Disrupting the photonics innovation cycle with data- and physics-driven algorithms

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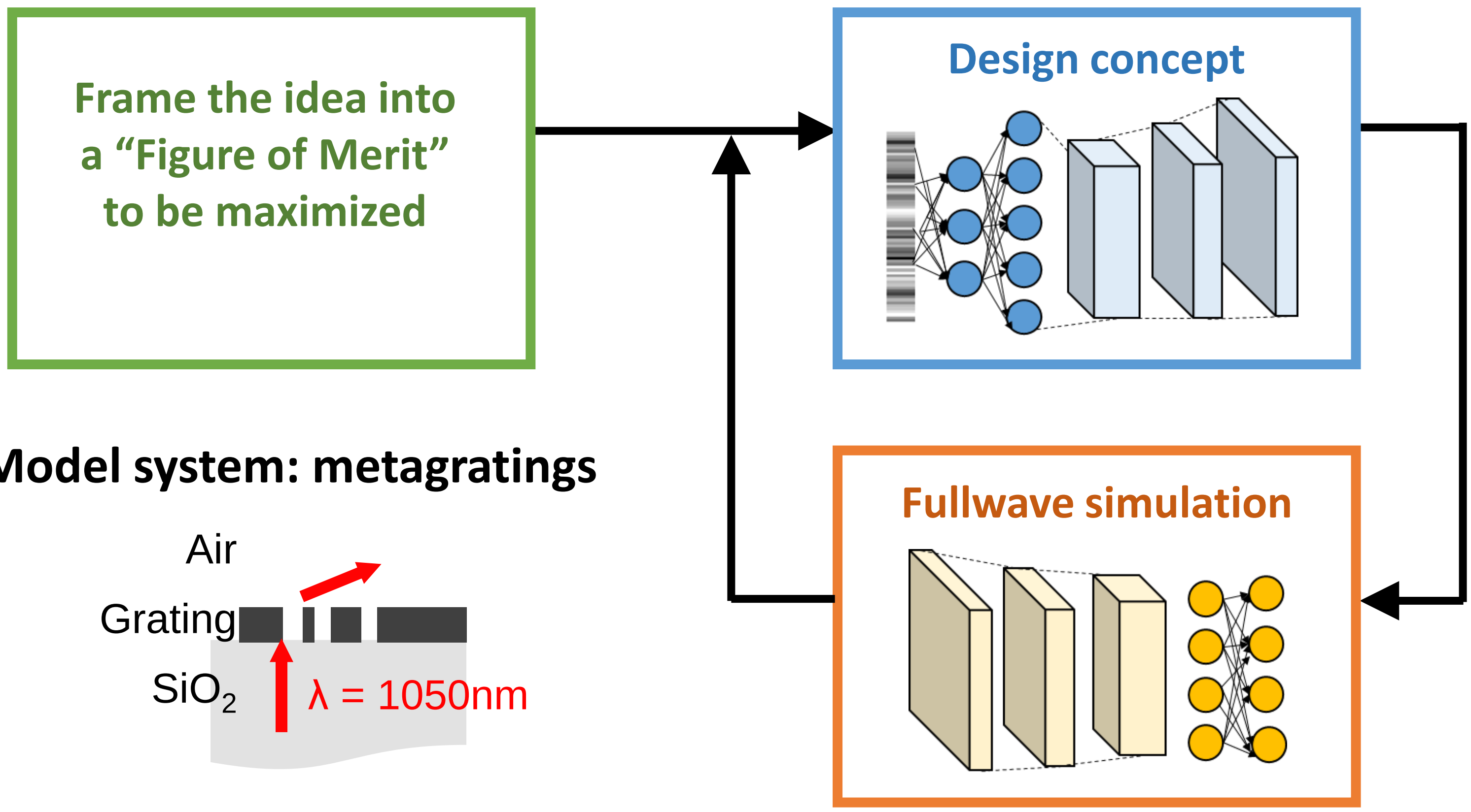
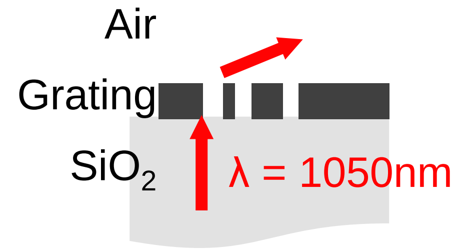
The innovation cycle in photonics

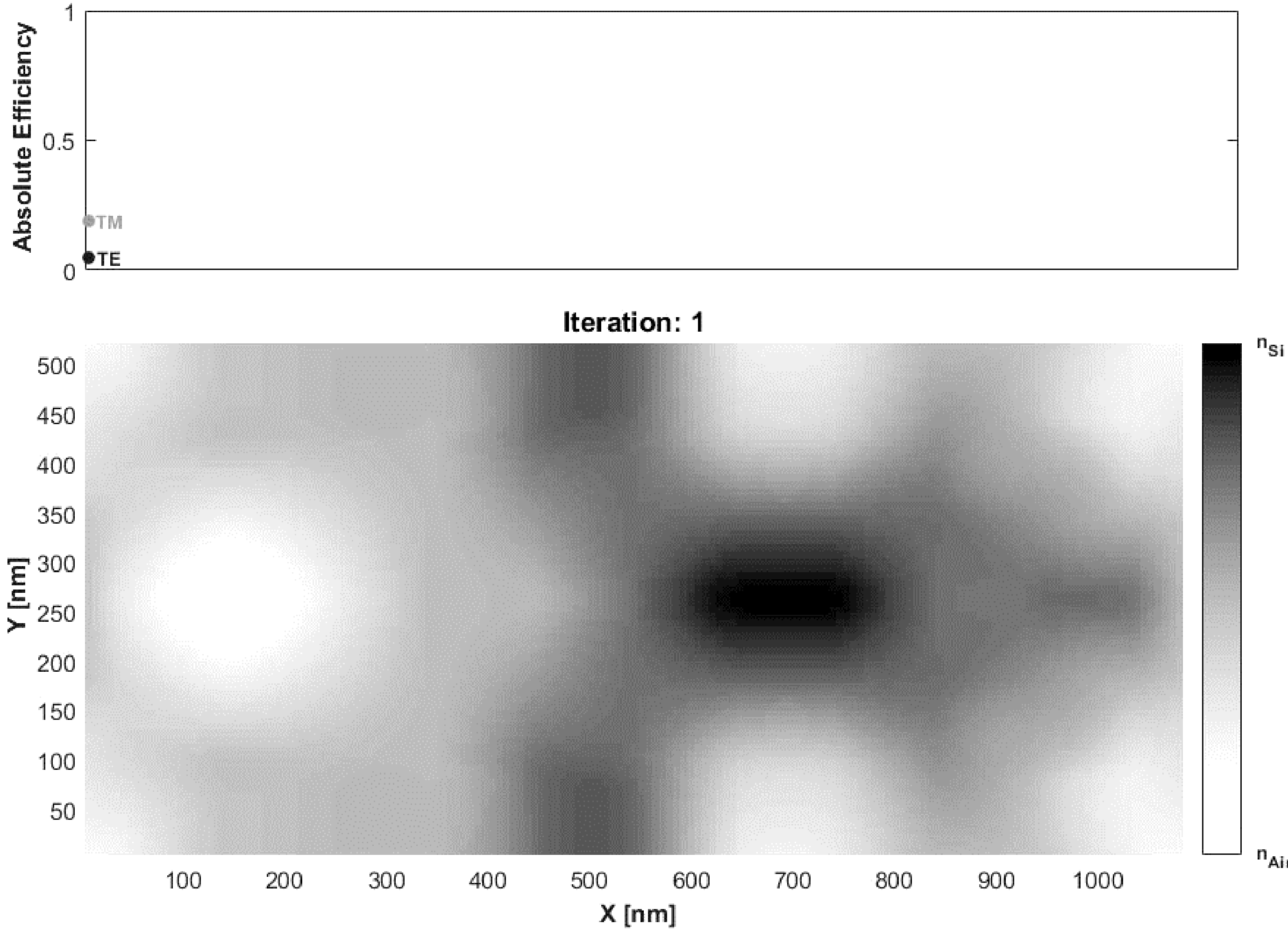
The time and cost required to design and simulate new photonic devices is a bottleneck in innovation.



