Inverse Photonic Design Using Deep Learning

Siddhant Gautam
Electrical Engineering, IIT Madras

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About

Title: Deep Neural Network Inverse Design of Integrated Photonic Power Splitters

Author: Mohammad H. Tahersima, Keisuke Kojima, Toshiaki Koike-Akino, Devesh Jha, Bingnan Wang, Chungwei Lin & Kieran Parsons

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Overview

Key Points:

- Using deep learning to predict optical response
- Inversely approximate designs for a targeted response
- Design power splitter with high efficiency and minimum reflection

Features:

- Minimum Reflection: 20 dB
- Transmission Efficiency: 90 %

Setting

Material

Artificially engineered subwavelength nanostructure

Purpose

Control EM fields into specific wavefronts

Applications

1. Optics
2. Integrated Photonics
3. Sensing, Metamaterials
4. Invisibility cloak

Drawbacks

Optimization of nanostructures - computationally intensive

E.g. FDTD simulation

Deep Learning based Inverse Design

Salient Features

- ❑ Models complex input-output relations
- ❑ Complex functions can be learnt in a data-driven fashion
- ❑ Uses: High energy physics, medical imaging, high energy physics

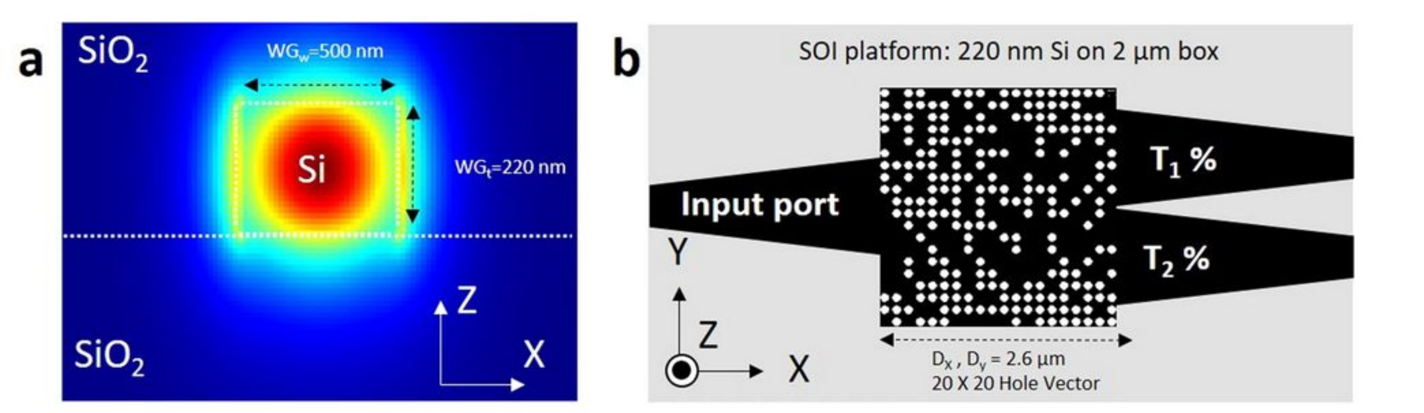
Usage

- Forward Design: Predict the optical response of a topology
- Inverse Design: Design a topology for a target optical response

