

AI for Materials Science: Tuning Laser-Induced Graphene Production and Beyond

Lars Kotthoff and others who did the actual work
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Leiden, 29 August 2019

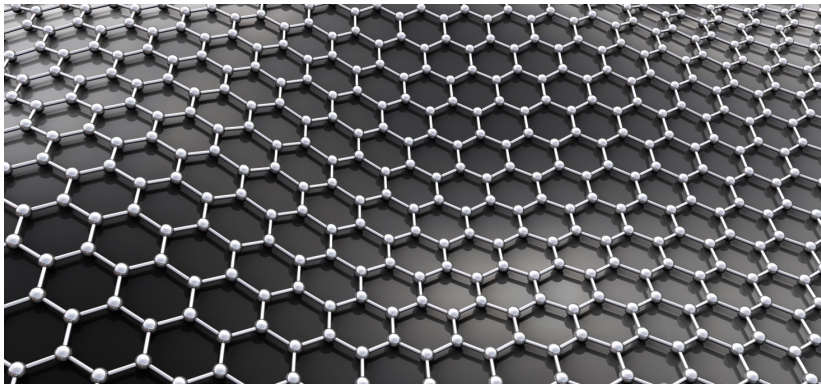
AI for Materials Science:
Tuning Laser-Induced
Graphene Production and
Beyond

*THE WORLD NEEDS
MORE COWBOYS.*



UNIVERSITY
OF WYOMING

Leiden, 29 August 2019

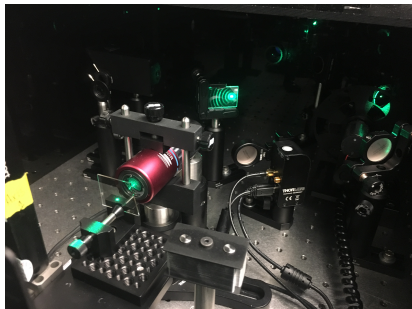


Automated Parameter Tuning

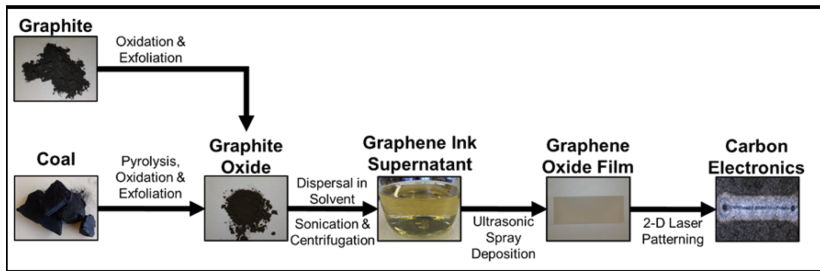
- ▷ treat tunable process as black box – no knowledge of inner workings required
- ▷ intelligently and iteratively select parameter settings likely to improve performance
- ▷ mature techniques used in many areas of AI

Optimizing Graphene Oxide Reduction

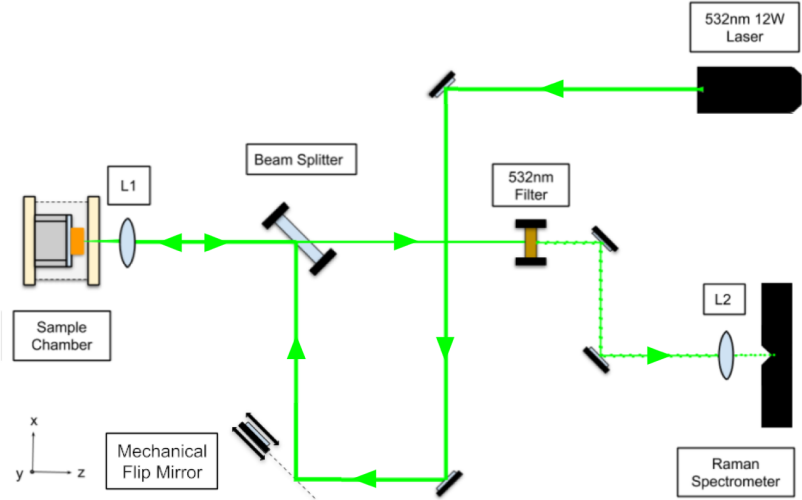
- ▷ reduce graphene oxide to graphene through laser irradiation
- ▷ allows to create electrically conductive lines in insulating material
- ▷ laser parameters need to be tuned carefully to achieve good results