Model system: metagratings

Local gradient methods



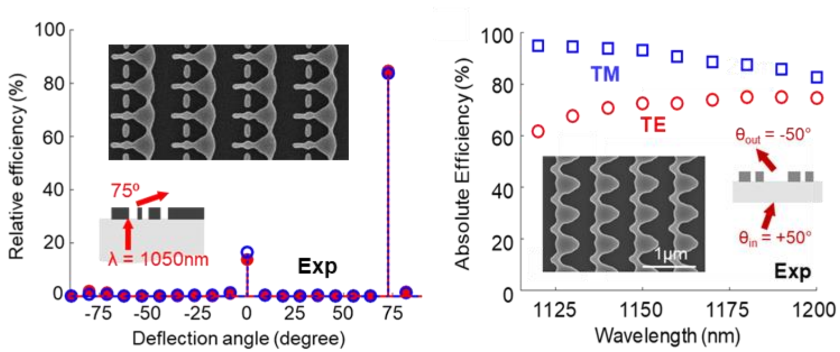


Nano Lett., **17**(6), 3752-3757 (2017)

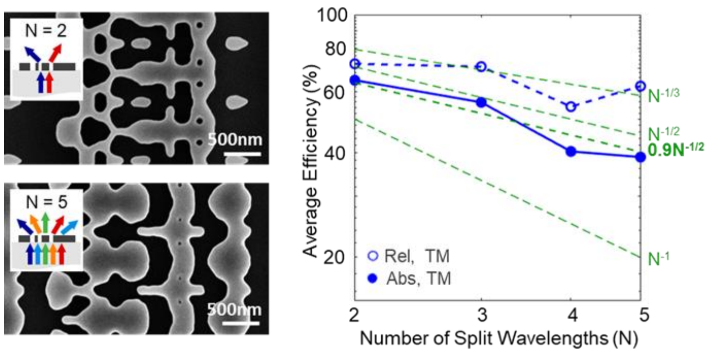
Potpourri of devices

We can design and experimentally realize a broad range of periodic and aperiodic metasurfaces.

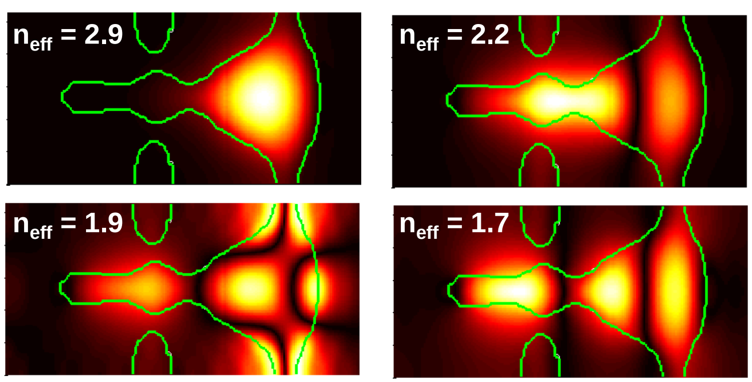
Metagratings



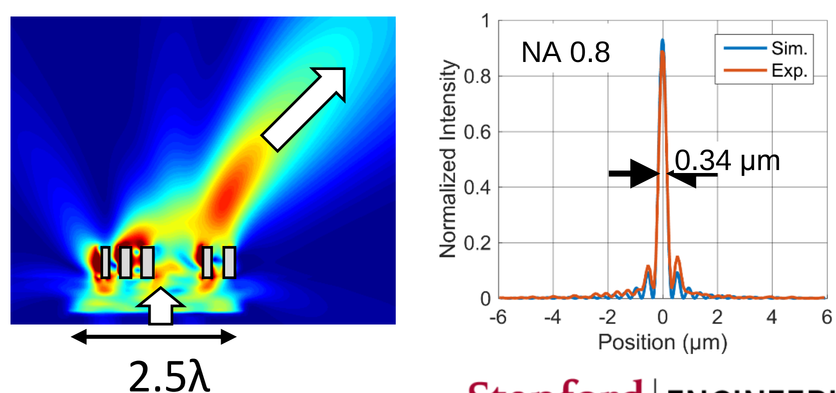
Multi-functional optics



Operating mechanisms



Metalenses



Nano Letters, 17(6), 3752 (2017)
Adv. Opt. Mat., 5, 1700645 (2017)

ACS Phot., 5 (6), 2402 (2018)
Light Sci. and Appl., 8, 48 (2019)

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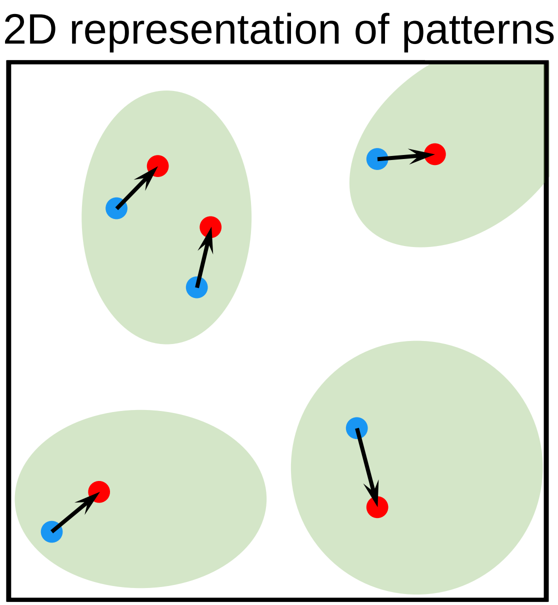
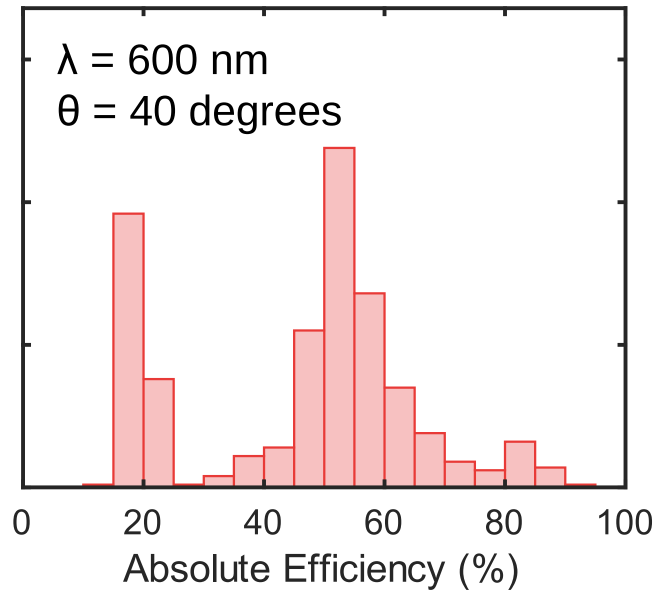
Topology optimization revisited

The adjoint variables method is a **local optimizer** and requires non-trivial computational overhead.

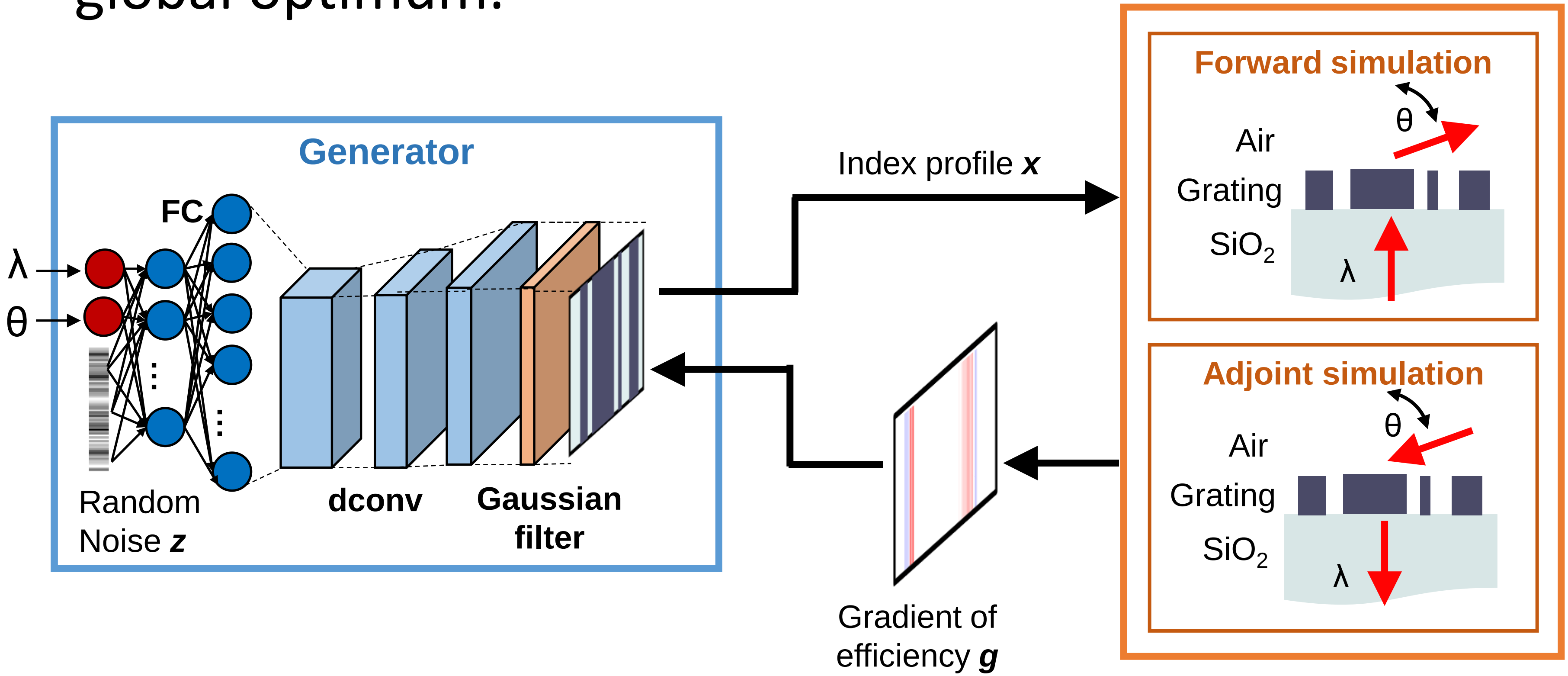




New methods are required to improve computational efficiency and our search for a global optimum.

