Scalable Deep-Learning-Accelerated Topology Optimization for Additively Manufactured Materials

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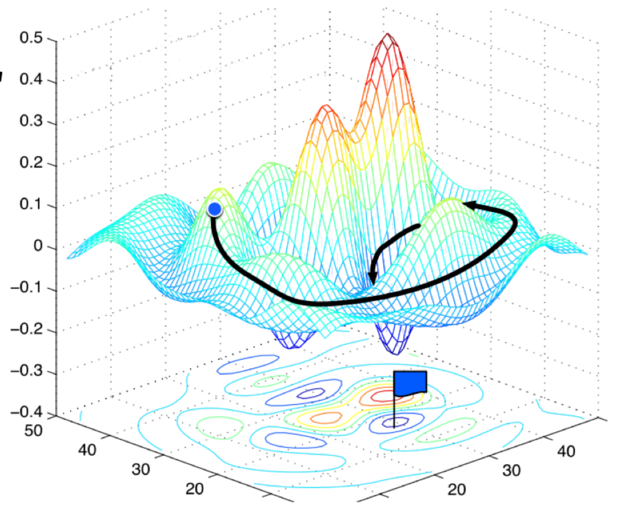
Motivation: high-dimensional optimization

Design variables

Find $\mathbf{x} = [x_1, x_2, \ldots, x_e, \ldots, x_d]^T$

Minimize $c(\tilde{\mathbf{x}}) = F(d, f(\tilde{\mathbf{x}}))$

Data Model