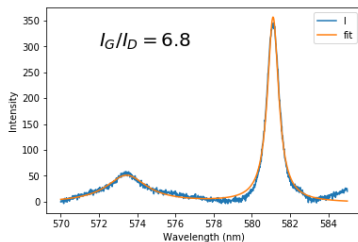
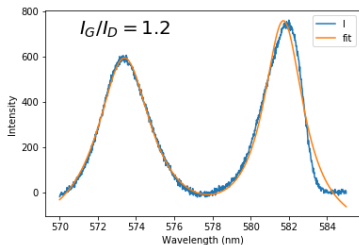
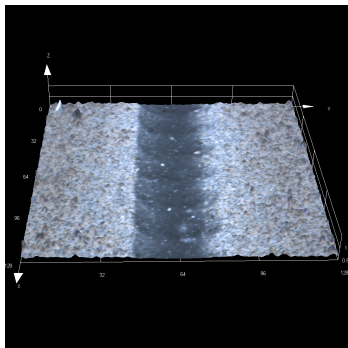
From Graphite/Coal to Carbon Electronics



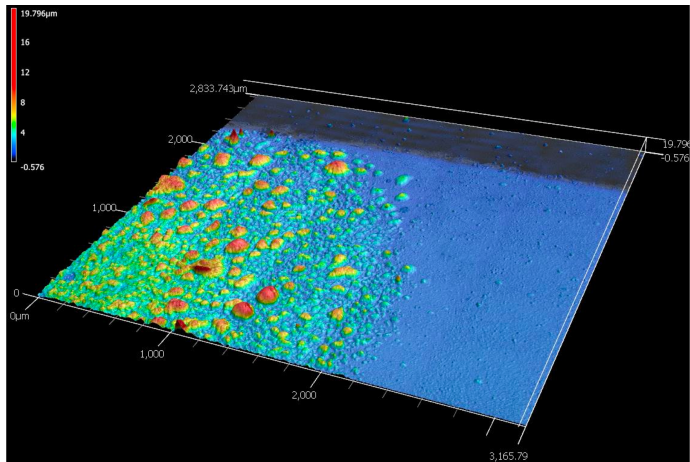
Experimental Setup



Evaluation of Irradiated Material



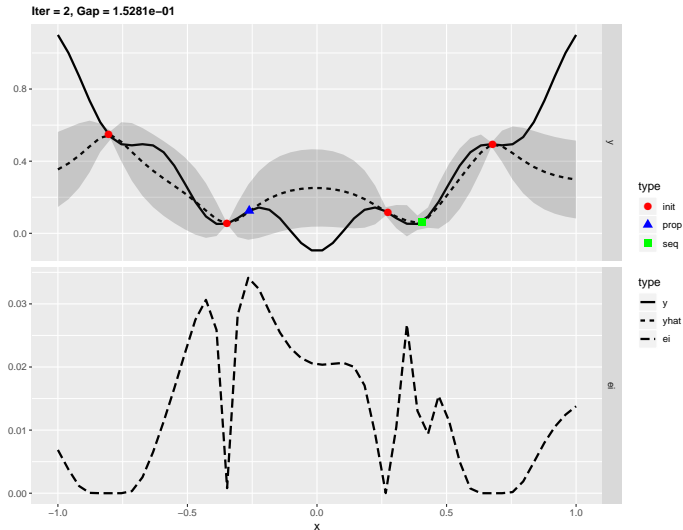
Morphology of Irradiated Material



Bayesian Optimization with Surrogate Models

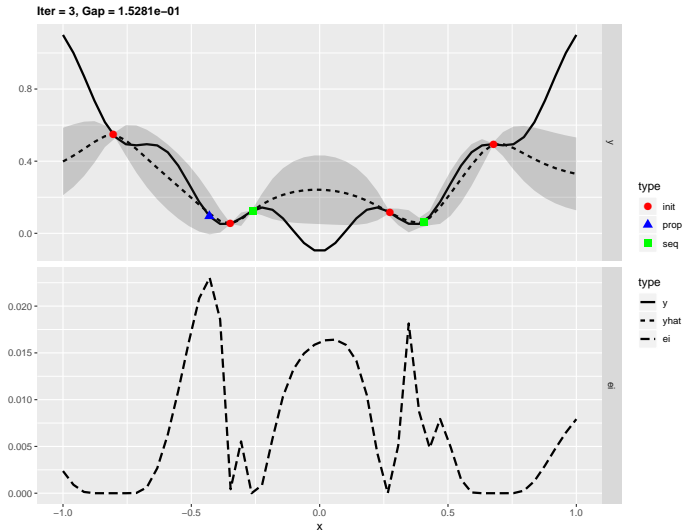
- ▷ evaluate small number of initial (random) configurations
