Periodic Metasurface Inverse Design via Deep Learning

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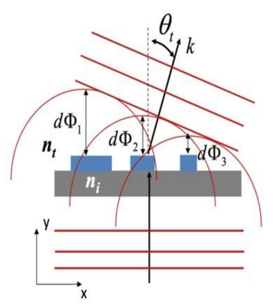
Background on Metasurface and Inverse Design:

- Metasurface is composed of metamaterial that human can control its optic property by control phase delay
- Application of Metasurface: replace any optic device with an extremely thin surface
- Inverse design is to design material based on functionality we need



Motivation:

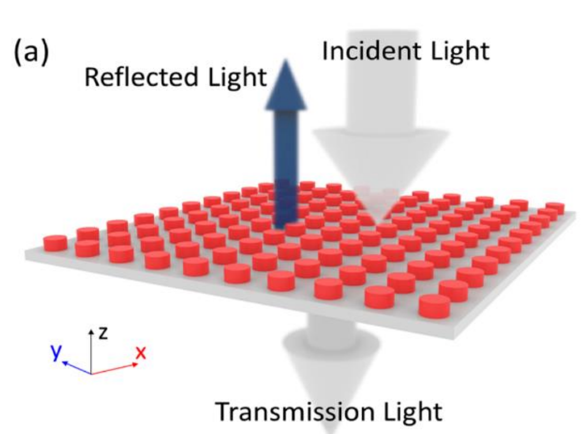
- Inverse design process of metamaterial is time consuming by traditional parameter sweeping method.
- Traditional parameter sweeping method lacks variety of spectrum

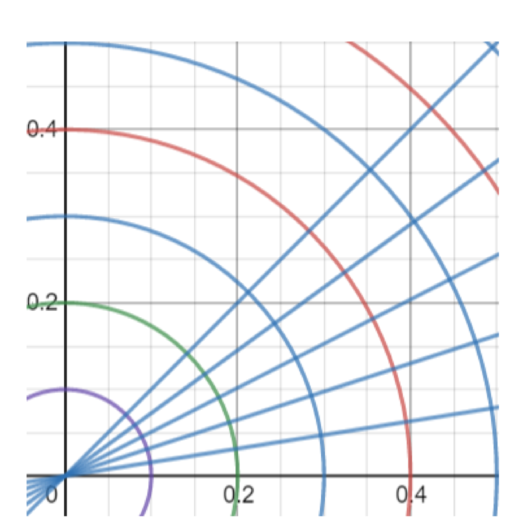
Goal:

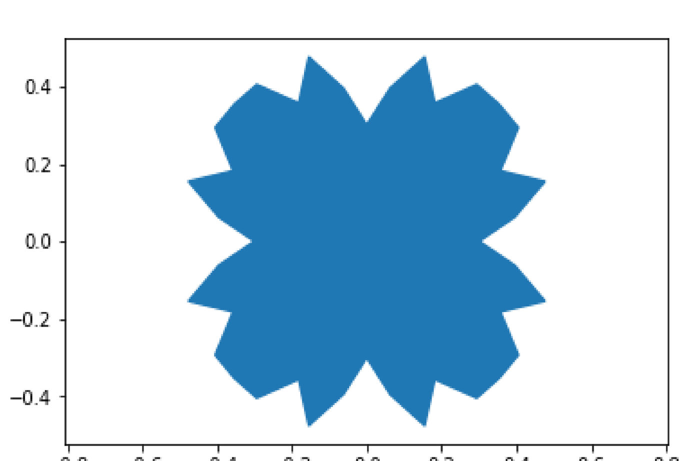
- This project focus on polarization insensitive periodic metasurface transmission spectrum inverse design.
- Use deep neural network to learn from dataset where spectrums are predictor and designs of periodic metasurface are the regression target.
- Predict accurate design according to given spectrum

