Master Project in Geometric Deep Learning: Gauge equivariant neural networks for learning topological order

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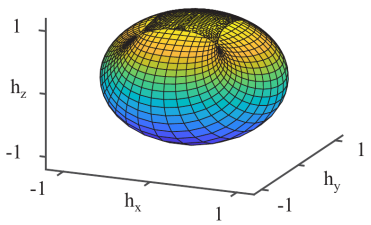

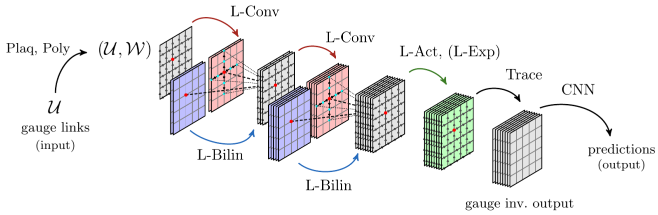

This project is in collaboration with Oleksandr Balabanov, Hampus Linander, Daniel Persson and Mats Granath.

Background

Geometric deep learning is an emerging field that includes several directions within the foundations of machine learning. It combines the power of deep learning with geometric and topological structures to model complex relationships between data points while taking inspiration from theoretical physics. In particular, the symmetries of the underlying problem are used to guide the design of the neural network architecture.

Symmetries are particularly important in the area of topological materials, a fascinating topic in condensed matter physics which involves mathematical questions from geometry and topology. One striking result in this field is the quantum Hall effect which has led to two Nobel prices. The project involves using gauge equivariant neural networks from geometric deep learning to learn topological invariants in condensed matter physics.

Problem setting

The system to be studied is a particular topological material, a two-dimensional multi-band Chern insulator. Here, the mathematical structure is well known and can be formulated rigorously on the discrete Brillouin zone. The relevant topological invariant is the integer-valued Chern number which is given by an aggregate over the Berry flux. Determining the Chern number for the Hamiltonian is a challenging task that conventional machine-learning models like residual- and convolutional neural networks fail to learn. This project is about using gauge equivariant neural networks, which take the symmetry of the learning problem into account, to learn the Chern number. Our preliminary studies show that these networks show superior performance on this task and their specific structure leads to interesting machine learning questions to be answered. Answering these questions may have broader implications for using these types of neural networks.

Prerequisites

This project requires familiarity with theoretical and practical basics of deep learning, i.e. a basic understand how usual deep neural networks work and experience in training them is necessary. The computations will be performed on a GPU computer-cluster, becoming familiar with the cluster environment is part of this project. To understand the physics background, a basic understanding of gauge theory and condensed matter physics is required. There is office space available for master's students at the department for mathematical sciences.

Reading material

Introduction to topological matter: `https://grushingroup.cnrs.fr/topointro2021/`
Gauge equivariant neural networks: `http://arxiv.org/abs/2012.12901`

Figure on the top left from:
Balabanov, O., & Granath, M. (2020). Unsupervised learning using topological data augmentation. Physical Review Research, 2(1), 013354. https://doi.org/10.1103/PhysRevResearch.2.013354
Figure on the top right from:
Favoni, M., Ipp, A., Müller, D. I., & Schuh, D. (2022). Lattice Gauge Equivariant Convolutional Neural Networks. Physical Review Letters, 128(3), 032003. https://doi.org/10.1103/PhysRevLett.128.032003.