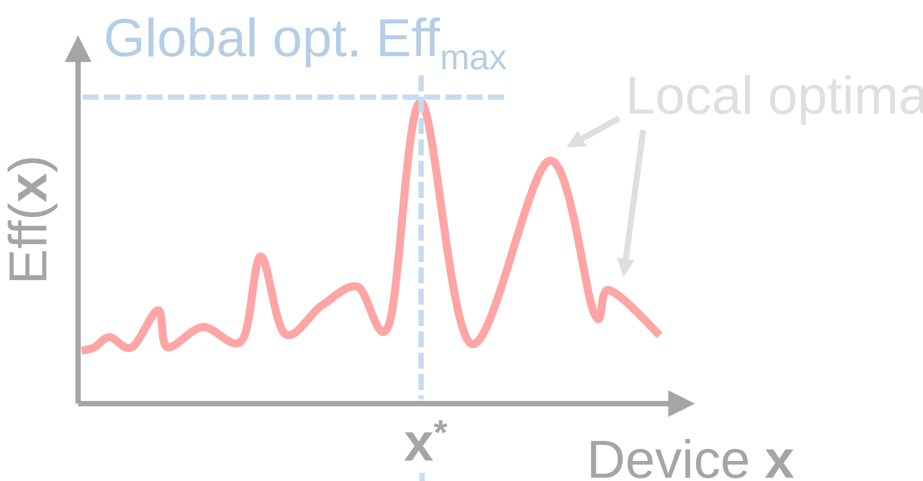
Reframing topology optimization

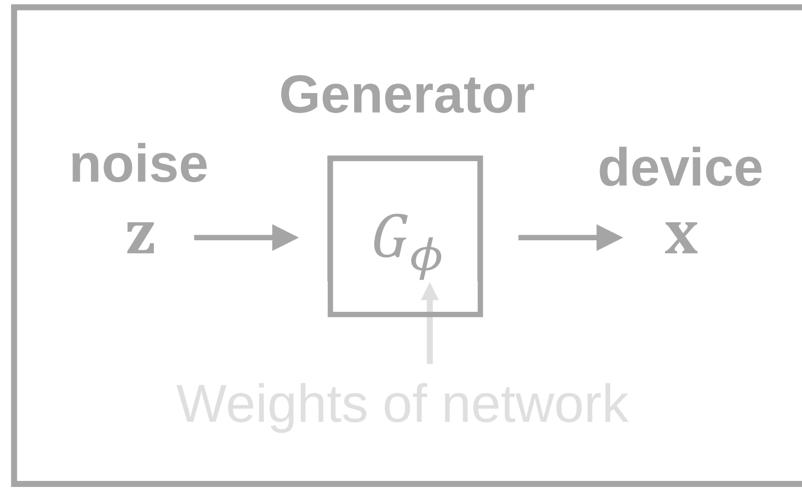
We introduce **global topology optimization networks** (GLOnets) as a new method for searching for the global optimum.



Nano Letters 19(8), 5366 (2019)

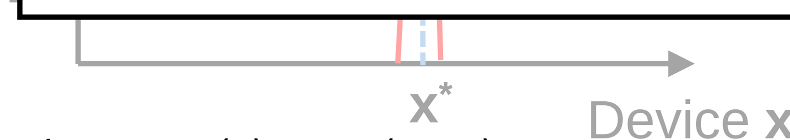
GLOnets: theoretical background





Optimization problem

$$\phi^* := \underset{\phi}{\operatorname{argmax}} \int_{\mathcal{S}} \delta\left(\text{Eff}(\mathbf{x}) - \text{Eff}_{max}\right) \cdot P_\phi(\mathbf{x}) d\mathbf{x}$$



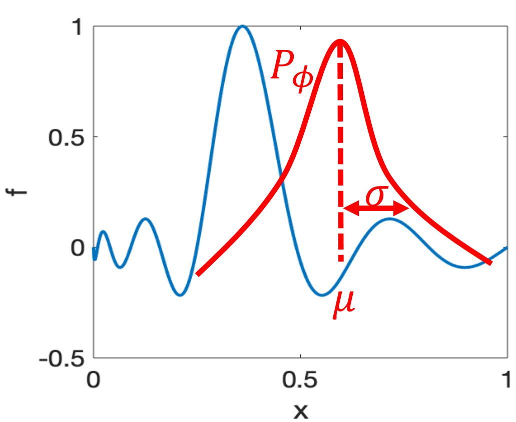
Nanophotonics 9(5), 1059 (2020)

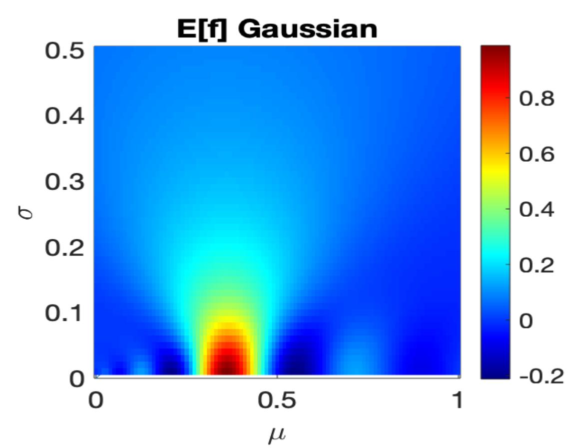
Conceptualizing GLOnets

We are solving a dual problem that transforms the original problem and optimization landscape:

$$\underset{\boldsymbol{x}}{\text{maximize}} \quad f(\boldsymbol{x}) \quad \xrightarrow{\int P_\phi(x) f(x) dx} \quad \underset{\boldsymbol{\phi}}{\text{maximize}} \quad \underset{\boldsymbol{x} \sim P_{\boldsymbol{\phi}}}{\mathbb{E}} f(\boldsymbol{x})$$

We can visualize these differences by considering $P_{\boldsymbol{\phi}}$ to be a simple Gaussian distribution:





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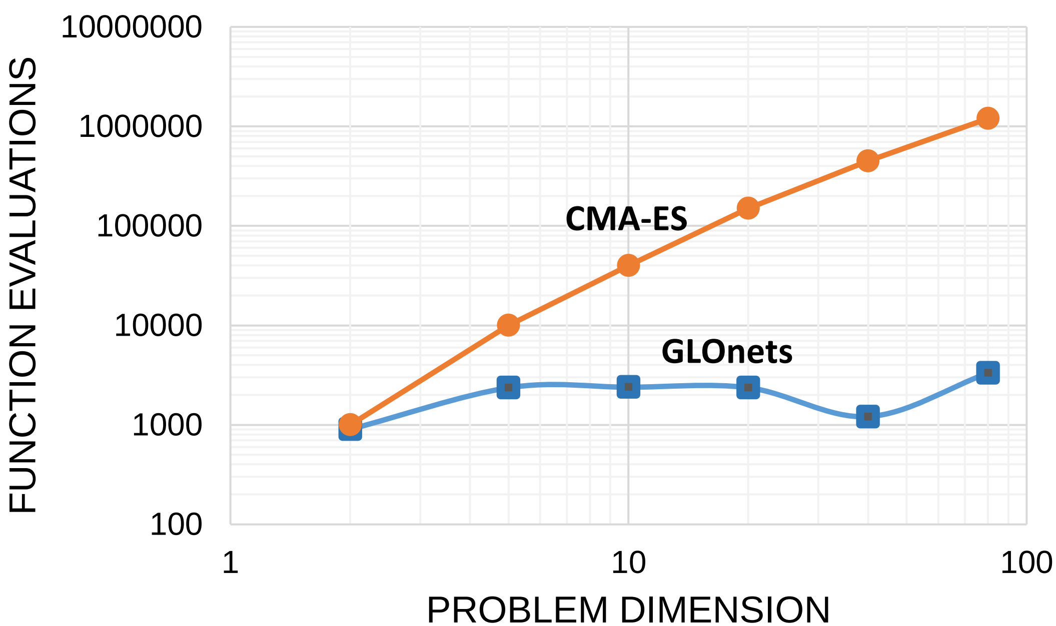
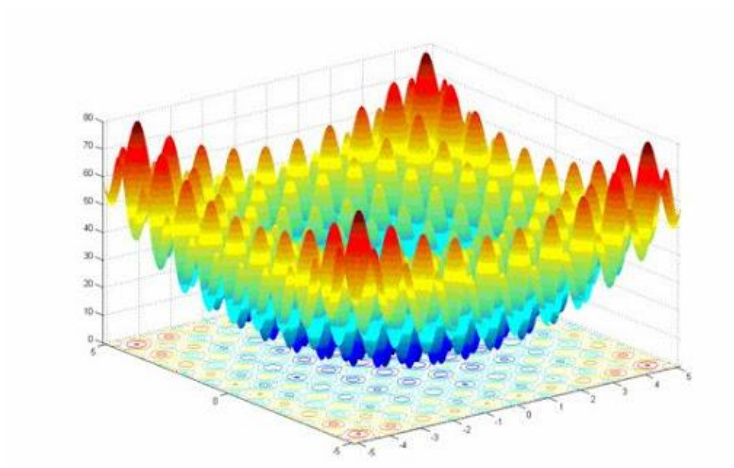
Scaling with dimensionality

The batch size used in GLOnets optimization does not depend on the dimensionality of the problem.