- ▷ build surrogate model of parameter-performance surface based on this
- ▷ use model to predict where to evaluate next
- ▷ repeat
- ▷ allows targeted exploration of new configurations

Bayesian Optimization with Surrogate Models



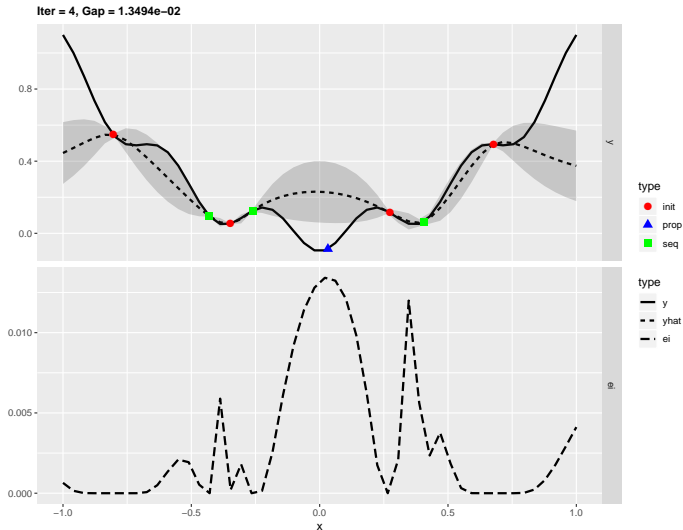
Bischl, Bernd, Jakob Richter, Jakob Bossek, Daniel Horn, Janek Thomas, and Michel Lang. "MirMBO: A Modular Framework for Model-Based Optimization of Expensive Black-Box Functions," March 9, 2017. <http://arxiv.org/abs/1703.03373>.