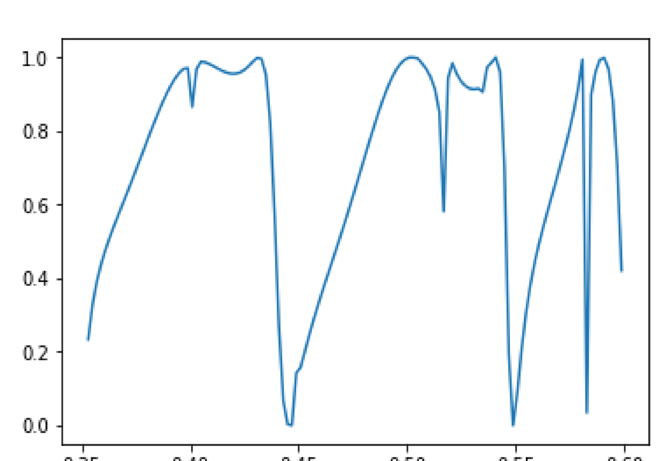
Dataset:

- Predictor is the transmission spectrum and regression target is the design of metasurface.
- Periodic metasurface is composed of uniform unit cells. Our design of unit cell fixes the height on z-axis and explores shapes on xy-axis.
- 4-fold symmetry is applied to design to ensure polarization insensitive.
- Design a polar-coordinate based depth search first algorithm that produces all possible 4-fold geometries.
- Use Meep to generate spectrum. Spectrum is validated by CST and S4.
- Total data size 4988. Predictor is a vector (4988, 200) and regression target is (4988, 6)

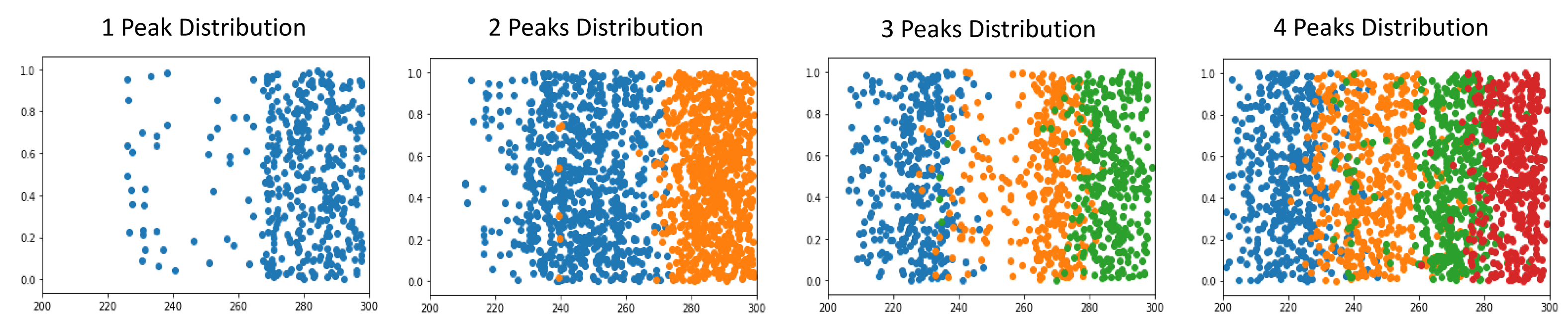








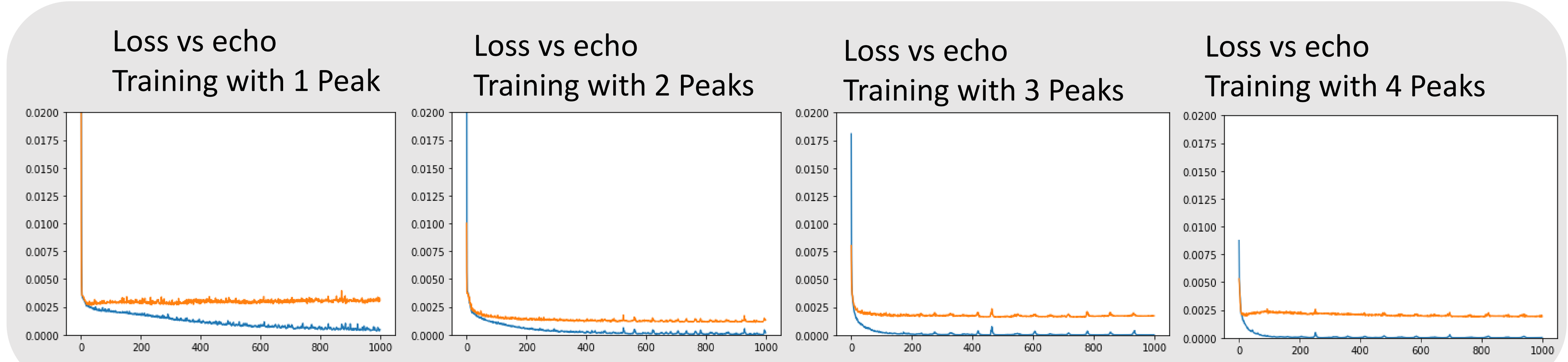
Peaks Distribution in Data Set:

