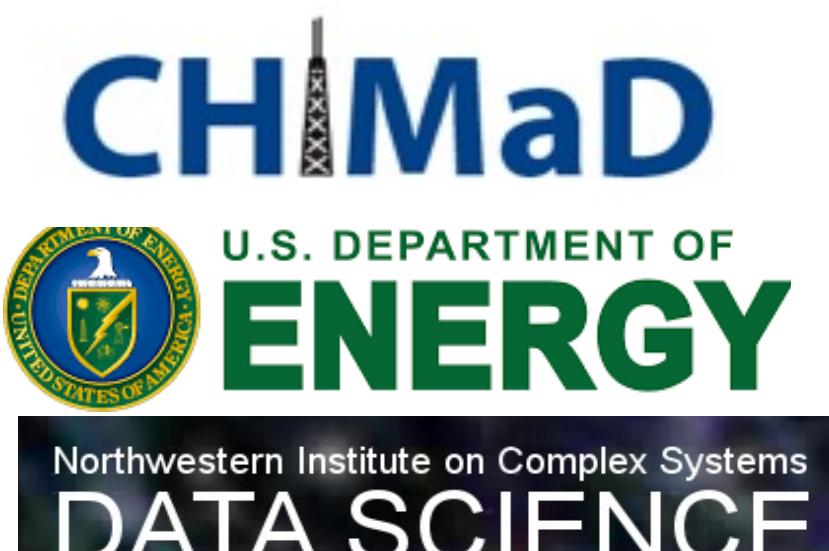
**Team Members:** Alok Choudhary, Wei-keng Liao, Sunwoo Lee, Rosanne Liu, Dipendra Jha, Arindam Paul, Zijiang Yang, Vishu Gupta, Yuwei Mao, Kewei Wang, Youjia Li, Alexandra Day, Talha Kilic, Sayak Chakrabarty

**Collaborators:** Surya Kalidindi (GaTech), Greg Olson (MIT, QuesTek), Chris Wolverton (NU), Peter Voorhees (NU), Veera Sundaraghavan (UMich), Marc De Graef (CMU), Wei Chen (NU), Michael J Bedzyk (NU), Yip-Wah Chung (NU), Jian Cao (NU), Wing Liu (NU), Gianluca Cusatis (NU), Chad Mirkin (NU), Vinayak Dravid (NU), Roberto dosReis (NU), Cate Brinson (Duke), Pinar Acar (VT), Wei Xiong (UPitt), Ian Foster (UC), Logan Ward (UC/ANL), Kasthurirangan Gopalakrishnan (ISU), Carelyn Campbell (NIST), Kamal Choudhary (NIST), Francesca Tavazza (NIST), Brian DeCost (NIST), Gilad Kusne (NIST), Andrew Reid (NIST), Daniel Wines (NIST), Stefanos Papanikolaou (WVU), Prasanna Balaprakash (ANL), Richard Archibald (ORNL), Tetsushi Watari (Toyota), Yoshinori Suga (Toyota)

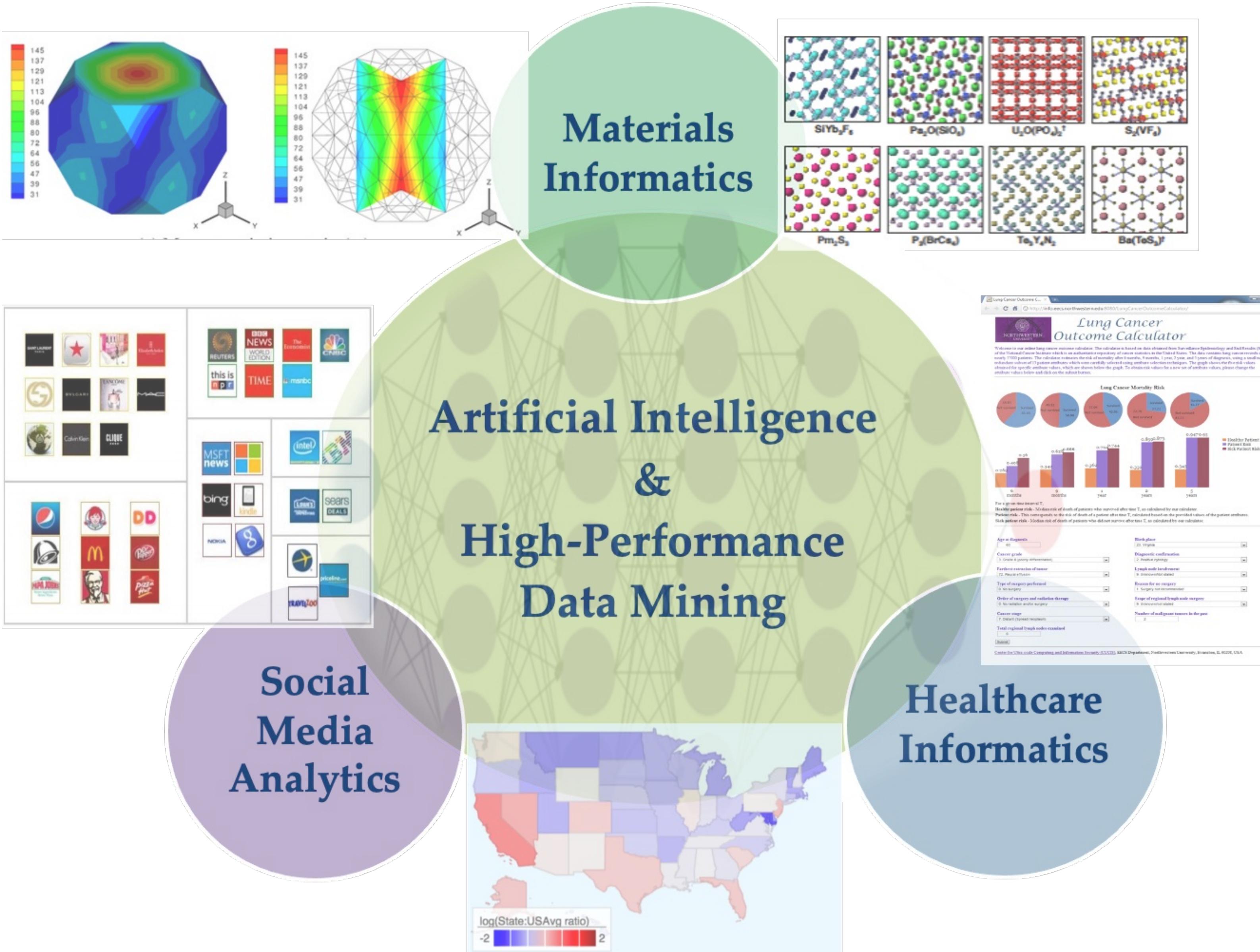


Artificial Intelligence for Materials Science (AIMS) Workshop

Rockville, MD  
July 09, 2025



# Research Thrusts



# AI for Materials: Current and Past Projects

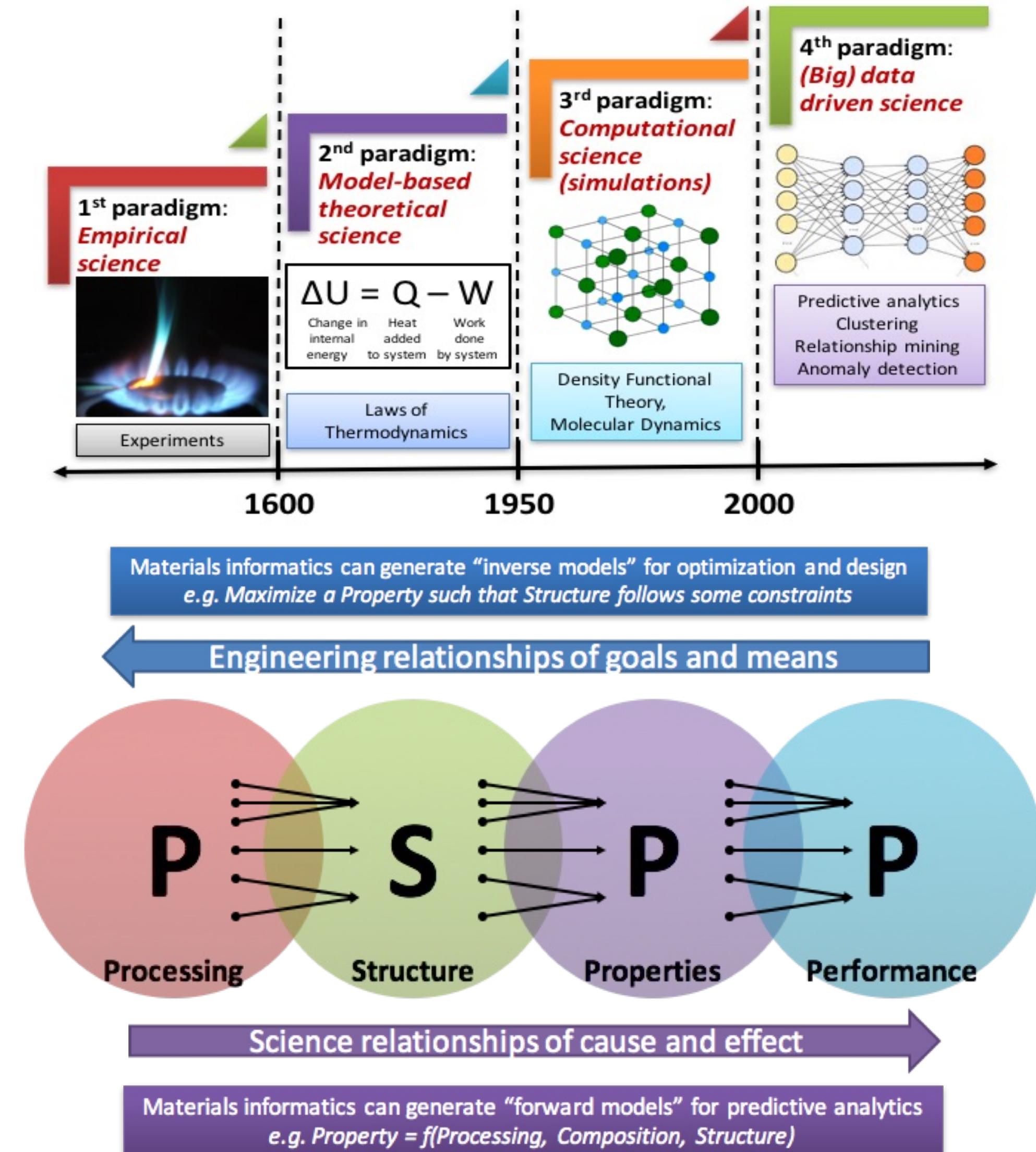
- **NIST Center of Excellence:** Center for Hierarchical Materials Design (CHiMaD)
- **AFOSR MURI:** Managing the Mosaic of Microstructure
- **DARPA SIMPLEX:** Data-Driven Discovery for Designed Thermoelectric Materials
- **NSF BigData:** SPOKE: MIDWEST: Collaborative: Integrative Materials Design (IMaD): Leverage, Innovate, & Disseminate
- **NSF CMMI:** Collaborative Research: AI-Driven Multi-Scale Design of Materials under Processing Constraints
- **NSF EAGER:** XAISE: Explainable Artificial Intelligence for Science and Engineering
- **NU Data Science Initiative:** Data-driven analytics for understanding processing-structure-property-performance relationships in steel alloys
- **DLA/SFSA:** Digital Innovation Design (DID)
- **IIN Center for Nanocombinatorics:** AI-Driven Nanocombinatorics for Accelerated Structural and Functional Characterization
- **Toyota Motor Corporation:** The investigation of machine learning for material development



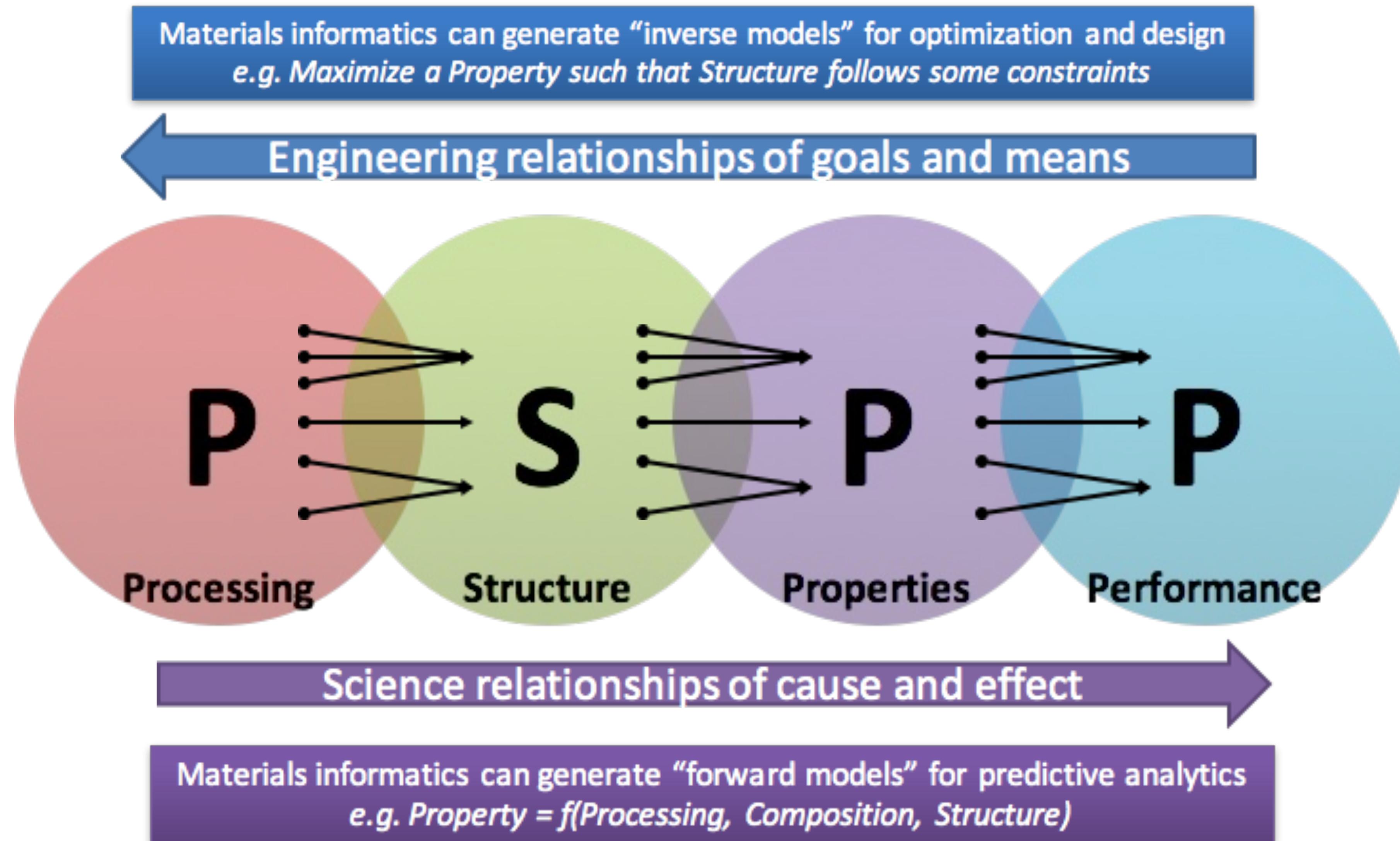
# AI for Materials: Overarching Goal

Accelerate materials property prediction, discovery, and design via:

- AI and data-driven informatics on heterogeneous materials databases (AI-ready data?) to extract actionable insights (PSPP relationships)
- Develop AI software deploying materials informatics for the community to enable AI-driven R&D at scale



# How Can AI Advance Materials Science?



# Artificial Intelligence Applications in Materials Science & Engineering

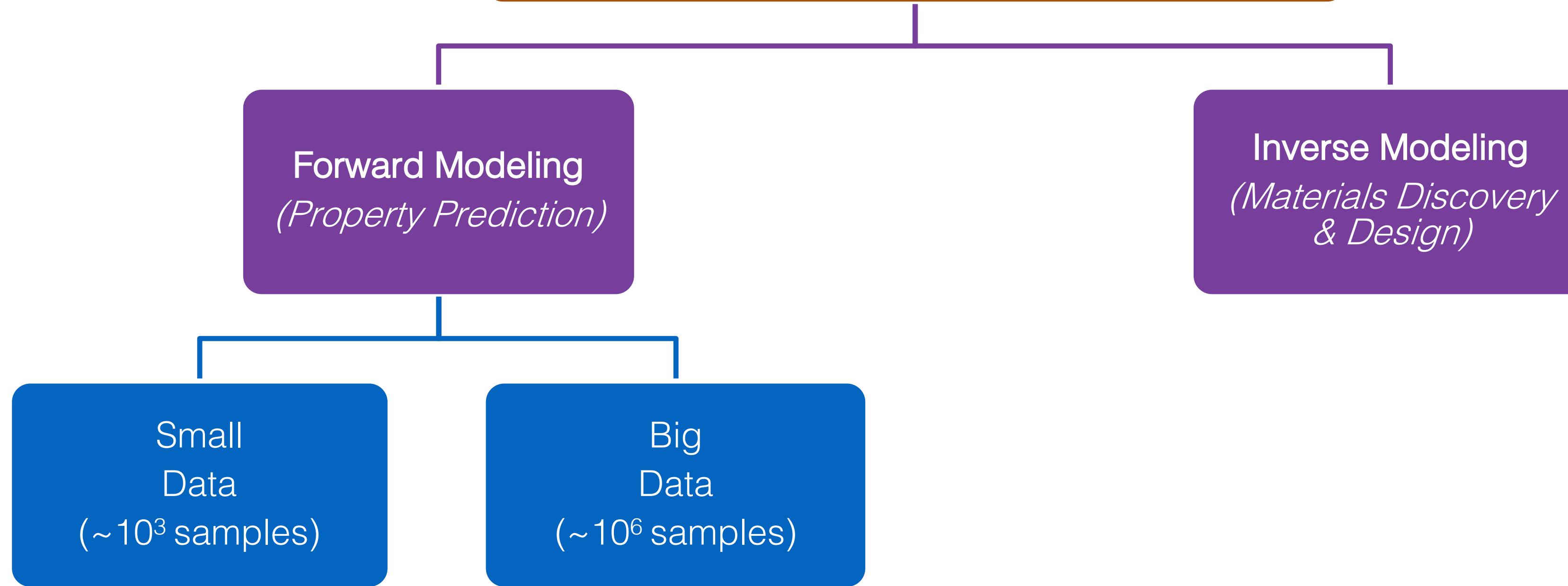
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# Artificial Intelligence Applications in Materials Science & Engineering