Deep Learning for Forward Modeling to Predict Optical Response

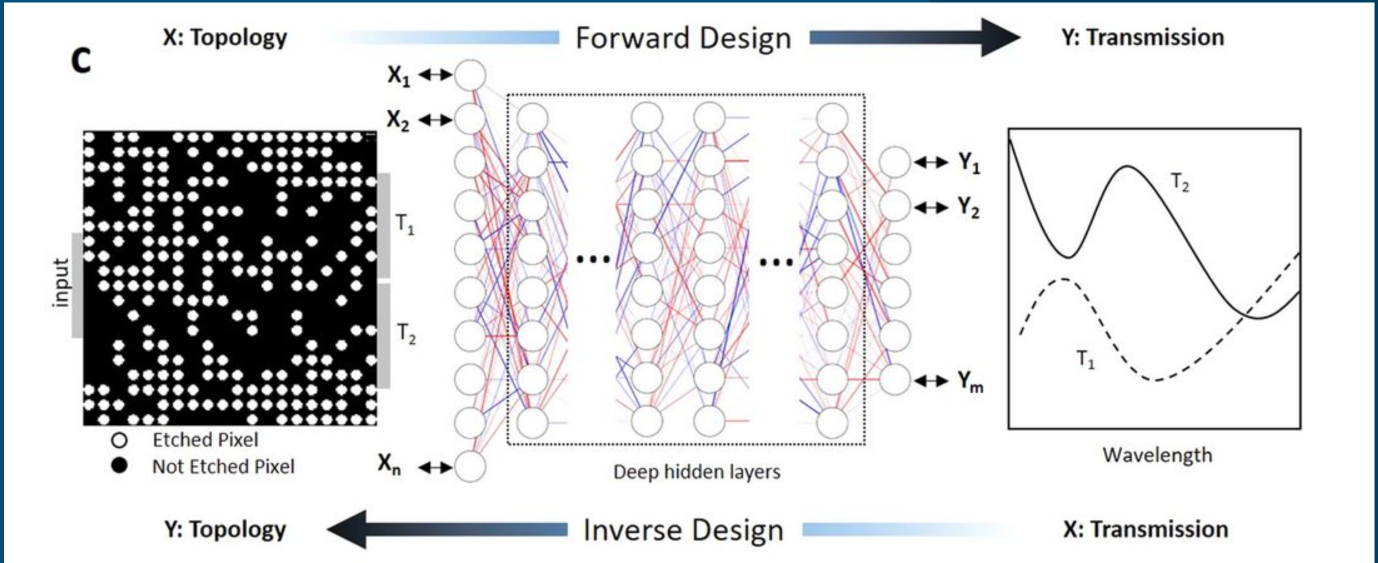
Physics Involved

- Change in refractive index - reflection, refraction and scattering
- Scattering guides the beam to a target port



Training the Neural Network

- Generate labeled data for training using FDTD
- Feed DNN with numerical optical experimental data
- **Input:** Binary images of hole locations
- **Output:** Spectral response at T1&T2 and reflection from R



Pixel:

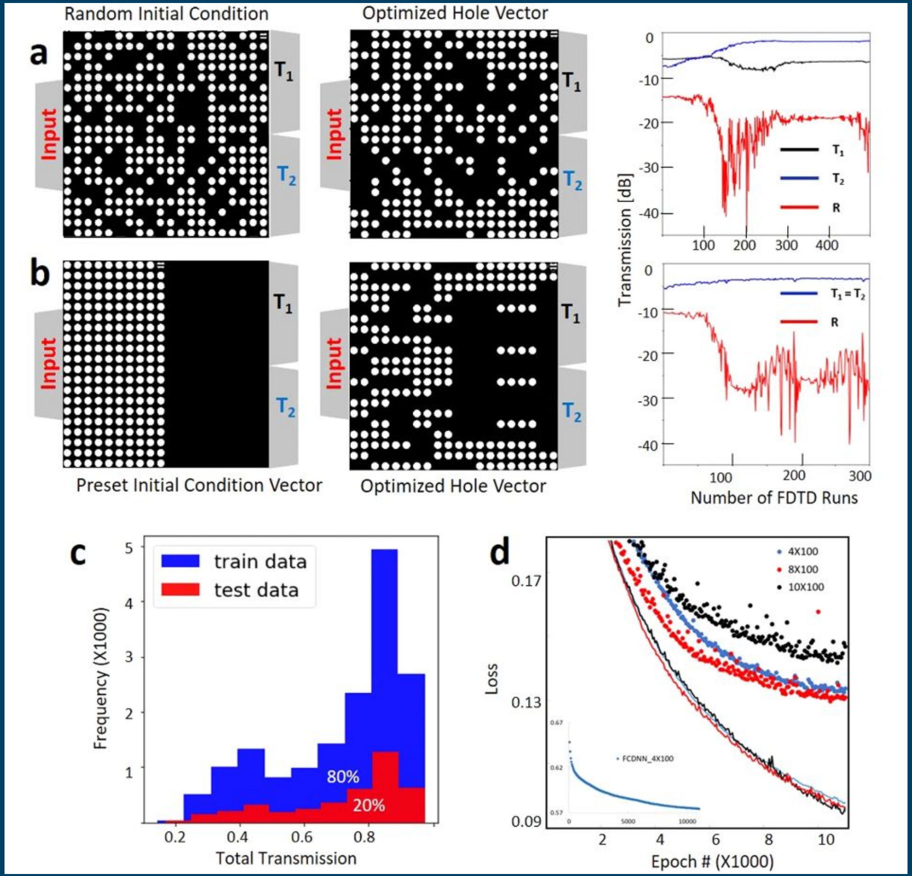
- **1 - Etched (silicon)**
- **0 - Not Etched (silica)**

