Learning on Graphs and Manifolds with Geometric Wavelet Scattering Transforms

Feng Gao, Matthew Hirn*, Michael Perlmutter, Guy Wolf
Department of Computational Mathematics, Science & Engineering, Department of Mathematics, Michigan State University, USA
Email: `mhirn@msu.edu`

Convolutional neural networks (CNNs) are revolutionizing imaging science for two- and three-dimensional images over Euclidean domains. However, many data sets are intrinsically non-Euclidean and are better modeled through other mathematical structures, such as graphs or manifolds. This state of affairs has led to the development of geometric deep learning, which refers to a body of research that aims to translate the principles of CNNs to these non-Euclidean structures. In the process, various challenges have arisen, including how to define such geometric networks, how to compute and train them efficiently, and what are their mathematical properties.

In this talk I will introduce the geometric wavelet scattering transform, which is a type of geometric CNN for graphs and manifolds consisting of alternating multiscale geometric wavelet transforms and nonlinear activation functions. As the name suggests, the geometric wavelet scattering transform is an adaptation of the Euclidean wavelet scattering transform, first introduced by S. Mallat, to graph and manifold data. Like its Euclidean counterpart, the geometric wavelet scattering transform has several desirable properties. In the manifold setting these properties include isometric invariance up to a user specified scale and stability to small diffeomorphisms. Numerical results on manifold and graph data sets, including graph and manifold classification tasks as well as others, illustrate the practical utility of the approach.