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Q-ONE

A PERSPECTIVE ON RECENT TRENDS IN INVERSE DESIGN OF INTEGRATED PHOTONIC DEVICES AND CIRCUITS

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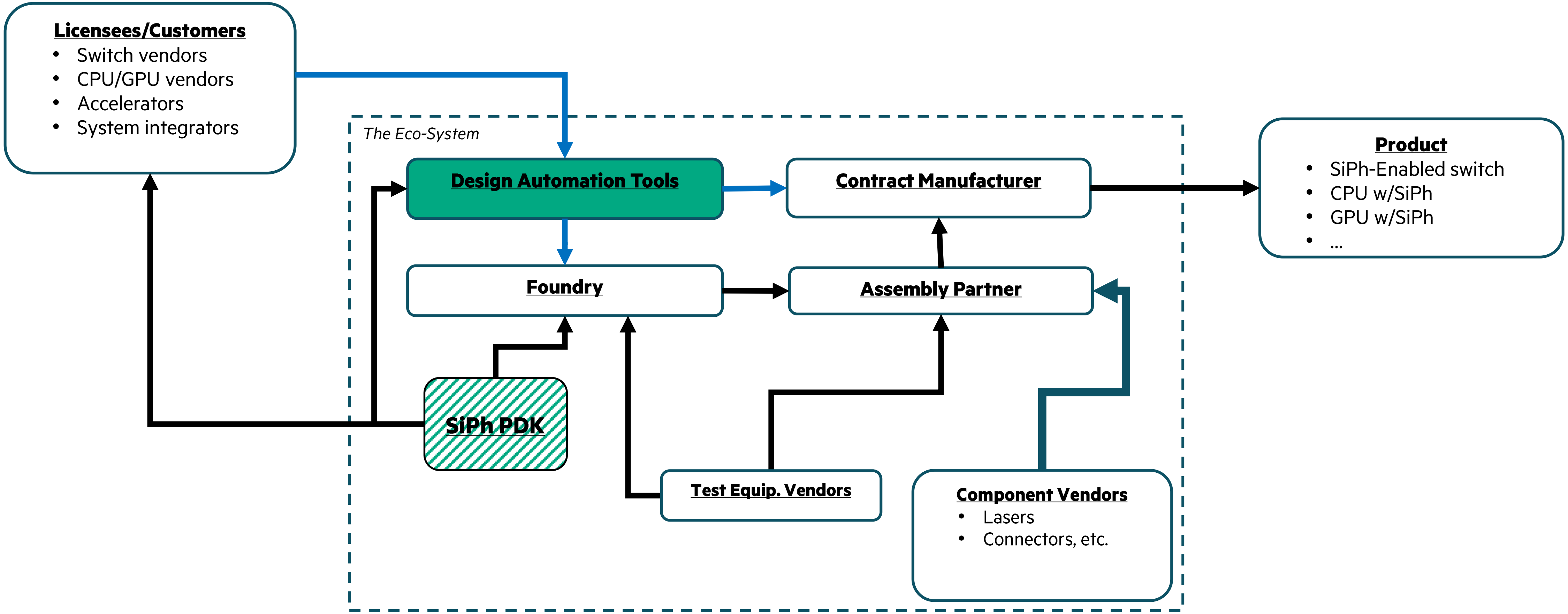
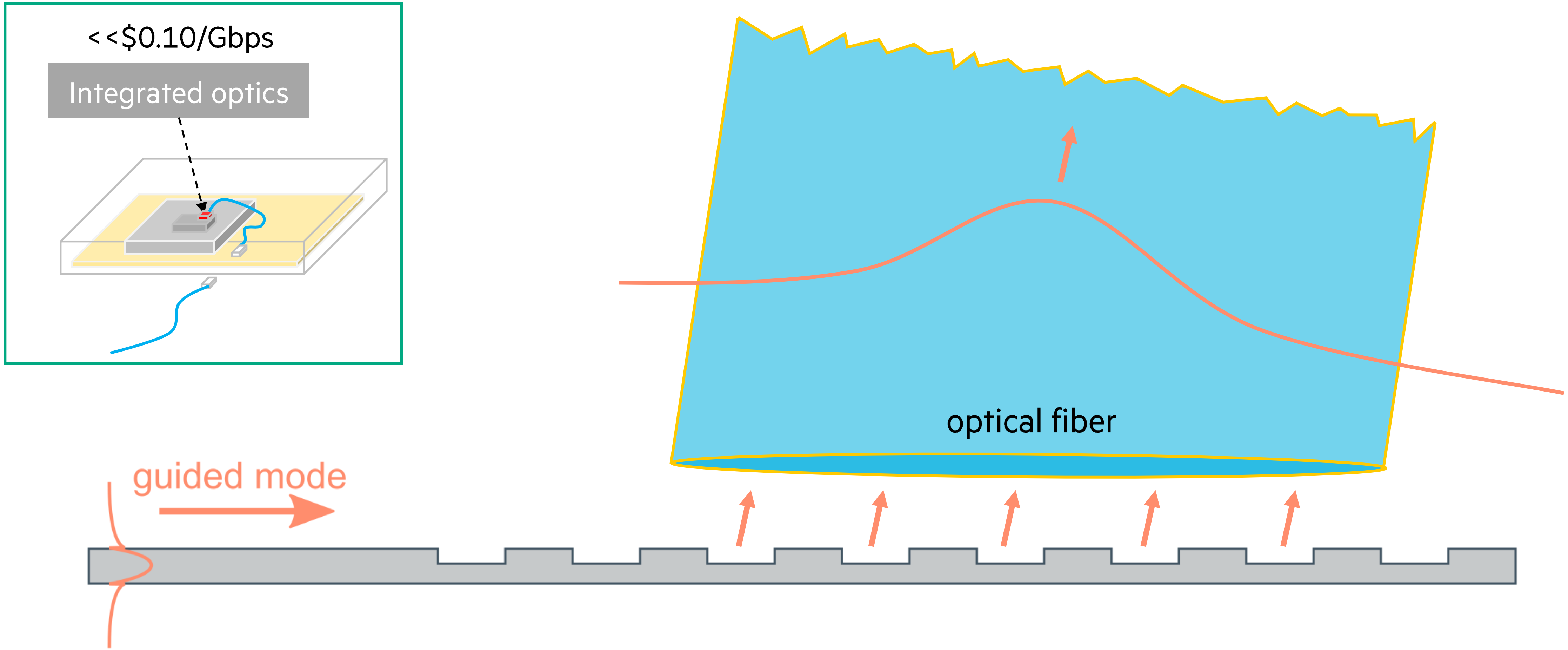
A SILICON PHOTONICS ECOSYSTEM