Example: Rastrigin function $f(x) = 10d + \sum_{i=1}^{d}\left[x_i^2 - 10\cos(2\pi x_i)\right]$

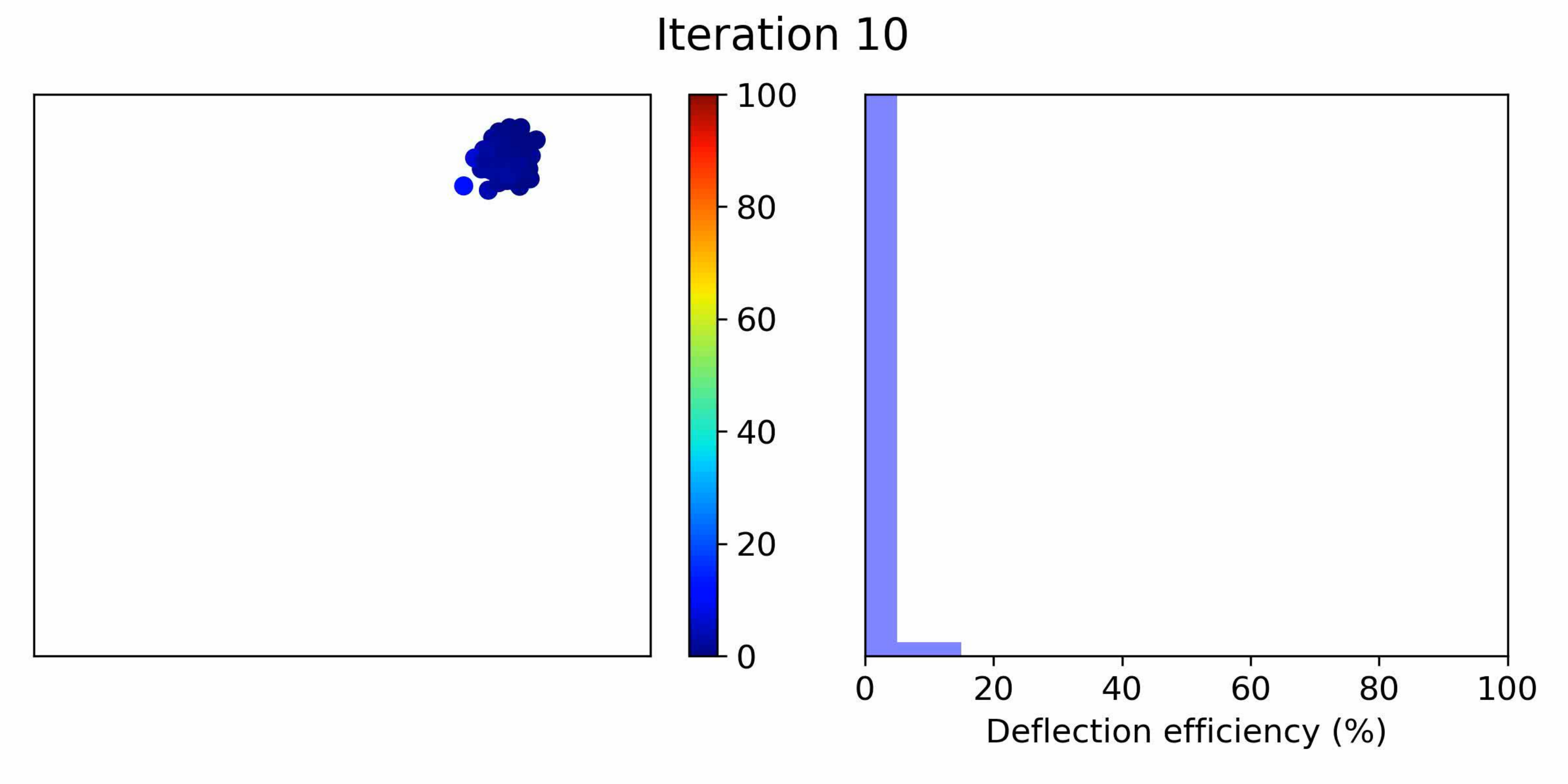




Visualizing GLOnet

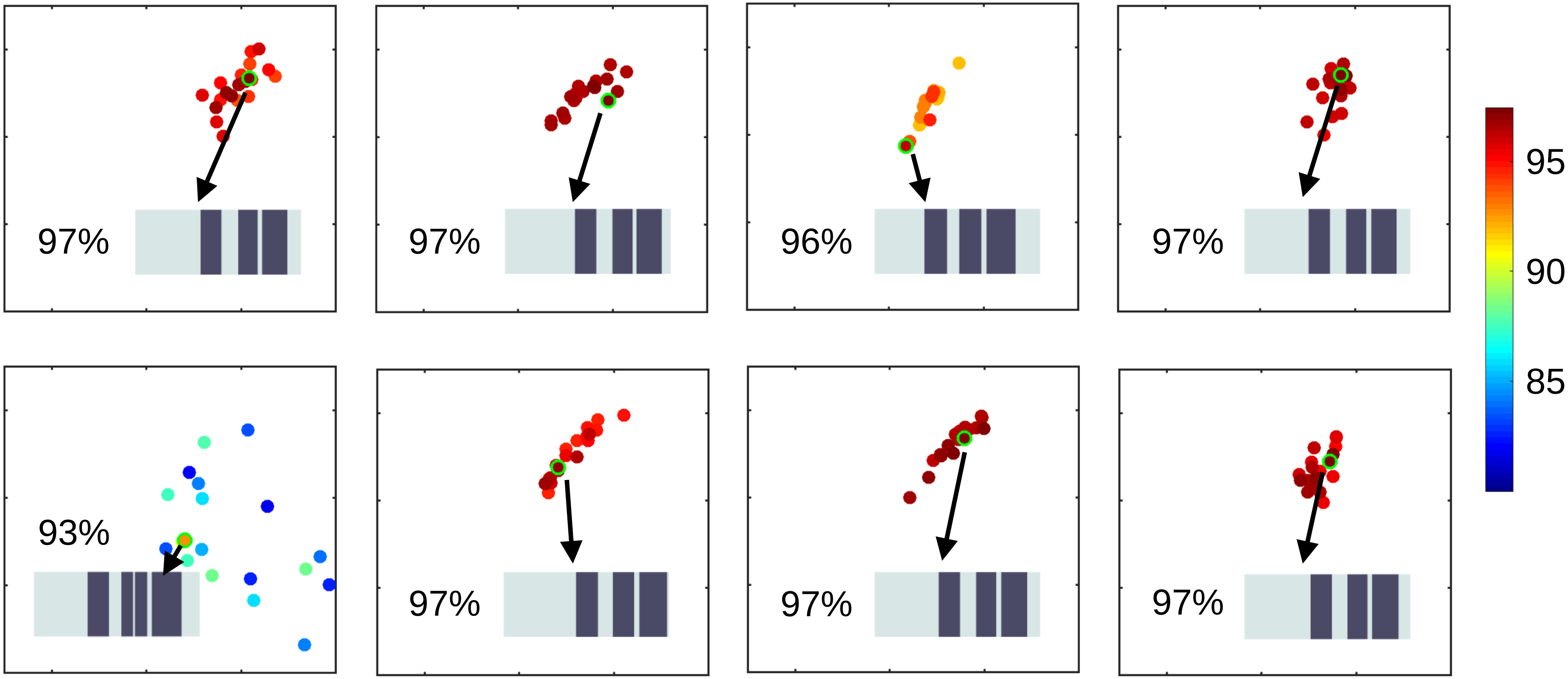
Plot of device efficiencies and geometries, depicted using principle components analysis.