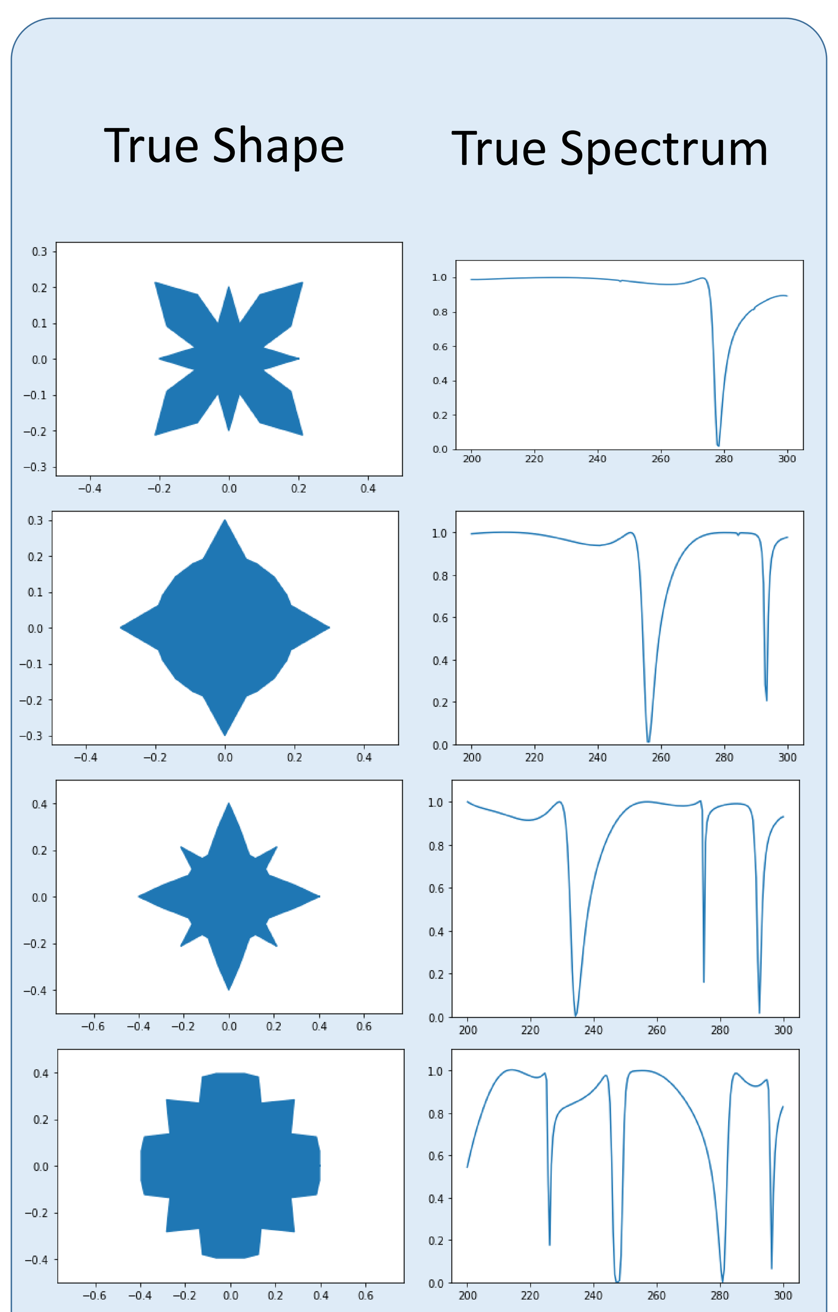


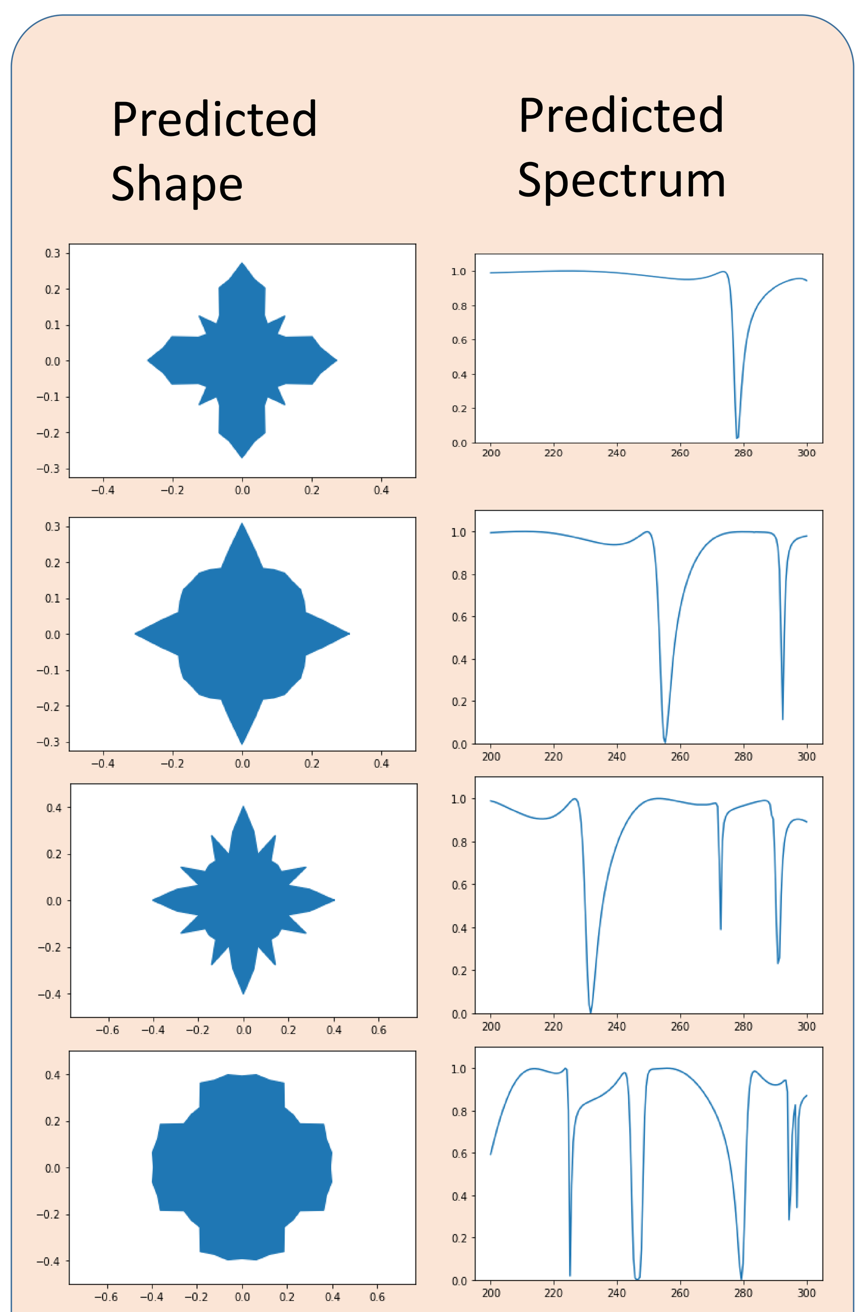
	1 Peak statistical info	2 peaks statistical info		3 peaks statistical info			4 peaks statistical info			
	1st peak	1st peak	2nd peak	1st peak	2nd peak	3rd peak	1st peak	2nd peak	3rd peak	4th peak
Mean	278	246.36	285.77	226.5	264.3	286	220.5	246.1	269.4	288.2
Median	280	246.25	286.5	227.3	267.8	287	220.1	245.4	270.3	289.3
Max	298	285.25	299	249	283.8	299	248.3	282.8	293.8	299.3
Min	226	210.75	239.25	206.3	227.8	287	200.8	220.5	233.8	260.8
Std	15.3	12.47	8.48	8.64	11.9	8.54	9.42	11.23	9.88	6.63

