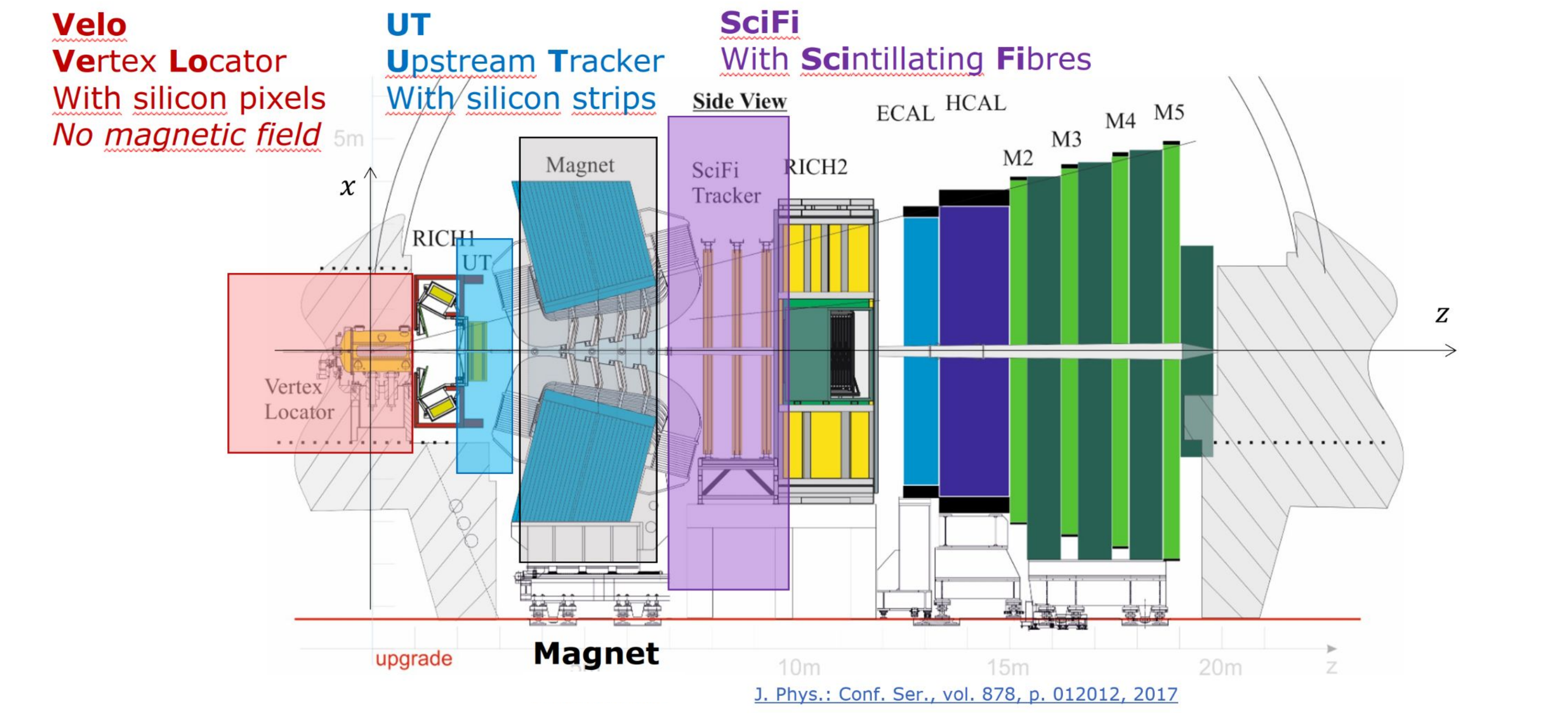
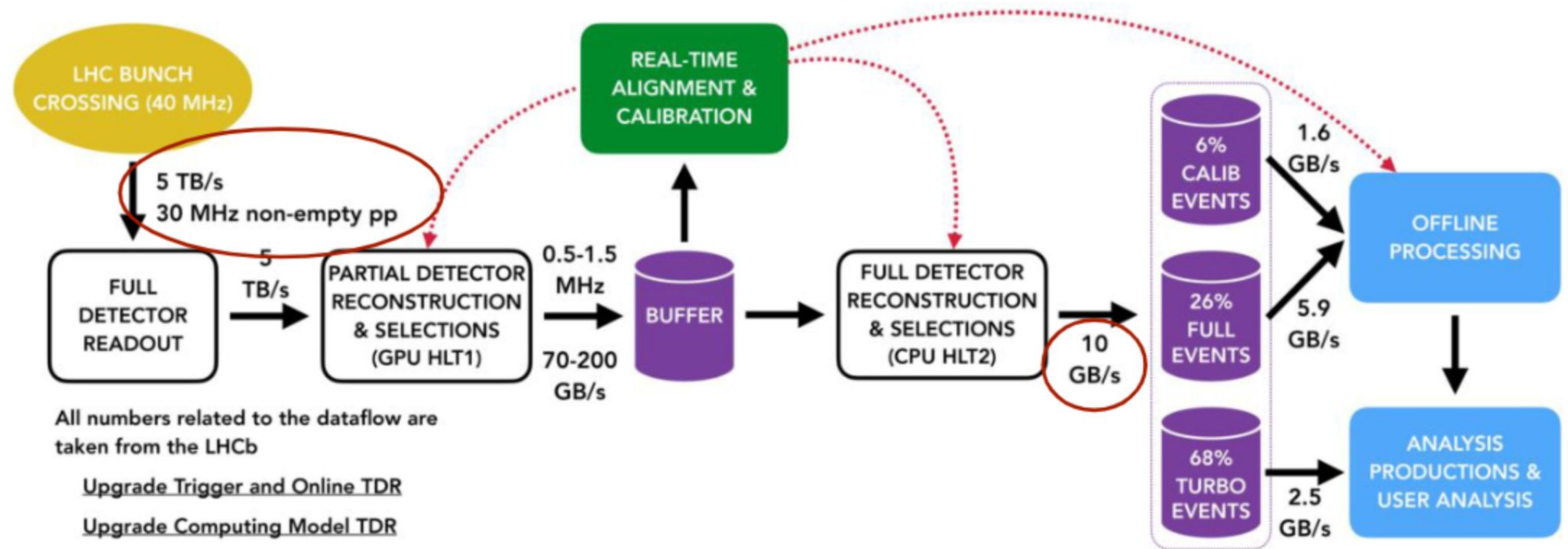
IA Activity