Training Data for supervised learning

Optimization:

- Start with initial hole vector
- Using single stride binary search, solve max FOM = min(T1) + min(T2) − α×max(|R|)

1) An asymmetric optimization (α=2) with a random initial vector
2) A symmetric search (α=4) with a patterned initial vector
3) Histogram of all transmission train and test data label
4) Learning curve for training (lines) and test (dots) losses

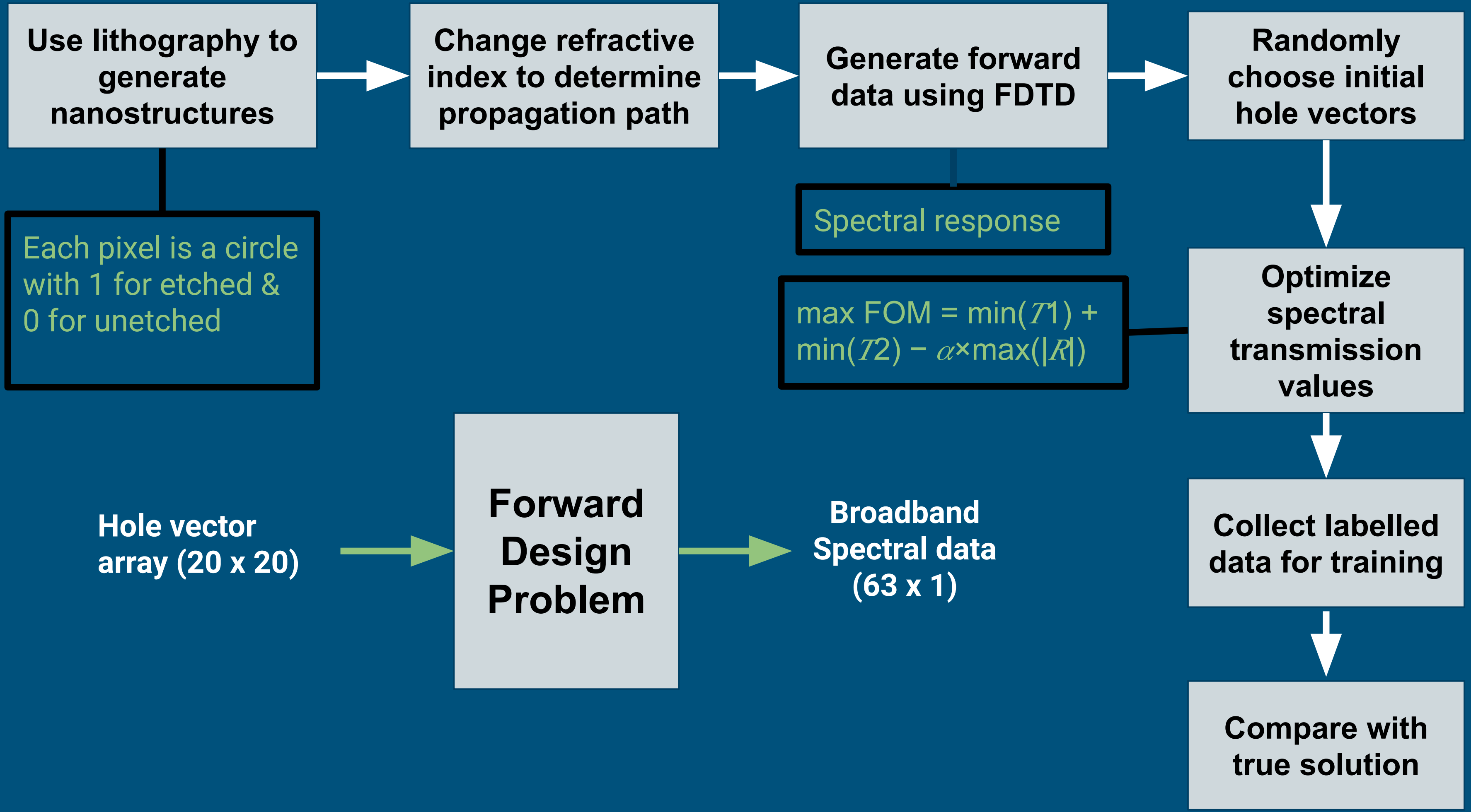


Design	Forward Model	Inverse Model
Inputs	20×20 HV arrays	63 x 1 SPEC vector
Type	Regression	Classification
Loss Function	Gaussian Log Likelihood	Bernoulli Log Likelihood

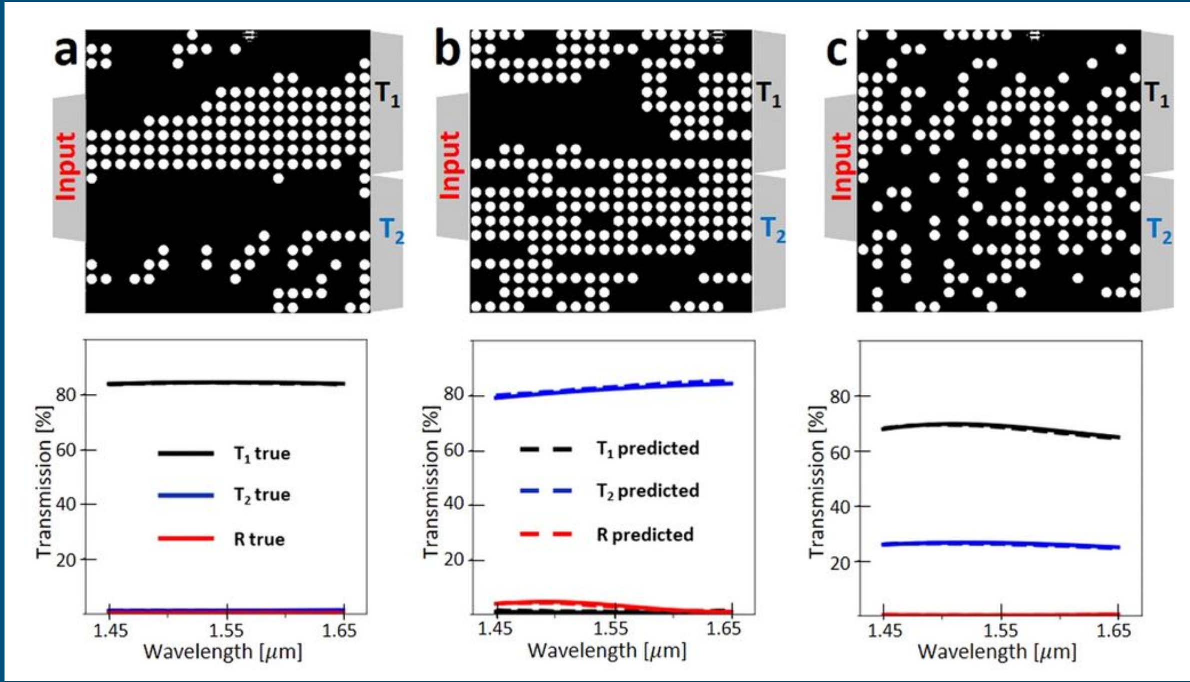
Gaussian log-likelihood loss function:

$$-\log P(Y|X,W) = 1/K \, \Sigma_n \, ½ \log(2\pi\sigma^2) + 1/2\sigma^2(y_n - w^T x_n)^2)$$