Bayesian Optimization with Surrogate Models



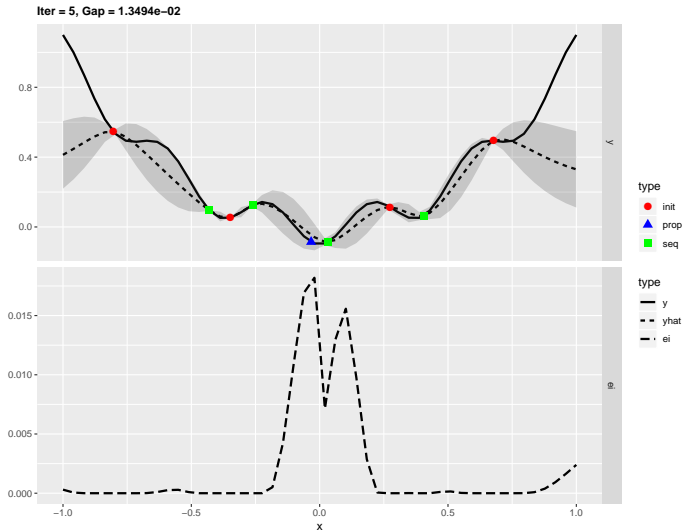
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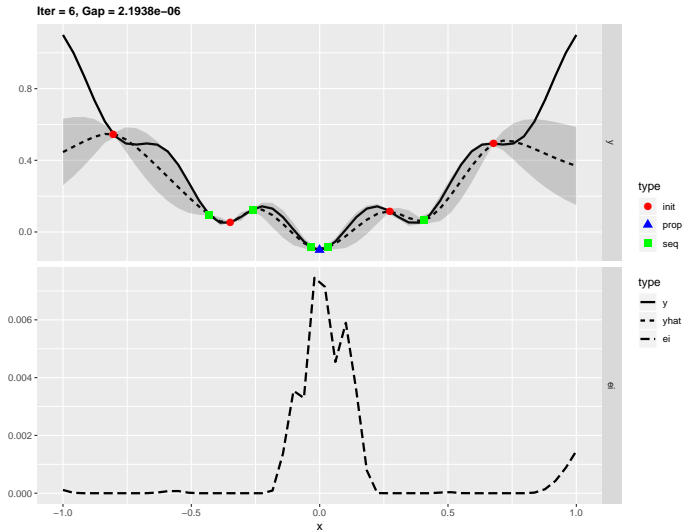
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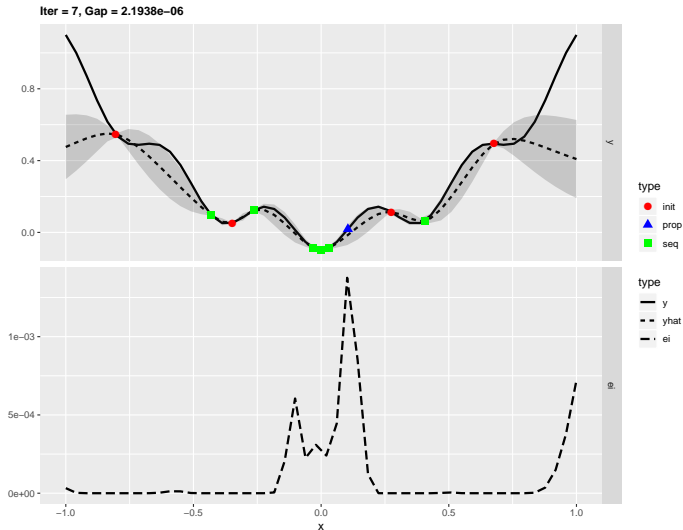
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The Springer Series on Challenges in Machine Learning

Frank Hutter
Lars Kotthoff
Joaquin Vanschoren *Editors*

Automated Machine Learning

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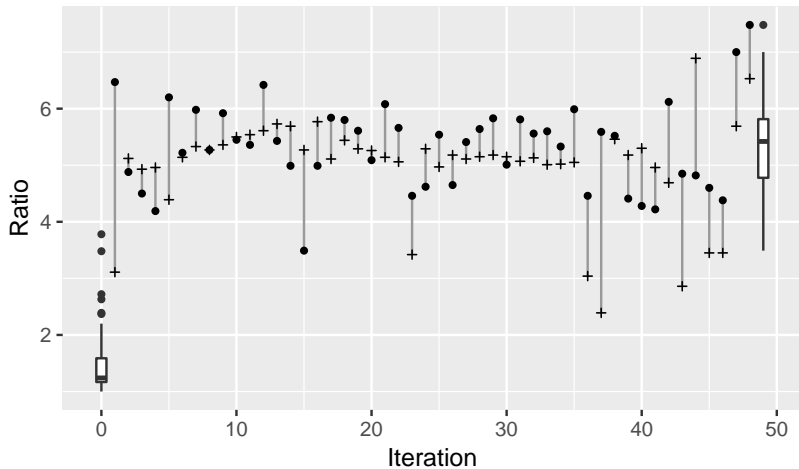
 Springer

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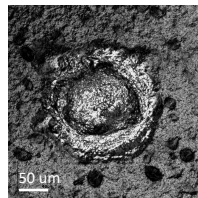
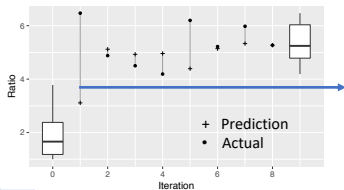
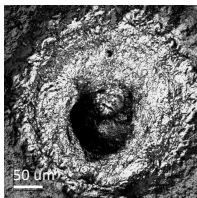
Tuned Parameters