- Device parameters: λ = 850 nm and θ = 65°



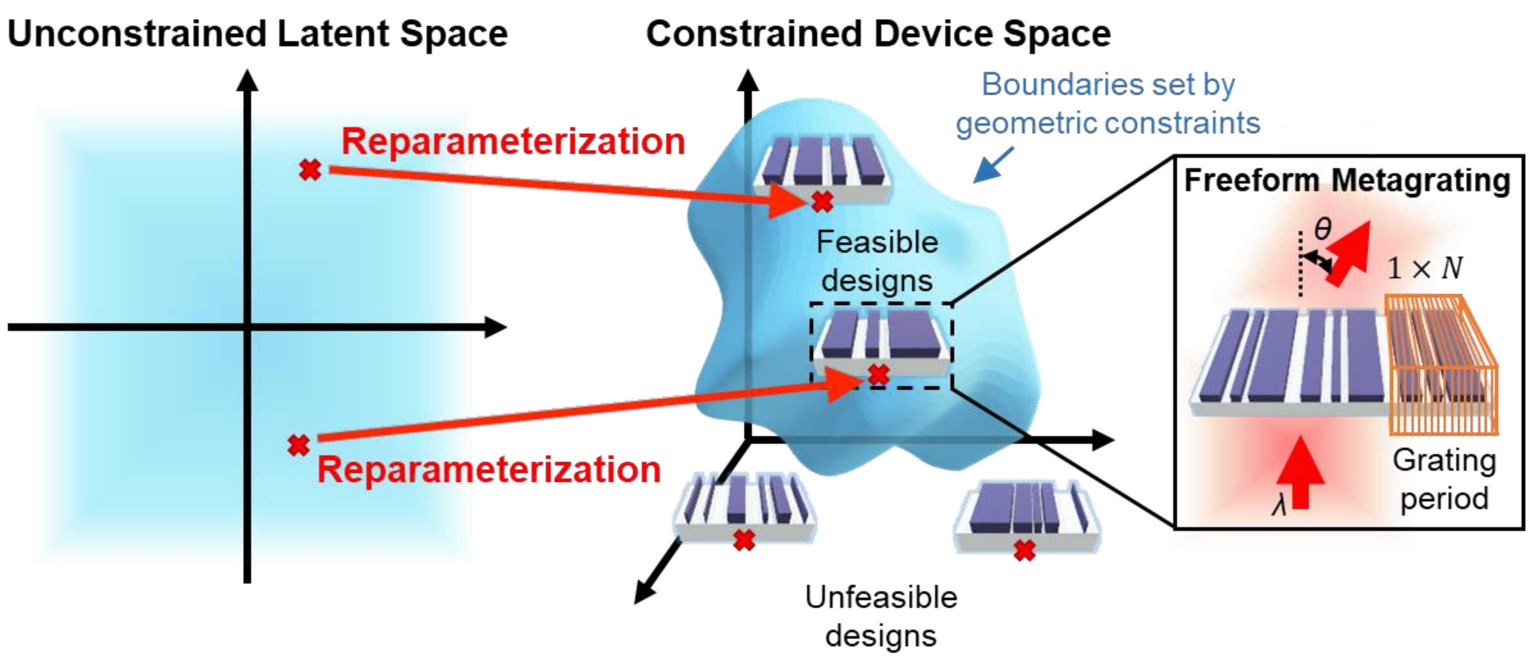
GLOnet stability

We train 8 unconditional GLOnets independently and the networks converge to the same optimal device 6 times.



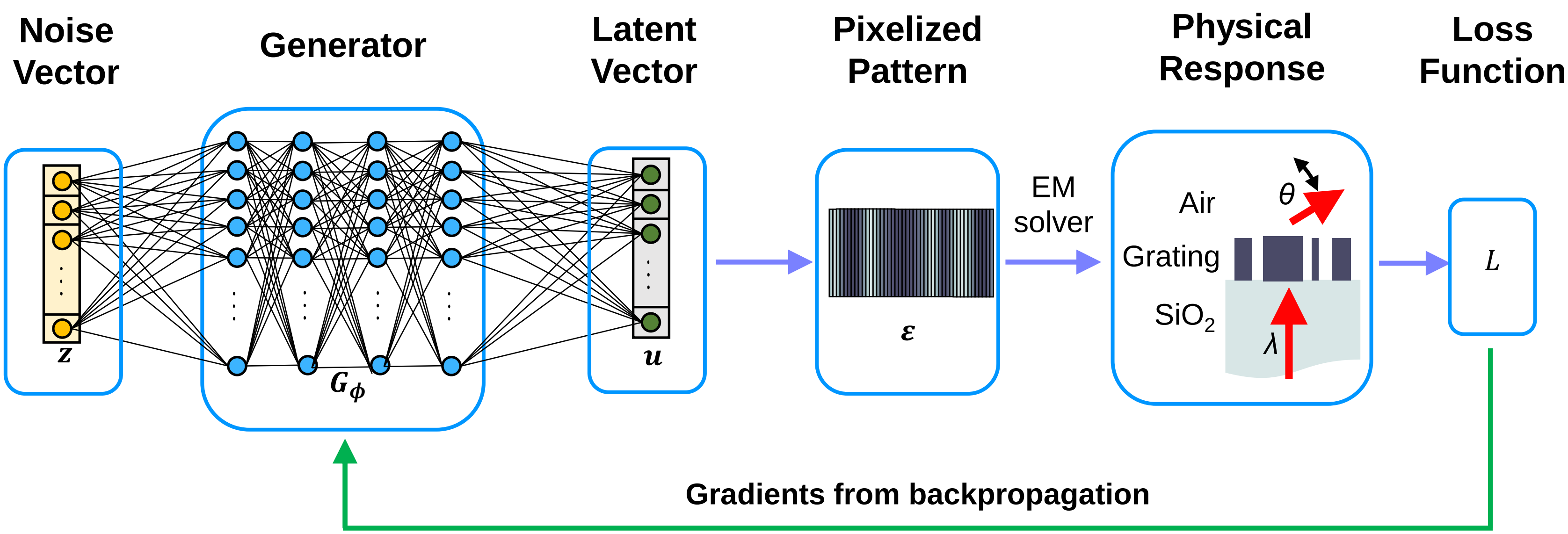
Enforcing constraints through reparameterization

We design devices within an unconstrained latent space, followed by mathematical transformations to a real constrained device space.



Reparameterization with GLOnets

We can use a generative neural network to output a distribution of base parameters, which are then transformed to permittivity profiles via reparameterization.



ACS Photonics 7, 3141 (2020)

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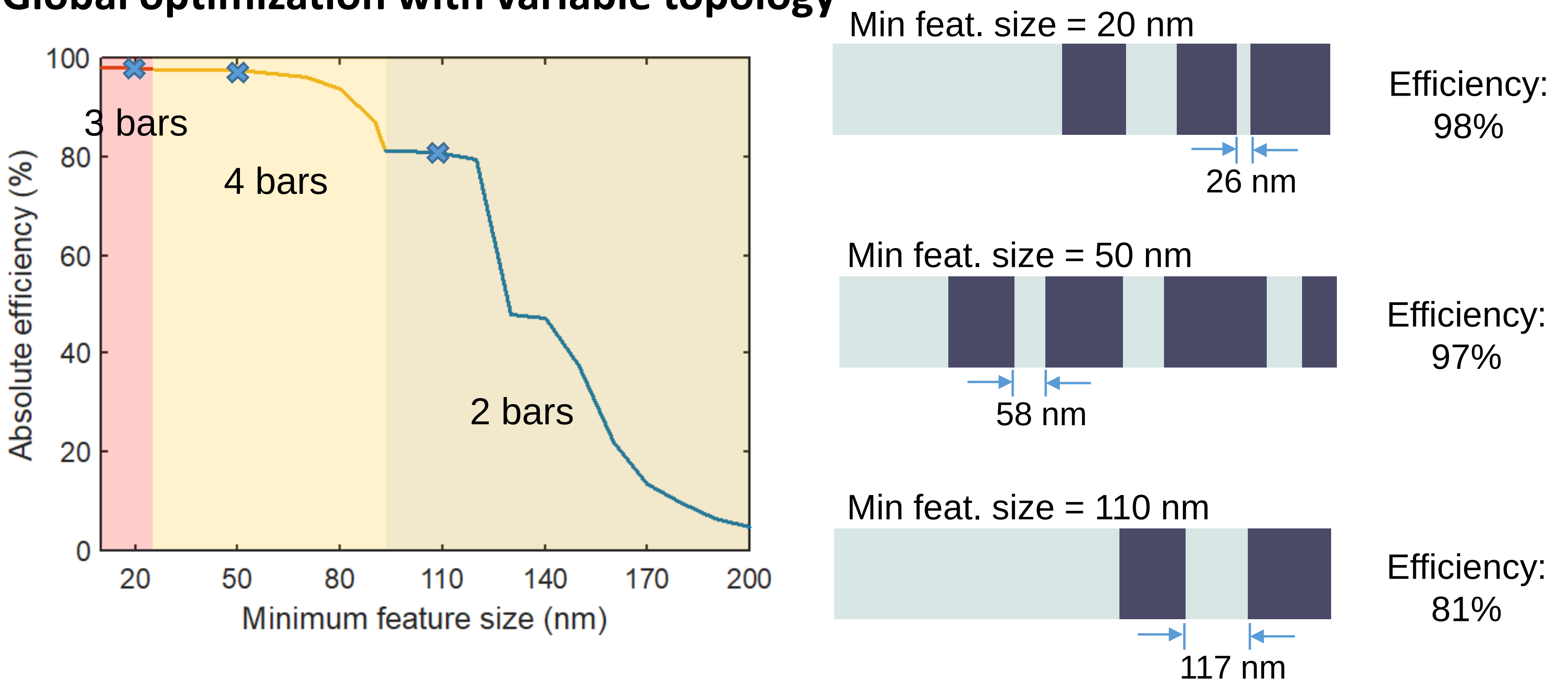
Global optimization with constraints

The topology of the globally optimal device changes as a function of minimum feature size.