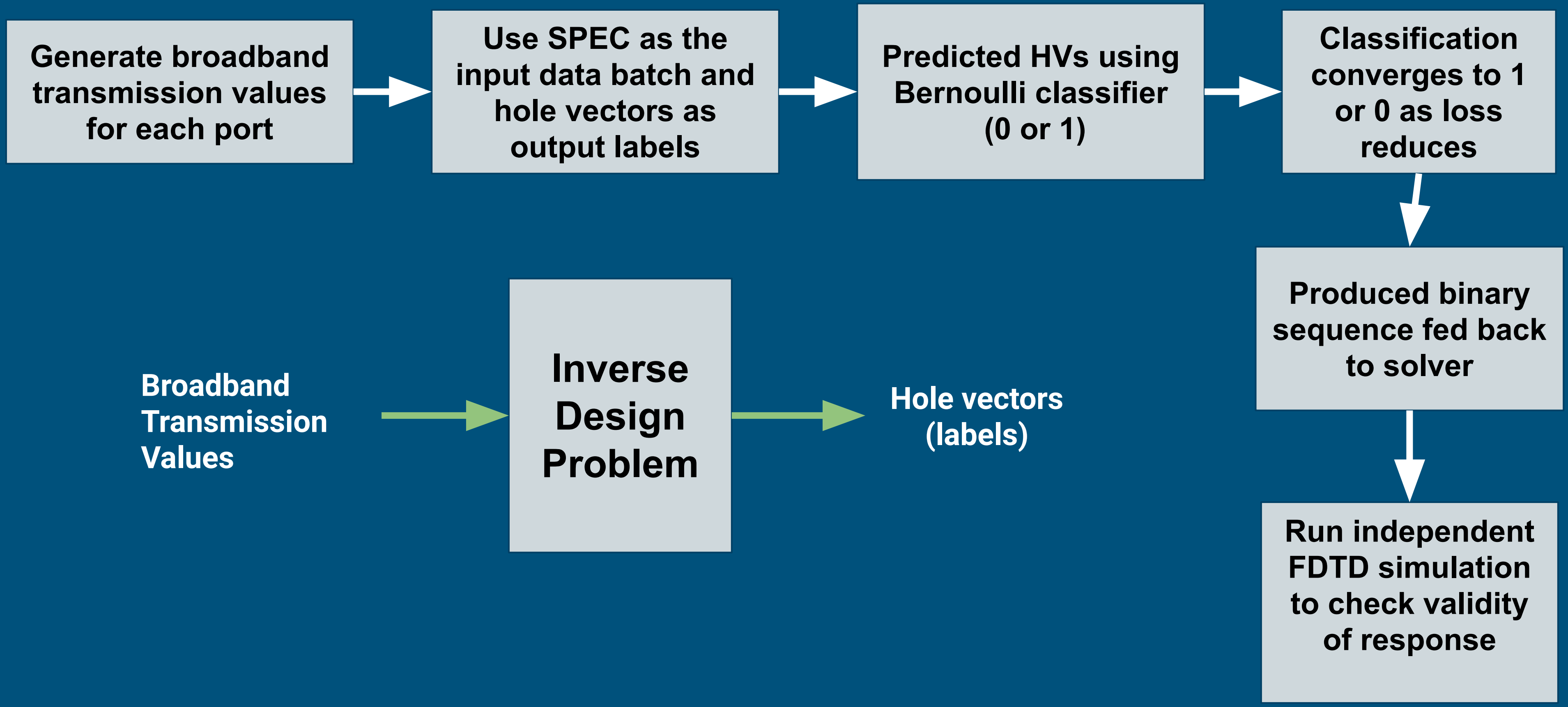
where W denotes the model parameters, K is the number of training data