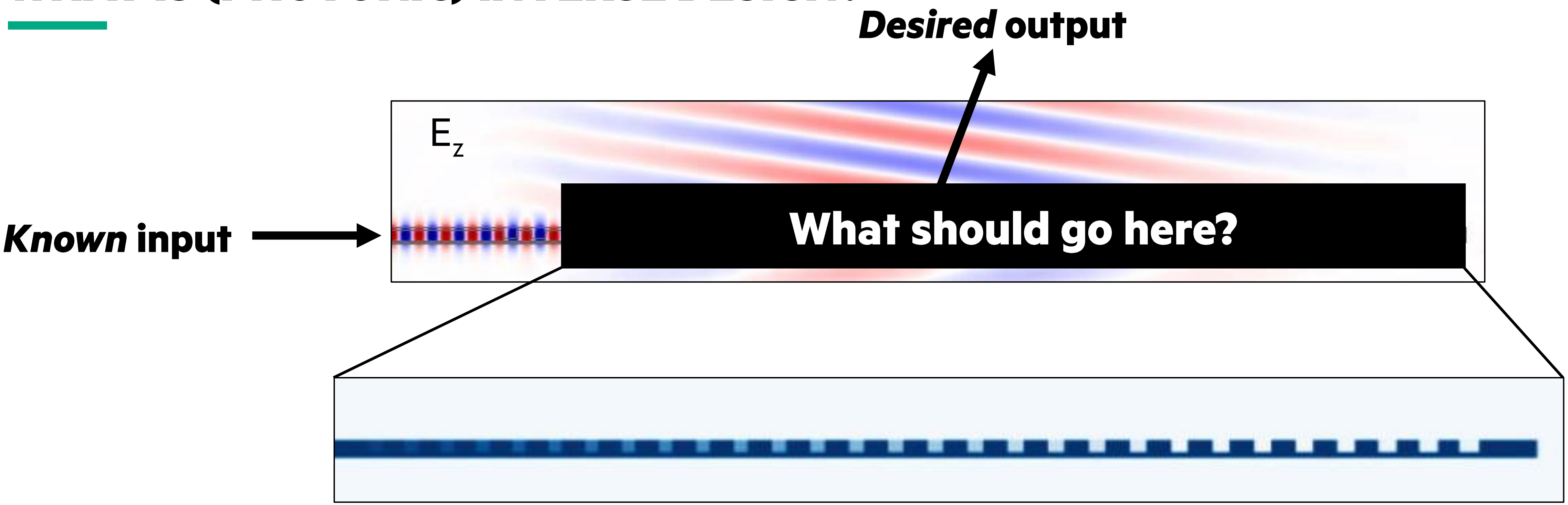
Fiorentino, M., et al., 2021. In *Silicon Photonics IV: Innovative Frontiers*

MOTIVATING EXAMPLE:
Grating coupler to efficiently scatter light off chip



Typical Insertion Loss ≈ −1.0dB (80% Efficiency)

WHAT IS (PHOTONIC) INVERSE DESIGN?



inverse design:

which design results in best match with desired output?

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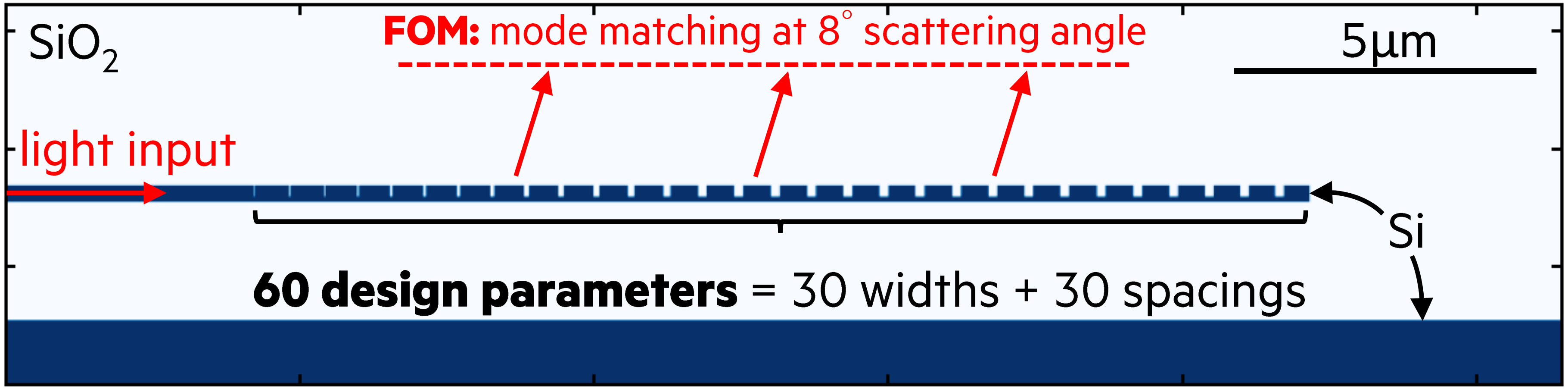
optimization problem:

find optimal design among all possible designs

HOW TO PERFORM (PHOTONIC) INVERSE DESIGN?

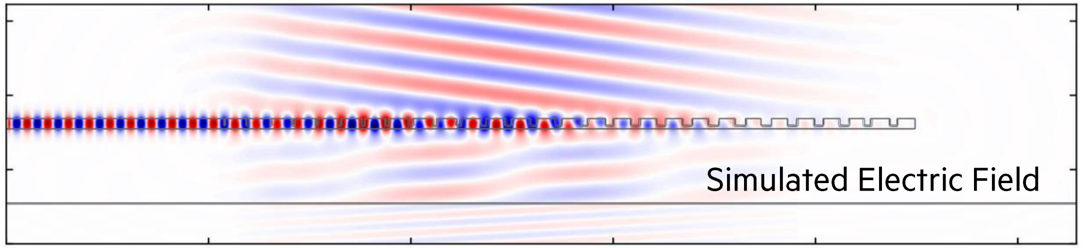
- **Step 1a**: problem specification



- **Step 1b**: set up simulation tool

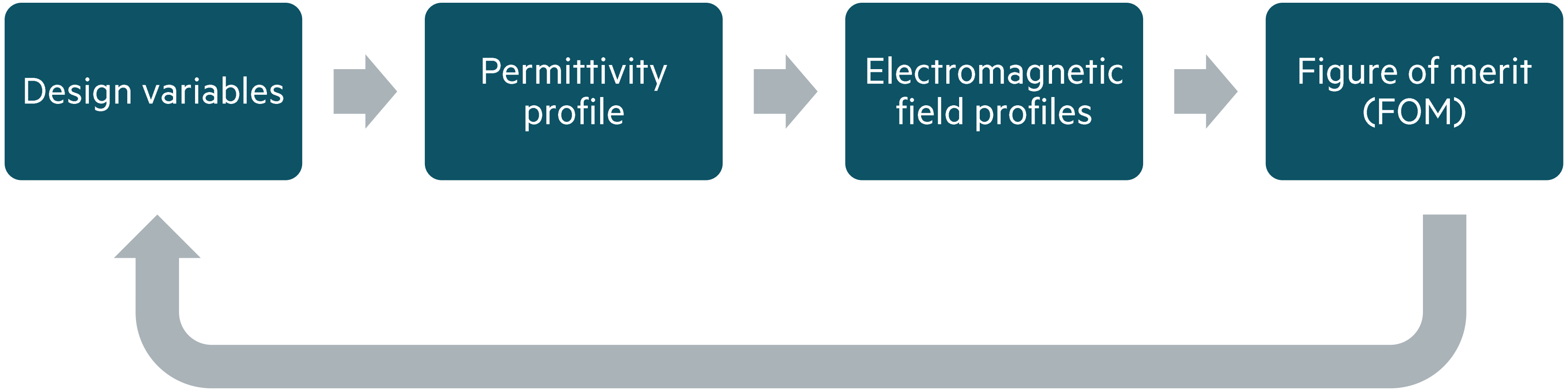
Design variables → Permittivity profile → Electromagnetic field profiles → Figure of merit (FOM)

  - Finite difference solvers, etc.
  - Data-driven machine learning models
  - Self-supervised physics-informed machine learning models



HOW TO PERFORM (PHOTONIC) INVERSE DESIGN?