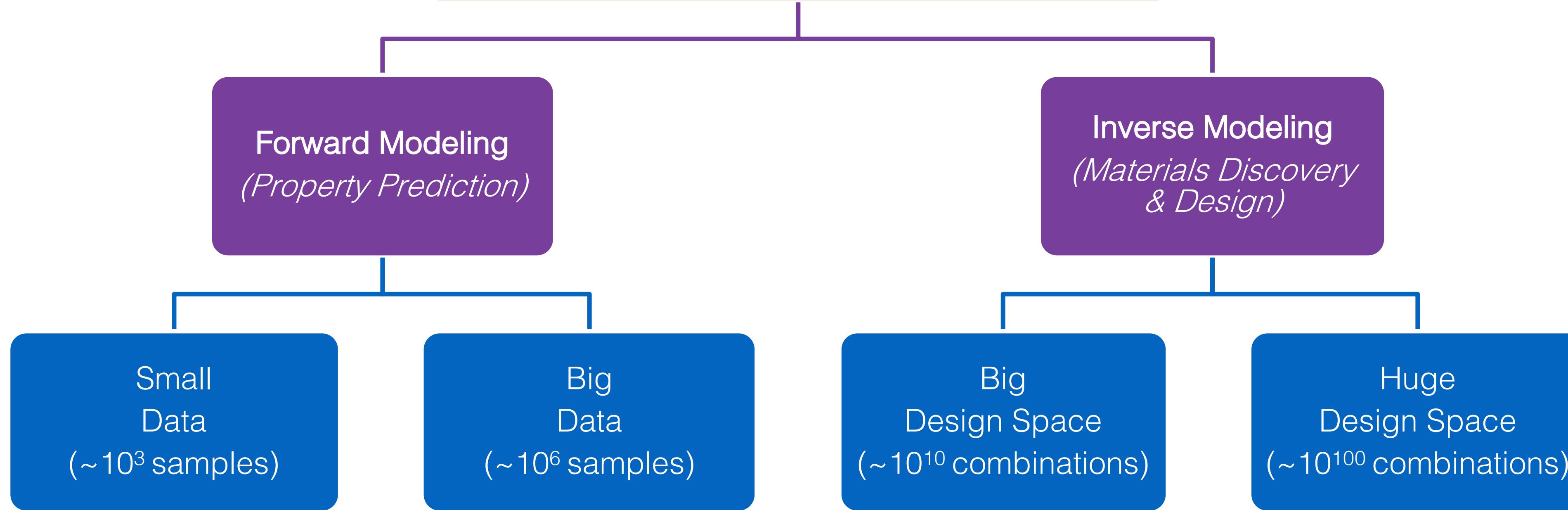
**Forward Modeling**  
*(Property Prediction)*

**Inverse Modeling**  
*(Materials Discovery  
& Design)*

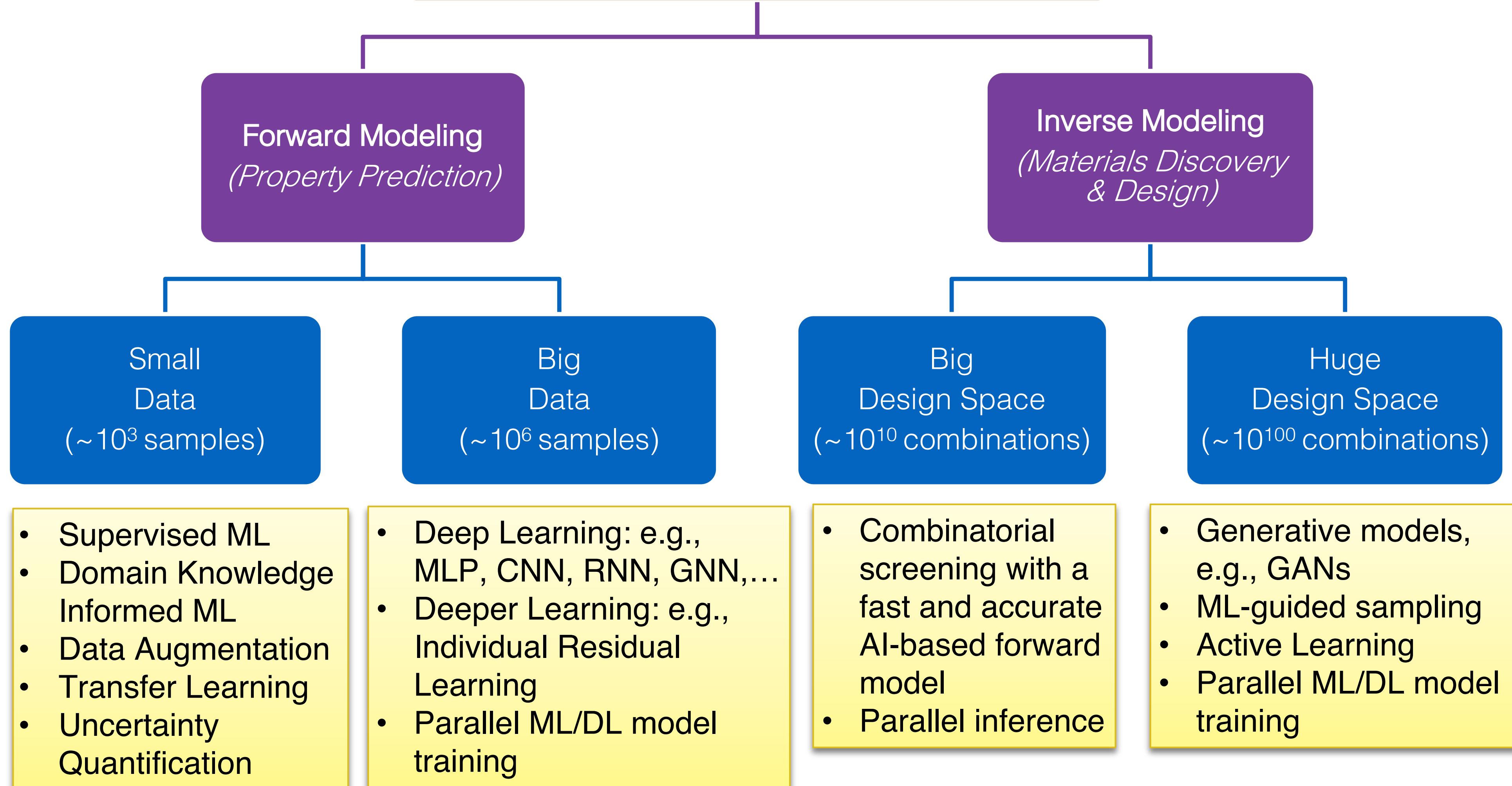
# Artificial Intelligence Applications in Materials Science & Engineering



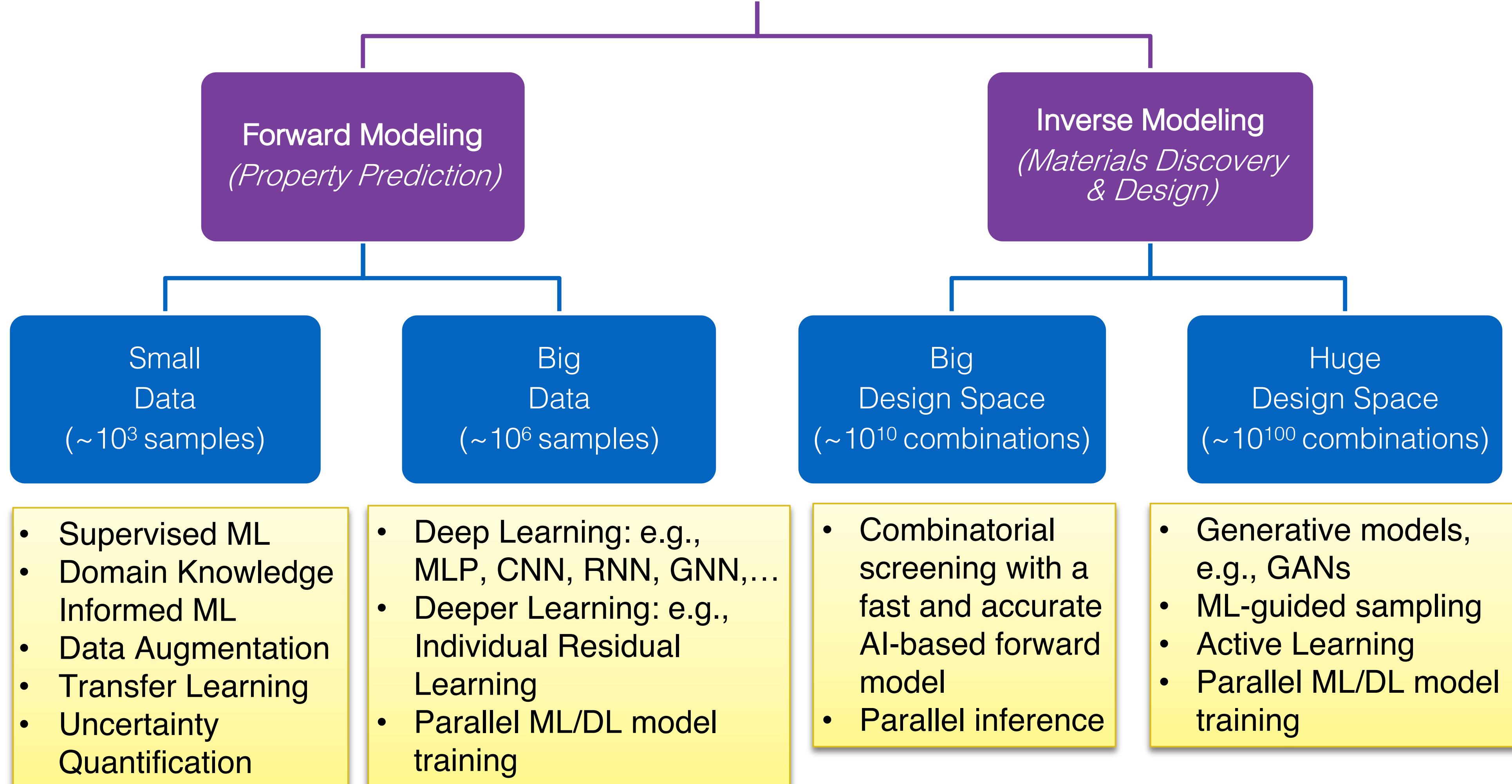
# Artificial Intelligence Applications in Materials Science & Engineering



# Artificial Intelligence Applications in Materials Science & Engineering



# Artificial Intelligence Applications in Materials Science & Engineering



Need advanced AI/ML/DL methods driven by HPC!

# AI for Materials: Selected Research Accomplishments

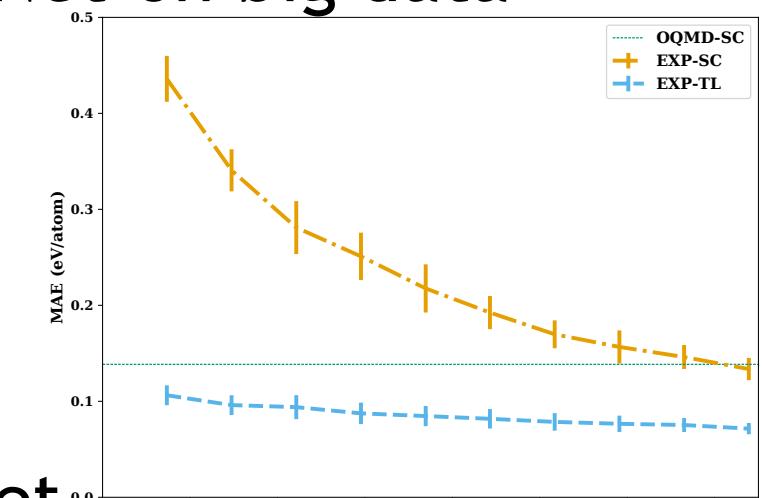
## ElemNet/ALIGNN-based Transfer Learning

Accurate models on **small data** by transferring knowledge learnt by *ElemNet* on **big data** (representation learning)

Up to 50% more accurate models

*Cross-property transfer learning, ALIGNN, XElemNet, combinatorial screening of big design space*

[SciRep 2018, NatComm 2019, NatComm 2021, JCIM 2023, IJCNN 2023, npjCM 2024, ICMLA 2024, SciRep 2024]

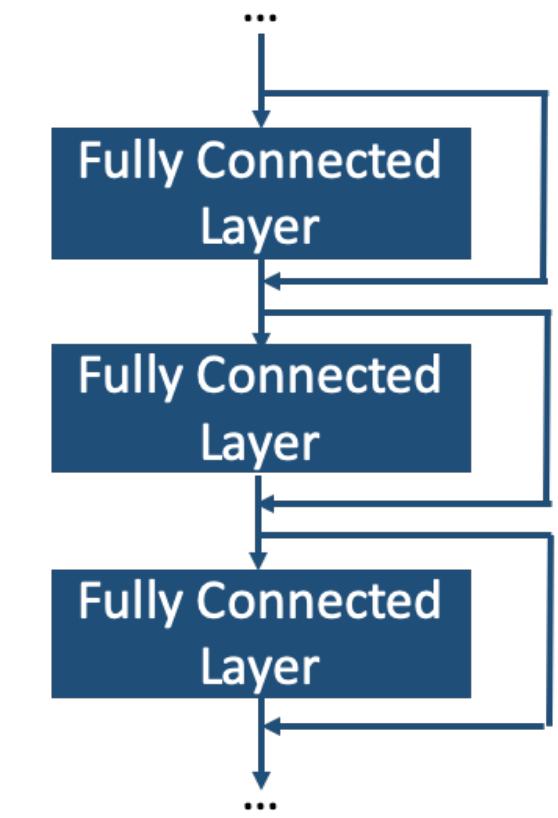


## IRNet/BRNet: Individual/Branched ResNet

Enables deeper learning on **big data** without the issue of *vanishing gradients*

Multiple property prediction models on OQMD, AFLOW, Materials Project, JARVIS

[KDD 2019, SciRep 2021, SciRep 2022 SDM 2022, JCheminformatics 2024]



## Cumulative Summary: 2014-ongoing

- 75+ publications (60+ as first/last author)
  - 25+ computer science publications
  - 50+ domain publications
  - 10000+ citations
- 5+ software tools
  - 25000+ hits from 50+ countries
- 10+ open-source code repositories
- 1 patent awarded, 2 pending

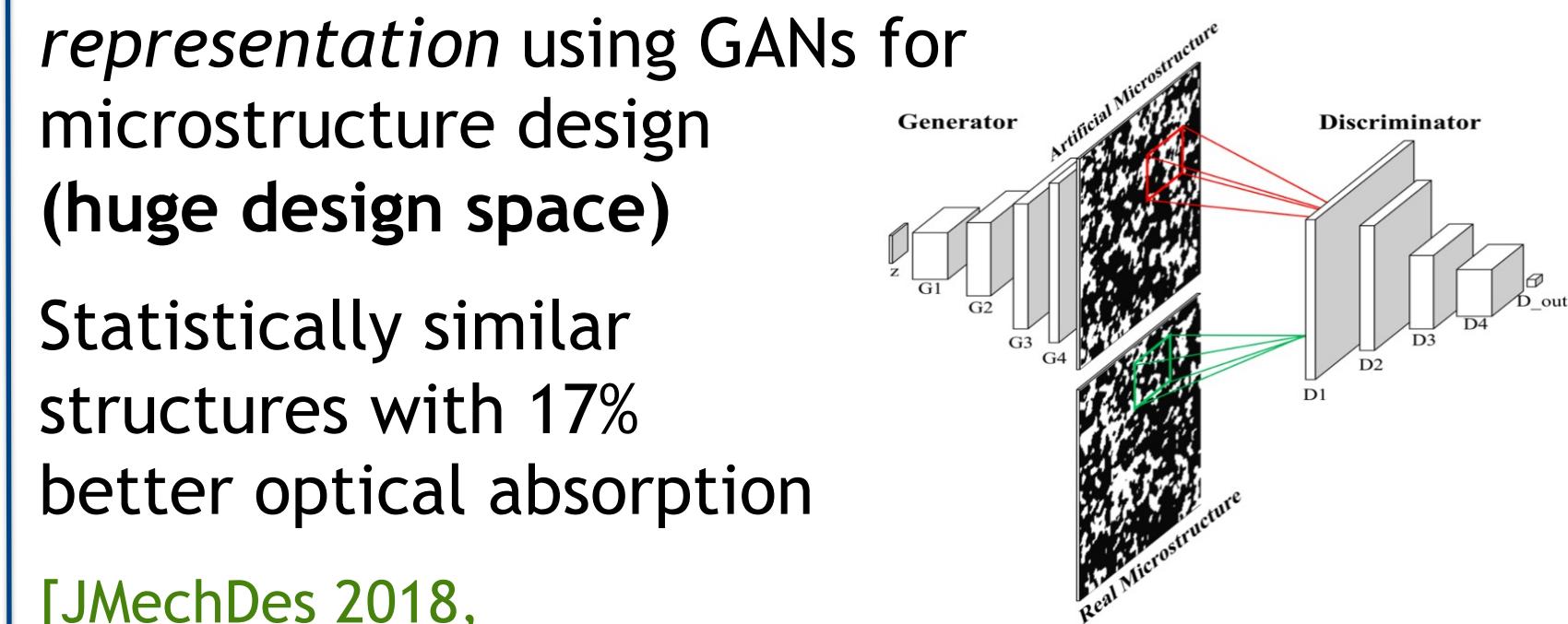
<http://ai.eecs.northwestern.edu/>

## Generative AI for Materials Design

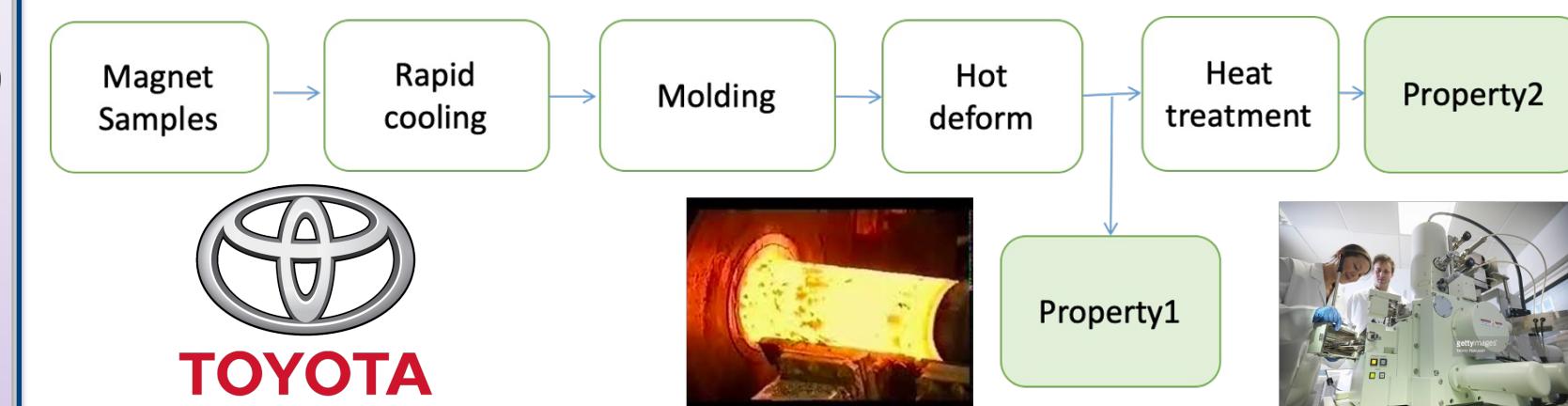
Learns a *low-dimensional microstructure representation* using GANs for microstructure design (**huge design space**)