Use lithography to generate nanostructures
Change refractive index to determine propagation path
Generate forward data using FDTD
Randomly choose initial hole vectors
Each pixel is a circle with 1 for etched & 0 for unetched
Spectral response
max FOM = min($T1$) + min($T2$) − α×max(|R|)
Optimize spectral transmission values
Collect labelled data for training
Compare with true solution
Hole vector array (20 x 20)
Forward Design Problem
Broadband Spectral data (63 x 1)

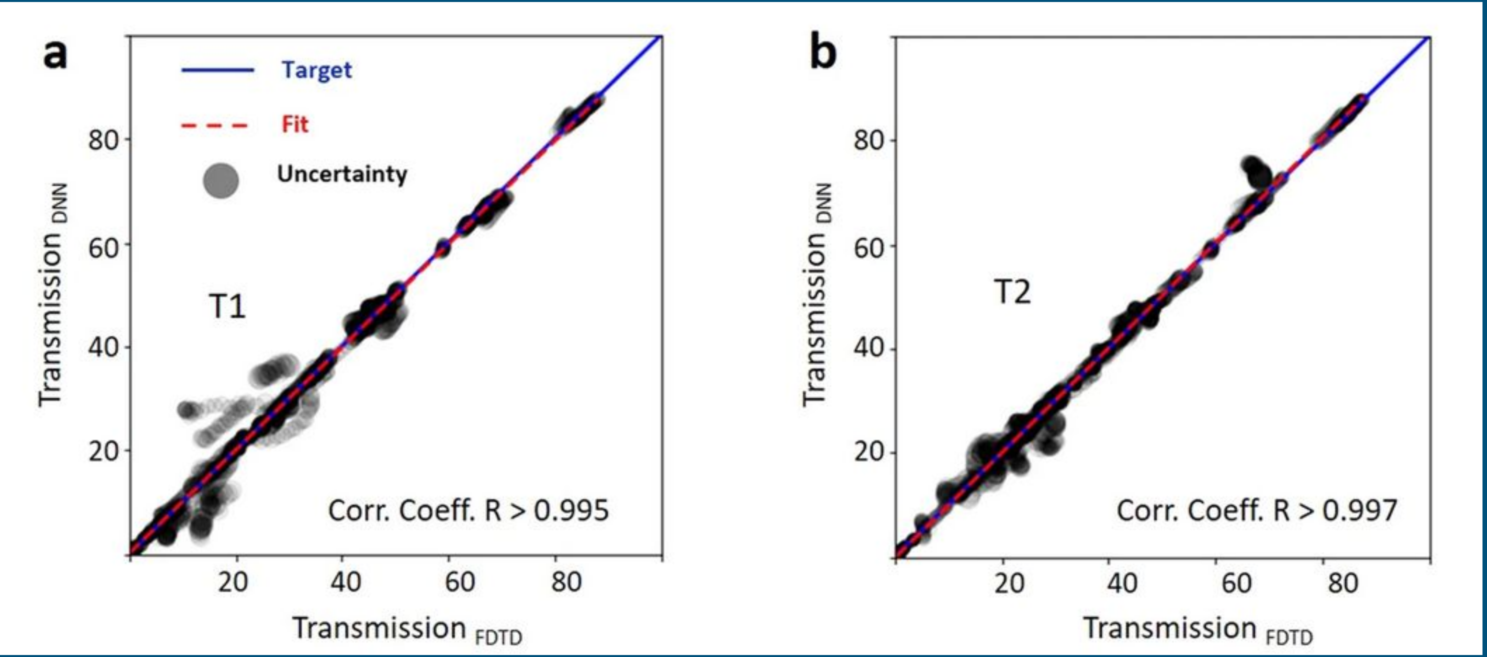
Forward Design Results



Spectrum approximation using deep ResNet; 80% input data for training and 20% of the total data for testing. a, b, and c represent predicted spectral response of three different power splitters


