Development of a mathematical framework to represent a 2D/3D smooth geometric structure

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A lot of machine learning methods rely on learning the coefficients of particular basis functions to represent the true hidden function of interest from data. The ability to represent a large, possibly infinite, collection of functions compactly (using for example Fourier decomposition) is a major tool for addressing many learning problems from data. A variety of function decompositions exist, various Wavelet and Fourier decompositions being the most notable ones.

The field of shape representation is unfortunately not as well developed. Various 2D and 3D shapes are usually represented by a mesh, yet no fundamental decomposition to represent such shapes (useful in a machine learning context) is known at the moment. Identifying various ways to represent shapes can have significant implications for the ability of machine learning techniques to link the mapping of shapes to some measure of performance (for example).

Among others, such developments can have direct impact on the ability to design effective nanophotonic components. Two examples are given below demonstrating how various unintuitive shapes are optimized to perform a certain function. If we hope to train a machine learning model to predict performance given the shape, pixelization of the shape is currently the only way to represent designs. Better representations, akin to Fourier and Wavelets for functions, are needed to train successfully predictive models without collecting initially an extremely large database of designs and their performance characteristics.

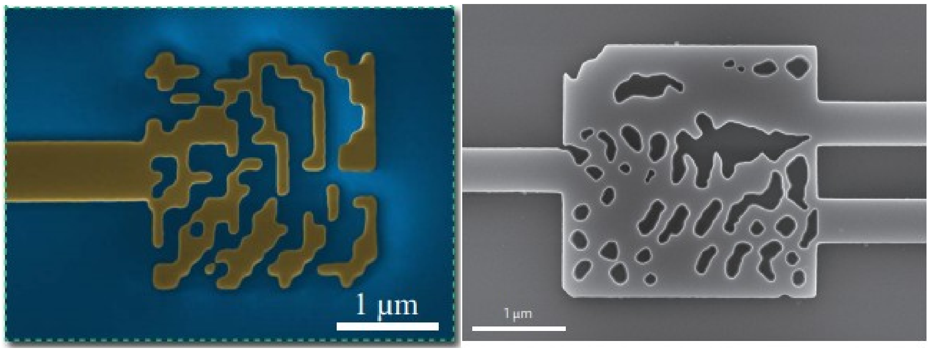

Figure 1: Left - Yu Z., et. al "Genetically optimized on-chip wideband ultracompact reflectors and Fabry–Perot cavities" '17. Right - Pigott A. et. al. "Inverse design and demonstration of a compact and broadband on-chip wavelength demultiplexer" '15.