- **Step 2**: optimize design variables to maximize figure of merit

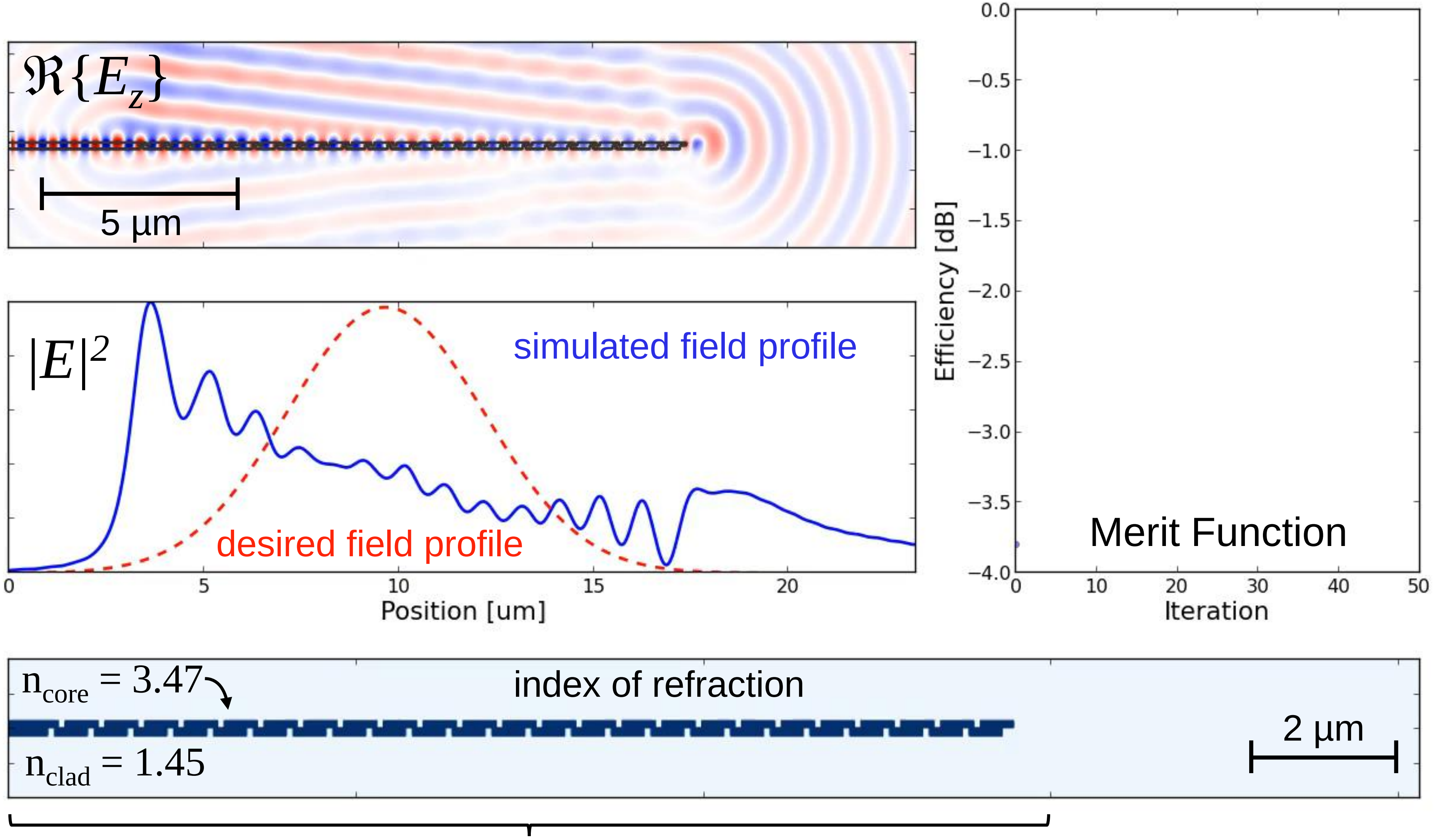


Update design variables to further improve FOM:

- Gradient-based methods (via adjoint method)
- Bayesian optimization
- Genetic algorithms
- Reinforcement learning
- …

A. Michaels et al., *Opt. Express.*, 2018.

INVERSE DESIGN OF GRATING COUPLERS



Simultaneously optimize 10s of grating corrugations

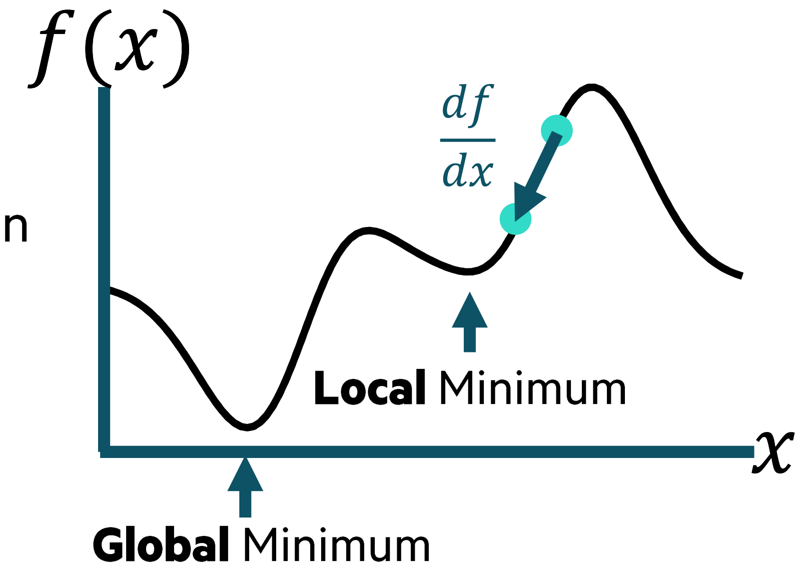
GRADIENT-BASED METHODS FOR PHOTONIC INVERSE DESIGN

- Inverse design is high-dimensional, non-convex optimization problem
  - Exhaustive search is strictly impossible
  - FOM has local minima and saddle points

- FOM is unknown and fairly expensive to simulate for individual design

- Gradient-based techniques aim to roll down the hill
  - Need access to gradient of FOM
    - Can use *adjoint state method*, needs single additional simulation
  - May get stuck in *local* optimum
    - Can try to initiate descent from several points
    - Can try to leverage physics intuition to start in right basin
  - Not very sampling efficient
    - Particularly problematic if (gradient) evaluations are expensive