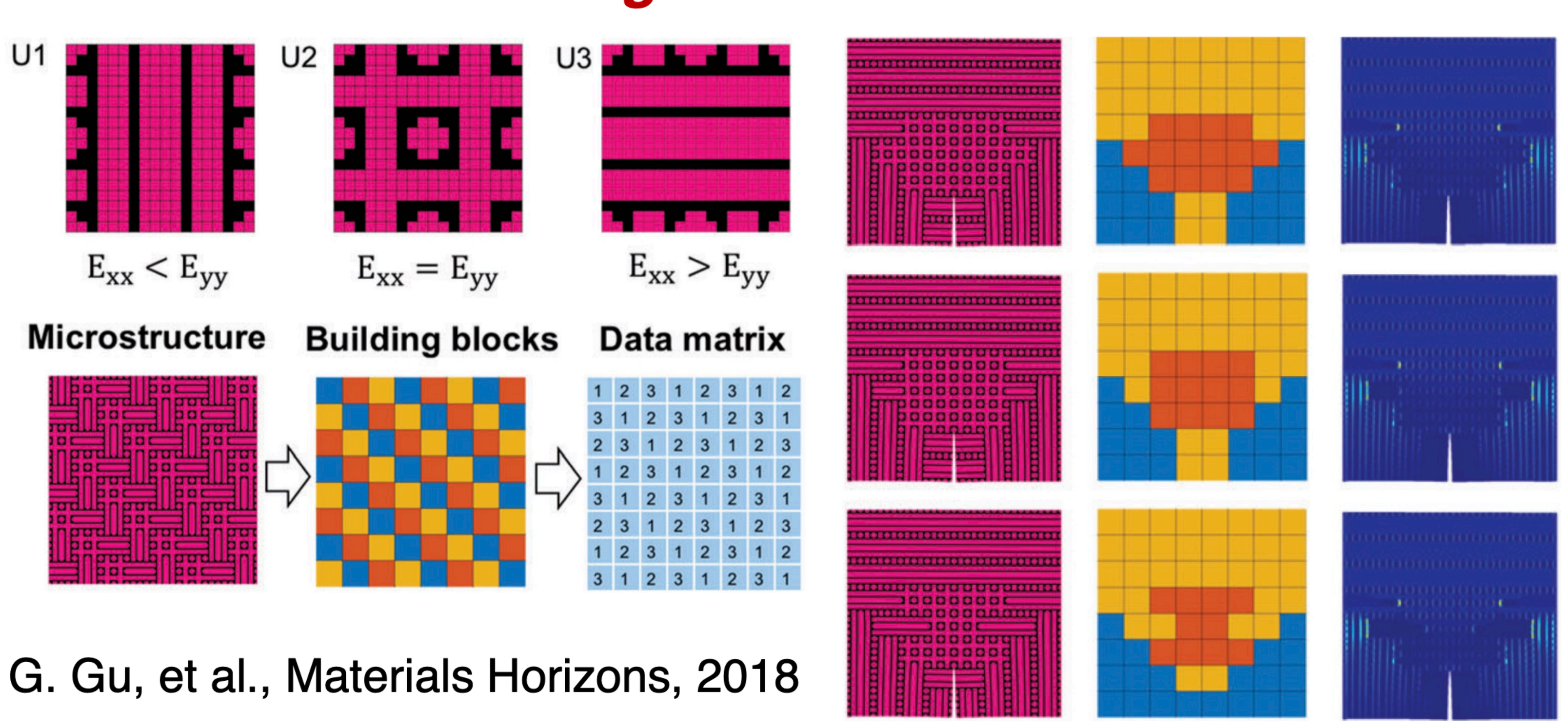


Grand challenges:

- High dimensions: a large number of design variables
- Expensive model simulation: high fidelity
- Sequential optimization: step-by-step search

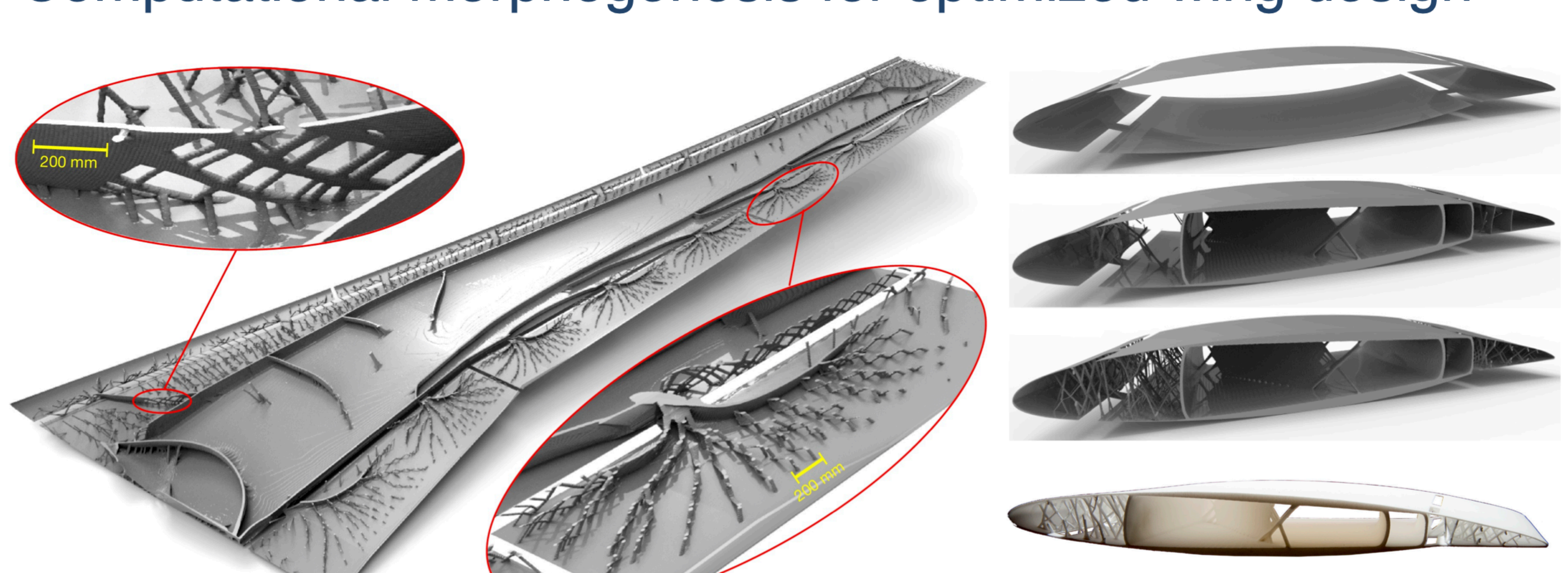
Driving application: AM material design

Design optimization for advanced composite materials with ***Additive Manufacturing***