- ▷ laser power (1 mW to 4400 mW), duration for irradiating spot (710 ms to 20 210 ms), pressure in reaction chamber (10 psi to 100 psi)
- ▷ ≈ 7.8 billion configurations
- ▷ individual graphene oxide sample allows for max 361 evaluations, about 2 weeks of human operator time

Tuned Parameters

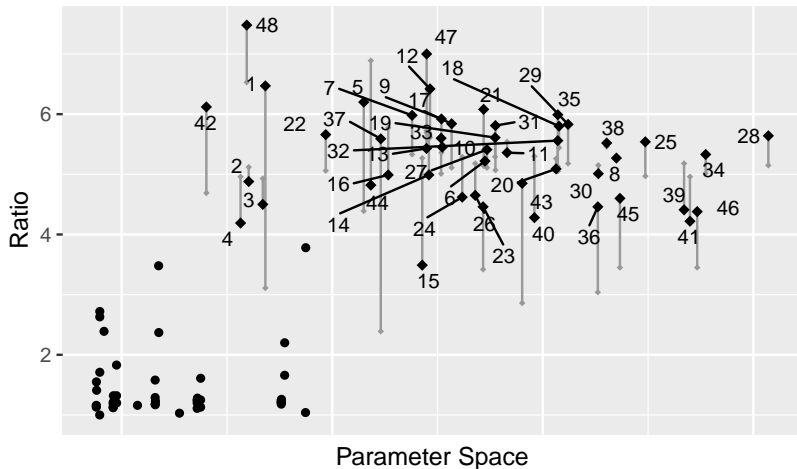


Tuned Parameters



- ▷ improvement of factor of two over best result in literature
- ▷ good results even with small amount of initial data (19 evaluations)
- ▷ code can be used by domain experts with no background in machine learning

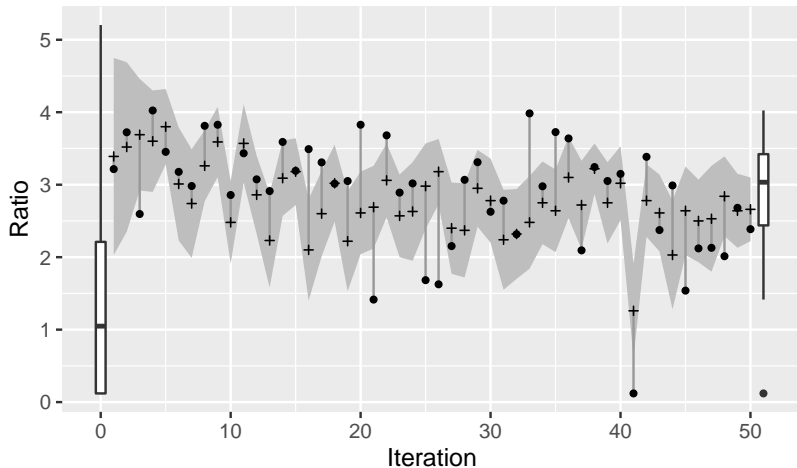
Explored Parameter Space



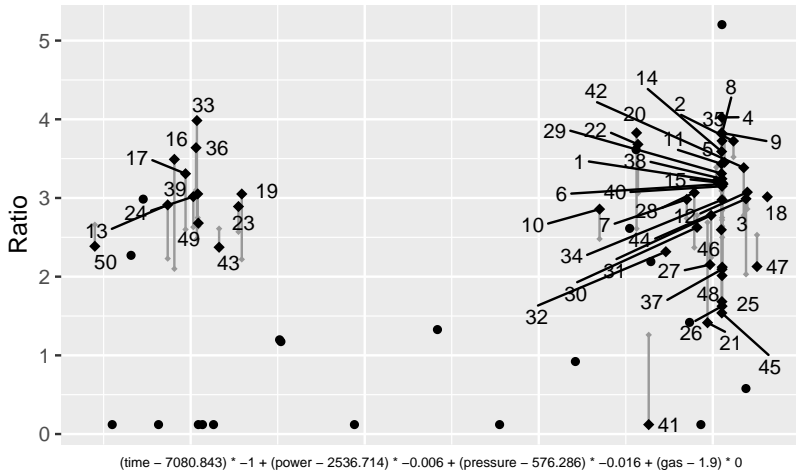
Tuned Parameters – Kapton

- ▷ extend parameter space with gas in reaction chamber – air, argon, nitrogen
- ▷ extend ranges of other parameters
- ▷ more and longer experimental campaigns

