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Machine Learning in Particle Physics Experiments : The Case of LHCb

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Abstract. Particle physics is a source of engineering challenges, also for Machine Learning techniques. We showcase three current uses of Machine Learning in the LHCb experiment, one of the four main experiments of the Large Hadron Collider (LHC) at CERN. Two are in the Real Time Analysis framework, which is in charge of processing the detector 4TB/s dataflow in real time: one to locate the points where particles issued from the accelerator collisions decay, and the other to ensure a smooth choice in the data to be stored. A third use is about speeding the detector simulation with generative techniques. In all three cases, computing speed is the key factor for using Machine Learning algorithms.

Keywords. Particle Detectors, LHCb, Machine Learning.

1. Introduction

High Energy Physics experiments have been for a long time good customers of Machine Learning (ML) applications. As soon as the late 80's and early 90's, Neural Network models where applied to solve several of the challenges met in the intepretation of data, as reference [1] shows. Later on, the dectectors for the Large Hadron Collider (LHC) at CERN continued to selectively use ML techniques at different stages of the data processing. In the case of the LHCb detector, neural networks where currently used for particle identification at several stages of the data processing flow and also Boosted Decision Trees where applied to select the collisions worth keeping for physics analysis [2]. After two very successful data taking periods, the LHC has undergone an upgrade which increases the average number of collisions per time unit, and so, increases the detector data rate. In the case of LHCb this amounts to processing 4TB/s to select what data is worth

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storing for physics analysis. In this note, we overview some examples of machine learning solutions applied in the current version of the detector. For this, we shall first explain through LHCb how a particle detector works and what are requirements in terms of data processing. Next we shall highlight some ML uses to finally elaborate on possibilities and drawbacks of these techniques in this framework. It is not the objective of this note to give an exhaustive review of all possible applications but rather to illustrate some uses and raise the awareness of a potential field of application with a number of challenges.

2. Particle Physics Experiments

Particle Physics Experiments generally use dectectors to observe the decay of particles coming from external sources or, as in the case of the LHC, issuing from the collision of accelerated particles. The physics analysis related to these observations consists in determining what are the products, the features and the rates of some decay modes with respect to others and compare those with theoretical models. Particle dectectors are divided in several subdetectors that measure different features of the particles issued from these decays. Roughly, subdetectors may have three functions; tracking that is determining the trajectories of the particles; identification, determining the type of particle and finally the measure of the energy or the momentum of the particles. Each subdetector has its own type of sensors. The data collected is put together and processed in order to translate the measurements of the sensors into the descriptors needed for physics analysis. One common issue in this type of experiment is the overabundance of data. The amounts of collected data cannot be possibly stored, while some some decays may not be of interest and can be discarded. The system in charge of keeping or discarding an event is called the Trigger.

3. LHCb

The LHCb experiment is one of the four main experiments of the LHC [3]. Its goal is to test the current standard model of particle physics and look for indirect evidence of new phenomena mainly by studying the decays particles containing b and c quarks. Such particles are produced in abundance in the proton-proton collisions provided by the LHC. Because of the kinematics of the decays, the detector just needs to cover a part of the solid angle around the collision point. In exchange, the search for indirect evidences requires precision measurements for which LHCb is designed and built. Figure 1 shows the layout of the detector [4]. Each chamber uses different sensing technology, being the total number of channels of around 1 million. The frequency of collisions provided by the LHC is 30MHz, so that the actual data flow in data taking conditions is around 4TB/s. In order to deal with this data flow, a system call Real Time Analysis has been put in place to select the events that are with relevant information for physics analyses purposes. The scheme of this system is depicted in Figure 2.

4. Machine Learning Opportunities

The operations performed on the detector data both to evaluate the interest of the observed decaying particle, and the posterior physics analysis, are suited to use machine

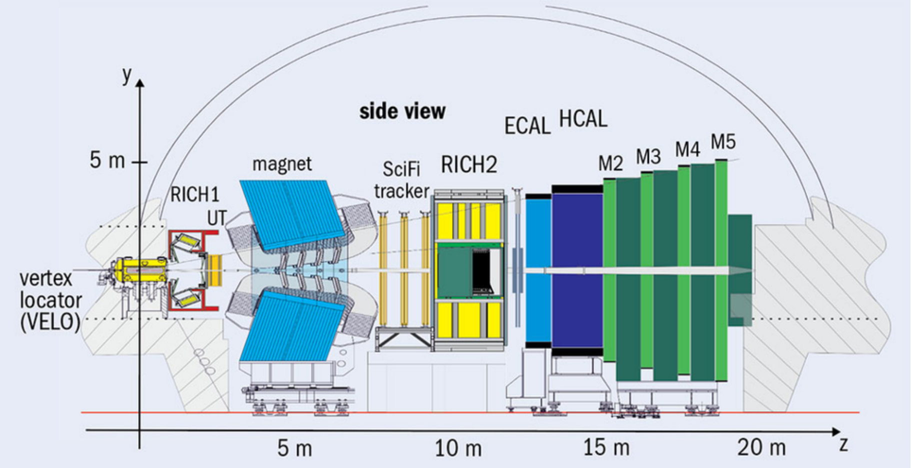

Figure 1. Layout of the LHCb detector. The detector elements, in order are the Vertex Locator, the first Cherenkov Radiation Imaging Chamber, the upstream tracker, the magnet, the scintillator fiber tracker, the second Cherenkov Radiation Imaging Chamber, the electromagnetic calorimeter, the hadronic calorimeter and the muon chambers.

