

Deep learning technique for highly vivid structural color filter metasurfaces

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Arthur Clini de Souza, Stéphane Lanteri, Hugo Enrique Hernandez-Figueroa, Marco Abbarchi, David Grosso, et al.. Deep learning technique for highly vivid structural color filter metasurfaces. Nanophotonics and Micro/Nano Optics International Conference 2023, Nov 2023, Barcelona (Spain), Spain. hal-04355081

HAL Id: hal-04355081

https://hal.science/hal-04355081

Submitted on 31 Dec 2023

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CÔTE D'AZUR Deep Learning Inverse Design Methodology



for Structural Color Filter Metasurfaces

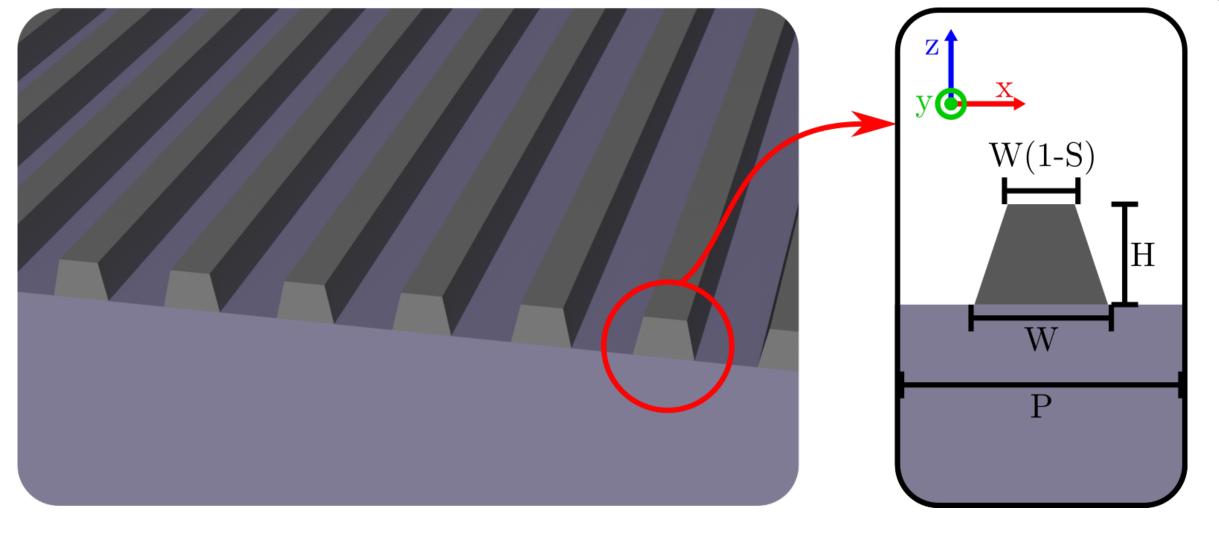
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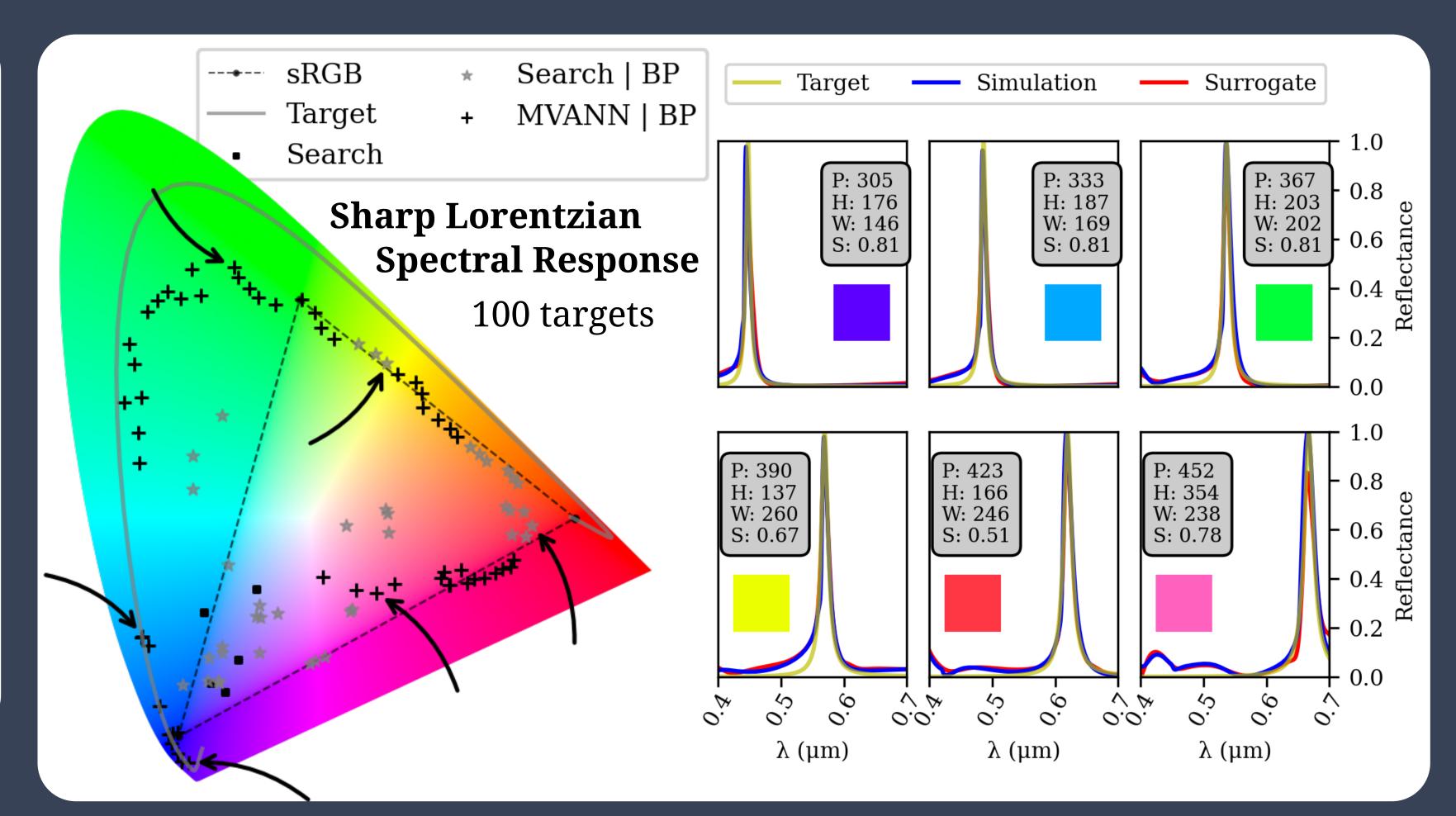
Arxiv paper:

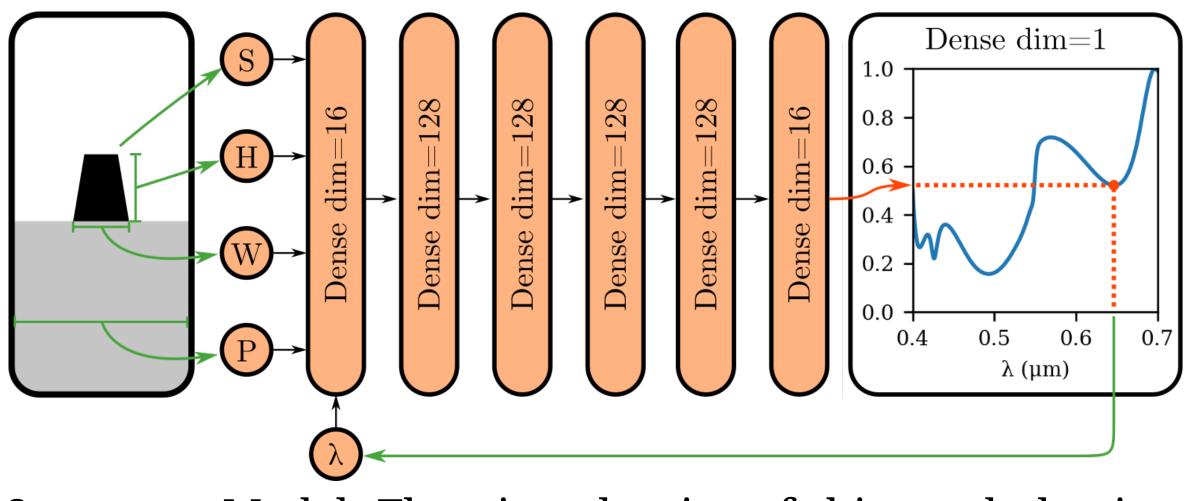


We introduce a novel technique for designing color filter metasurfaces using a data-driven approach based on deep learning. Our innovative approach employs inverse design principles to identify highly efficient designs that outperform all the configurations in the dataset, which consists of **585 distinct geometries solely**. By combining Multi-Valued Artificial Neural Networks and back-propagation optimization, we overcome the limitations of previous approaches, such as poor performance due to extrapolation and undesired local minima. Consequently, we successfully create reliable and highly efficient configurations for metasurface color filters capable of producing exceptionally vivid colors that go beyond the sRGB gamut. Furthermore, our deep learning technique can be extended to design various pixellated metasurface configurations with different functionalities.



Schematic diagram of the structure under consideration. We simulated the reflection spectrum of 585 structures. Xpolarized light is injected from top. The motivation behind slanted resonators is to break symmetry in Z, attenuating high order modes.