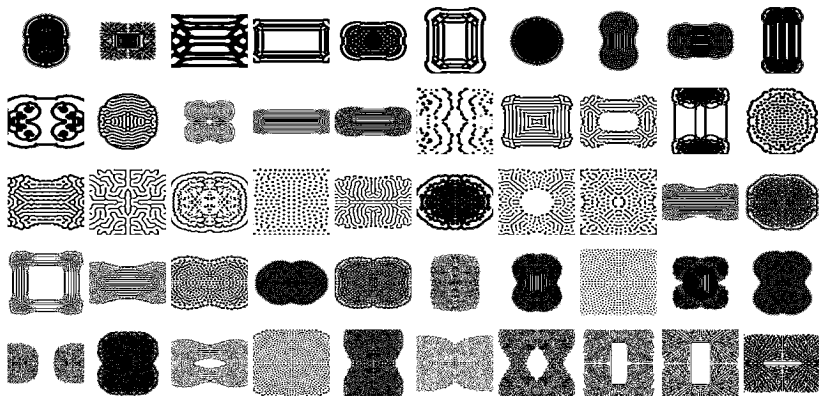
Tuned Parameters – Kapton



Explored Parameter Space – Kapton

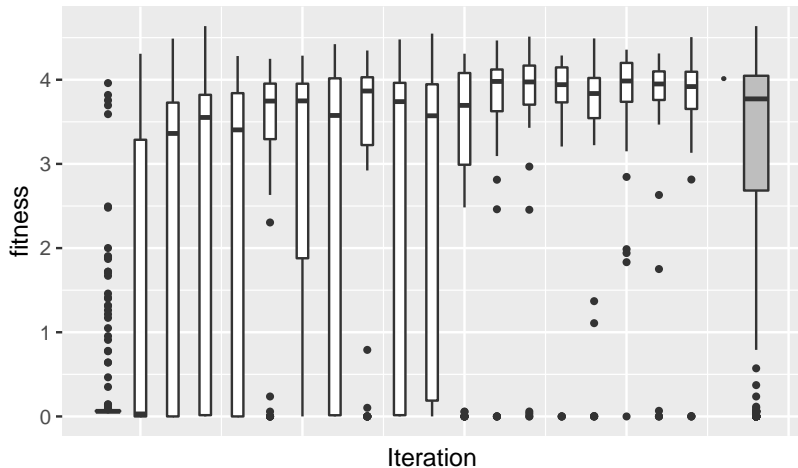


Design of New Materials

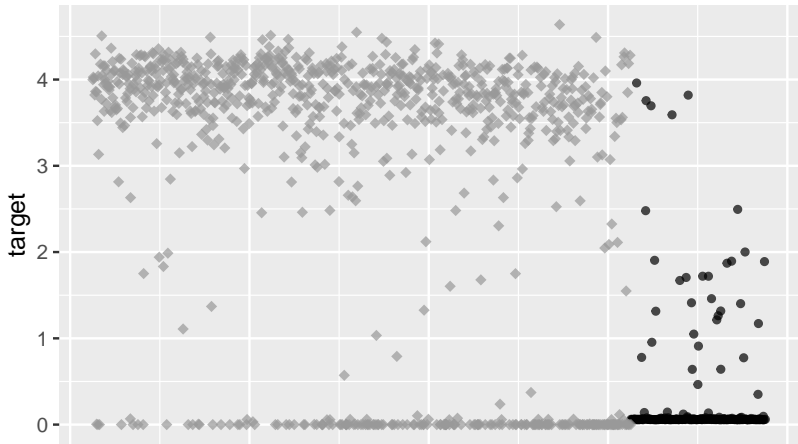


- ▷ optimize parameters of pattern generator for energy absorption of material
- ▷ six numeric parameters
- ▷ computational evaluation of candidates