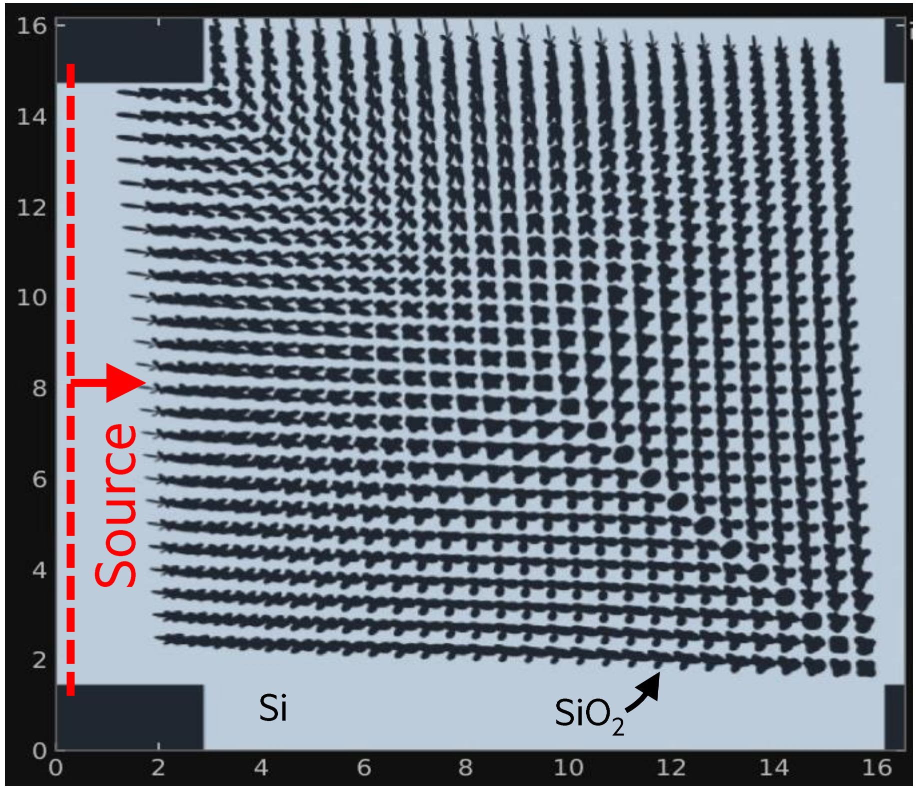
- Nevertheless, de facto standard method with many state-of-the-art results!



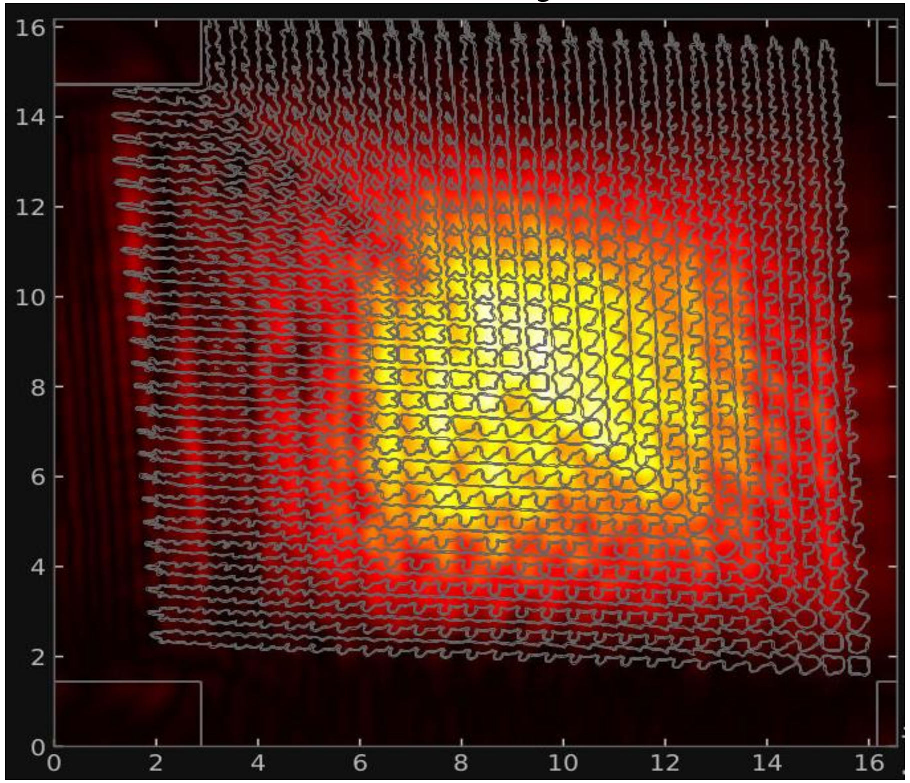
ADJOINT STATE METHOD FOR PHOTONIC INVERSE DESIGN

- Advanced example: polarization-splitting grating coupler. Results in PSGC of 1.2dB peak loss

Materials and Sources



Simulated Electric Field Magnitude (FDTD)



- Gradient-based methods tend to be slow:
  - **20 days on 144 CPU processes**: 8 days for simulations, 12 days for gradient calculations