Statistically similar structures with 17% better optical absorption

[JMechDes 2018, NeurIPS-ML4Eng 2020, IMMI 2022, ICMLA 2024]



## Industrial Materials Design



VGG16-based *deep transfer learning* on small, heterogeneous experimental data

<5% error for Hcj and Br, *huge \$\$\$ savings, faster magnets design*

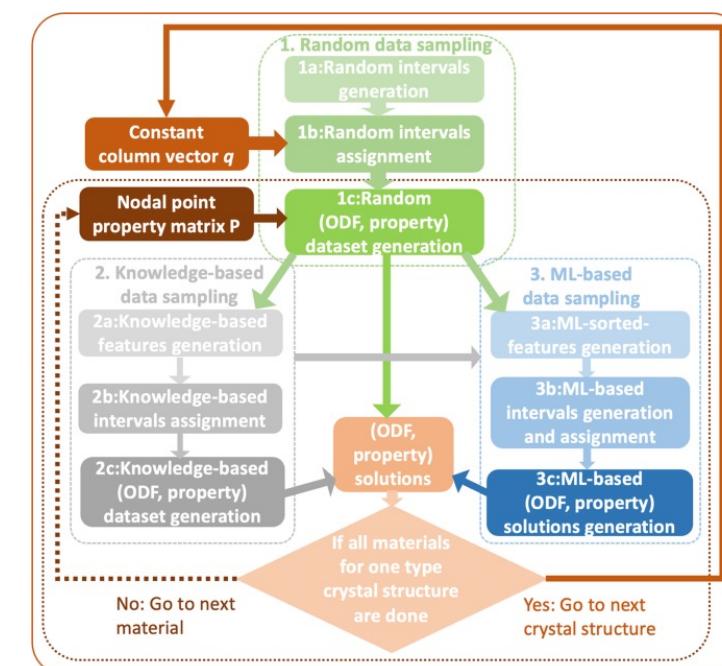
[ICDM-LMID 2019, ICPR-IML 2021]

## AI-Guided Sampling for Optimization

*Intelligent ODF sampling (huge design space)*

Galfenol (Fe-Ga) and Titanium (Ti): *Multiple, polycrystalline* microstructures discovered with *optimum properties*

Up to 70% more efficient than previous methods  
[SciRep 2015, IC3 2015, AIAA 2018, CMS 2019, npjCM 2023]



# Deep Transfer Learning for (Small) Experimental Datasets

## Motivation

- Most materials datasets (esp. experimental) are *small*
- DFT vs experiment: Formation enthalpy MAE =  $\sim 0.08$  eV/atom

## Methodology

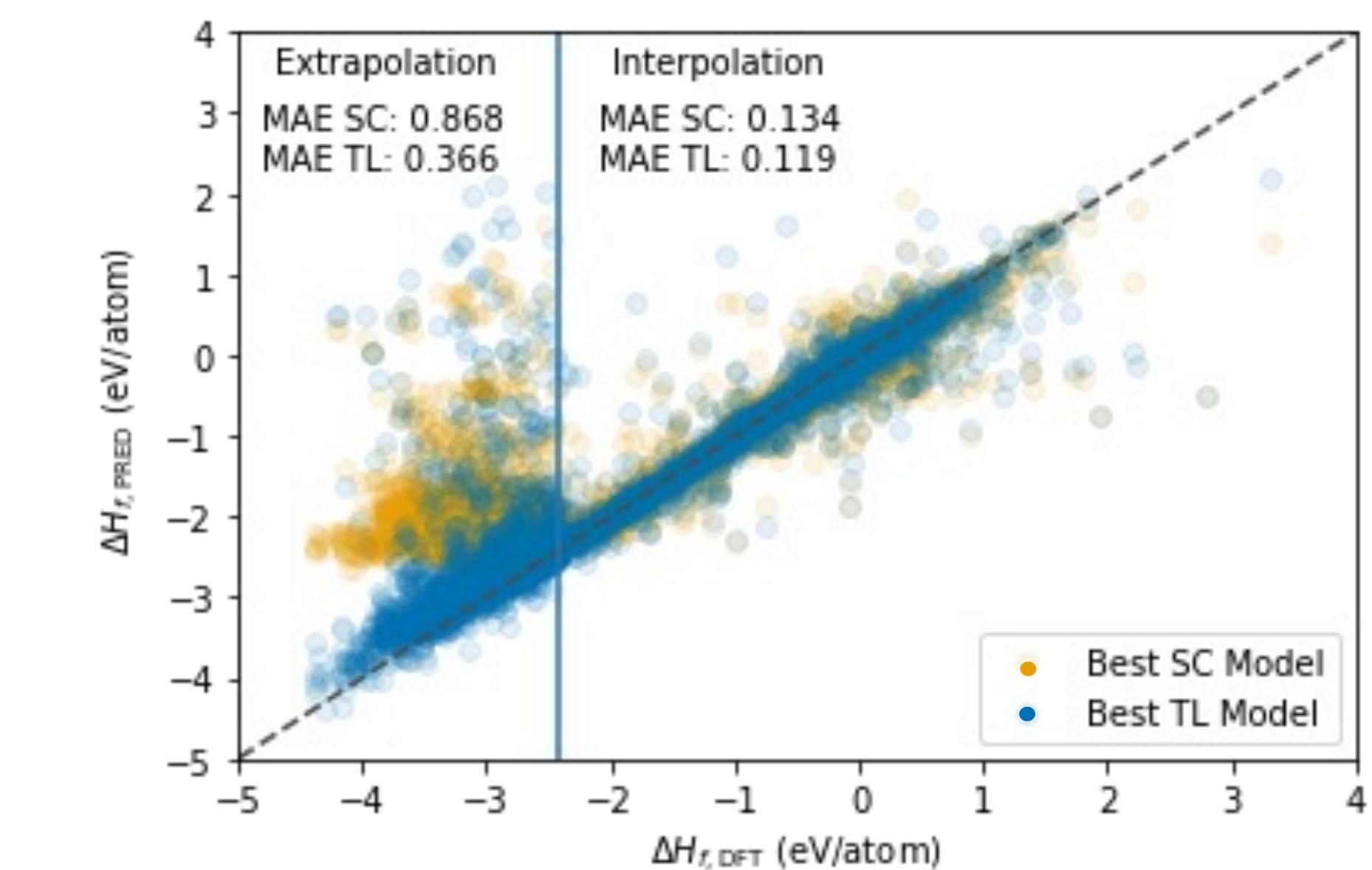
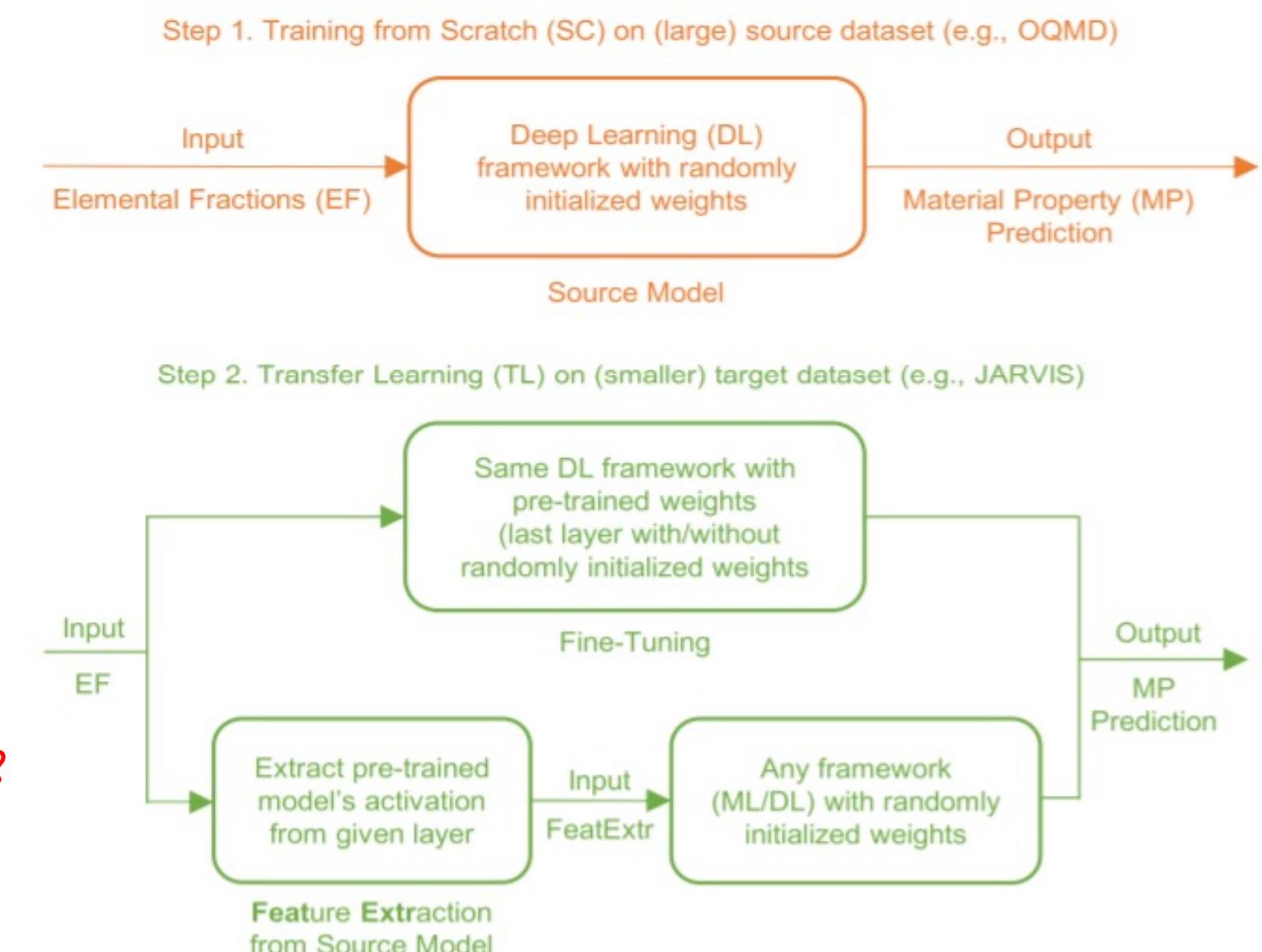
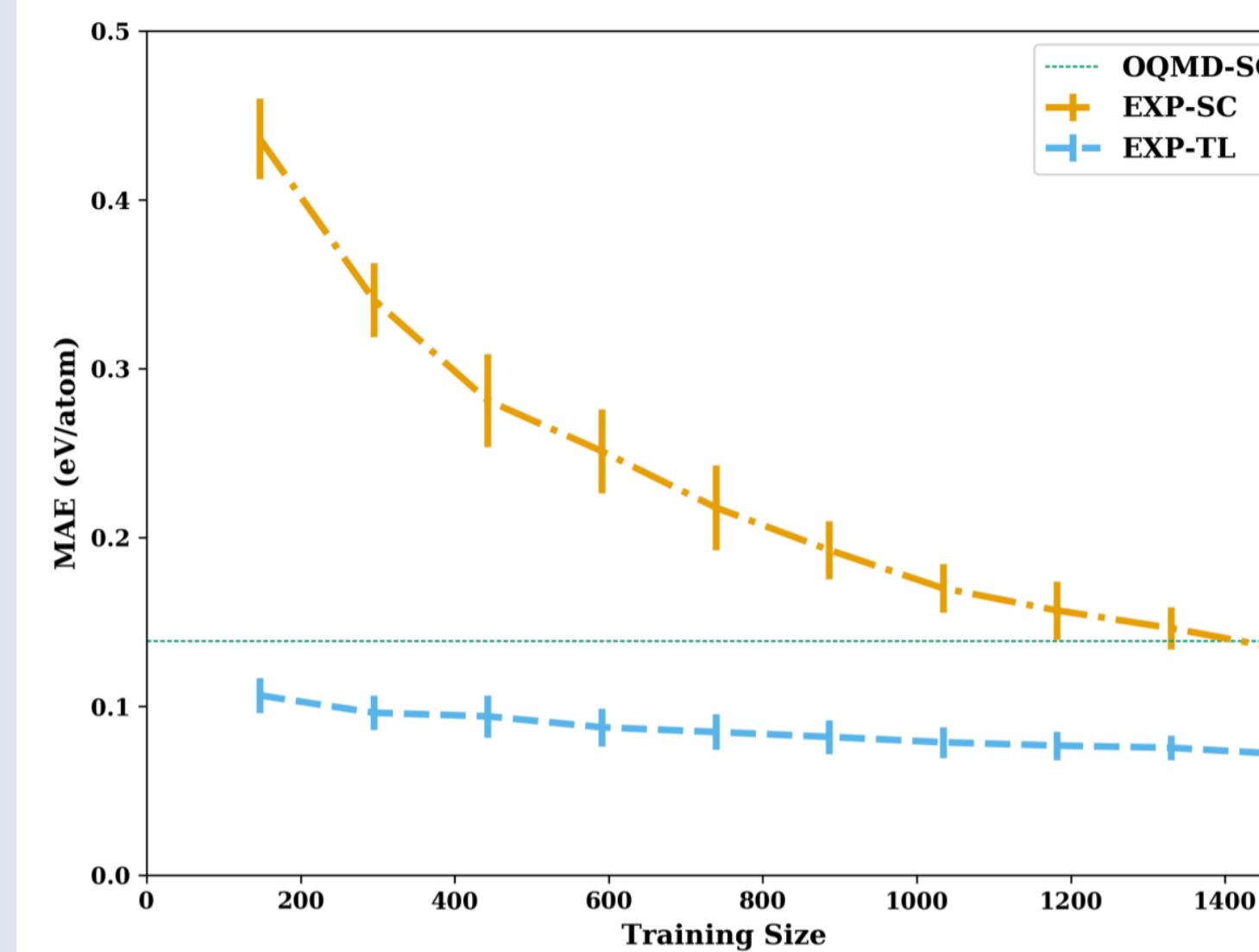
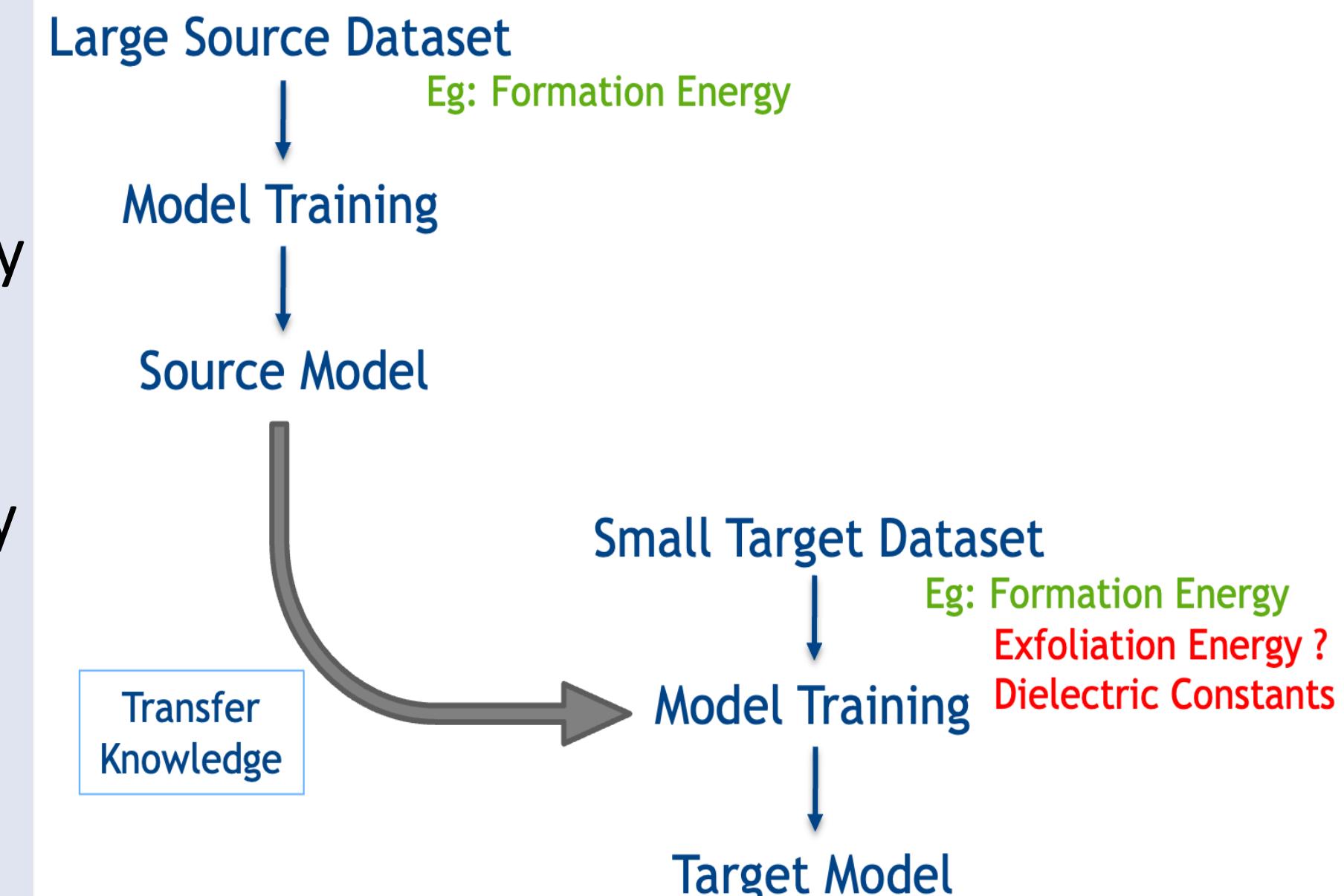
- ElemNet/ALIGNN-based cross-property *deep transfer learning*
- Fine-tuning, feature extraction, LLMs

## Datasets

- Source: OQMD
- DFT Target: JARVIS (39 properties)
- Experimental Target: 2 properties

## Results

- About 50% reduction in MAE on small (<2K) experimental data
- TL model > SC model (38/39)
- TL model > SC-PA model (27/39)
- $MAE_{FE} = \sim 0.07$  eV/atom
- Better extrapolative potential
- <http://ai.eecs.northwestern.edu/MPpredictor>