ML-Optimized Generator Parameters

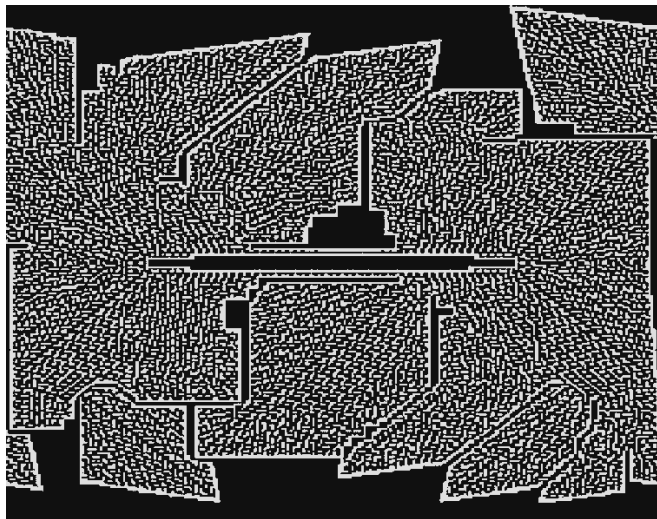


ML-Optimized Generator Parameters



$$.086) * 0 + (k - 0.05) * 0 + (du - 0) * 0 + (dv - 0) * 0 + (y - 93.618) * -0.007 + (x - 81.067) * -0.01 + (sequence - 338.5) * -1 + (part - 6$$

ML-Optimized Generator Parameters



Outlook

- ▷ automate experimental setup
- ▷ application to other materials
- ▷ more in-depth investigation of Bayesian Optimization performance (and other approaches)
- ▷ inform understanding of process by what surrogate model has learned

Other Projects

- ▷ optimization of wear of buttons
- ▷ density functional theory (DFT) calculations of properties of graphene
- ▷ optimization of DFT calculations

Challenges and Opportunities

- ▷ sparsity of data
- ▷ multi-scale measurements
- ▷ combination of optimization with experiments and simulations

Do Try This at Home

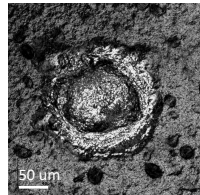
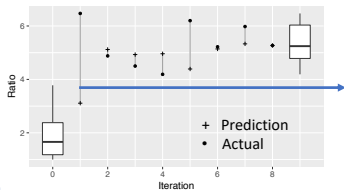
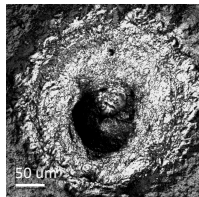
Tutorial on AI for Materials Science @ IJCAI 2019

<https://www.cs.uwo.edu/~larsko/aimat-tut/>

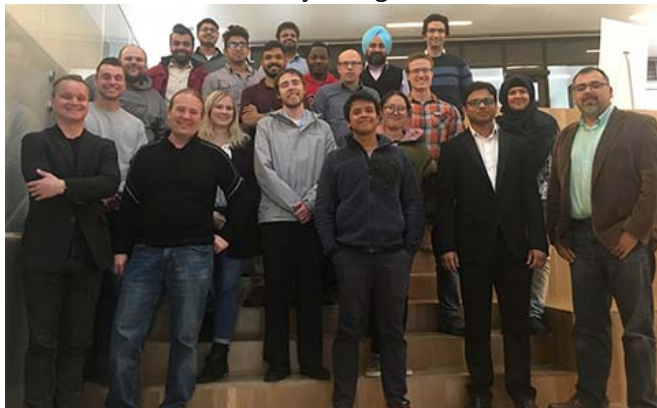
Simulator optimizers available

- ▷ build surrogate model based on (relatively) large amount of data
- ▷ Bayesian Optimization based on this surrogate model
- ▷ playground to try your own approaches

Summary



Artificially Intelligent Manufacturing Center @ University of Wyoming



www.uwyo.edu/aim