Improvement of GNN-based algorithm for full-event filtering and interpretation at the LHCb trigger

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1 Introduction

The high luminosity upgrade of the Large Hadron Colider (HL-LHC) will deliver an integrated luminosity that is 20 times larger than the present LHC dataset [1]. Such an increase in event complexity will pose unprecedented challenges to the online-trigger system. On one side, the current algorithms would be too slow to deal with the high level of particle combinatorics. On the other side, the event size will become too large to afford the persistence of all the objects in the event for offline processing. This will oblige to make a very accurate selection of the interesting parts in each event for all the possible channels, which constitutes a gargantuan task

Promising candidates for the solution of this problem are deep learning algorithms, specifically those based on Graph Neural Networks (GNNs), since graph structures are able to effectively capture complex relationships and dependencies between objects. For particle physics data, graph-based representations provide several advantages over alternative data representations: unlike vector- or grid-like structures, graphs allow for variable sized data and they are better suited for dealing with sparse and heterogeneous detector data that can be difficult to project into image-based representations [2]. Hence, GNNs do not require the application of an information loosing and artificial ordering scheme as required by sequence-based representations. Graphs are able to represent a broad range of particle physics data including energy deposits in a detector, individual physics objects like tracks or missing energy, individual particles or groups of particles, or even heterogeneous information.

DFEI (Deep Full Event Interpretation) is a project that aims to implement a GNN-based algorithm for the LHCb experiment which will use, in real time, already reconstructed final-state particles in each event, with two goals: identifying which of them come from the decay of a beauty or charm heavy hadron and reconstructing the hierarchical decay chain through which they were produced. This high-level reconstruction will allow to automatically and accurately identify the part of the event which is interesting for physics analysis, allowing to safely discard the rest of the event.

2 Project Proposal

While the graph structure provides an optimal layout to represent information, it comes at a computationally high cost. Since DFEI aims to be implemented into the trigger, where a low latency is important, the current algorithm needs to be optimized for speed. This can be done by replacing some of the dynamic elements of the graph with a static ones, trading off accuracy for speed.

The goal of the project is to implement a new, distance-weighted, approach [3] as also used in CMS, in order to improve speed performance of the existing algorithm. The results and deliverables will be used to implement the algorithm into the RTA (real time analysis) system of LHCb.

3 Timeline

The duration of the project is planned to be 10 weeks (June 27 - September 2) at 100% FTE. Supervision will be provided mainly by Jonas Eschle (University of Zurich) as well as other members in the DFEI project group, which is led by Julian Garcias (University and INFN, Milano-Bicocca). The work plan and deliverables are provided below.

Week 1 (June 27 – July 1)

Read papers and tutorials on Graph Neural Networks to understand their abilities, limitations and ways for optimization.

Week 2-3 (July 4 – July 15)

Understand the current implementation of the DFEI algorithm. Get familiar with the code and data. By the end, be able to run the code and understand what each part of it does

Week 4-6 (July 18 – August 5)

Study and implement new approaches, like the GRAVNET and GARNET layers [3], to improve the algorithm.

Week 7-8 (August 8 – August 19)

Finish implementation, fine-tune the new approaches. Compare performance with the current architecture by running tests on the simulated events.

Week 9-10 (August 22 – September 2)

Wrap up the project. Prepare report on the results of research. General cleanup of the code including in terms of readability, documentation. Create and present a final presentation of the project

References

[1] Dustin Anderson Kim Albertsson, Piero Altoe et al. Machine learning in high energy physics community white paper. 2019.

[2] Grigorios Chachamis Savannah Thais, Paolo Calafiura et al. Graph neural networks in particle physics: Implementations, innovations, and challenges. 2022.

[3] Yutaro Iiyama Maurizio Pierini Shah Rukh Qasim, Jan Kieseler. Learning representations of irregular particle-detector geometry with distance-weighted graph networks. 2019.