Developing Symmetric Graph Neural Networks for Charged Particle Tracking

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1 Proposed Project

Charged particle tracking is essential in characterizing particles produced in colliders; traditional tracking algorithms scale up poorly, and new methods need to be developed. One approach is to use geometric deep learning to classify connections between tracker hits as true or false, and then link them together to form final track candidates. This can be done using graph neural networks (GNNs) by first constructing a graph of tracker events and then processing the graph with an intelligent network (IN) or similar architecture. Graphs are a natural representation of particle data because hits can be represented as nodes and track segments can be represented as edges [1].

This project proposes constructing the GNN, and implementing the function that the GNN learns on using the equivariant approach. Under joint supervision of Dr. Savannah Thais and Dr. Daniel Murnane and in collaboration with Jason Wong, I will investigate the rotational, CPT, and other symmetries that the dataset should have and construct and train the GNN to be equivariant to these symmetries to help constrain the network size and improve the accuracy of the machine learning algorithm. The application of GNNs to charged particle tracking is a fairly new approach, and other physics-related applications of similar neural networks have involved utilizing a time component, which most charged particle tracking datasets do not have. Thus, a sizeable part of the research process will be problem definition and sourcing or building a dataset that would be usable in this context. I will start with an already well-understood symmetry that has already been studied in steerable neural networks like rotation, which will help build intuition for the more exotic symmetries and for the dataset construction [2]. By the end of the three-month fellowship, I plan to have established a usable dataset, investigated possible symmetries and their equivariance and/or invariance, and begun and/or completed implementation and training of the GNN for charged particle tracking.

2 Student Background

During the fellowship, I will not be in school so I will have no other responsibilities and will work full-time on the project starting mid-May through mid-August (three months). I have done previous ML research at Princeton University where I implemented an algorithm to sort massive online open course (MOOC) data into seven distinct learner types in hopes of individualizing and improving the success rate of online instruction. Additionally, I worked briefly on a personal project developing a CNN that would be able to read and diagnose x-ray scans for pneumonia. Through these projects and my undergraduate coursework, I have become proficient in Python, which will be mainly used in this project.

I will use my previous knowledge of neural networks and machine learning as well as my educational background in physics to assist in completing the project. In the proposed work, I would expand my skill set to include the construction and development of GNNs in a physics setting, which is extremely relevant to my intended career and educational goals. This will help prepare me to pursue a PhD in computational physics, where I hope to continue research on the intersection of computer science and physics as it relates to physical modelling and machine learning.

3 Timeline

Month	*Activity*
1 (May - June)	Complete a literature review of related works and begin brainstorming possible symmetries of the data to investigate. Once the symmetries are identified, source an existing dataset or begin construction of a new one.
2 (June - July)	Continue construction of dataset. Start making the GNN and the function it will learn on using the identified symmetries and their respective invariances and equivariances.
3 (July - August)	Continue implementation of GNN if not already completed. Fine tune the network and apply to LHC data.

4 References

[1] G. DeZoort & S. Thais et al., Charged particle tracking via edge-classifying interaction networks (2021), arXiv 2021.

[2] M. Weiler & M. Geiger et al., 3D Steerable CNNs: Learning Rotationally Equivariant Features in Volumetric Data (2018), arXiv 2018.