IRIS/HEP Fellowship Proposal: Implementation of ML algorithms for ambiguity resolution in ACTS track reconstruction

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The reconstruction of the trajectories of charged particles, particle tracking, is vital to understanding the events occurring within a detector. It provides position and momentum information on particles moving helically in a calibrated magnetic field, through their interactions with layers of the detector. This information has been used, for instance, in jet energy calibration, muon reconstruction and muon momentum measurement, and flavour tagging, which are all components used in analyses that search for new or interesting physical processes. These physical analyses, therefore, rely on an efficient and precise method for track reconstruction, making it a crucial component for development in high energy physics experiments.

In the ATLAS experiment, the number of collisions (pile-up) is expected to increase with the HL-LHC upgrade. An increase in events recorded by the Inner Detector will complicate the combinatorial process of track reconstruction, raising the amount of CPU resources required in an already CPU expensive process. Therefore, it is necessary to apply changes to the track reconstruction algorithm to mitigate the complexity of the unprecedented high-pile up scenario and preserve tracking performance. Sustainable computing requirements for the HL-LHC can be met by architectures that minimize CPU time for track reconstruction, while still providing high-quality tracks.

ACTS [1] was developed as an experiment and framework independent tool for track reconstruction. It aims to support High Energy Physics experiments, including ATLAS. However, with the increasing complexity of data-collection associated with the high-pileup collisions for the HL-LHC, the exploitation of new approaches to the pattern recognition algorithms in ACTS will be required, opening a window for machine learning (ML) based solutions to computationally expensive steps of track reconstruction. The steps of track reconstruction in ACTS include clustering of hits for space-point formation, seeding which creates a starting point for track reconstruction using triplets of space-points, track finding which combines seeds with other compatible space-points in iterations to create track candidates, and the ambiguity solver which removes track candidates with duplicate or incorrectly assigned hits and presents the final, resolved tracks.

This project seeks to explore the performance of ML algorithms, such as RNNs, CNNs, in various steps of track reconstruction, with a particular focus on the ambiguity solver. The ambiguity solver assigns a track score to each track candidate based on the likelihood that its fit correctly represents the trajectory of a particle, suppressing the score of "bad quality" tracks and removing individual seeds that increase the χ^2 fit. It returns the "good quality" tracks with high scores, ensuring optimal performance of the entire track reconstruction mechanism.

The ambiguity resolution algorithm is a particularly large contributor to the overall track reconstruction time [2]. Thus, ML algorithms implemented in this step have the potential to greatly reduce CPU consumption while still maintaining high-quality results. ML techniques can also have a significant impact on other steps of track reconstruction. This project may additionally explore these steps, in particular seeding formation: a classification problem for an efficient selection of good seed candidates.

ACTS FATRAS [3] will be used to generate simulated Monte Carlo samples of interesting physics processes with a pileup distribution corresponding to a high luminosity environment. The ACTS track reconstruction code, which supports a Combinatorial Kalman Filter approach among other possibilities, will be used to provide track candidates for my studies. The project will evaluate the performance of different ML algorithms in terms of both physics and CPU time and culminate in an incorporation of a selected model into the ACTS framework.

This project will build upon the previous work [4] of graduate student Irina Ene (UC Berkeley), who determined the feasibility of this study while ACTS was still in an early stage of development and studied model integration into ACTS using ONNX [5], an open-source format for ML models that supports portability among various frameworks including Keras/TensorFlow and enables the maximization of performance across hardware. I will be using ONNX to interface my model with ACTS. I will be working with Dr. Carlo Varni (UC Berkeley), Dr. Louis-Guillaume Gagnon (UC Berkeley) and Professor Heather Gray (UC Berkeley, LBNL).

Timeline: May - August 2021 (3 FTE-months)

- **Week 1-3:** Examine current ACTS code, determine potential ML-based improvements, and simulate data with ACTS FATRAS.
- **Week 4-7:** Train and evaluate the performance of various ML models and identify areas for improvements.
- **Week 8-9:** Continue to optimize algorithms and compare their performances.
- **Week 10-12:** Present results and implement selected model into ACTS software.

References

[1] https://github.com/acts-project/acts

[2] ATLAS Collaboration, *Fast Track Reconstruction for HL-LHC*, ATL-PHYS-PUB-2019-041 (Oct. 2019)

[3] https://github.com/acts-project/acts/tree/master/Fatras

[4] Irina Ene, *Ambiguity Resolution with Machine Learning and ACTS*, IRIS-HEP Topical Meeting (Sep. 2020)

[5] https://github.com/onnx/onnx