HCERES VISIT 2023

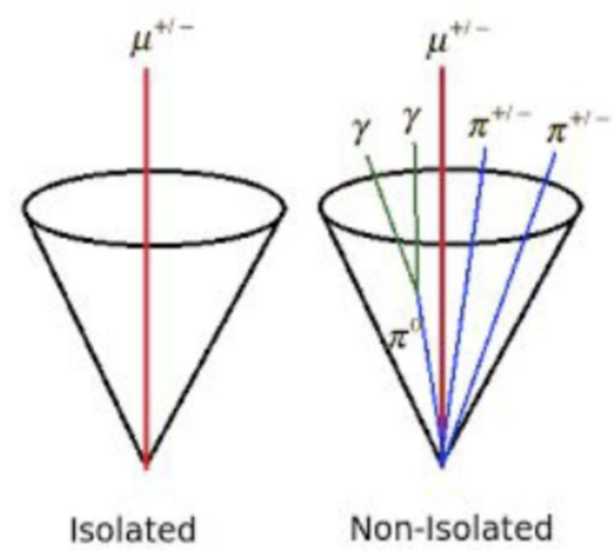
RTA

LHCb Detector and dataflow



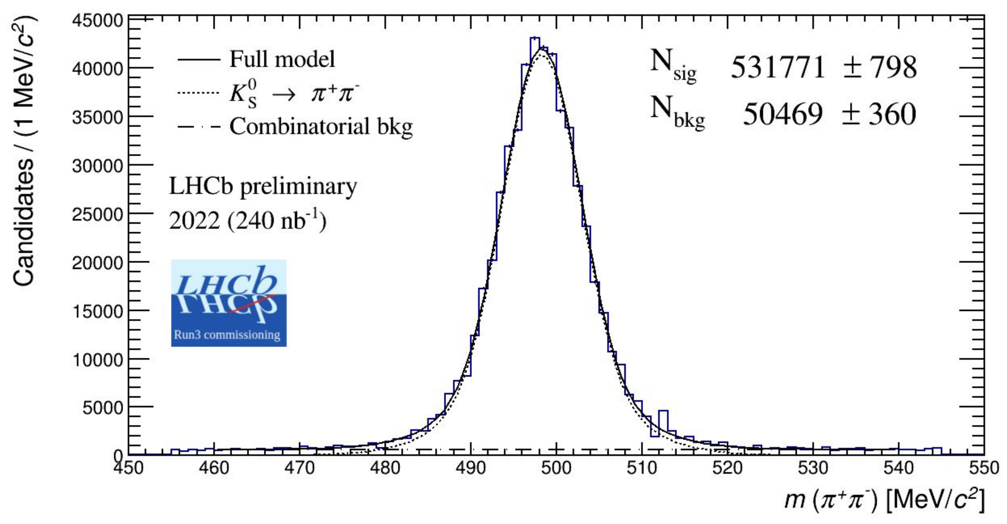


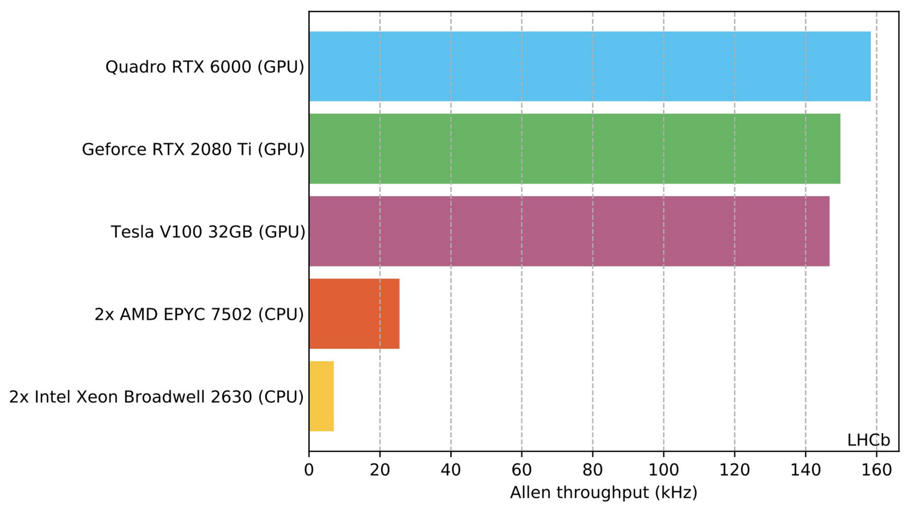
RTA / HLT2



For the second level of software trigger the group has developed general tools needed for filtering the events and also usable at the level of the offline analysis. This includes, for examples, developing the algorithm for evaluating the particles isolation, a powerful tool for background suppression. Selections for physics analysis have been designed and implemented, putting the basis for the exploitation of the Run3 dataset.

RTA / HLT1





The LPNHE group has been at the forefront of the development of LHCb's trigger system (called "Real Time Analysis" in the collaboration), including leading the trigger project from 2019 to 2023

In particular, the LPNHE group proposed moving the first level trigger from CPU to GPU processors and in a two year R&D demonstrated the feasibility of this solution and convinced the collaboration to adopt it. This is the first time in high-energy physics