Global optimization with variable topology

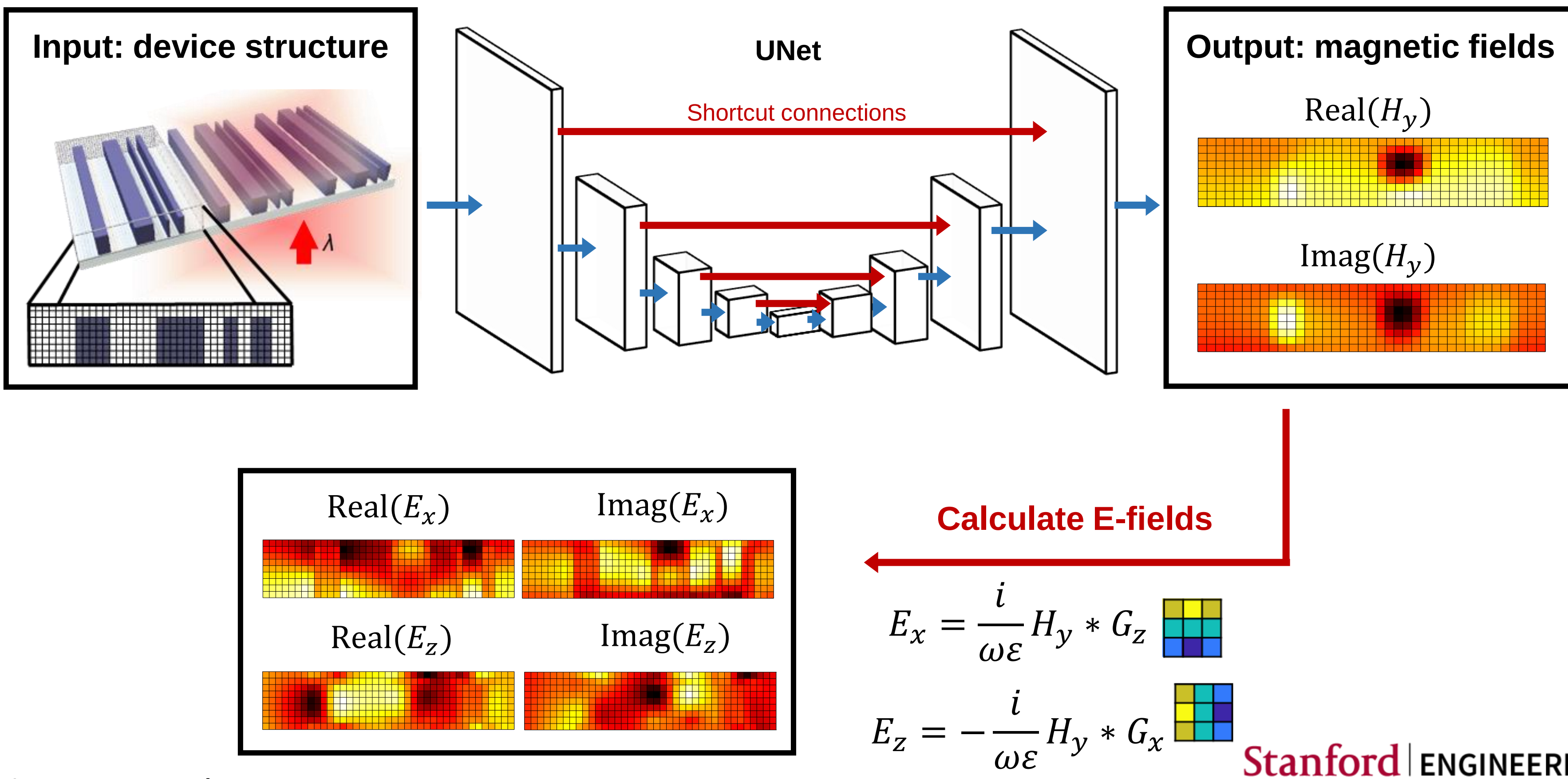


ACS Photonics ASAP (2020)

Surrogate electromagnetic simulators

We utilize a convolutional neural network to predict the EM fields from a device layout.

Inspiration: Muskens, *Nano Lett.* 20(1), 329 (2020)



In preparation

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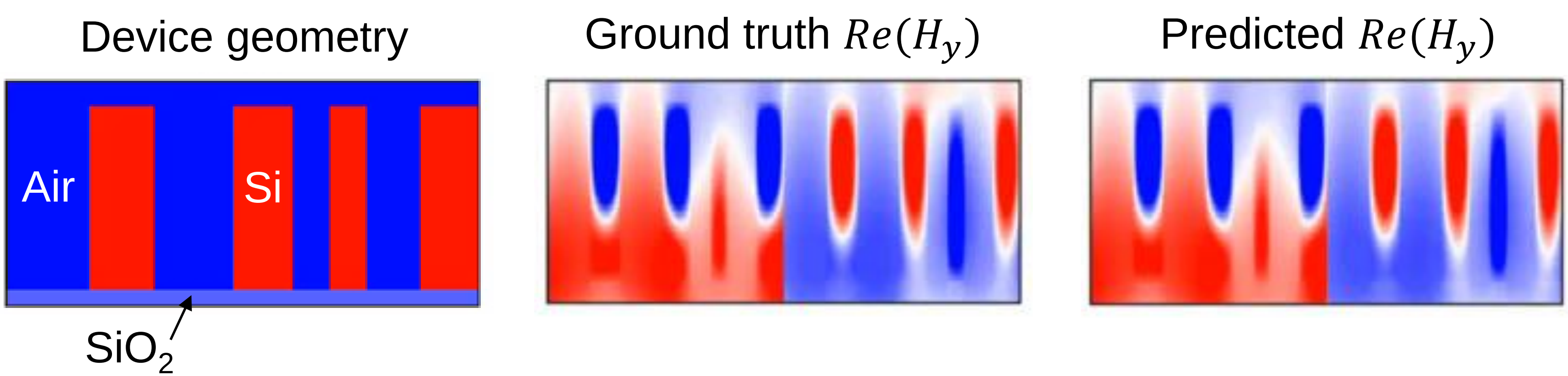
UNet training process

We train the UNet with 60,000 examples of device geometry-magnetic field pairs and use MSE loss:

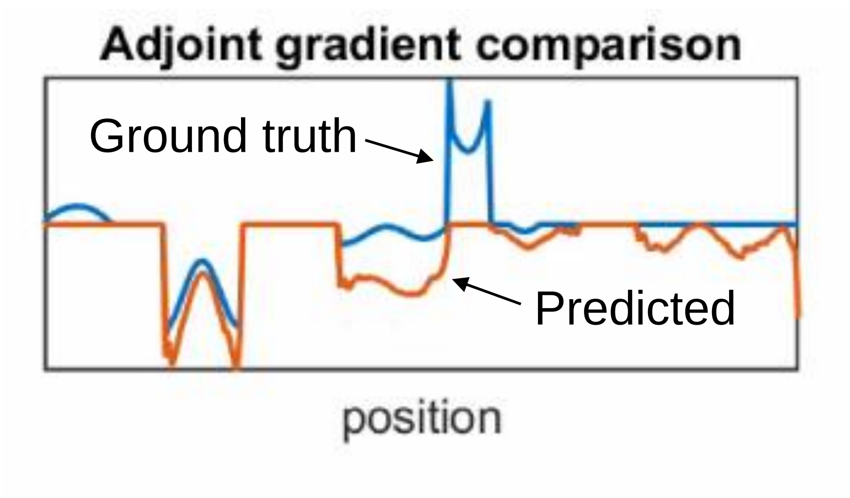
$$L = \frac{1}{N}\sum\left(\widehat{\boldsymbol{H}} - \boldsymbol{H}\right)^2$$

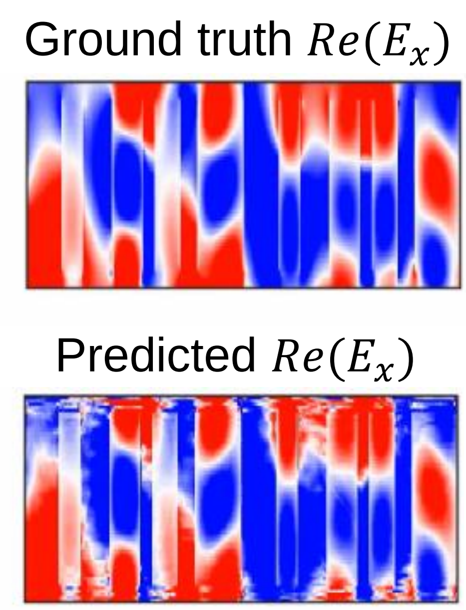
The UNet produces field solutions two orders-of-magnitude faster than an FDFD solver.