Generate broadband transmission values for each port
Use SPEC as the input data batch and hole vectors as output labels
Predicted HVs using Bernoulli classifier (0 or 1)
Classification converges to 1 or 0 as loss reduces
Produced binary sequence fed back to solver
Run independent FDTD simulation to check validity of response
Broadband Transmission Values
Inverse Design Problem
Hole vectors (labels)

Inverse Design Results

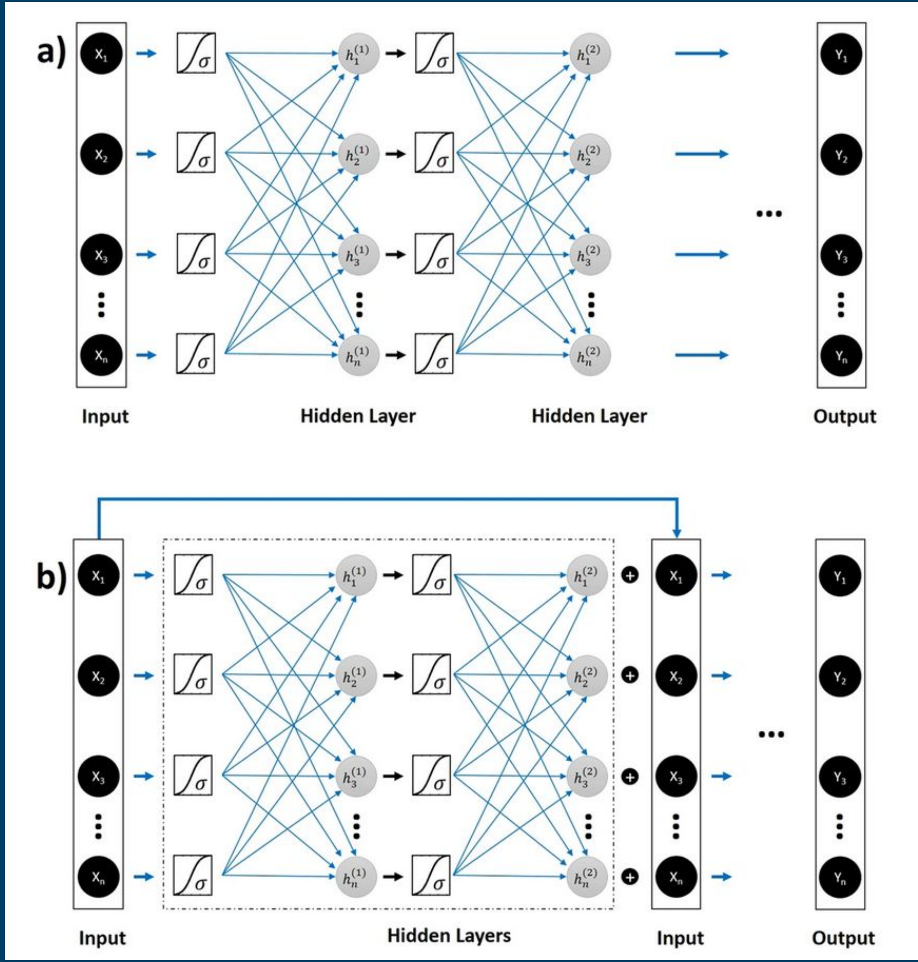


Correlation coefficient. Fitting ResNet predicted transmission values vs true transmission values for (a) port 1 and (b) port 2 (b). Gray circle symbol size is proportional to gradient uncertainty.