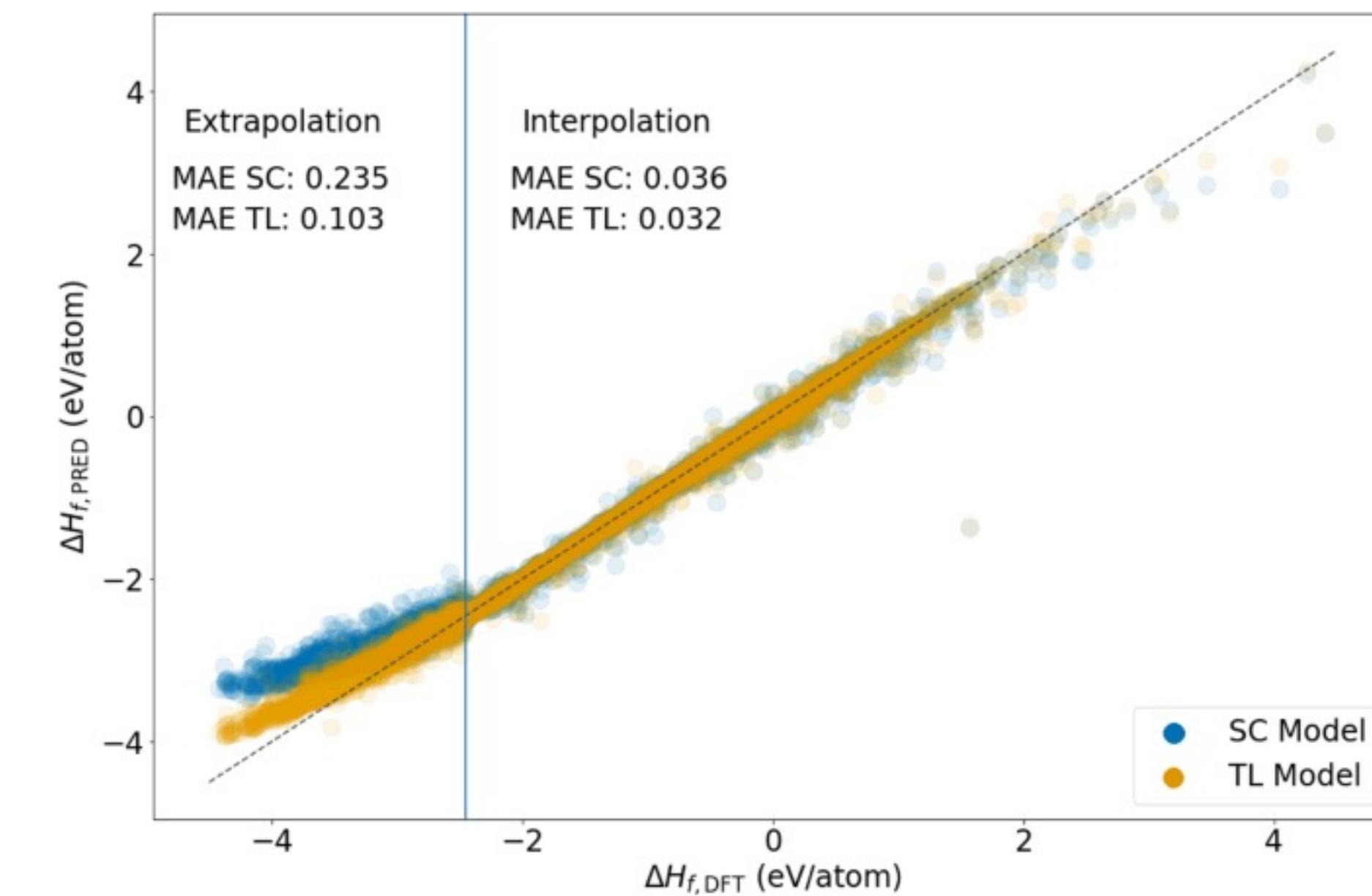
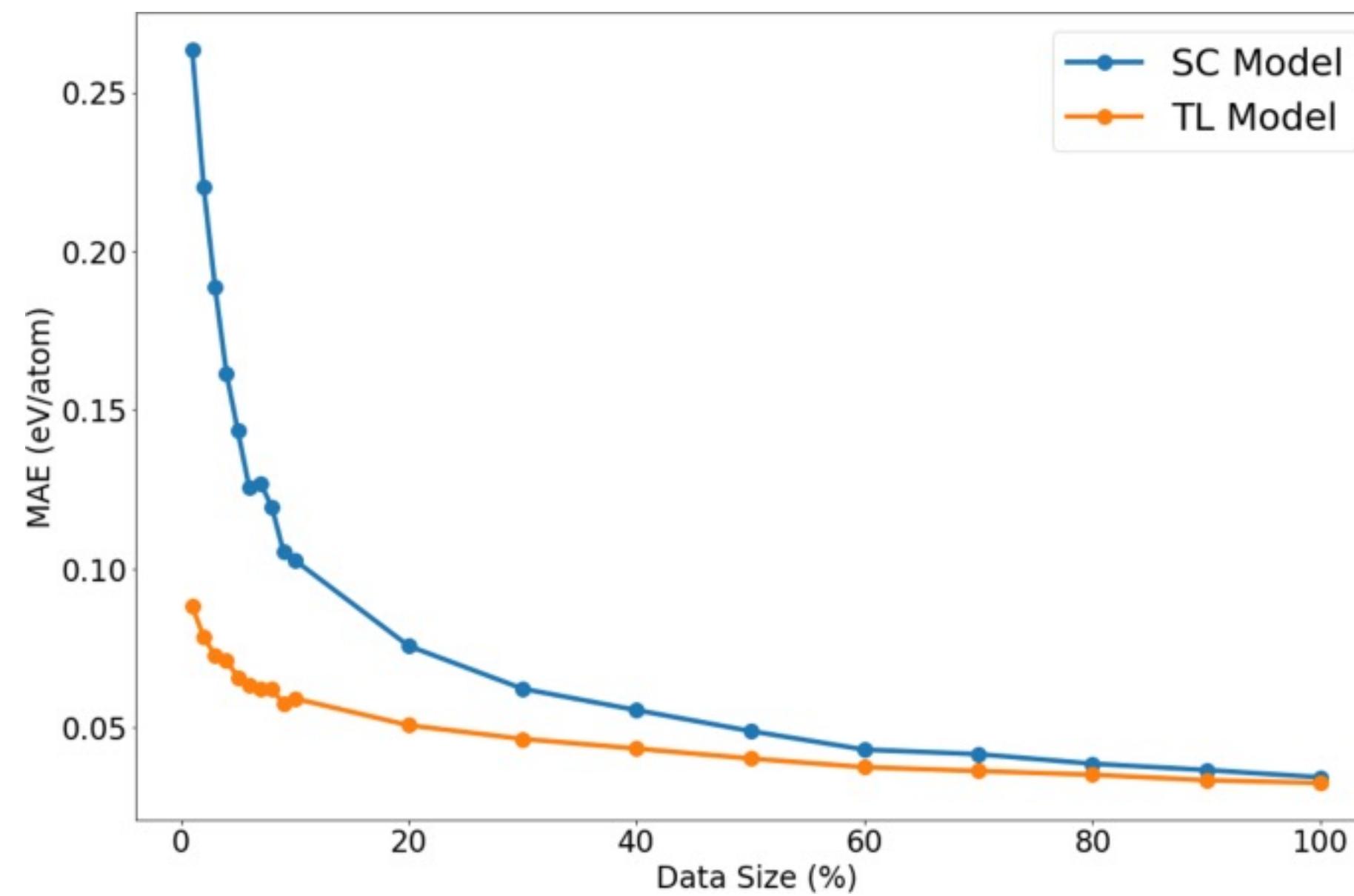
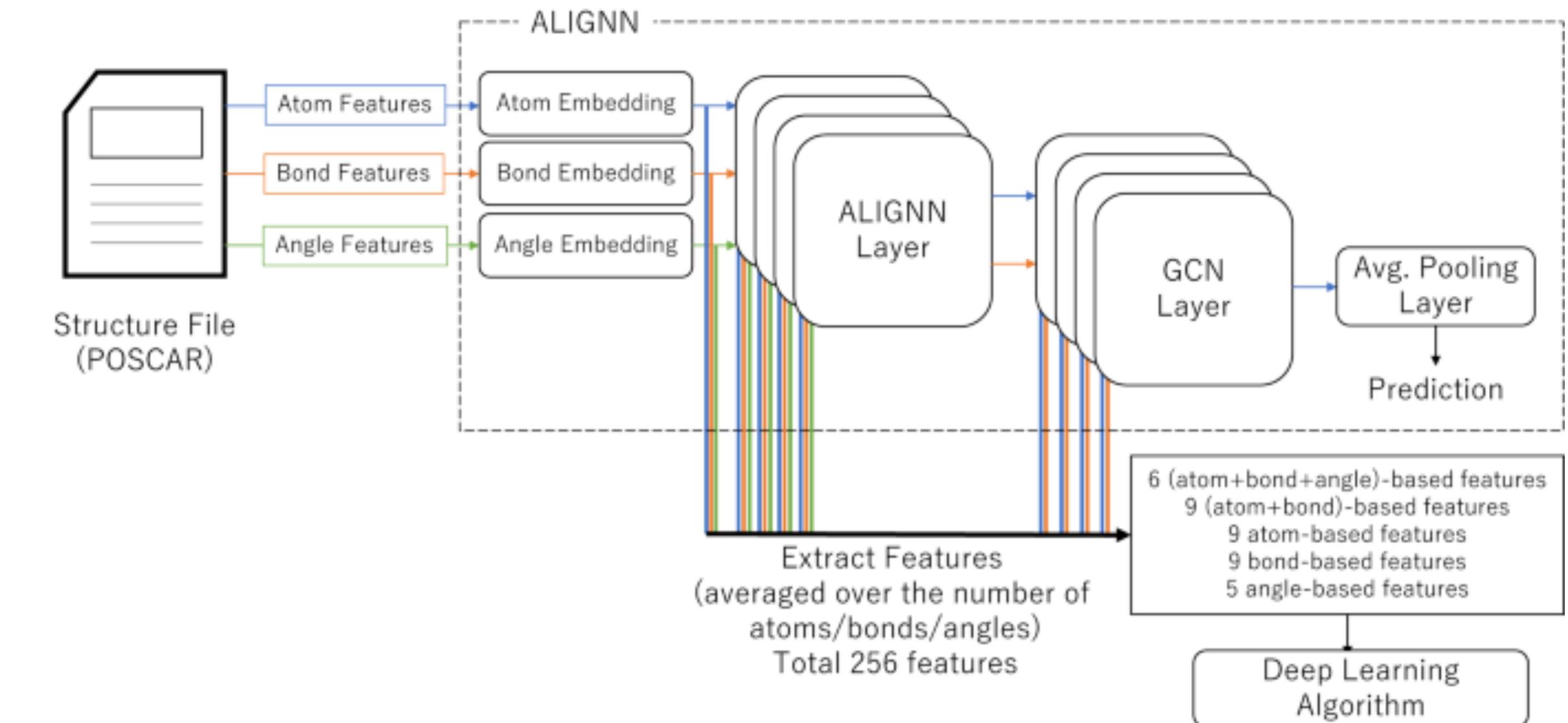


# Structure-aware graph neural network based deep transfer learning framework for enhanced predictive analytics on diverse materials datasets

[Vishu Gupta](#), [Kamal Choudhary](#), [Brian DeCost](#), [Francesca Tavazza](#), [Carelyn Campbell](#),

[Wei-keng Liao](#), [Alok Choudhary](#) & [Ankit Agrawal](#)

*npj Computational Materials* 10, Article number: 1 (2024) | [Cite this article](#)

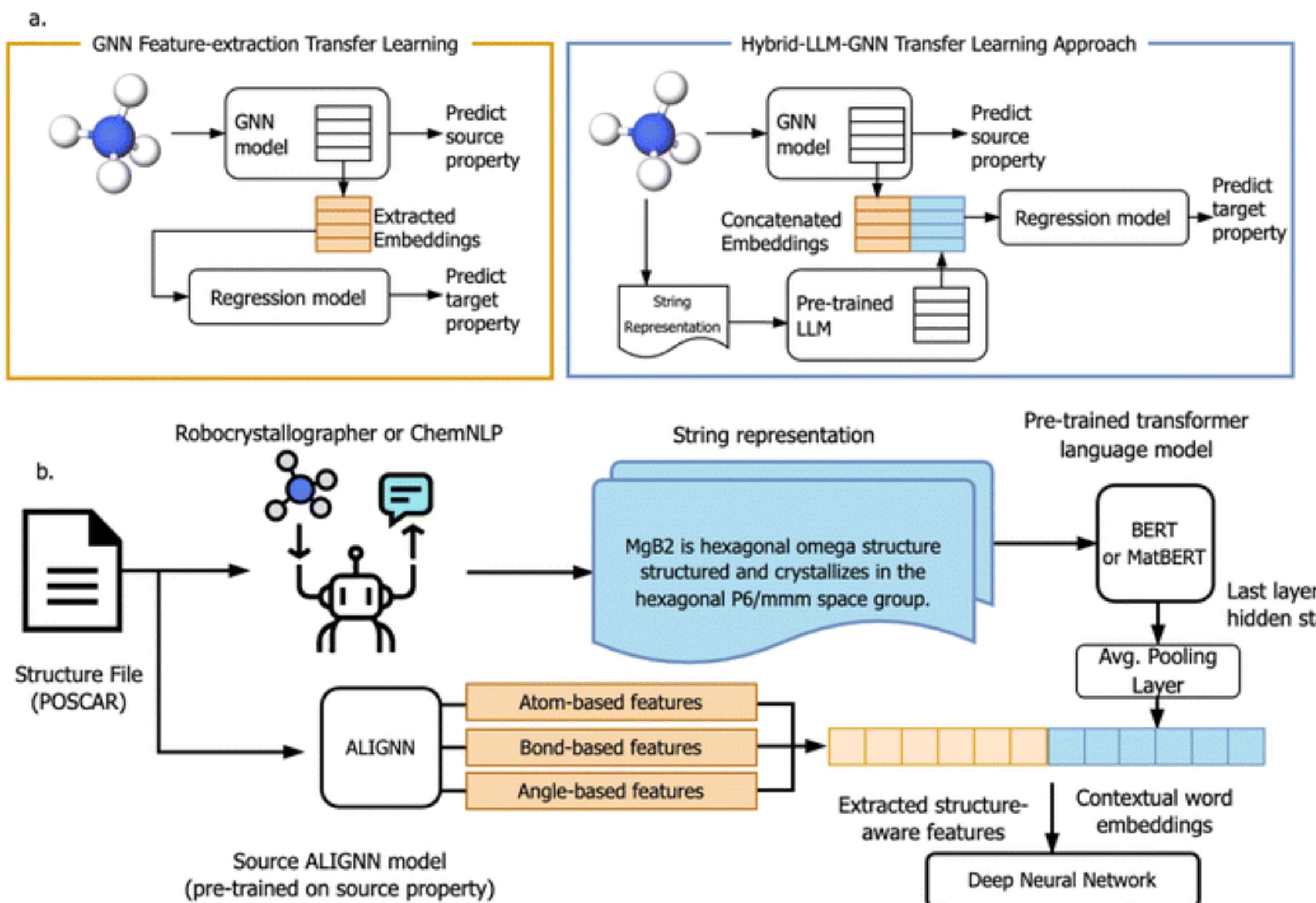


ALIGNN+TL framework evaluated on 115 diverse materials datasets (3D/2D, inorganic/organic, computational/experimental), outperformed GNN models trained from scratch in 104 cases

# Hybrid-LLM-GNN: integrating large language models and graph neural networks for enhanced materials property prediction<sup>†</sup>

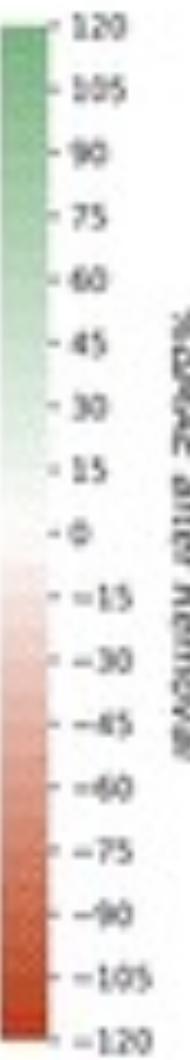
Youjia Li  <sup>\*a</sup>, Vishu Gupta  <sup>abc</sup>, Muhammed Nur Talha Kilic  <sup>d</sup>, Kamal Choudhary  <sup>ef</sup>, Daniel Wines  <sup>e</sup>, Wei-keng Liao <sup>a</sup>,

Alok Choudhary<sup>a</sup> and Ankit Agrawal<sup>\*a</sup>

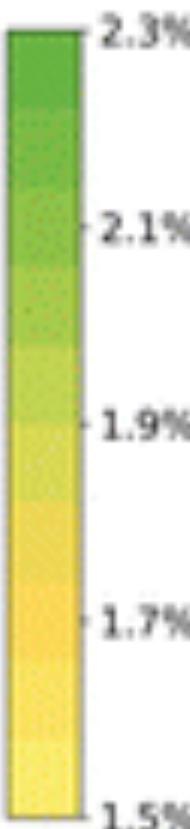


**Hybrid-LLM-GNN framework evaluated on 7 properties:**  
Outperformed GNN-only models in 5 cases, with up to 25% improvement in accuracy

|                           | No Removal | Chemical info | Structure info | Bond Length |
|---------------------------|------------|---------------|----------------|-------------|
| Formation Energy(eV/atom) | 0.0345     | 0.0390        | 0.0627         | 0.0345      |
| Ehull(eV/atom)            | 0.0359     | 0.0398        | 0.0770         | 0.0364      |
| Magout(μB)                | 0.3932     | 0.4498        | 0.5514         | 0.3923      |
| Bandgap_mBJ(eV)           | 0.2720     | 0.2693        | 0.3017         | 0.2697      |
| Spillage                  | 0.3215     | 0.3241        | 0.3400         | 0.3212      |
| SLME(%)                   | 4.6579     | 4.7388        | 5.1870         | 4.6488      |
| Tc_supercon(K)            | 2.2055     | 2.2392        | 2.2793         | 2.2087      |



MgB<sub>2</sub> is hexagonal omega structure structured and crystallizes in the hexagonal P6/mmm space group. Mg(1) is bonded to twelve equivalent B(1) atoms to form a mixture of edge and face-sharing MgB<sub>12</sub> cuboctahedra. All Mg(1)-B(1) bond lengths are 2.50 Å. B(1) is bonded in a 9-coordinate geometry to six equivalent Mg(1) and three equivalent B(1) atoms. All B(1)-B(1) bond lengths are 1.77 Å.