G. Gu, et al., Materials Horizons, 2018

Computational morphogenesis for optimized wing design



N. Aage, et al., Nature, 2017

A piece of wing printed using additive manufacturing

High dimensional optimization with expensive simulation

Method: scalable ML-based optimization

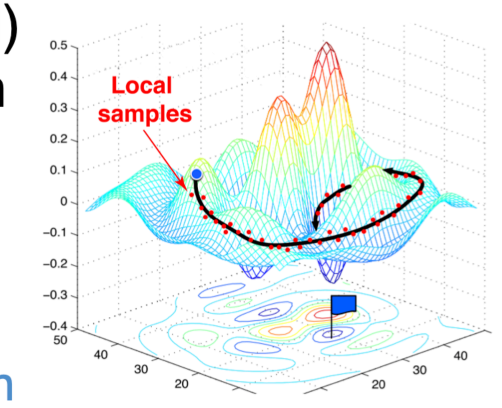
Optimal path guided learning with local sampling

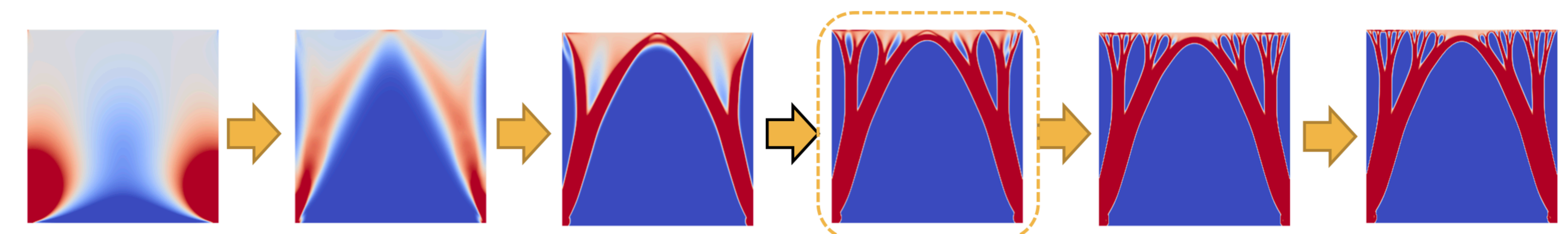
- Optimal path is low dimensional (ideally, 1d)
- Local sampling - closely follow optimal path

$$\tilde{x}^j_{\max} = \max\left\{\tilde{x}^{(j-1)}, \tilde{x}^{(j-2)}, \cdots, \tilde{x}^{(j-w)}\right\}$$

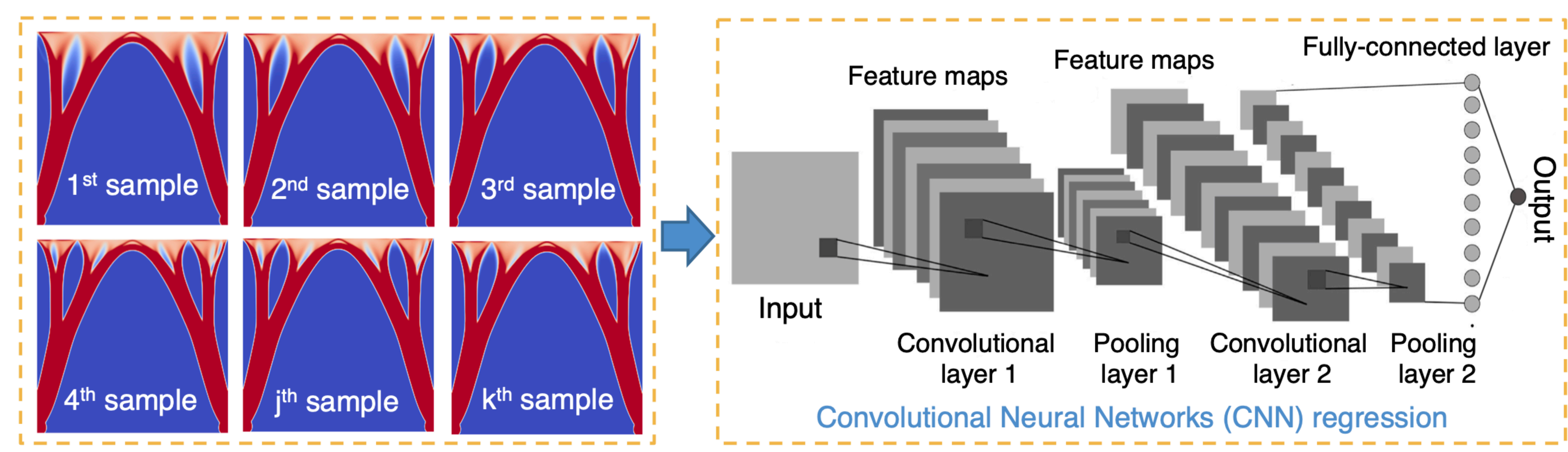
$$\tilde{x}^j_{\min} = \min\left\{\tilde{x}^{(j-1)}, \tilde{x}^{(j-2)}, \cdots, \tilde{x}^{(j-w)}\right\}$$