that GPU processors have been used for a first-level trigger system. Compared to the CPU baseline the GPU trigger allowed numerous additional physics functionality to be implemented: calorimenter reconstruction, low-momentum tracking, as well as finding tracks produced outside the LHCb vertex detector. These will have a very significant impact across the full LHCb physics program for the upgrade.

Implementing this trigger on 340 GPU processors also resulted in very substantial cost savings with respect to the CPU baseline system. Three postdoctoral researchers who worked on this project obtained permanent jobs, and one obtained an ERC grant and a CNRS bronze medal.

Deep-Learning: Graph Neural Network -based pipeline for track finding in the Velo at LHCb

To continue the effort and evolution of RTA, we now focus on integrating deep learning algorithms in the GPU trigger.

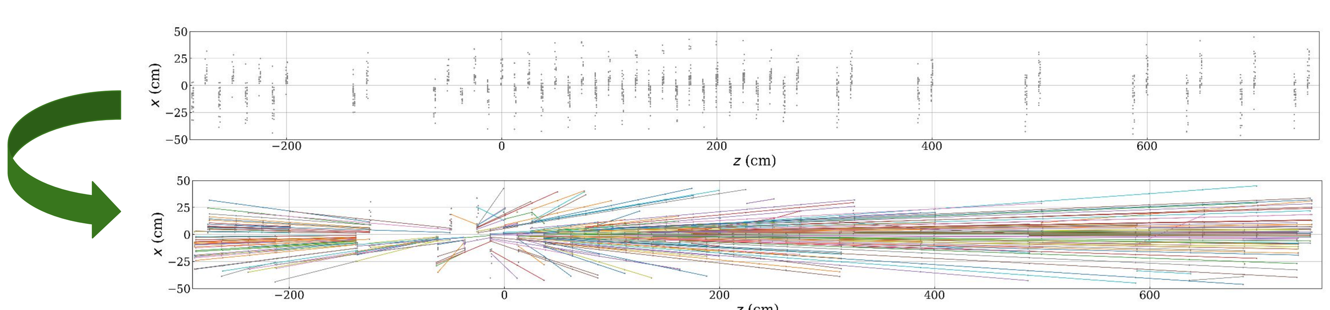
The focus is to evaluate deep-learning algorithms performance for EFFICIENCY and THROUGHPUT, and estimate how these models scale up with the increase of data rate.