*Erasure analysis for enhanced model explainability of ALIGNN-MatBERT TL models:*  
ChemNLP text with tag-level removal (top)  
Robocrystallographer text with word-level removal (bottom)

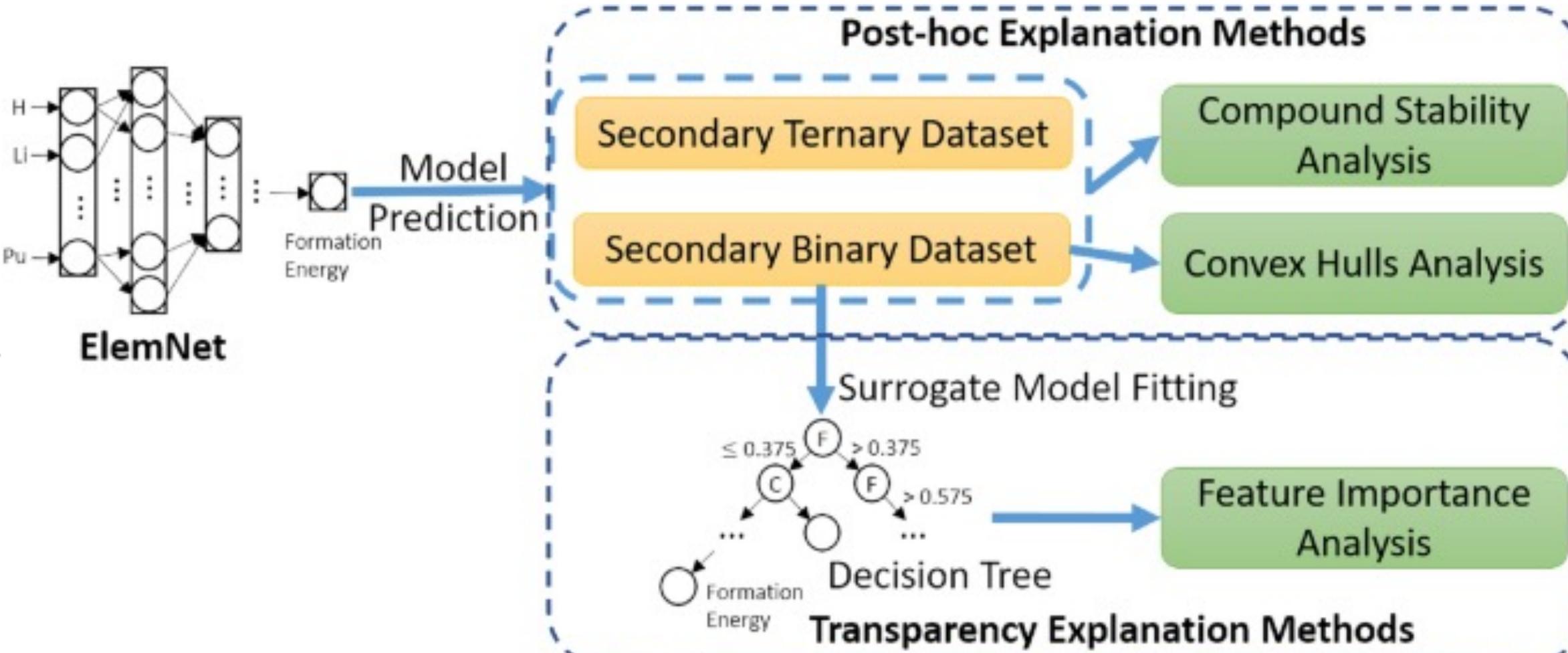
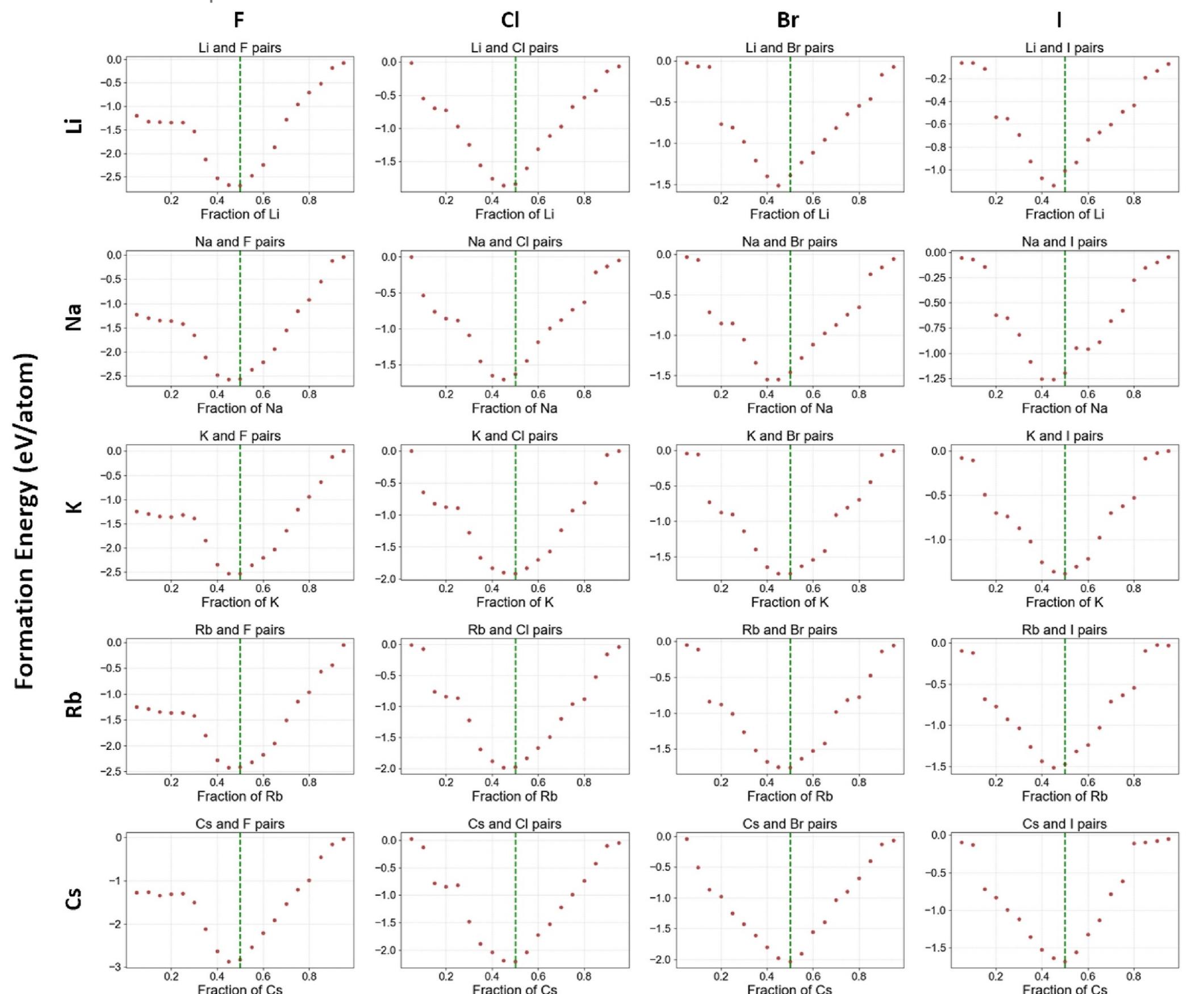
# XElemNet: towards explainable AI for deep neural networks in materials science

Kewei Wang, Vishu Gupta, Claire Songhyun Lee, Yuwei Mao, Muhammed Nur Talha Kilic, Youjia Li,

Zanhua Huang, Wei-keng Liao, Alok Choudhary & Ankit Agrawal 

[Scientific Reports](#) 14, Article number: 25178 (2024) | [Cite this article](#)

3449 Accesses | [Metrics](#)

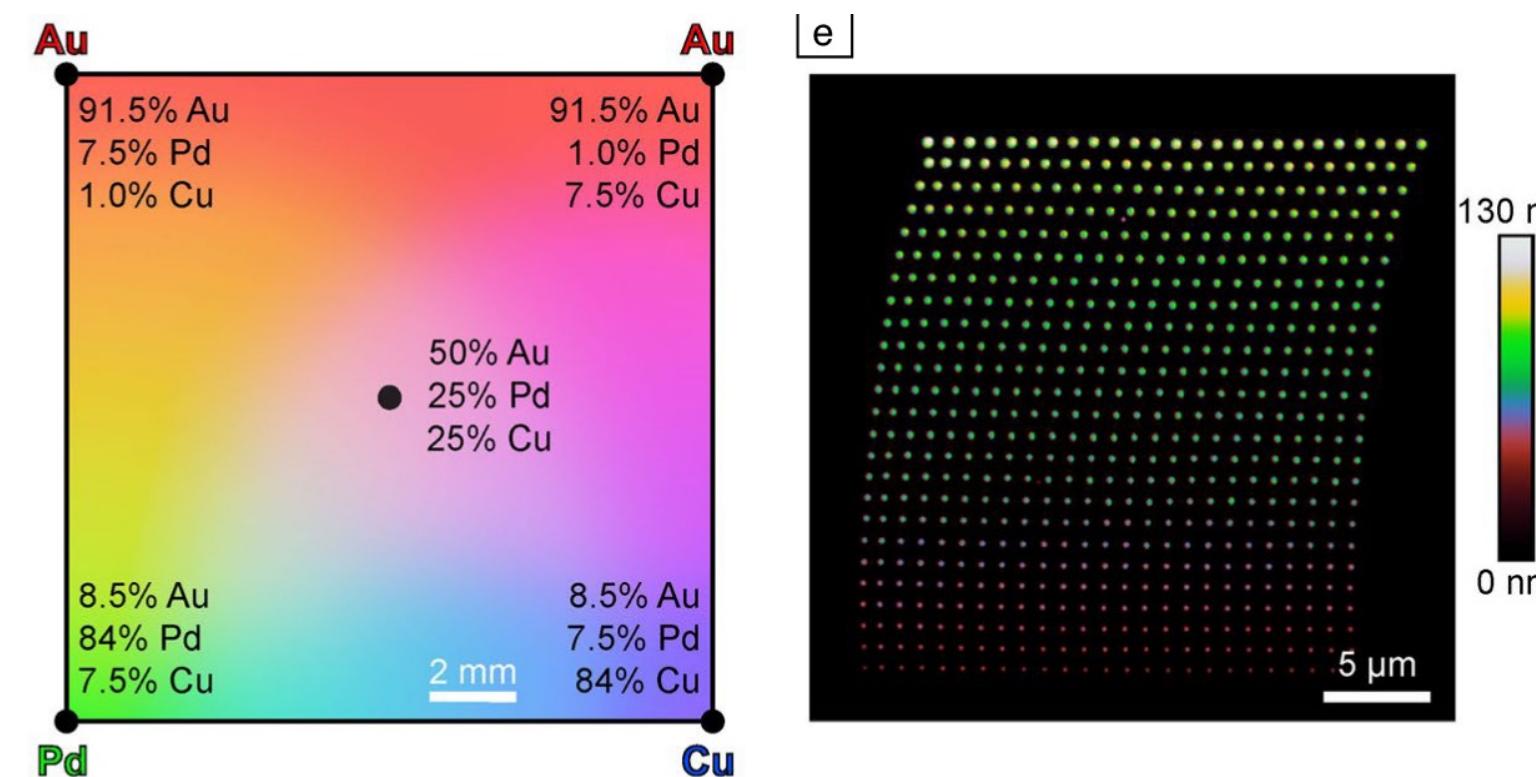


|          | F  | Cl    | Br    | I     | O     | S     | Se    | Te    | N     | P     | As    | Sb    | Bi    |       |
|----------|----|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Group 1  | Li | 0     | -0.15 | -0.15 | -0.15 | 0     | 0.11  | 0     | 0.21  | 0     | -0.45 | 0     | -0.1  | -0.21 |
| Group 2  | Na | -0.15 | -0.15 | -0.32 | -0.15 | -0.12 | -0.12 | -0.24 | -0.38 | 0.09  | -0.1  | -0.1  | 0     | 0     |
| Group 3  | K  | -0.15 | 0     | 0     | 0     | -0.12 | 0     | 0     | 0     | -1.91 | -0.91 | -0.45 | 0.09  | 0.09  |
| Group 4  | Rb | -0.15 | -0.15 | 0     | -0.15 | -0.24 | -0.24 | 0     | 0     | -1.32 | -1.1  | -0.45 | -0.45 | -0.45 |
| Group 5  | Cs | -0.15 | 0     | 0     | 0     | -0.24 | -0.12 | 0     | 0     | -1.91 | -1.1  | -0.91 | -0.58 | 0.09  |
| Group 6  | Be | 0     | 0     | 0     | -0.81 | -0.32 | 0     | -0.32 | -0.51 | -0.13 | -0.78 | -0.26 | -0.26 | -0.26 |
| Group 7  | Mg | 0     | 0     | 0     | -0.22 | 0     | 0.26  | -0.51 | 0.14  | 0.22  | 0.12  | 0.12  | 0.12  | 0     |
| Group 8  | Ca | 0     | 0.19  | 0.19  | 0     | 0     | 0.14  | 0.14  | -0.15 | 0     | -0.26 | 0     | 0     | 0     |
| Group 9  | Sr | 0     | 0     | 0     | 0     | 0     | 0     | 0     | -0.15 | -0.26 | -0.42 | -0.13 | 0     | -0.13 |
| Group 10 | Ba | 0     | 0     | 0     | 0     | 0     | 0     | 0     | -0.15 | 0.12  | 0     | 0     | -0.13 | 0     |
| Group 11 | B  | 0     | 1.93  | 1.93  | -2.32 | 0     | -2    | -3    | 1.25  | 0.77  | -3.32 | -2.32 | -3.32 | -3.32 |
| Group 12 | Al | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0.26  | -3.32 | -3.32 | -3.32 |
| Group 13 | Ga | 0     | 0     | 0.26  | 0.26  | 0     | 0     | 0.17  | 0.17  | 0.26  | -3.32 | -0.32 | 0.93  | 0.93  |
| Group 14 | In | 0     | 0.26  | 0.26  | 0.49  | 0     | 0.17  | 0     | 0.17  | 0.93  | -3.32 | -0.32 | 0.93  | 0.93  |
| Group 15 | Tl | 0.49  | 0.68  | 0.85  | 0.85  | 0     | 0.32  | 0.32  | 0.58  | 0.93  | -3.32 | -3.32 | -2.32 | -3.32 |

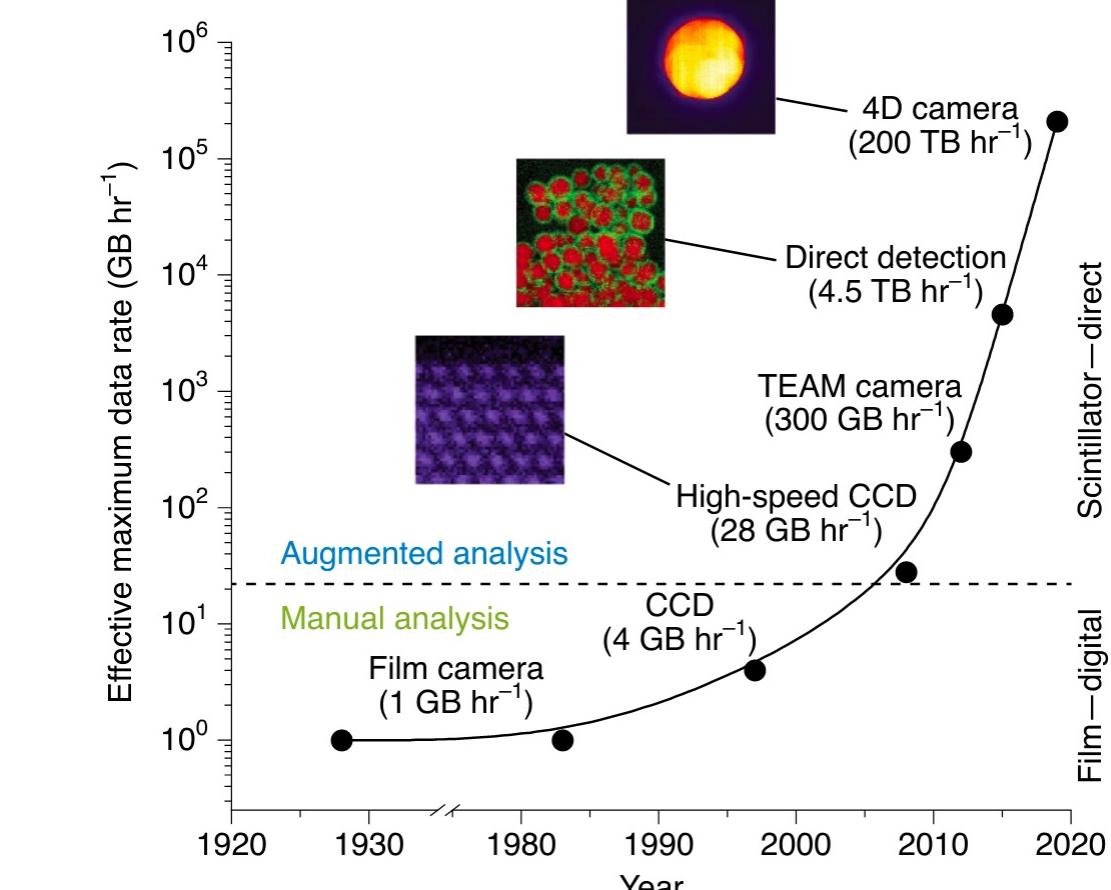
# AI-Driven Nanocombinatorics for Accelerated Structural Characterization: *Automated High-Throughput Nanoparticle Library Screening and Analytics*

## Motivation

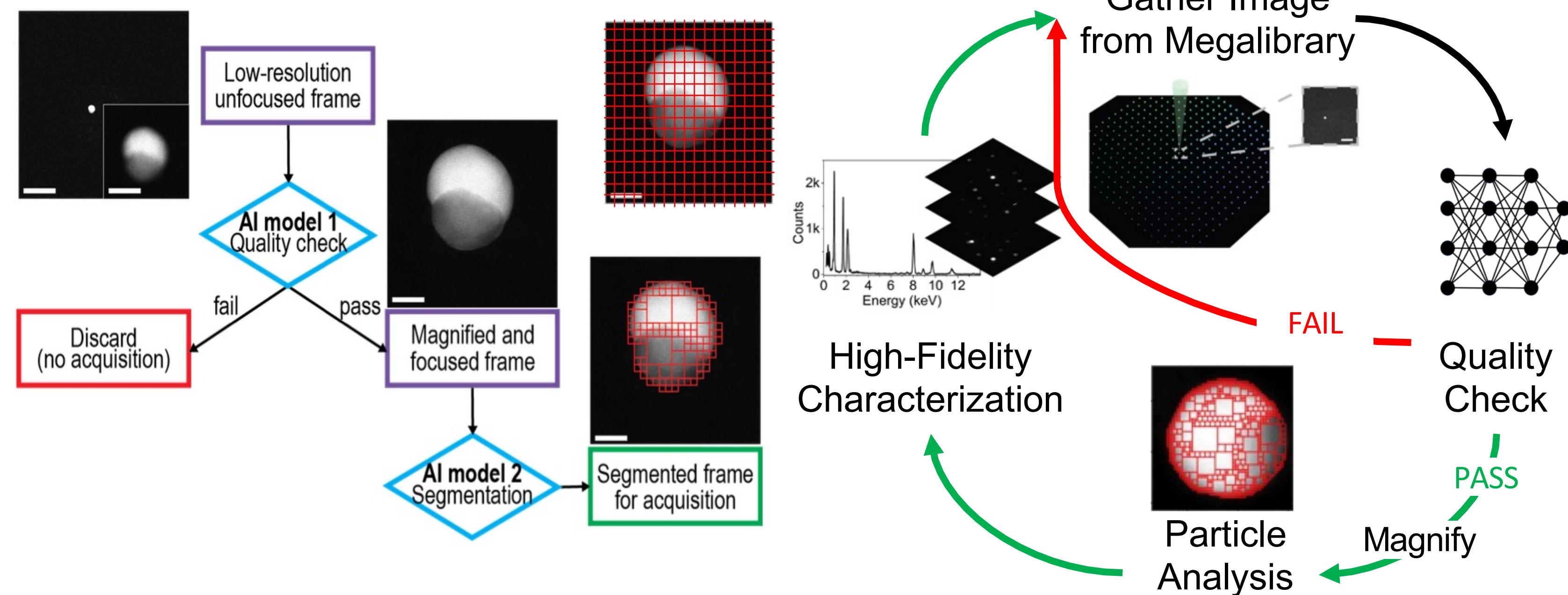
- Analysis and screening of megalibraries at scale to enable high-throughput characterization and discovery
- AI-driven nanocombinatorics to automate key steps