$$\tilde{x}^j_{rs} = U(\tilde{x}^j_{\max} + \delta,\ \tilde{x}^j_{\min} - \delta)$$ Dimension reduction





- Low-dimensional ML model (e.g., CNN) trained by local data



Scalable implementation (CPU+GPU) on Summit

Sequential optimization with iterative high fidelity simulations h_s

x_i → x_{i+1} → x_j → x_{j+1} → x_{j+2} → x_{k+1} → x_n

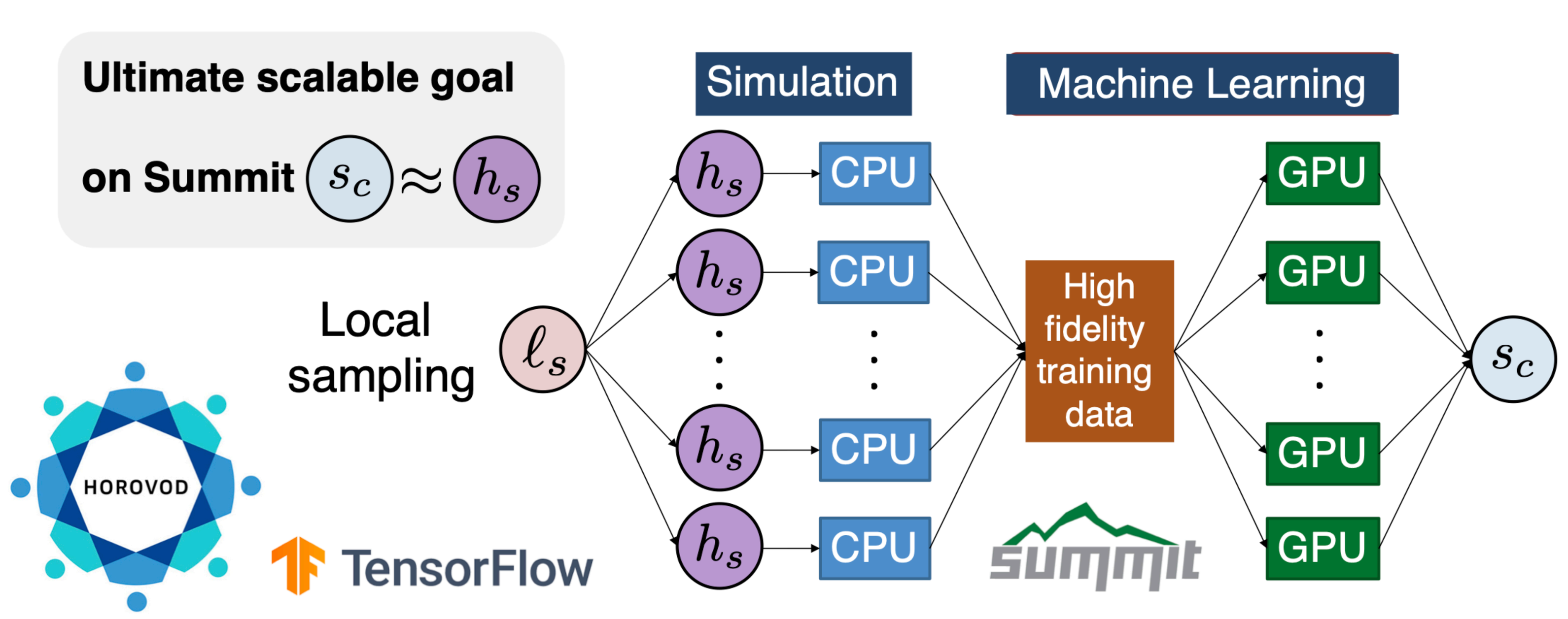
h_s h_s … h_s h_s h_s … h_s …

Scalable ML-based optimization with interval CNN learned s_c

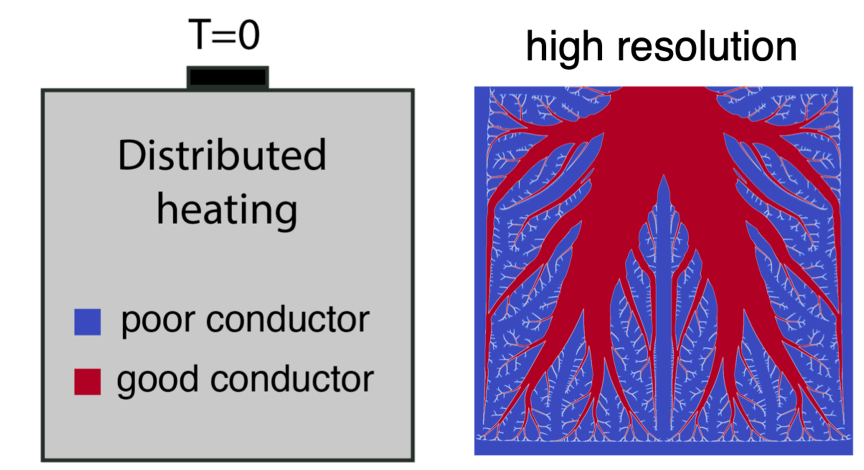
x_i → x_{i+1} → x_j → x_{j+1} → x_{j+2} → x_{k+1} → x_n