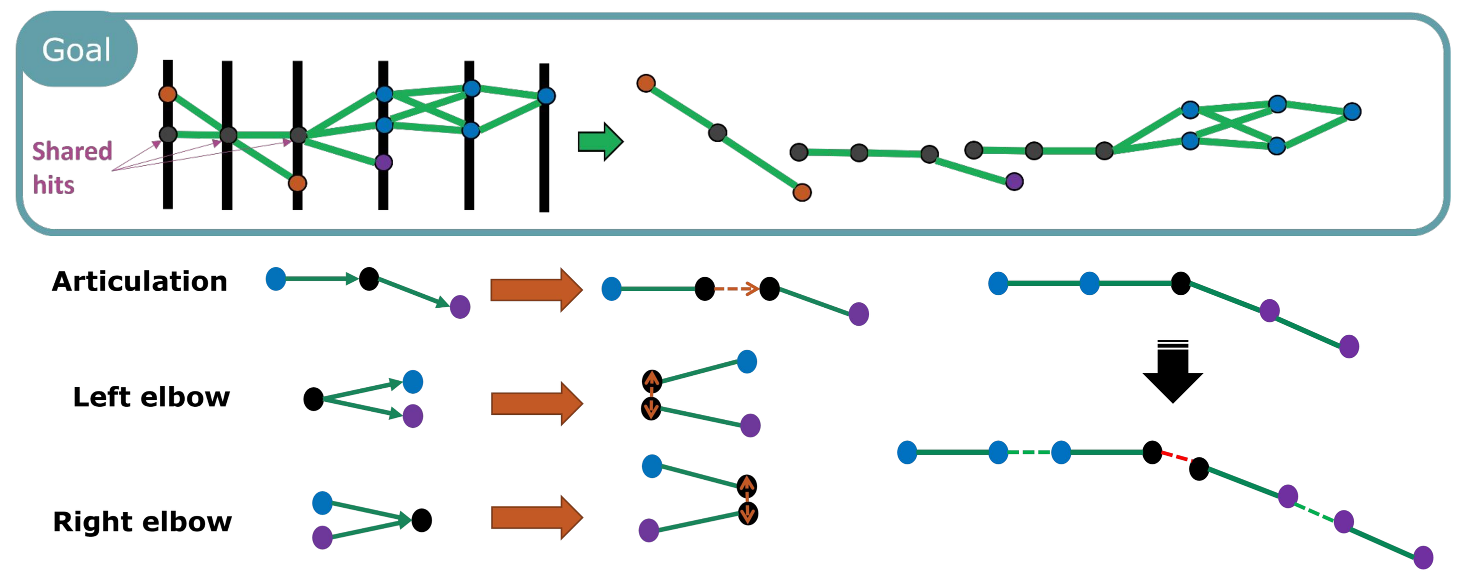
For this purpose we developed the ETX4VELO pipeline which focuses on developing Graph Neural Networks (GNNs) algorithms for track reconstruction.

1. First step: construction of deep-learning datasets using XDIGI2CSV, which are the first deep-learning dataset shared at the level of LHCb collaboration.

1. Second step of this work focused on the reconstruction efficiency, the efficiency reached at this level is higher than Allen. The ETX4VELO pipeline is based on edge and triplet GNN model that can reconstruct harsh cases of shared hits between tracks.

1. Third step: make the inference in Allen Framework in C++/Cuda to compare the throughput performance





High-Efficiency GNN reconstruction pipeline

Category	Metric	Allen	ETX4VELO *smaller graph*	ETX4VELO *Larger graph*
Long, no electrons ✓ In acceptance ✓ Reconstructible in the velo ✓ Reconstructible in the SciFi ✓ Not an electron	Efficiency	99.26%	99.28%	99.51%
	Clone rate	2.54%	0.96%	0.89%
	Hit efficiency	96.46%	98.73%	98.90%
	Hit Purity	99.78%	99.94%	99.94%
Long electrons ✓ In acceptance ✓ Reconstructible in the velo ✓ Reconstructible in the SciFi ✓ Electron	Efficiency	97.11%	98.80%	99.22%
	Clone rate	4,25%	7.42%	7.31%
	Hit efficiency	95.24%	96.54%	96.79%
	Hit purity	97.11%	98.46%	98.46%
Long, from strange ✓ In acceptance ✓ Reconstructible in the velo ✓ Decays from a strange *Good proxy for displaced tracks*	Efficiency	97.69%	97.50%	98.06%
	Clone rate	2.50%	0.92%	0.81%
	Hit efficiency	97.69%	98.22%	98.77%
	Hit purity	99.34%	99.68%	99.68%
X	Ghost rate	2.18%	0.76%	0.81%

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