Adjoint optimization with UNets

- We train separate UNets to perform forward and adjoint simulations.
- We perform a near-to-far field transformation from the forward simulation to calculate efficiency.



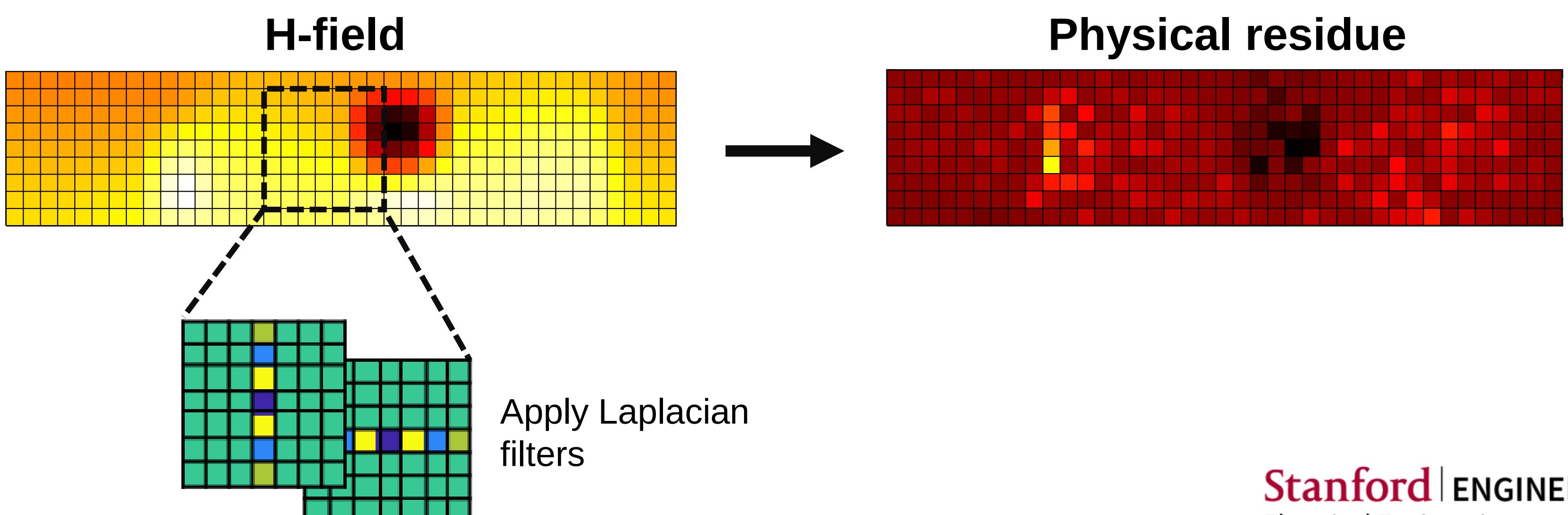


Adding physics to the training process

We train the network using a training data set, together with physical loss to ensure that the outputted fields obey Maxwell's equations.

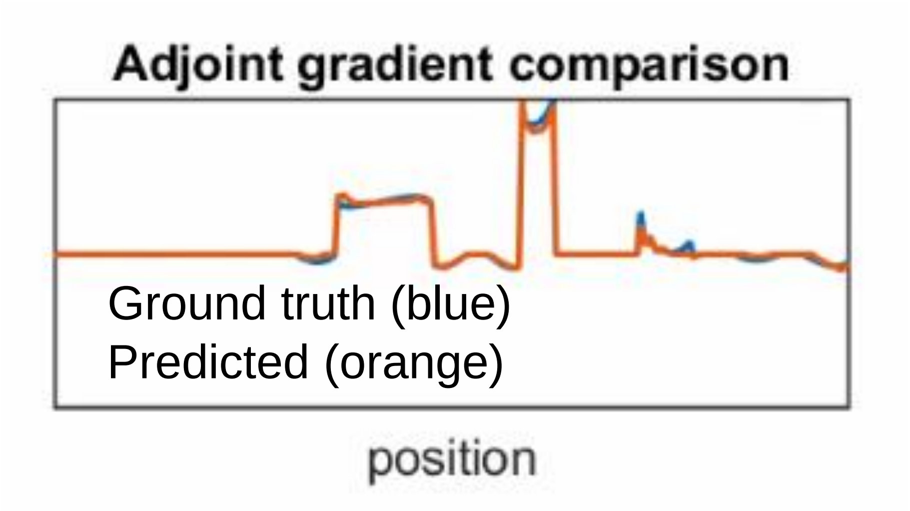
Data loss | Physical loss

$$L = \frac{1}{N}\sum\left(\widehat{\boldsymbol{H}} - \boldsymbol{H}\right)^2 + \nabla \times \left(\frac{1}{\varepsilon}\nabla \times \boldsymbol{H}\right) - \omega^2\mu_0\boldsymbol{H}$$

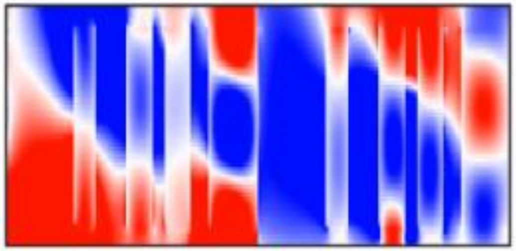


Physically regularized UNet

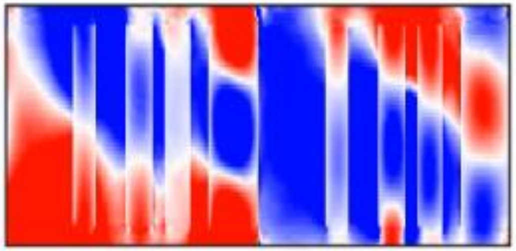
- We again train separate UNets to perform forward and adjoint simulations.
- Physically-regularized UNets produce significantly improved electric field and gradient calculations.



Ground truth $Re(E_x)$



Predicted $Re(E_x)$



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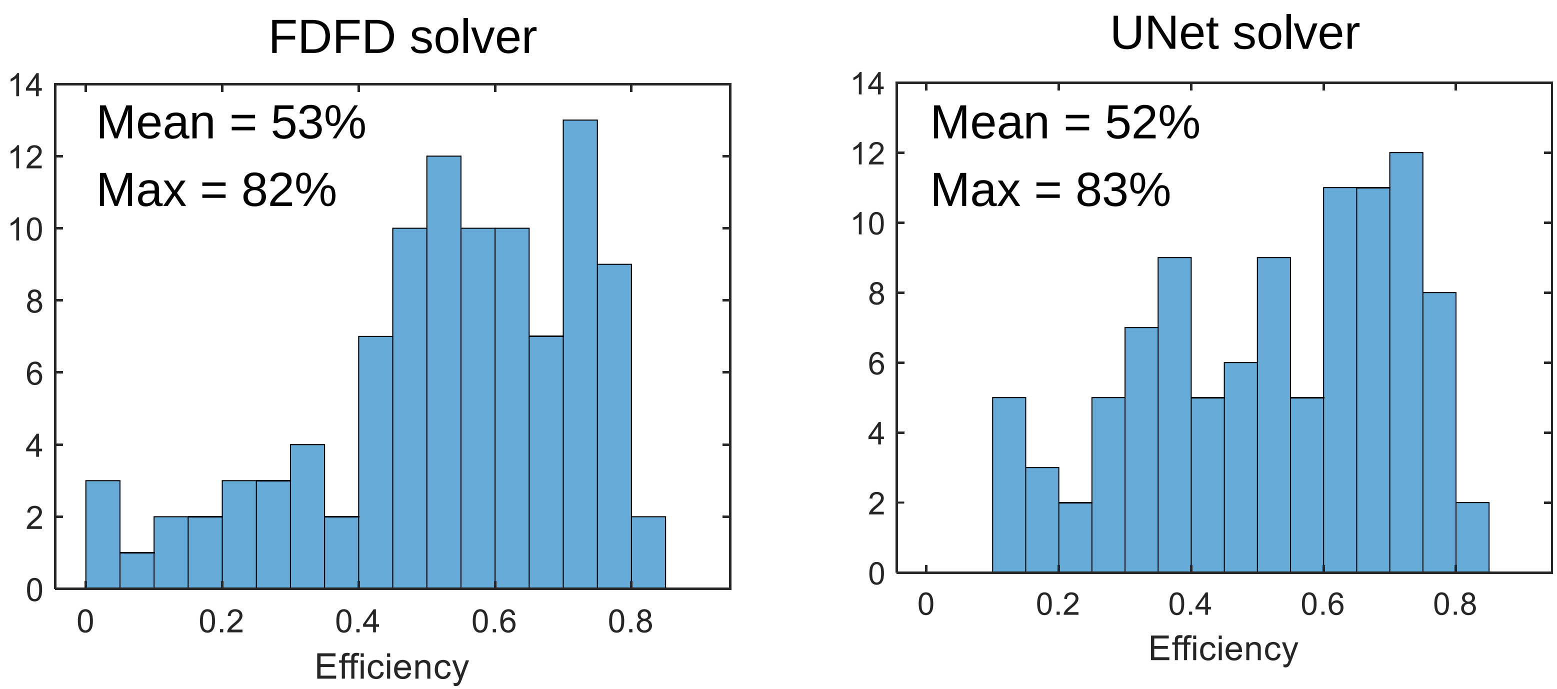
Benchmarking local optimizers

The physically regularized UNet-based optimizer produced results consistent with the FDFD-based optimizer.