s_c ℓ_s Extremely efficient … s_c ℓ_s Extremely efficient … …

Time cost: parallel simulation + scalable ML ≈ high fidelity simulation

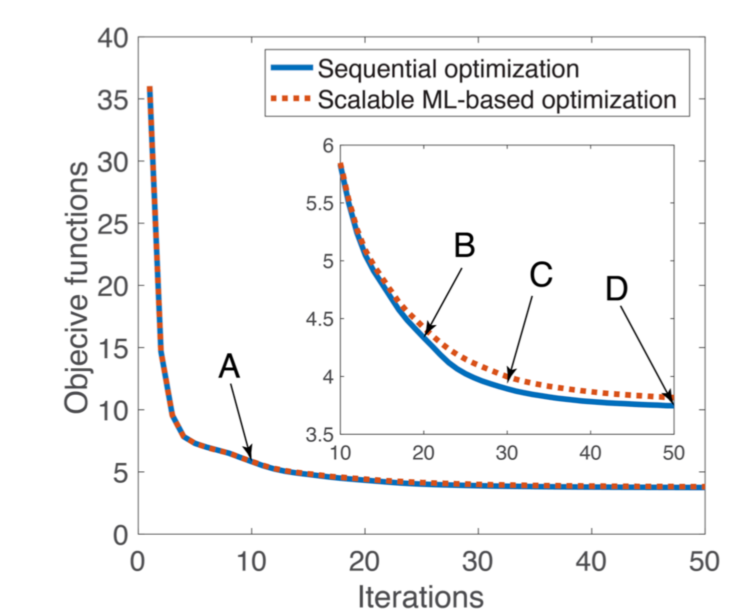


Results: two materials heat conduction

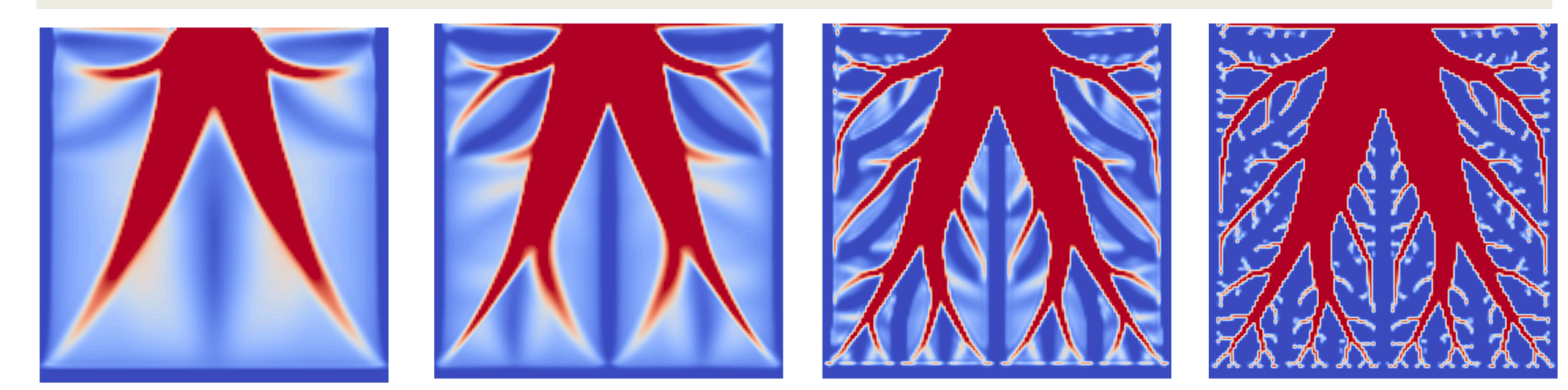


60% "good" thermal materials, k1 = 1.0

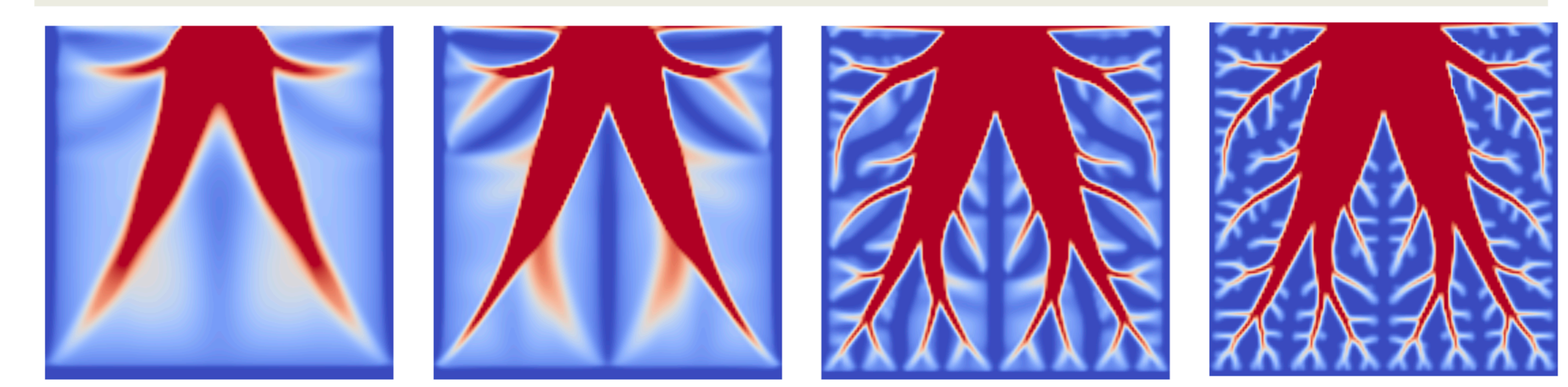
40% "poor" thermal materials, k2 = 0.001



Sequential optimization: 50 expensive simulations

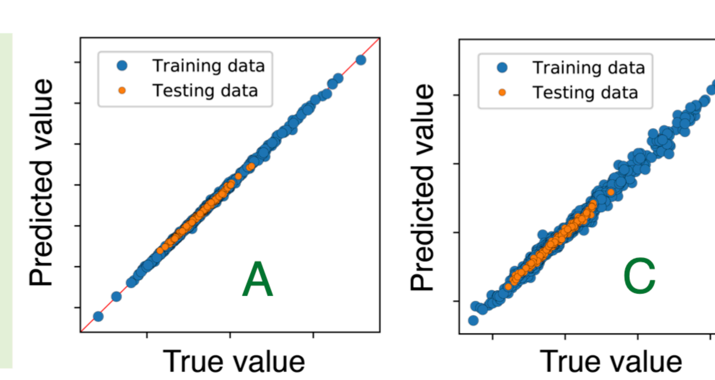


Scalable ML- optimization: 5 CNN-based learning



A B C D

- Finite element for simulation: 128x128 mesh (up to 1024x1024) - expensive
- Local sampling: 10,000 total data
- Training: **32 nodes (192 GPUs) on Summit**
- **Time cost: 15% of classical method**



Significant reduction of 85% time cost with acceleration 6.7x

Summary and future work

- Improve scalability and optimality for complex design requirement a) high resolution, b) irregular design domain, c) multi-material, d) 3D
- Adaptive local sampling strategy: dimension reduction