Combinatorial megalibraries  
[Smith et al. MRS Bulletin 2023]



Advanced detectors  
[Spurgeon et al. Nature Materials 2021]



# AI-Driven Nanocombinatorics for Accelerated Structural Characterization: Automated High-Throughput Nanoparticle Library Screening and Analytics

## Motivation

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## 1: Nanoparticle image quality check

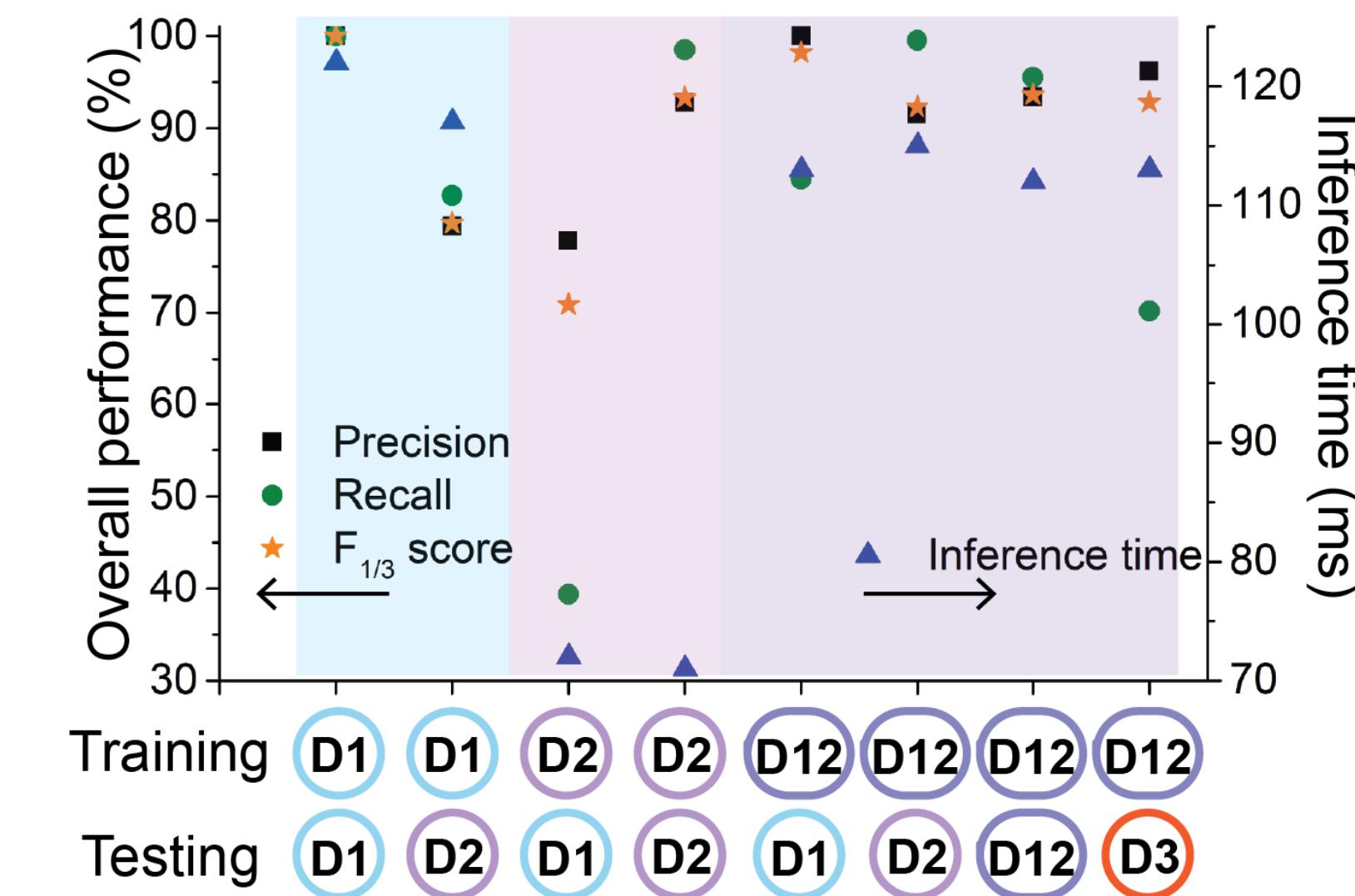
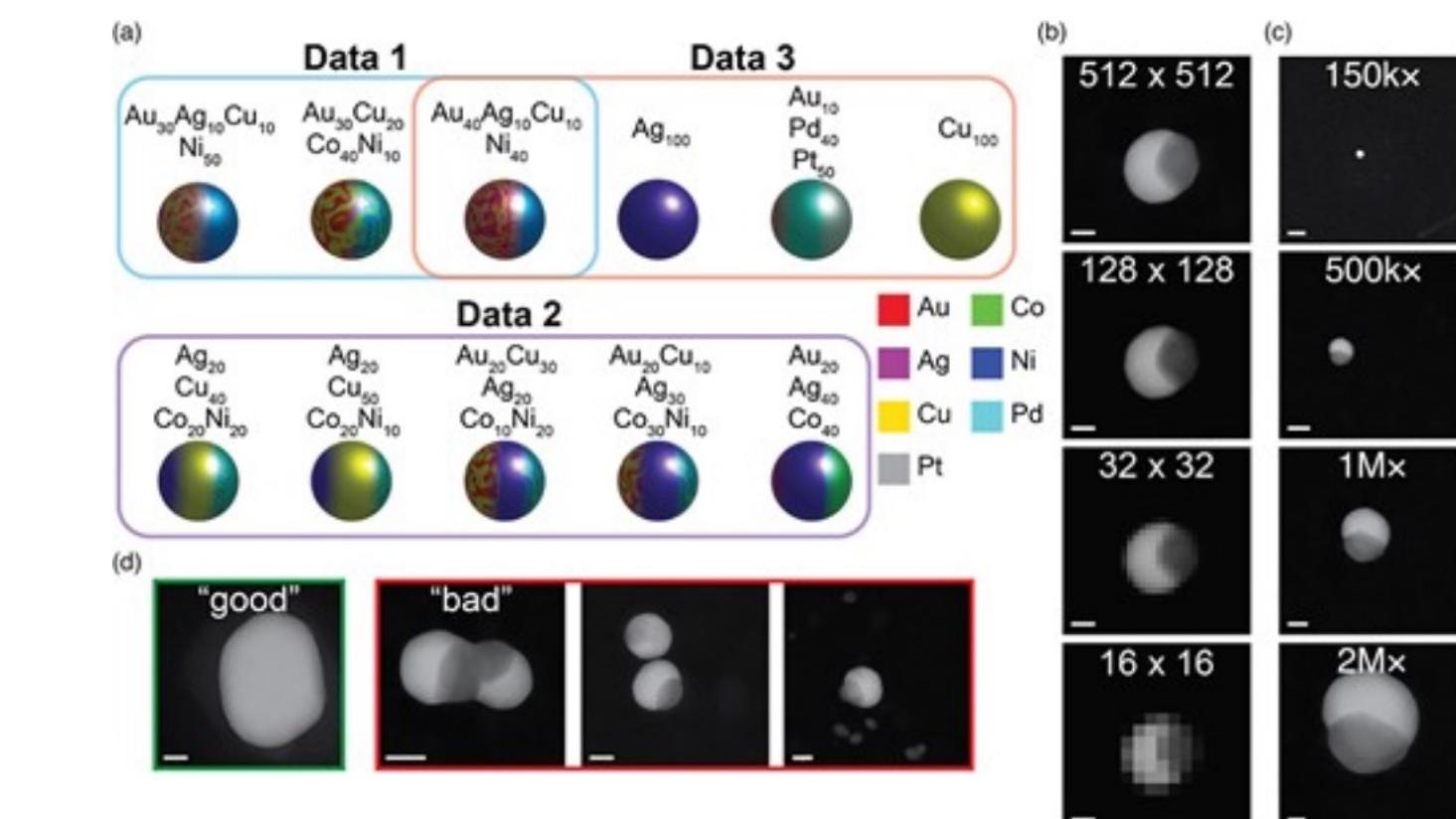
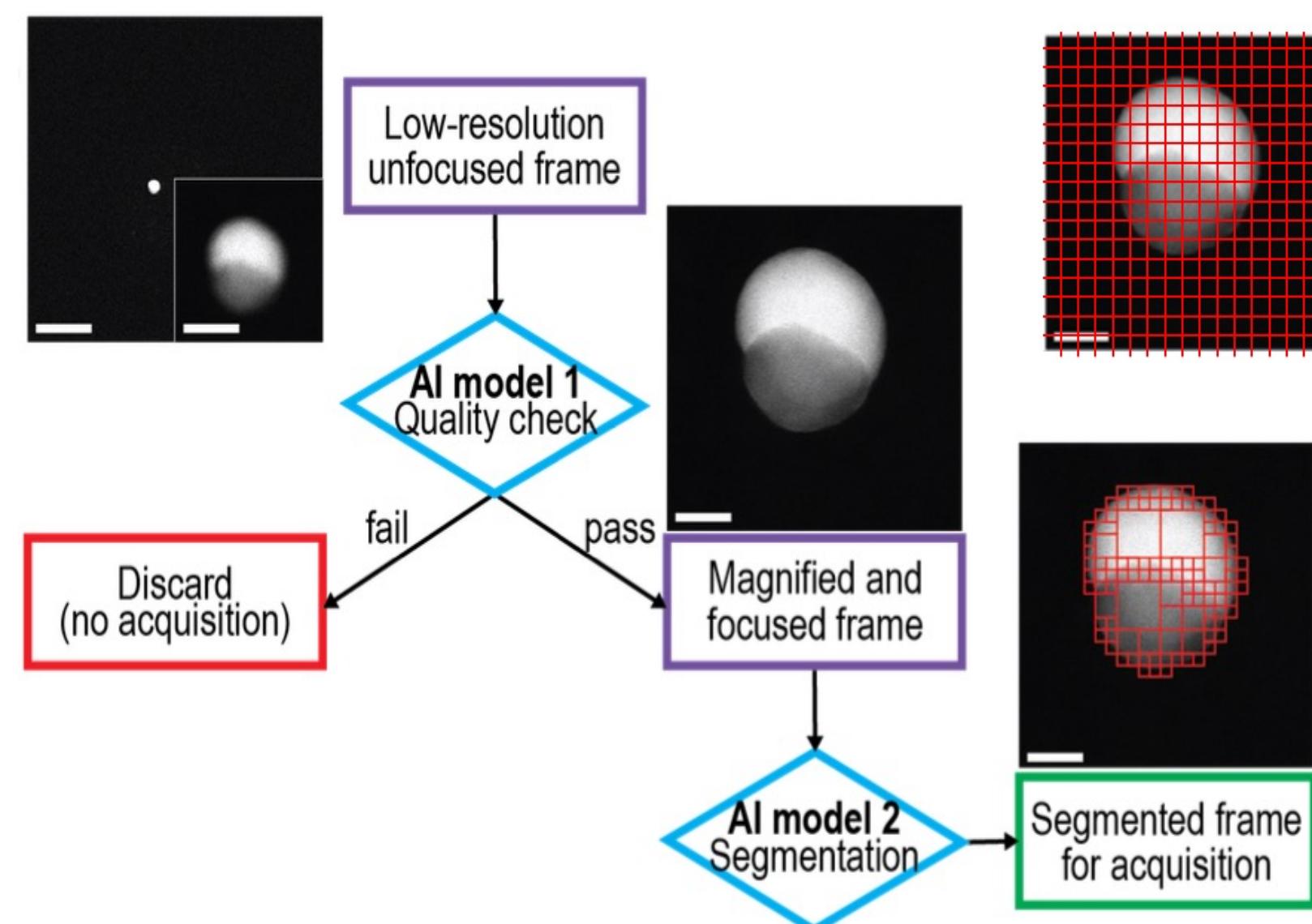
- Neural architecture search (NAS) creates AI model with >95% precision, >90%  $F_{1/3}$  score, and inference time of <125 ms.

JOURNAL ARTICLE

## Machine Learning-Enabled Image Classification for Automated Electron Microscopy

Alexandra L Day , Carolin B Wahl , Vishu Gupta , Roberto dos Reis , Wei-keng Liao , Chad A Mirkin , Vinayak P Dravid , Alok Choudhary , Ankit Agrawal ✉ Author Notes

*Microscopy and Microanalysis*, Volume 30, Issue 3, June 2024, Pages 456–465, <https://doi.org/10.1093/mam/ozae042>