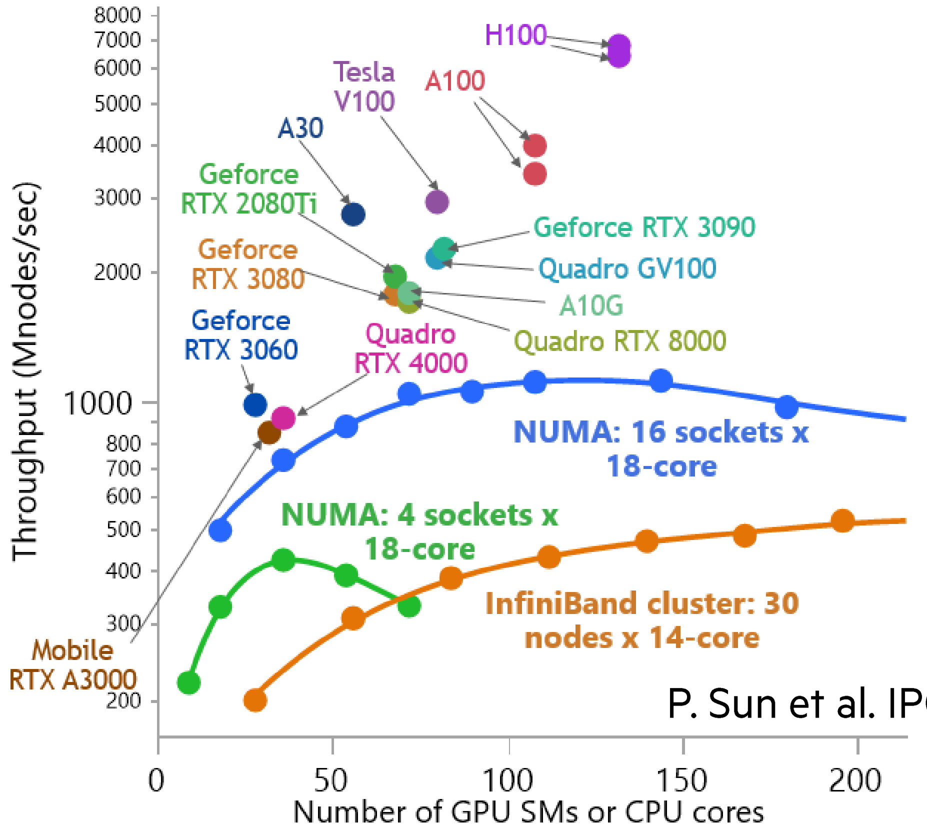
P. Sun et al., "Adjoint optimization of polarization-splitting grating couplers," Opt. Express 31, 4884-4898 (2023).

SPEEDING UP ADJOINT STATE METHOD

Hooten, S., et al., CLEO (2023)
https://arxiv.org/pdf/2311.05646.pdf
github.com/smhooten/emopt

CPU → GPU: at least factor two improvement

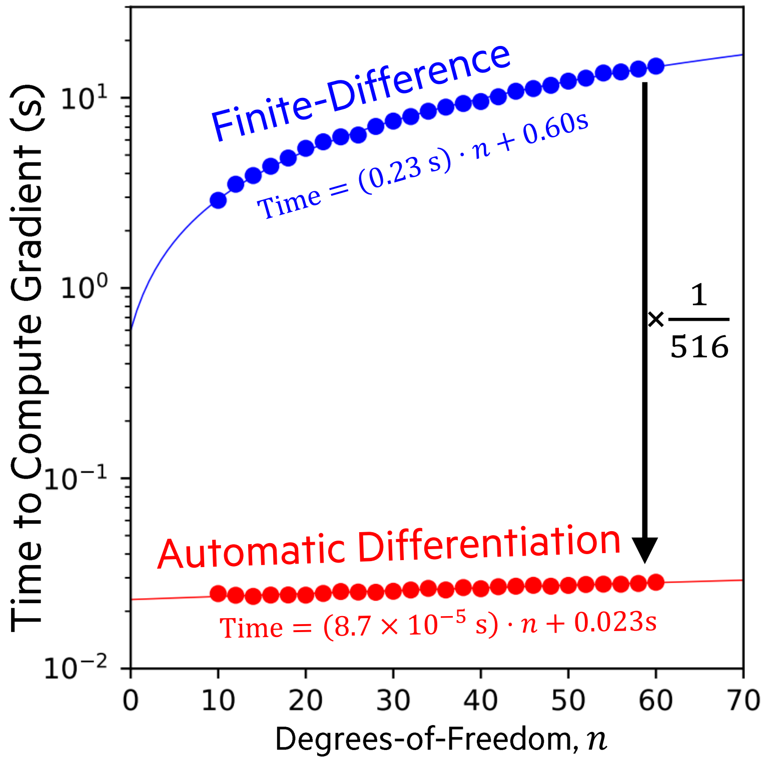
- Open-source: EMopt, fdtd-z, …
- Several commercial solvers: Lumerical, Tidy3d, …



P. Sun et al. IPC (2023)

Leverage automatic differentiation

- Adjoint state method also needs gradient of permittivity w.r.t. design variables
- Slow to compute using finite differences
- Describe permittivity profile using differentiable shapes