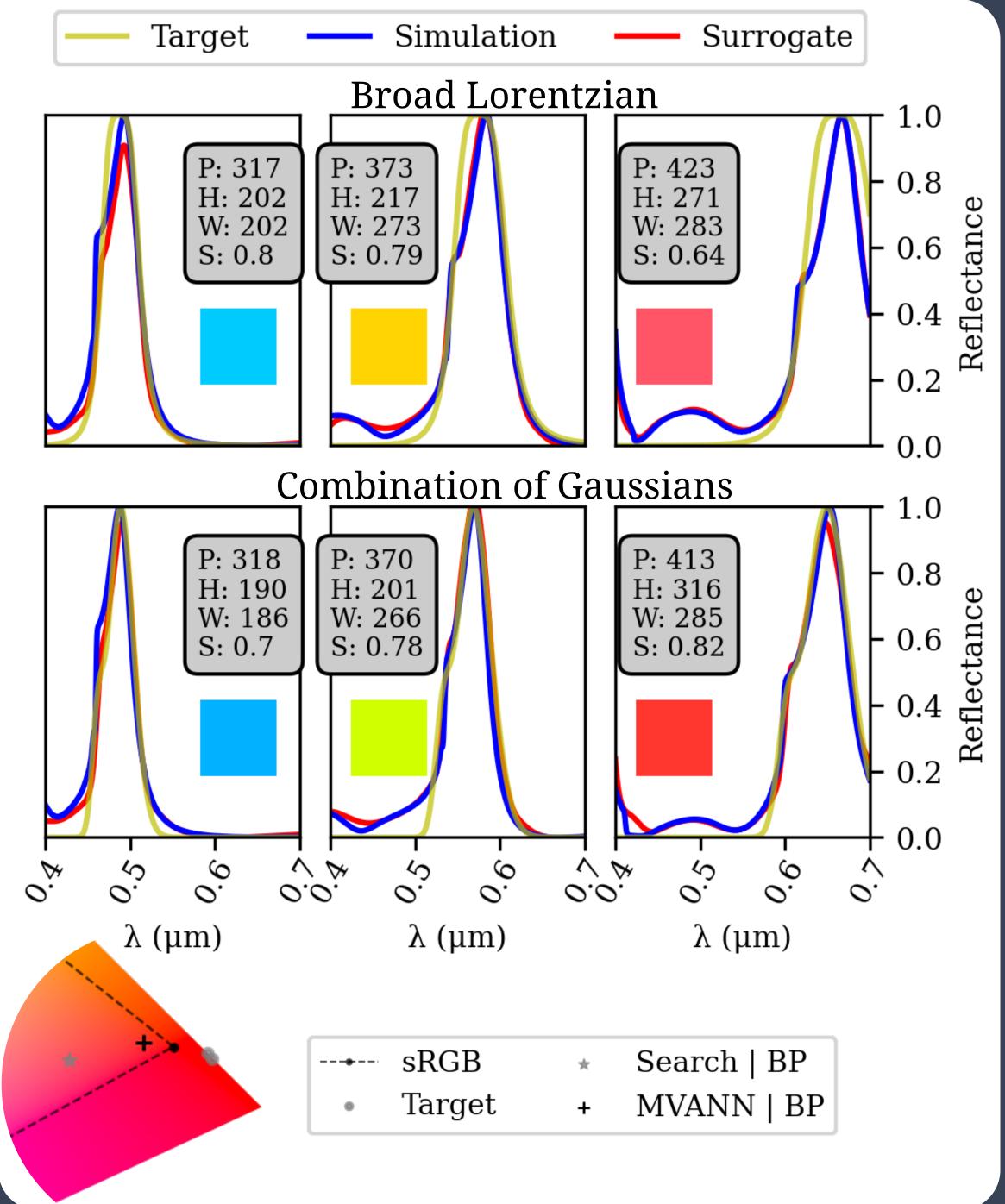


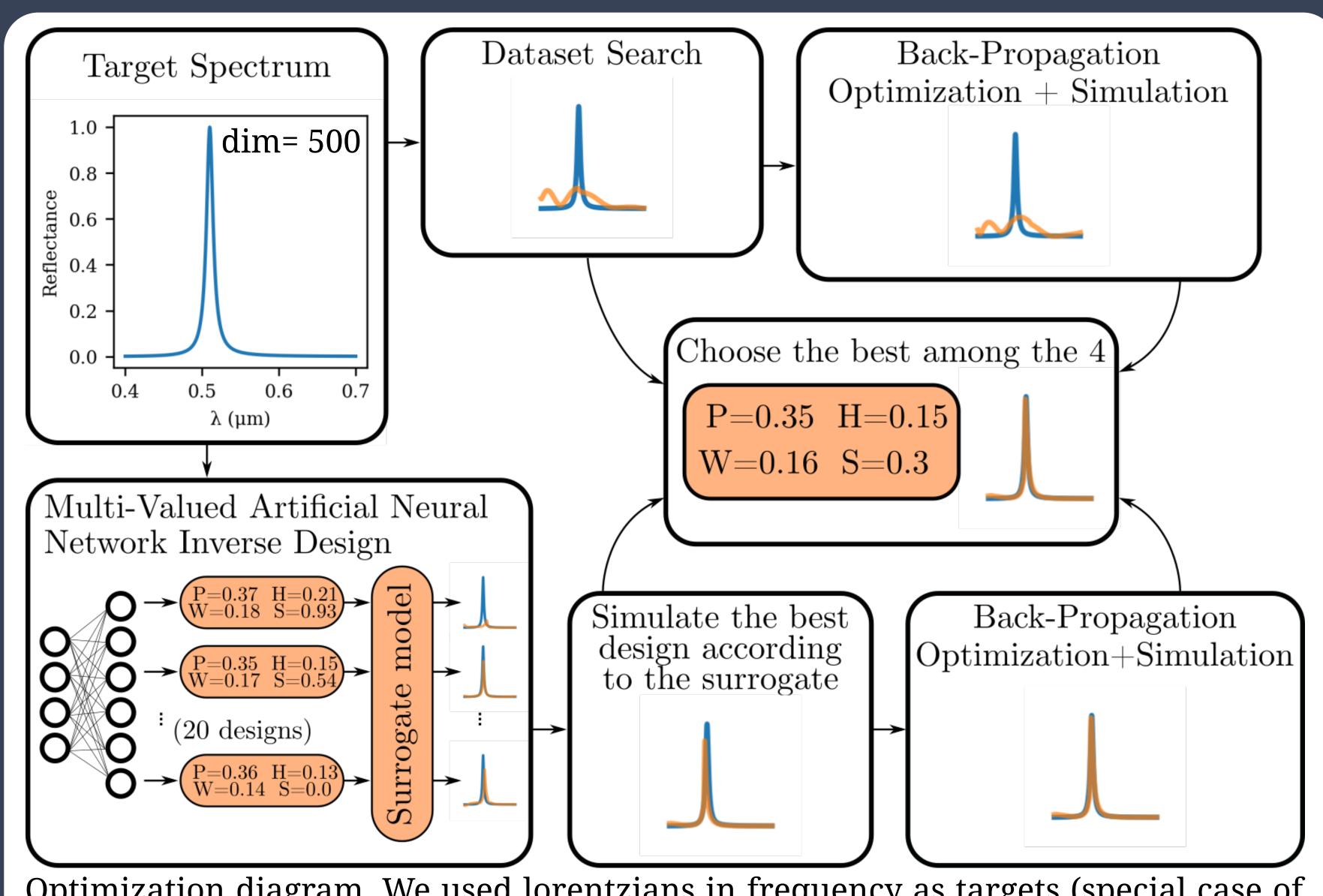


Surrogate Model. The pivotal point of this work, having multiple functions. Will be used for rapid estimation of spectral responses, generate data that will be used to train the MVANN and operates as a differentiable solver, facilitating efficient design variable optimization through automatic differentiation. An important trick is to bring the wavelength to the input rather than considering a multi-dimensional output.

Different Objectives

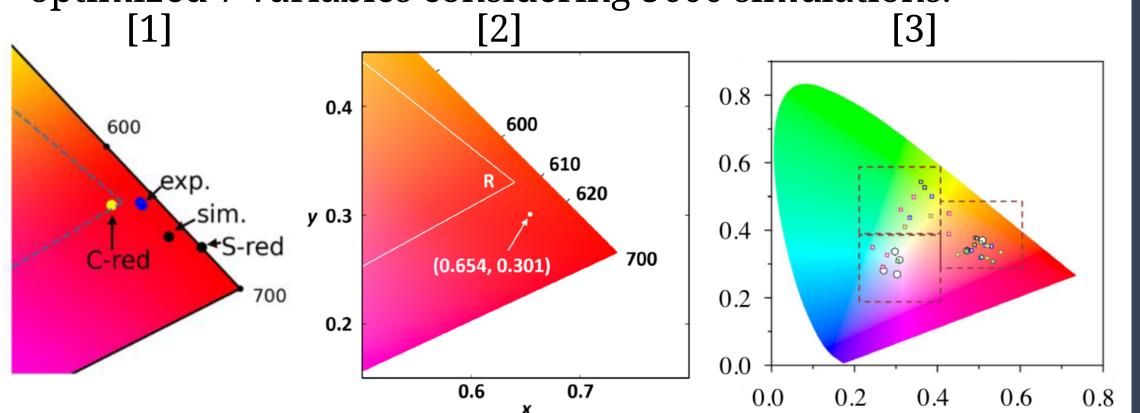
We are not limited in finding pure lorentzian. In this case we search for a broad with the resonance objective of finding a pure red. Comparing to the literature, [1,2], we were able to find good reds with a method also find other able to colors.





Optimization diagram. We used lorentzians in frequency as targets (special case of Fano resonance). The MVANN is used to predict geometries given a target spectrum. Trained with 7839 predictions. We didn't perform the dataset search for the fixed height and looked at the 5 best designs of the MVANN to find designs with similar H.

Other approaches requires more data to optimize a single objective. In the case of [1,2] the authors focus solely in the red color. In [1] they optimized 13 variables using 360 simulation while in [2] was performed 9600 simulations to optimize 6 variables. Other example is [3] where it is optimized 7 variables considering 5600 simulations.



[1] Lin, R., et al. (2023). arXiv preprint arXiv:2304.13516 [2] Dong, Z, et al. (2022) Science Advances 8(8) eabm4512

Panda, S. S., & Hegde, R. S. (2020). Journal of Nanophotonics, 14(1), 016014-016014