Abstract

This thesis presents a comprehensive account of five years of research conducted within the LHCb experiment at CERN. The work focuses on developing and applying machine learning techniques to enhance track reconstruction and detector performance. The work is organised into two phases, each addressing distinct but related challenges in particle tracking and data analysis.

The thesis explores strategies to leverage these software triggers to maximise reconstruction efficiency without compromising physics data. The second phase focuses on the Upstream Tracker (UT), a detector positioned upstream of the dipole magnet critical for precise momentum measurements.

The first phase focuses on improving downstream track reconstruction by developing two machine learning models. The first selector aims to enhance the quality of SciFi track segments, which serve as the seeds for more complex downstream track reconstruction. The second selector is designed to identify the downstream tracks and eliminate combinatorial tracks, commonly called "ghost tracks," which do not correspond to real particle trajectories. This phase represents one of the most technically demanding aspects of the research, involving rigorous metric evaluation and performance assessment of the models, followed by their integration and deployment within the Gaudi software framework and the LHCb track reconstruction algorithms. The second project aims to build a monitoring methodology for analysing and recalibrating the UT detector, helping to optimise the signal-to-noise ratio for improved track reconstruction.

Keywords: Downstream Tracks, Machine Learning, High-Level Trigger, Neural Networks, Track Reconstruction

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