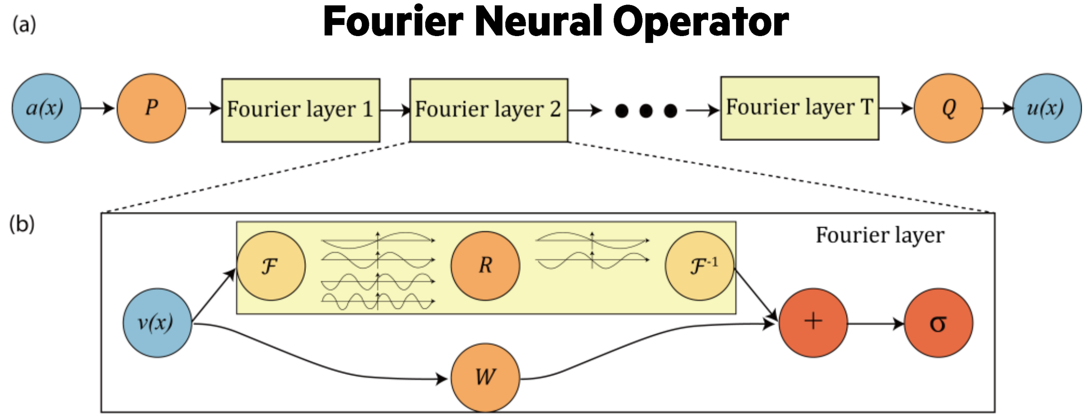


Combined effect: ~20 days → 4 days optimization time

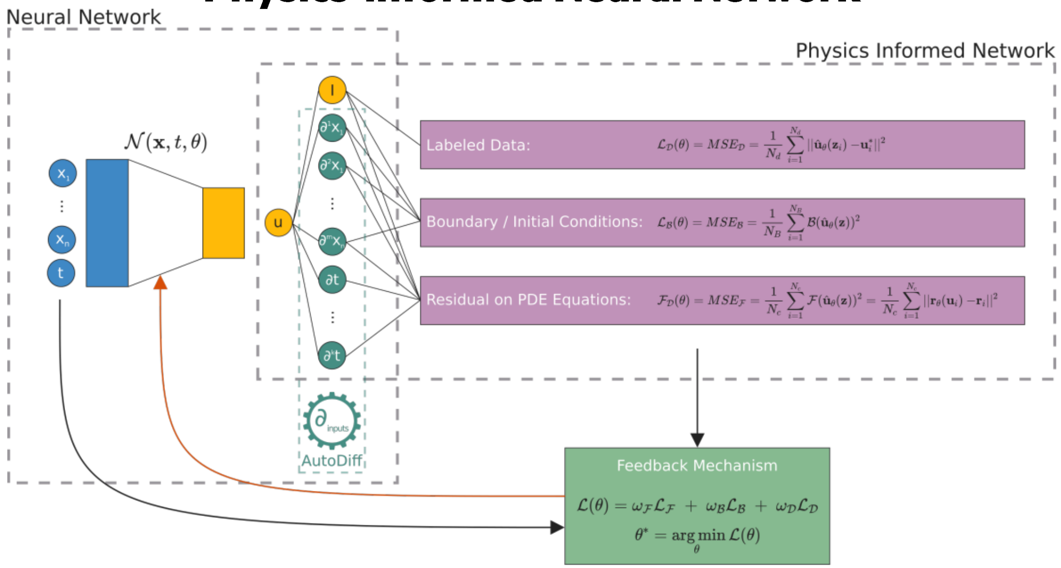
BEYOND STANDARD ELECTROMAGNETIC SOLVERS

- Can one circumvent expensive simulations altogether by leveraging machine learning model?
  - Data-driven methods are less favorable in this context
  - Self-supervised, physics-informed models:
    - Often lack in reliability and struggle out-of-distribution
    - Expensive training, but fast inference
    - Train once, use forever
    - Equally easy for non-linear PDEs