Training neural network:

- Deep forward neural network(DFNN) is set to have 8 layers with each layers having 200-80-80-100-80-40-30-20-6 units. The spectrum S = [S1, S2, …, S200] is taken as the input of the DFNN. A design is calculated as outputs. The training is done by minimizing the cost function.



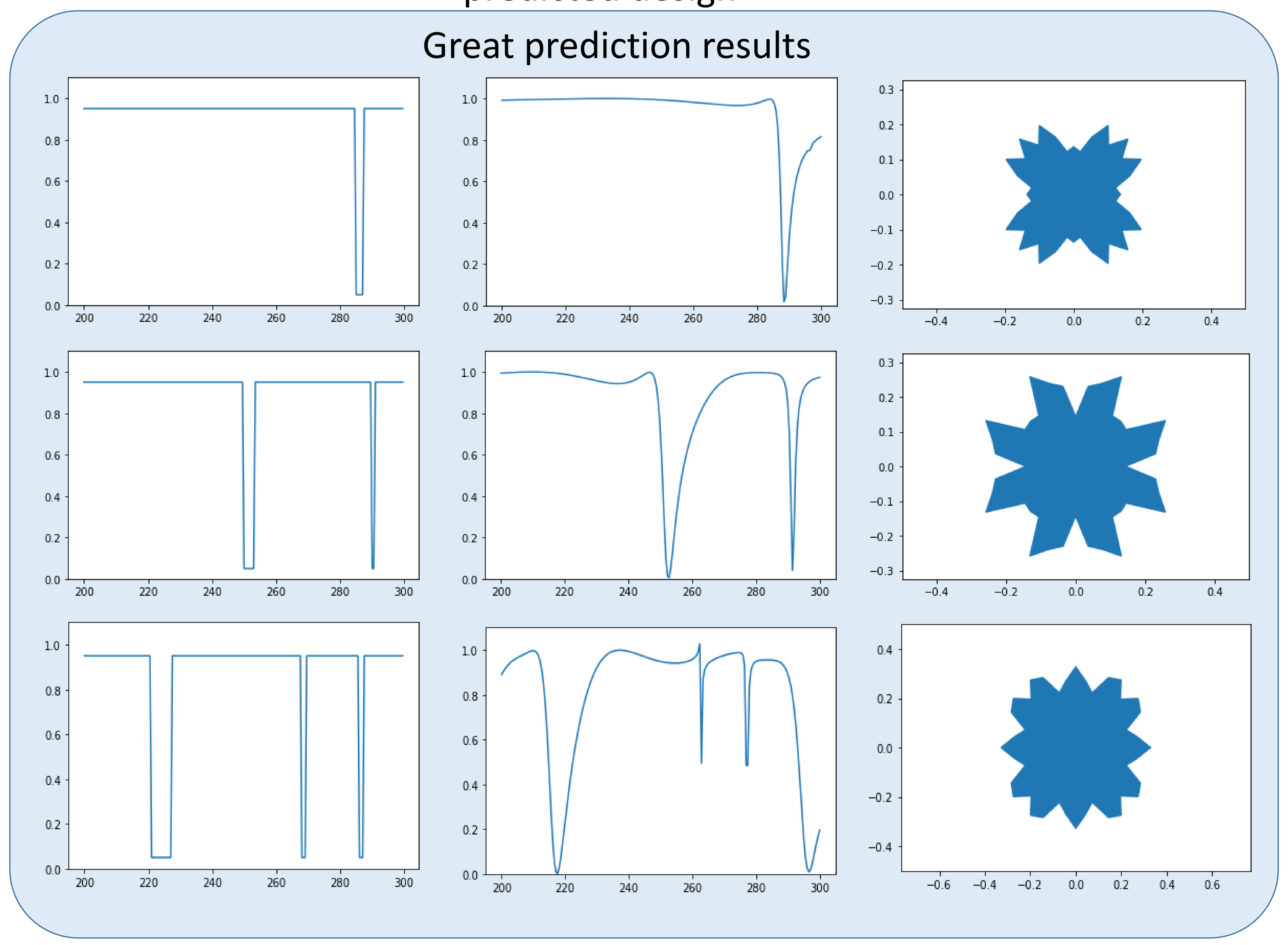


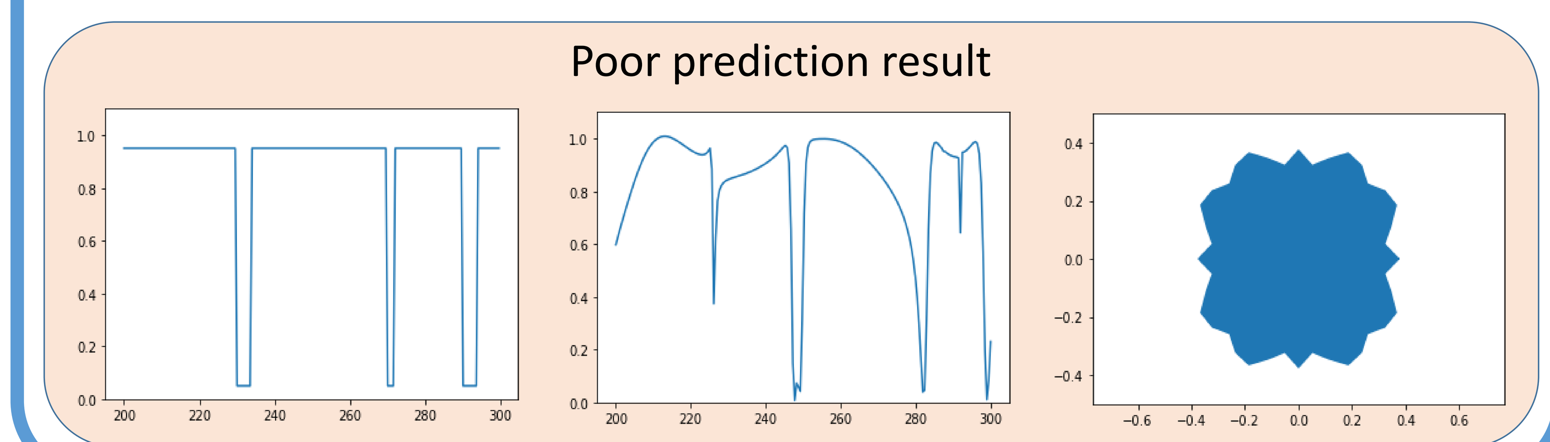


User Application:

- User can specify position and width of peaks.
- Experiment shows that with approximate spectrum, neural network can find the a design that produce a fit to this spectrum.
- Result is compromised due to the quality of approximate spectrum but neural network has shown great potential in predicting design according to given spectrum

Desired spectrum | Spectrum generated by predicted design | Predicted design





Summary:

- Neural network works well with periodic neural network inverse design.
- Polar coordinate based 4 fold geometry generating methods is capable of generating different geometry that produces peaks across the frequency.
- The quality of the spectrum produced by predicted geometry is heavily depends on if there's similar spectrum in the data set.

Future Work:

- Explore cavity, height, and material effect on spectrum to increase data set size and hope that peaks can spread evenly across frequency.
- Create a better user interface that mimics shape of exiting spectrum according to given peaks' positions and widths.
- Create a simulator and applied to the output of inverse design neural network and loss will be evaluated by the mean square error of given spectrum and spectrum generated by the predicted design.