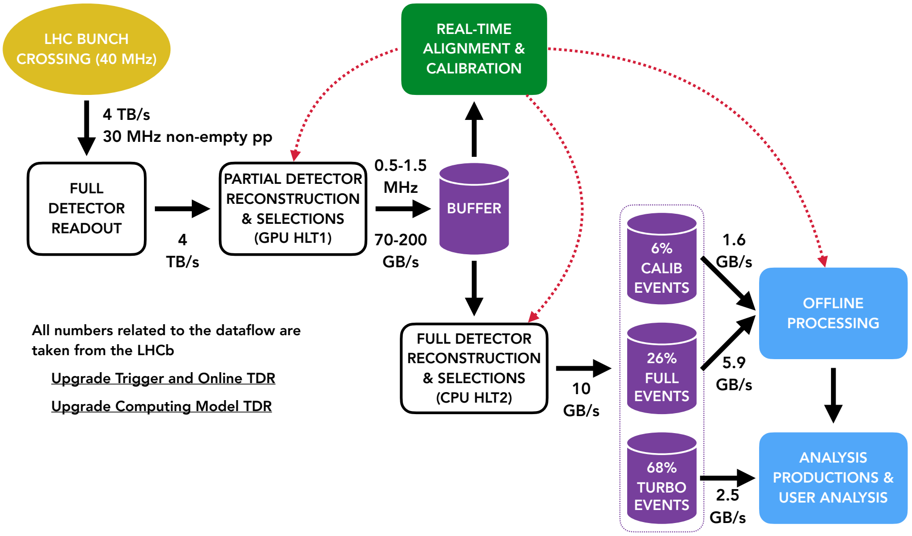

Figure 2. Scheme of the Real Time Analysis System. Data are first analysed in a GPU-based system called Allen, then buffered and finally reconstructed. The events with potentially interesting features are stored while the rest are discarded [5]

learning algorithms. Many require advanced pattern recognition or are based on classifiers. Moreover, another important aspect in the analysis processes are Monte Carlo simulations. A full model of the interaction and the detector response is used to evaluate the analysis procedures and test algorithms. These simulations are very detailed and thus time and resource consuming. We shall single out three interesting approaches among the current investigations to apply ML techniques in LHCb.

4.1. Lipschitz Neural Newtorks for selection algorithms

The function providing the selection variable that shall determine whether the event under study is relevant for further physics analysis or not should meet two essential requirements: robustness and interpretability. By robustness is understood that it has mitigated sensitivity to experimental instabilites during the data taking and inacuracies in the simulation. Interpretability would be implemented through a built in inductive bias on some selected input variables. These two conditions can be met by designing neural network architectures monotonic with respect to a set of input features and by enforcing Lipschitz constraints. These requirements are embedded into the learning algorithm of a neural network. This strategy is successfuly applied to the so-called LHCb inclusive heavy-flavour trigger as shown in reference [6].

4.2. Deep Learning for identifying and locating primary vertices

One of the most important requirements to achieve LHCb's desired precision is an accurate location of the points where the particles produced in the LHC proton-proton collisions decay, the so-called Primary Vertices (PV). In reference [7], a refinement of the actual method, which is found to be very slow, based on comparing histograms is presented. It consists of using the VELO tracks parameters to feed a system of two consecutive neural networks, a fully connected Multi Layer Perceptron with a UNet that constructs the final predicting histogram. The efficiency in detecting the actual PVs, on simulation data, and the accuracy of the position is found to be below the bin width of the target histogram.

4.3. CaloGAN

One of the most time consuming parts of the simulation software is computing the energy deposit of particles in the calorimeters. This task makes heavy use a very accurate software describing the interaction of particles with matter called GEANT [8]. A strategy to reduce the simulation time would be to be able to obtain equaly accurate simulations on a faster bases. The approach of references [9] and [10] is to use Generative Techniques, both Generative Adversarial Networks and Variational Autoencoders, trained from actual GEANT simulations. These approaches are on the way of being incorporated in the simulation software framework of LHCb called Gaussino [11].

5. Discussion and Overview

The three cases described in the previous section are good examples of challenging problems for Machine Learning experts. Again, let us insist that the list is not exhaustive, but rather illustrative. Another example can be found in reference [12]. Actually, the field has a peculiarity. Unlike many other situations where Machine Learning is used for complex problems that require advanced solutions, here, many applications depend on the ability to speed up calculation of neural network parallel inference. Not only complexity but also speed is a good reason to use ML. However, one of the limitations found in some applications is that inference sofwares do not deliver the required data throughput. This involves both the programming of the inference algorithms, but also the underlying hardware. A sample discussion on this topic can be found in [13]. The coming challenges to be faced in this field will require of sensible ML experts with deep understanding of training procedures, model optimisation and a sensitivity to find the simplest solution for each problem. In exchange, many interesting lessons may be learned and extrapolated to other fields.

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