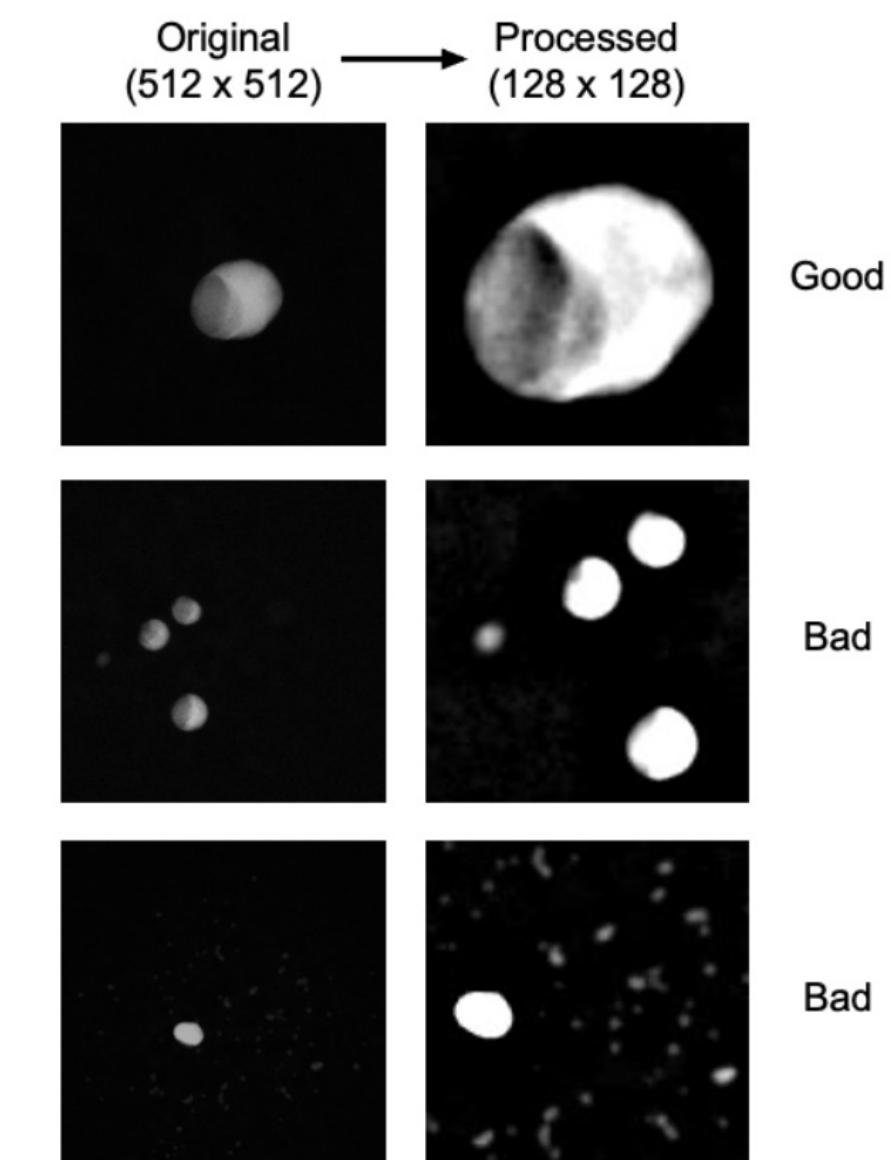
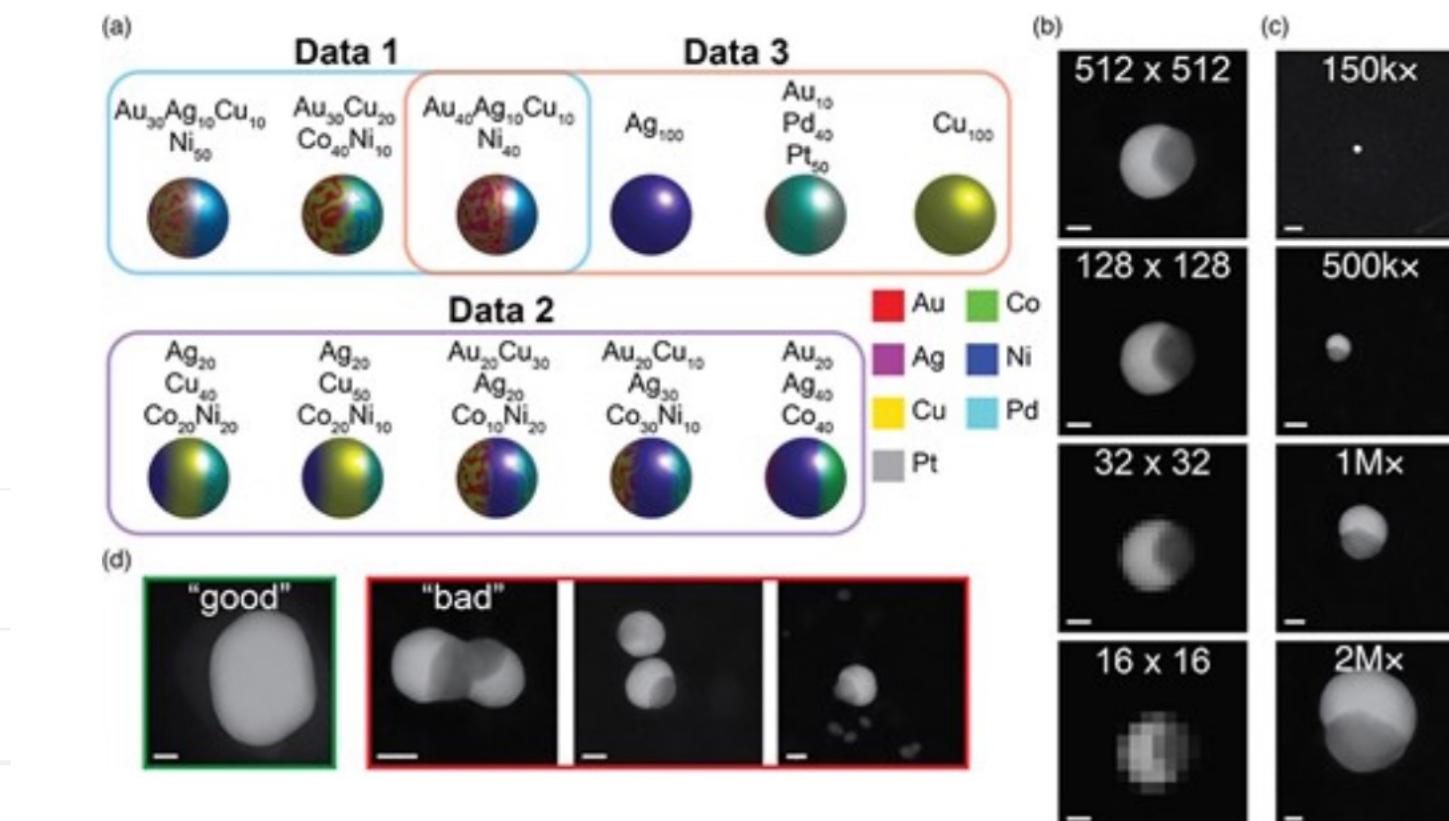
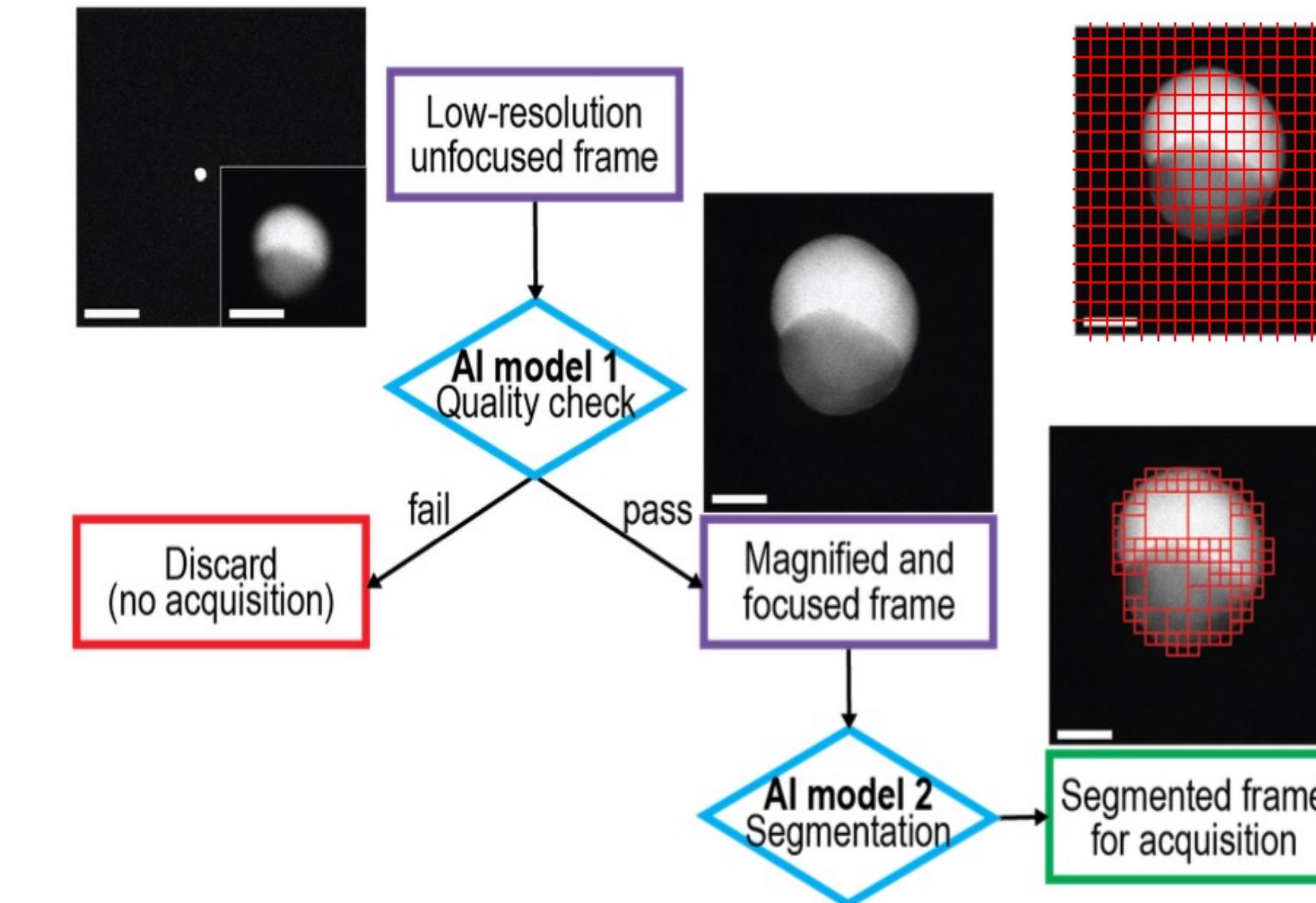
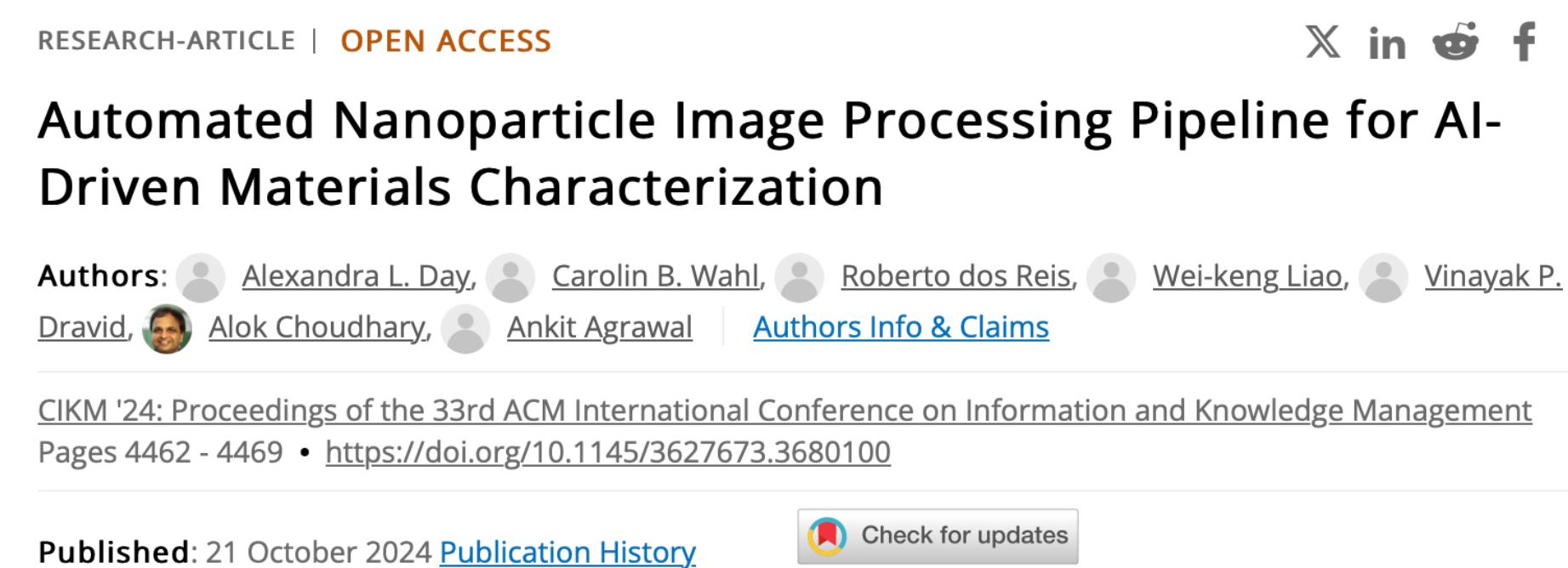
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- Neural architecture search (NAS) creates AI model with >95% precision, >90%  $F_{1/3}$  score, and inference time of <125 ms.
- Custom image preprocessing pipeline improves model performance, with lower training time (hours->min), >97% precision, >95%  $F_{1/3}$  score, and inference time of <400 ms.



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## 2: Segmentation for faster data acquisition

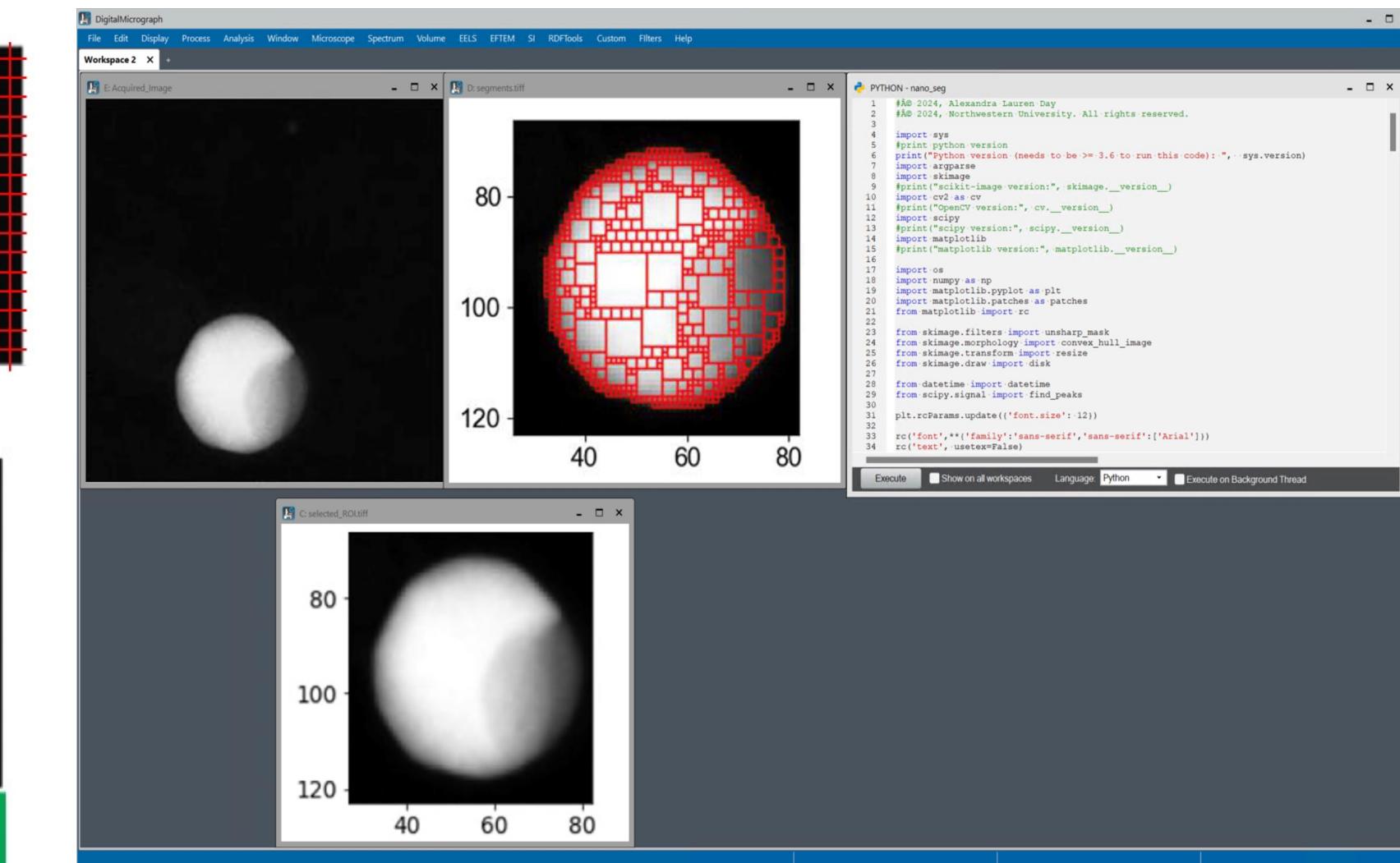
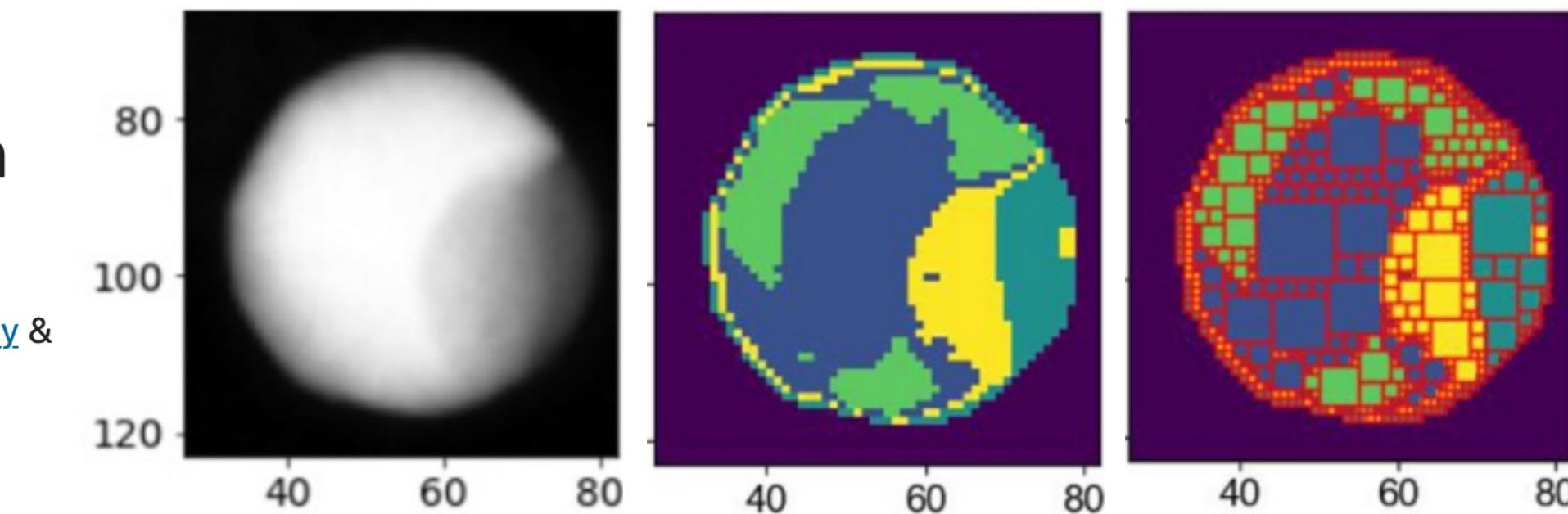
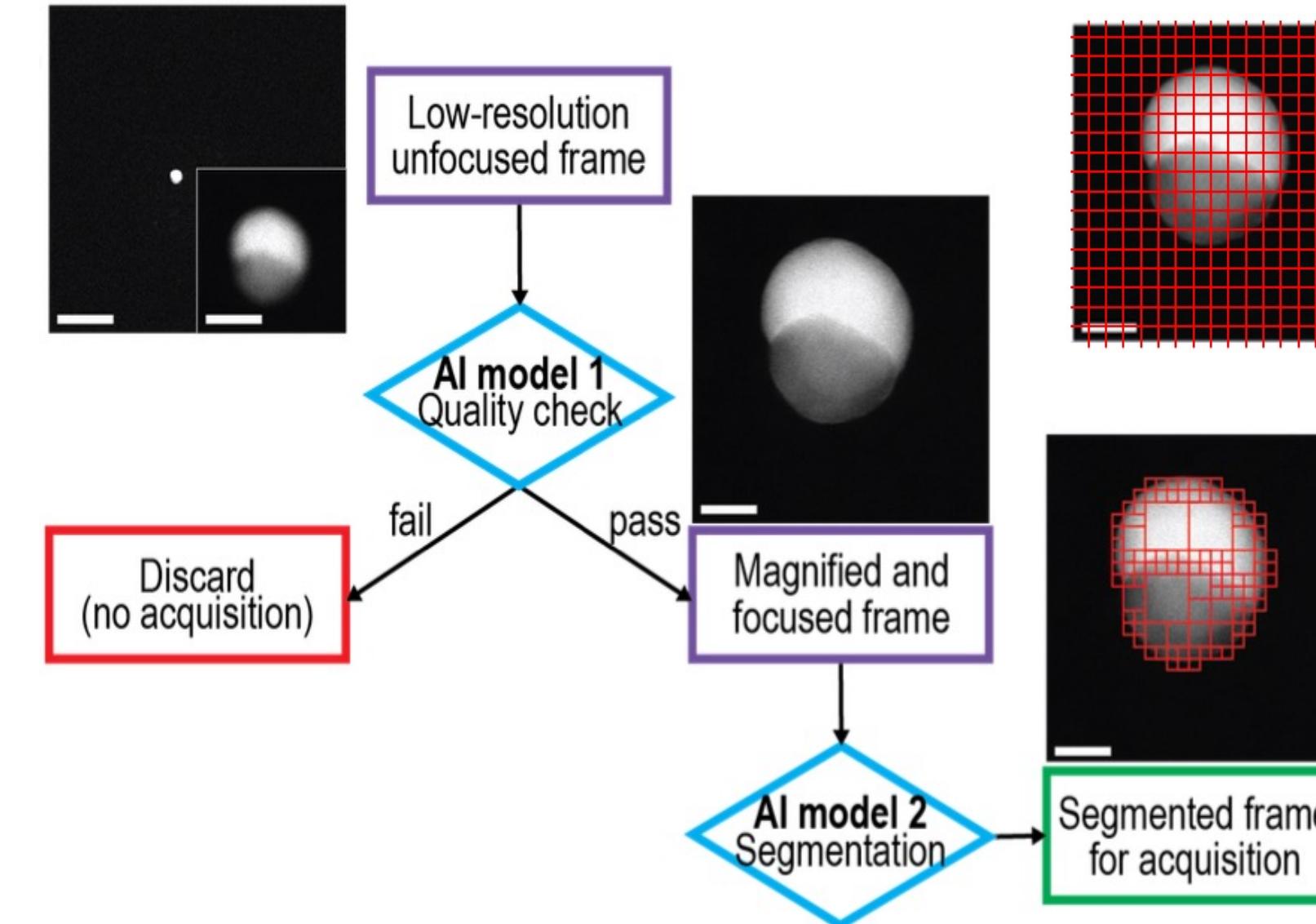
- Custom procedure based on 1-D clustering to return acquisition boxes for downstream analysis, >25x faster and require >29x lower storage space
- Implemented using Gatan DigitalMicrograph® v. 3.60 with Python