Histograms are of 100 adjoint optimizations for each solver.

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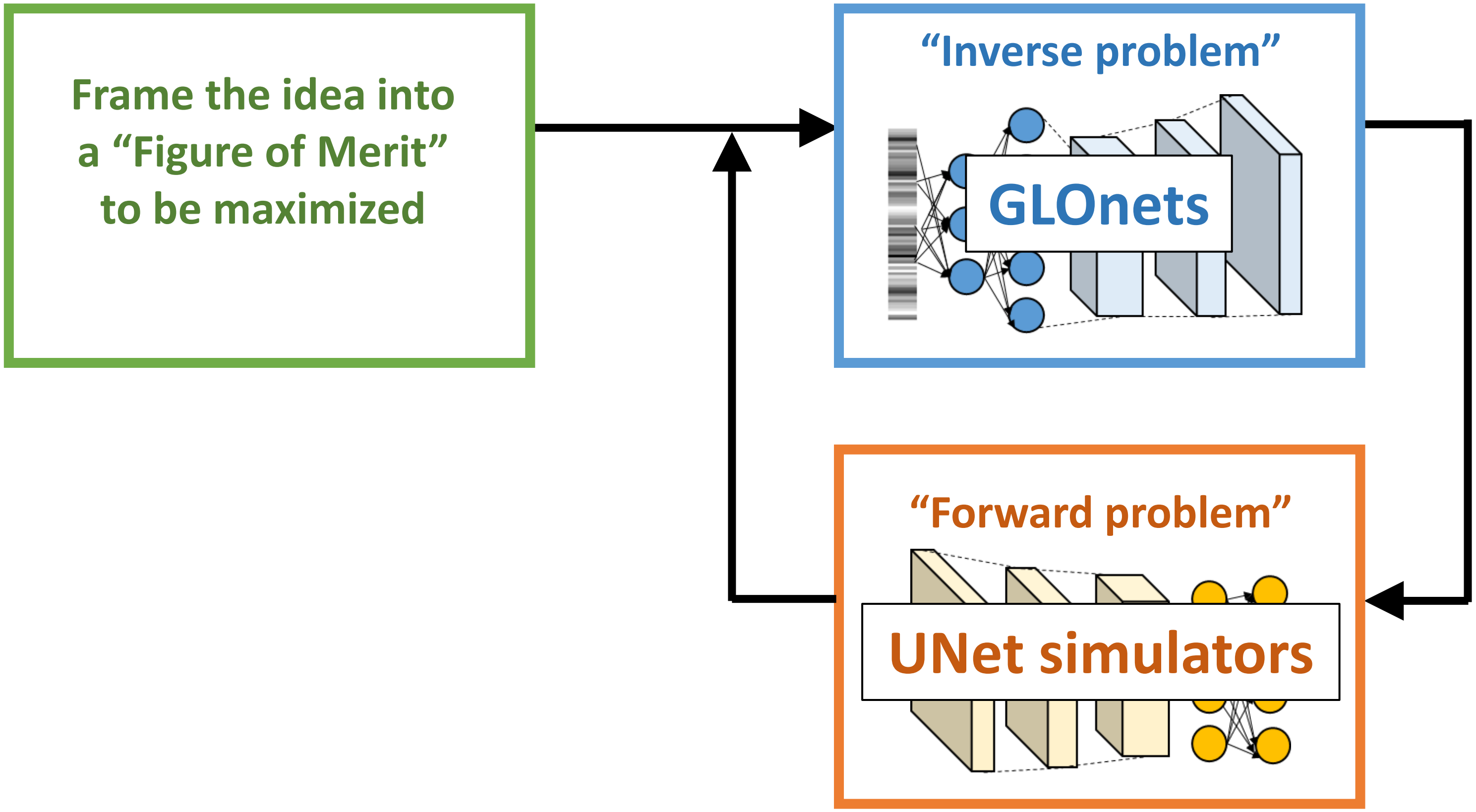
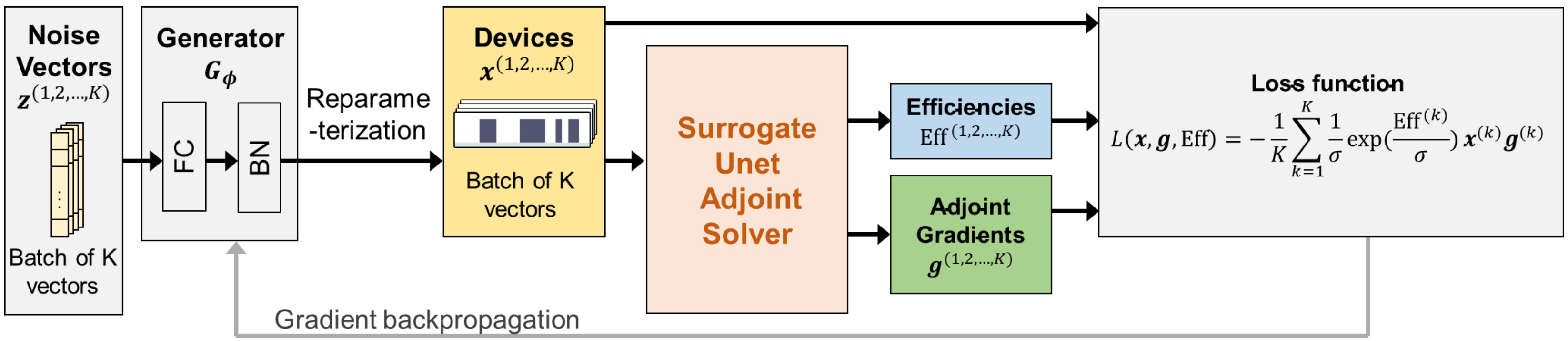
Revisiting the innovation cycle

The design process can be automated and accelerated by three orders of magnitude, disrupting the way devices and systems are engineered.

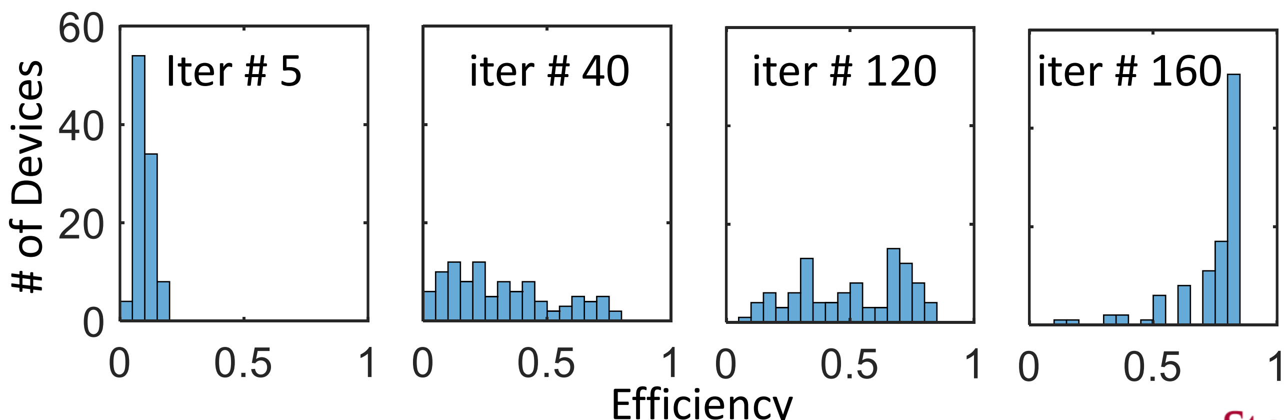


All neural network global optimizer

The combined UNet-GLOnet computational graph:



The global optimum is found 3-4 orders of magnitude faster than with conventional solvers.



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Summary

- Deep learning is the foundation for the next generation of CAD-based inverse design tools in photonics.
- Hybrid algorithms that combine physics and physical constraints with neural networks is key.
- More innovations are required to scale up these concepts to large area, 3D systems.

http://fanlab.stanford.edu

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