Deep Residual Networks

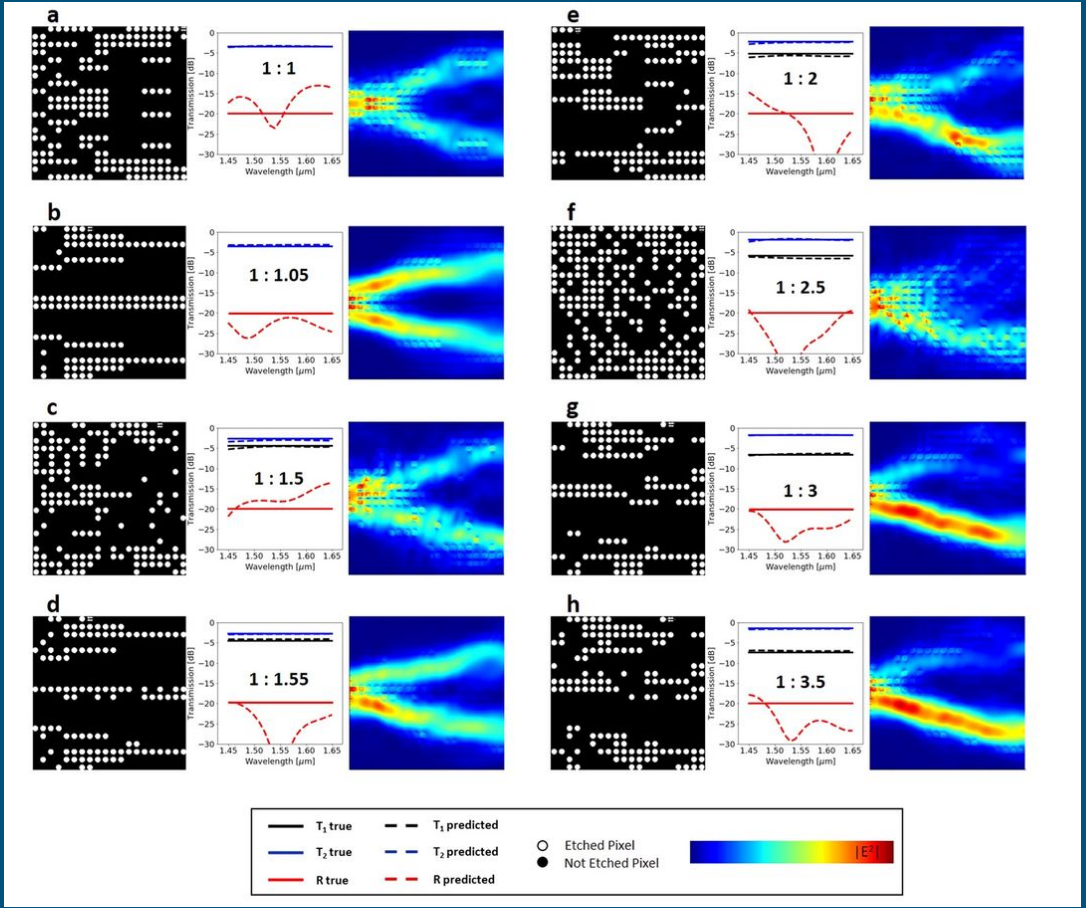
- **Drawbacks of FCDNNs:**
  - Suffers from the problem of vanishing gradients
  - Increasing depth of doesn't improve performance

- **Remedy - Using ResNet**
  - Improves the depth of training by using "identity shortcut connections"
  - Uses an additional identity function to allow smooth forward and backward propagation of gradients



DNN Inverse Design for various splitting ratios

DNN inverse design for devices with different splitting ratios. Electro--magnetic energy density plots calculated using FDTD simulations.



Summary

- NN used for fast approximation of the optical response instead of computationally heavy numerical methods
- Inverse design: NN takes an optical response as input and provides an approximate solution nanostructure in a fraction of second
- ResNet DNN architecture (8 layers) which allows smooth forward and backward propagation of gradients

Applications: a) A network that can approximate the spectral response of an arbitrary hole vector within this design space b) Use the inverse network to design a power splitter topology for any ratio