IRIS-HEP Fellowship Proposal:

Conformal Mapping for Particle Track Reconstruction

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Most of the exotic particles produced by proton collisions in detectors (such as the LHC) decay too quickly to be directly detected; their characteristics can be inferred from those of the resulting daughter particles. Thus, tracking these particles' trajectories and measuring their energies is crucial to understanding the events within the detector. Due to the increased rate of collisions expected in the HL-LHC, the probability of observing rare particles and events will be increased tenfold. However, this 'denser' data will require efficient ways to distinguish physically interesting events from background noise and distinguish between individual particle tracks. This task can be approached with instance segmentation algorithms studied in computer vision. Geometric deep learning is inherently suited to this task due to its ability to capture the geometric relationships and patterns in the data, and perhaps even model causal dependencies. In comparison, traditional machine learning models are agnostic to the geometric nature of the data and are thus prone to overfitting.

Particle detectors like the HL-LHC record point clouds of hits; to reconstruct the trajectories of particles, it is necessary to determine which hits belong to these individual trajectories. This, along with the sparse nature of the detector data, makes graph neural networks (GNNs) a promising tool for particle tracking, given their strong performance on instance segmentation tasks. The GNN pipeline (Interaction Network) built by Dr. Thais' team extracts track parameters in addition to grouping hits belonging to the trajectories of individual particles. The algorithm exploits natural symmetries in the detector data, in particular those arising from mapping to conformal space, to facilitate the learning process.

Extraction of track parameters can be attempted by fitting a simple linear or parabolic model to the data in conformal (u-v) space, in which circular tracks which pass through the origin (in the x-y plane) are mapped to straight lines. However, not all tracks have this specific nature; displaced tracks, often caused by particles undergoing multiple scattering, do not generally pass through the origin. A parabolic fit can be used to extract parameters of such tracks. A drawback of conformal fitting for this dataset is its numerical instability; the large radii of the helical particle paths of high transverse momentum particles, in particular, impede fitting and cause the existence of multiple local optima in the parameters space. Over the past two months, as an intern with Dr. Thais' team, I focused on creating a numerically stable fit to the data in conformal space. Currently, this is done using a three-stage method; tracks are rotated to be roughly parallel to the u-axis, then a linear model is fitted to the data, and the resulting fit parameters are used to inform initial guesses for the parabolic fitting.

We propose a contribution to this project that would consist of further improvement of the conformal space fit and its stability, and potentially optimising certain aspects of the network's architecture for this purpose. The quality of the fit can be best judged by direct comparison to a helical fit to the data in x-y space, which we plan to begin implementing in the coming week. Should this comparison reveal significant discrepancies, a secondary neural network embedded within the GNN may provide improved results. Additionally, the transformation to a conformal mapping of the data can be done at any of a number of steps within the GNNs architecture. The model's performance could be improved by optimising the stage of processing at which this is done, e.g. testing to see whether results are improved by having the entire architecture operate in conformal space as compared to the transformation being applied 'at the end', i.e. to reconstructed trajectories. Another possibility involves branching the neural pipeline and applying separate loss functions to the cartesian and conformal ‘sections’ of the network.

Due to my current informal participation in this project, I believe I am familiar with the theory behind and the current codebase of the Interaction Network. Additionally, last year, as an intern at MIT's Winslow Lab, I worked on applying machine learning methods for the simulation of events in the KamLAND-zen neutrino detector. During that time, I gained significant experience in machine learning, implementing multiple models, including autoencoder and GAN networks, also using the PyTorch library. In particular, I designed, implemented and tested a novel pointnet autoencoder architecture, which proved capable of learning geometric relationships between observed hits and mapping them to a certain canonical representation. This project has several strong similarities; it also features point clouds of data and utilises coordinate transformations and feature extraction. I found working with both Professor Winslow and Dr. Thais’ teams very rewarding, and it has deepened my interest in the subject. As a physics student, I believe that my background knowledge of the theory behind the experiment, coupled with my experience in using machine learning for physics applications, makes me a good fit for this project.

We plan to begin this phase of the project around February 15th, 2022. The first task will be to compare the accuracy of track parameters extracted from conformal space fitting to a direct helical fit to the data. We also hope to improve on the numerical stability of the current conformal space fit. Nonetheless, we expect to need to improve on the conformal space fitting’s precision, so the next step would be to replace this fitting algorithm with a neural network approach, which could allow us to include the fitting phase in the end-to-end differentiable pipeline, trainable with gradient-based optimisers. Finally, the GNN can be modified to optimise the point at which the conformal mapping is introduced. We predict this stage of the project can be concluded within three months, and we hope to present the results at the CTD2022 conference.