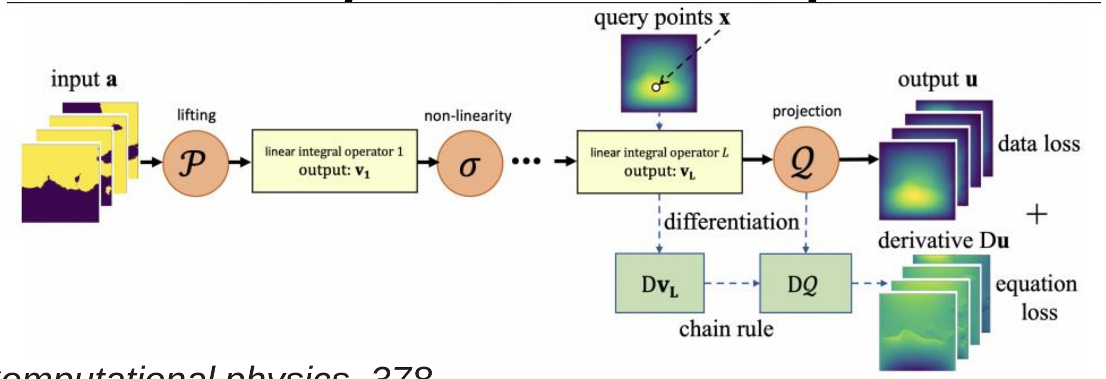
Fourier Neural Operator



Physics-Informed Neural Network



Physics-Informed Neural Operator



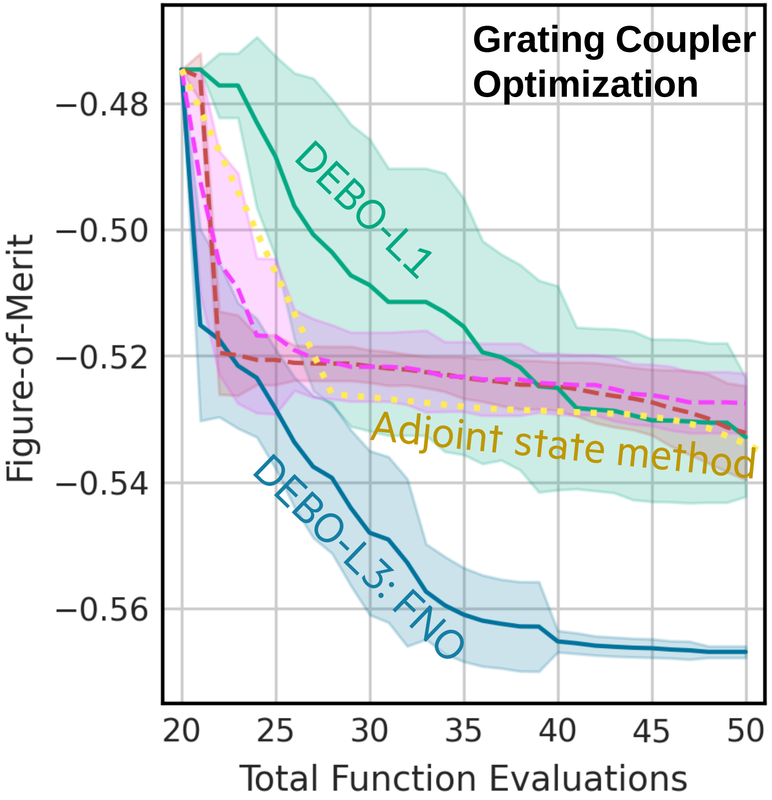
Raissi, M., et al., 2019. *Journal of Computational physics*, *378*
Li, Z., et al., ICLR 2021.
Li, Z., et al., 2021. *ACM/JMS Journal of Data Science*.

NON-GRADIENT BASED METHODS FOR INVERSE DESIGN

- To make each (expensive) simulation count, we need an optimal way to choose the query design
  - should balance *exploitation* of known information and *exploration* of unknown regions in design space

- Bayesian optimization
  - Leverages surrogate model that is iteratively updated to approximate FOM given current simulated designs
  - Is *global* optimization method

- Deep Ensemble Bayesian Optimization (DEBO)
  - Use ensemble of deep neural networks as surrogate model
  - Can directly include additional information, e.g.,
    - compositeness
    - gradient information
    - equations of motion via physics-informed models
    - other inductive biases
  - Doesn't suffer from out-of-distribution or reliability issues



Kim, S., et al., 2021. *arXiv preprint arXiv:2104.11667*.
Hooten, S., et al. 2023.

CIRCUIT DESIGN

Motivating example: photonic tensor core

- Universal matrix-vector multiplication can be achieved via meshes of Mach-Zehnder interferometers (Reck, Clements, etc.)
- Specific machine learning task doesn't need universal mesh

circuit design:

which sequence of meshes results in best performance of the ML task, while also, for example, minimizing the footprint?

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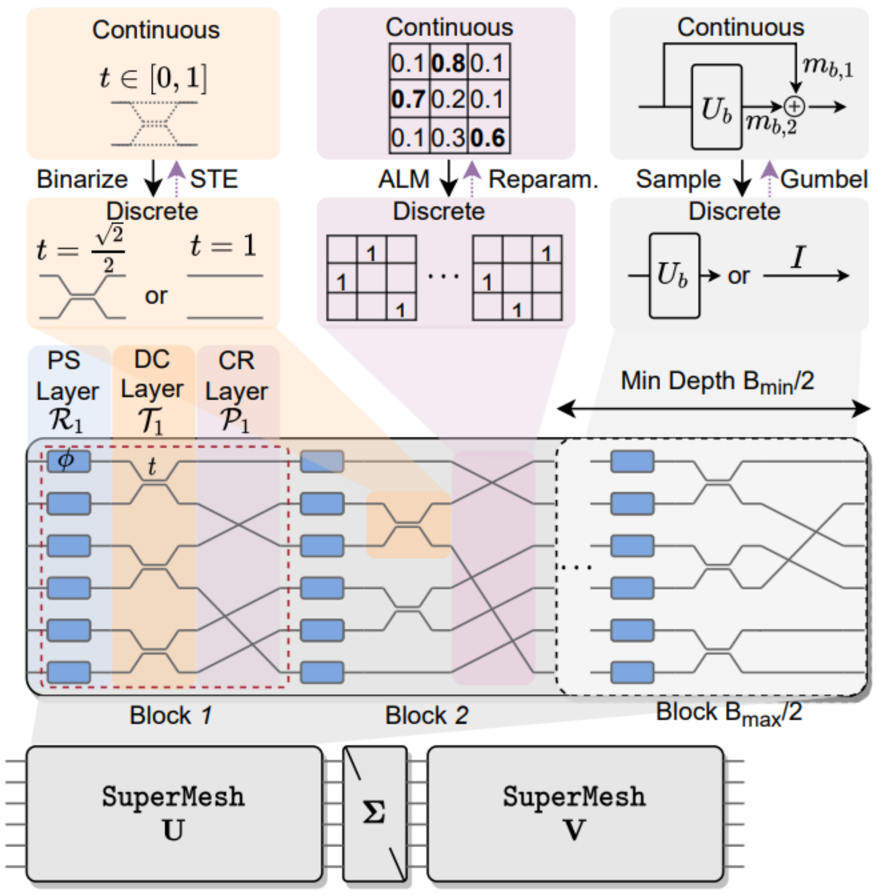
optimization problem:

find optimal circuit among all possible circuits

- Search space contains both continuous and discrete components
  - Borrow techniques from Neural Architecture Search (NAS) literature!



Gu, J., et al., 2022. *59th ACM/IEEE Design Automation Conference*

THANK YOU

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