Article | [Open access](#) | Published: 17 May 2025

## Automated image segmentation for accelerated nanoparticle characterization

[Alexandra L. Day](#), [Carolin B. Wahl](#), [Roberto dos Reis](#), [Wei-keng Liao](#), [Youjia Li](#), [Muhammed Nur Talha Kilic](#), [Chad A. Mirkin](#), [Vinayak P. Dravid](#), [Alok Choudhary](#) & [Ankit Agrawal](#)

[Scientific Reports](#) 15, Article number: 17180 (2025) | [Cite this article](#)



# AI for Materials: Publications and Software

## • Forward PSPP models (prediction)

- Steels [ICME 2013, IMMI 2014, CIKM 2016, IJF 2018, DSAA 2019]
- DFT/Experimental (up to 41 properties) [PRB 2014, npjCM 2016, ICDM 2016, DL-KDD 2016, PRB 2017, SciRep 2018, KDD 2019, NatComm 2019, SciRep 2021, NatComm 2021, SDM 2022, SciRep 2022, JCM 2023, SciRep 2023, IJCNN 2023, npjCM 2024, JCheminformatics 2024, ICMLA 2024, DigitalDiscovery 2025]
- Thermoelectric properties prediction [RSC Adv 2016, JCompChem 2018]
- Multi-scale localization/homogenization [IMMI 2015, IMMI 2017, CMS 2018, ActaMat 2019, IJCNN 2019]
- Chemical/molecular properties prediction/scaling [JPCL 2017, NeurIPS-MLMM 2018, IJCNN 2019, MolInfo 2019]
- Magnetic properties prediction [ICDM-LMID 2019, ICPR-IML 2021]
- Processing to microstructure [ICMLA 2023, SciRep 2025]
- Explainable AI for forward models [SciRep 2024]

## • Inverse PSPP models (optimization/discovery/design)

- Stable compounds [PRB 2014]
- Magnetostrictive materials [SciRep 2015, AIAA 2018]
- Semiconductors and metallic glasses [npjCM 2016]
- Heusler compounds [PRM 2018]
- Microstructure design (GenAI) [IDETC 2018, JMD 2018, NeurIPS-ML4Eng 2020, IMMI 2022, ICMLA 2024]
- Titanium aircraft panels [CMS 2019]
- Microstructures elastic properties [IMMI 2022, npjCM 2023]
- Microstructure to processing [ICMLA 2024]

## • Structure Characterization

- EBSD Indexing [BigData-ASH 2016, M&M 2018]
- Crack/porosity detection [Transport 2013, CBM 2017, IJTTE 2018]
- XRD based phase detection/clustering [IJCNN 2019, ICPRAM 2021, SDM-DDDM 2021]
- Plastic deformation identification [IJCNN 2019, SciRep 2020]
- Additive manufacturing processes [DSAA 2019, ManufacLet 2018, JIM 2023]
- Crystal plasticity simulation acceleration [IJCNN 2023, ScriptaMat 2025]
- Nanoparticle image quality check [M&M 2023, M&M 2024, CIKM 2024]
- Nanoparticle image segmentation [M&M 2024, SciRep 2025]

## • Review/Perspective Articles

- AI/ML for materials science [APLMat 2016, MRSCComm 2019, npjCM 2020, npjCM 2022, MRSCComm 2023, npjCM 2024]

## Steel Fatigue Strength Predictor

**Disclaimer:** The results from this tool are estimates based on data consisting of a set of experimental measurements. All results are provided for informational purposes only, in furtherance of the developers' educational mission, to complement the knowledge of materials scientists and engineers, and assist them in their search for new materials with desired properties. The developers may not be held responsible for any decisions based on this tool.

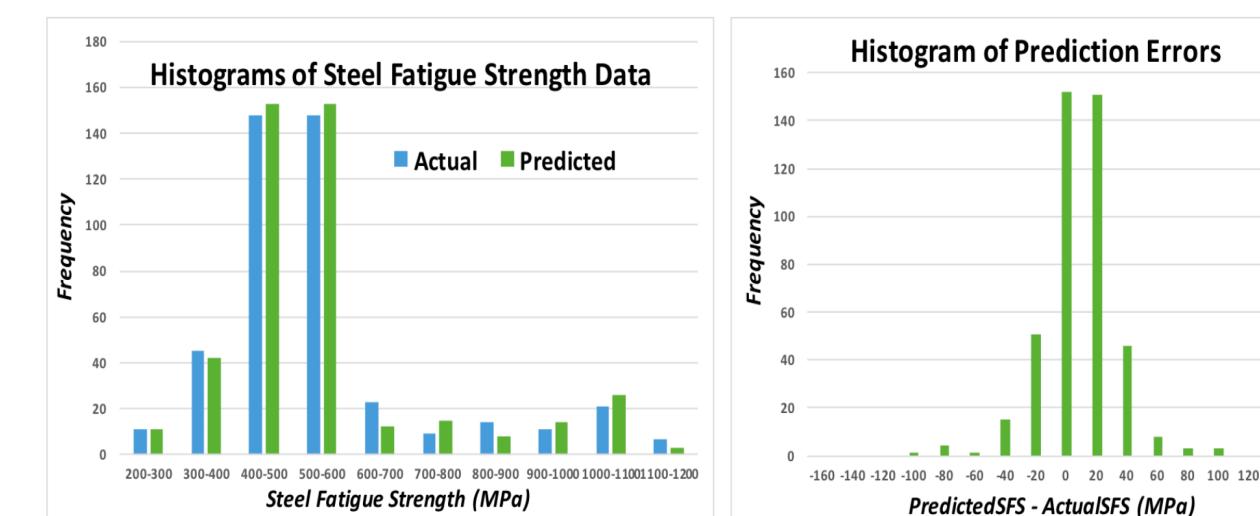
Welcome to the steel fatigue strength predictor. This tool is built using experimental data of more than 400 steels, available from the Japan National Institute for Materials Science (NIMS) MatNavi database. This database consists of processing and composition information of steels, along with the experimentally measured rotating bending fatigue strength (10 million cycles). Various data analytics techniques such as feature selection and regression modeling were used to obtain highly accurate fatigue strength prediction models using a small non-redundant set of six composition parameters and three processing parameters.

The tool estimates the fatigue strength of the steel based on the composition and processing parameters entered by the user. To obtain the fatigue strength prediction, please enter the attribute values below, and click the submit button.

|  |       |  |     |
|--|-------|--|-----|
| Carbon (C) (wt %) (0.17-0.63)  | 0.42  | Normalizing Temperature (°C) (825-930)                         | 870 |
| Silicon (Si) (wt %) (0.16-2.05)  | 0.29  | Through Hardening Temperature (°C) (3,825-865)                 | 855 |
| Manganese (Mn) (wt %) (0.37-1.6)   | 0.77  | Through Hardening Time (minutes) (0,30)                        | 30  |
| Phosphorus (P) (wt %) (0.002-0.031)  | 0.015 | Cooling Rate for Through Hardening (°C/hr) (0,8,24)            | 8   |
| Sulphur (S) (wt %) (0.003-0.03)  | 0.017 | Carburization Temperature (°C) (30,930)                        | 30  |
| Nickel (Ni) (wt %) (0.01-2.78)   | 0.12  | Carburization Time (minutes) (0-540)                           | 0   |
| Chromium (Cr) (wt %) (0.01-1.17)   | 1.1   | Diffusion Temperature (°C) (30,850-903)                        | 30  |
| Copper (Cu) (wt %) (0.01-0.26)   | 0.09  | Diffusion Time (minutes) (0.0-70.2)                            | 0   |
| Molybdenum (Mo) (wt %) (0.00-0.24)   | 0.15  | Quenching Media Temperature for Carburization (°C) (30,60,140) | 30  |
| Area Proportion of Inclusions Deformed by Plastic Work (0.00-0.13)   | 0.09  | Tempering Temperature (°C) (30-680)                            | 650 |
| Area Proportion of Inclusions Occurring in Discontinuous Array (0.00-0.05)                                       | 0.01  | Tempering Time (minutes) (0,60,120)                            | 60  |
| Area Proportion of Isolated Inclusions (0.000-0.058)   | 0.01  | Cooling Rate for Tempering (°C/hr) (0,0.5,24)                  | 24  |
| Do not have values for all attributes?<br>Try the <a href="#">calculator with reduced attribute set</a> instead! |       | Reduction Ratio (Ingot to Bar) (240-5530)                      | 500 |

**Get Steel Fatigue Strength Prediction**

Predicted fatigue strength of the given steel = **512.86 ± 49.43 MPa**



CS/AI Publications  
Domain Publications

<http://ai.eecs.northwestern.edu/>  
<http://github.com/NU-CUCIS>

**CUCIS Group**  
Software developed by members of CUCIS group at Northwestern University  
Northwestern University http://cucis.ece.northwestern.edu

**Popular repositories**

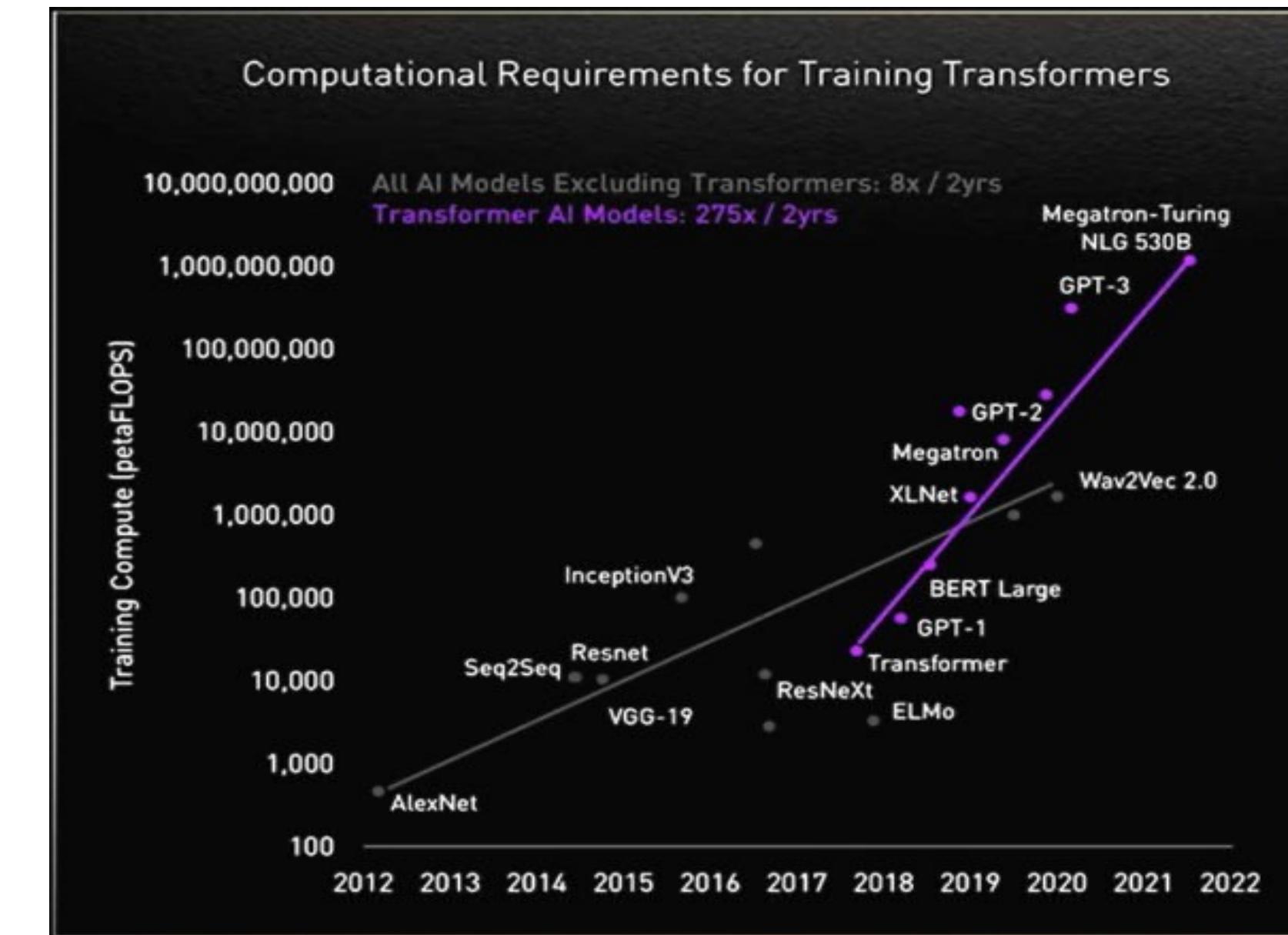
- ElemNet (Public) Deep Learning the Chemistry of Materials From Only Elemental Composition for Enhancing Materials Property Prediction
- CheMixNet (Public) Mixed DNN Architectures for Predicting Properties using Multiple Molecular Representations
- ml-iter-additive (Public) An iterative machine learning framework for predicting temperature profiles for an additive manufacturing process
- IRNet (Public) A General Purpose Deep Residual Regression Framework for Materials Discovery.
- PADNet-XRD (Public) Peak Area Detection Network for Directly Learning Phase Regions from Raw X-ray Diffraction Patterns.
- MDN-GAN (Public) A General Framework Combining Generative Adversarial Networks and Mixture Density Networks for Inverse Modeling in Microstructural Materials Design

**Repositories**

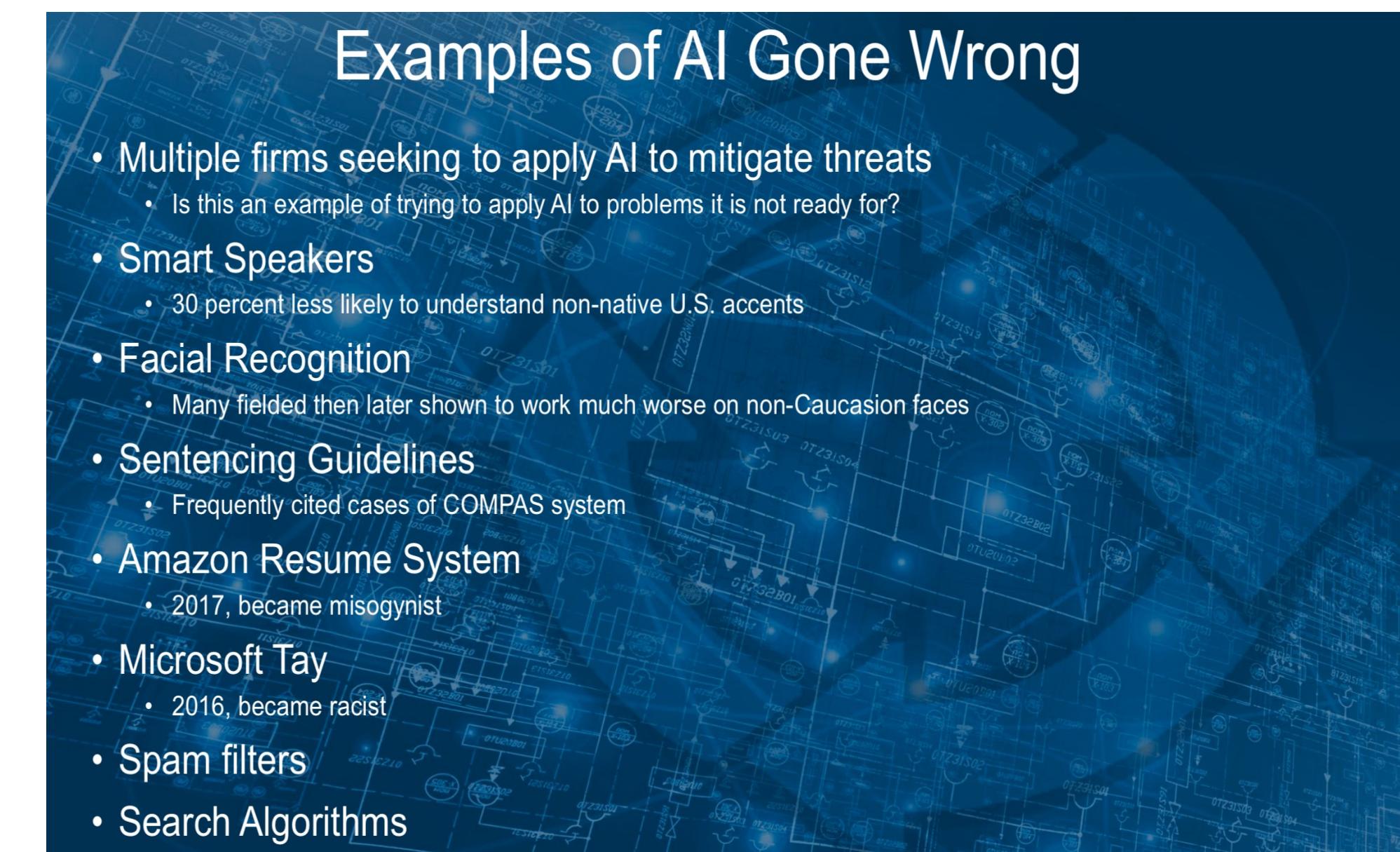
- Find a repository... Type Language Sort
- ElemNet (Public) Deep Learning the Chemistry of Materials From Only Elemental Composition for Enhancing Materials Property Prediction
- IRNet (Public) A General Purpose Deep Residual Regression Framework for Materials Discovery.
- pcnn (Public) Parallel Convolutional Neural Network Framework
- CrossPropertyTL (Public) Parallel Data Concatenation for High Energy Physics Data Analysis
- ph5concat (Public) Parallel Data Concatenation for High Energy Physics Data Analysis
- LocalizationDL (Public) A Deep Learning Model For Localization of Two-Phase High-Contrast Three-dimensional Materials
- ml-iter-additive (Public) An iterative machine learning framework for predicting temperature profiles for an additive manufacturing process
- edsr-tensorflow-rapids (Public) Parallel Data Concatenation for High Energy Physics Data Analysis

# AI for Materials: Challenges and Opportunities

- Ensuring **AI-ready materials data**
  - Small, big, heterogeneous, noisy, missing, multi-fidelity
  - Data quality assessment
  - Incentivize FAIR data practices, metadata standards
  - Do not discard negative data!
- Enabling **AI-driven materials R&D**
  - Computational requirements
  - Big/huge design space exploration
  - Self-driving laboratories
  - Translate to manufacturing
- Ensuring **correct** application of AI
  - CS+MS collaborative efforts
  - Materials informaticians with cross-disciplinary training



[NVIDIA, 2022]



[Bob Gourley,  
AI World 2019]

# Thank you!



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