CERN IT Machine Learning Infrastructure Workshop:

Inputs from LHCb

October 11th 2023

Simon Akar on behalf of the LHCb collaboration



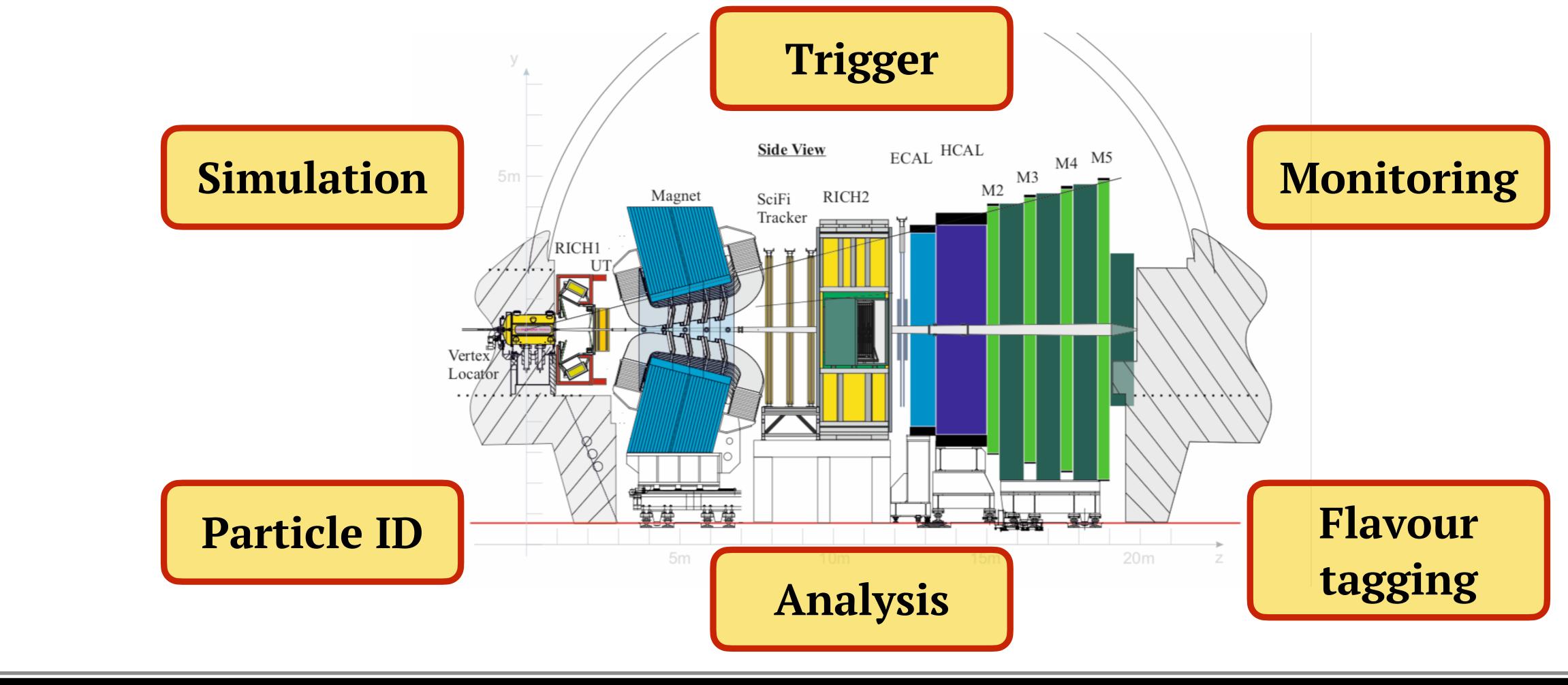








A long and diversified history of ML applications in LHCb:



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Disclaimers:

Simulation

- Not an exhaustive overview of ML applications in LHCb, but a highlight of relevant use cases for today's workshop
 - (I) Identify the challenges for a fully exploited implementation of ML/DL
 - (II) Which common services / solutions would we most benefit from as a community
- Wide range of concepts covered in this talk:
 Detailed discussions on certain specific technical considerations might be better covered offline

Particle

Analysis

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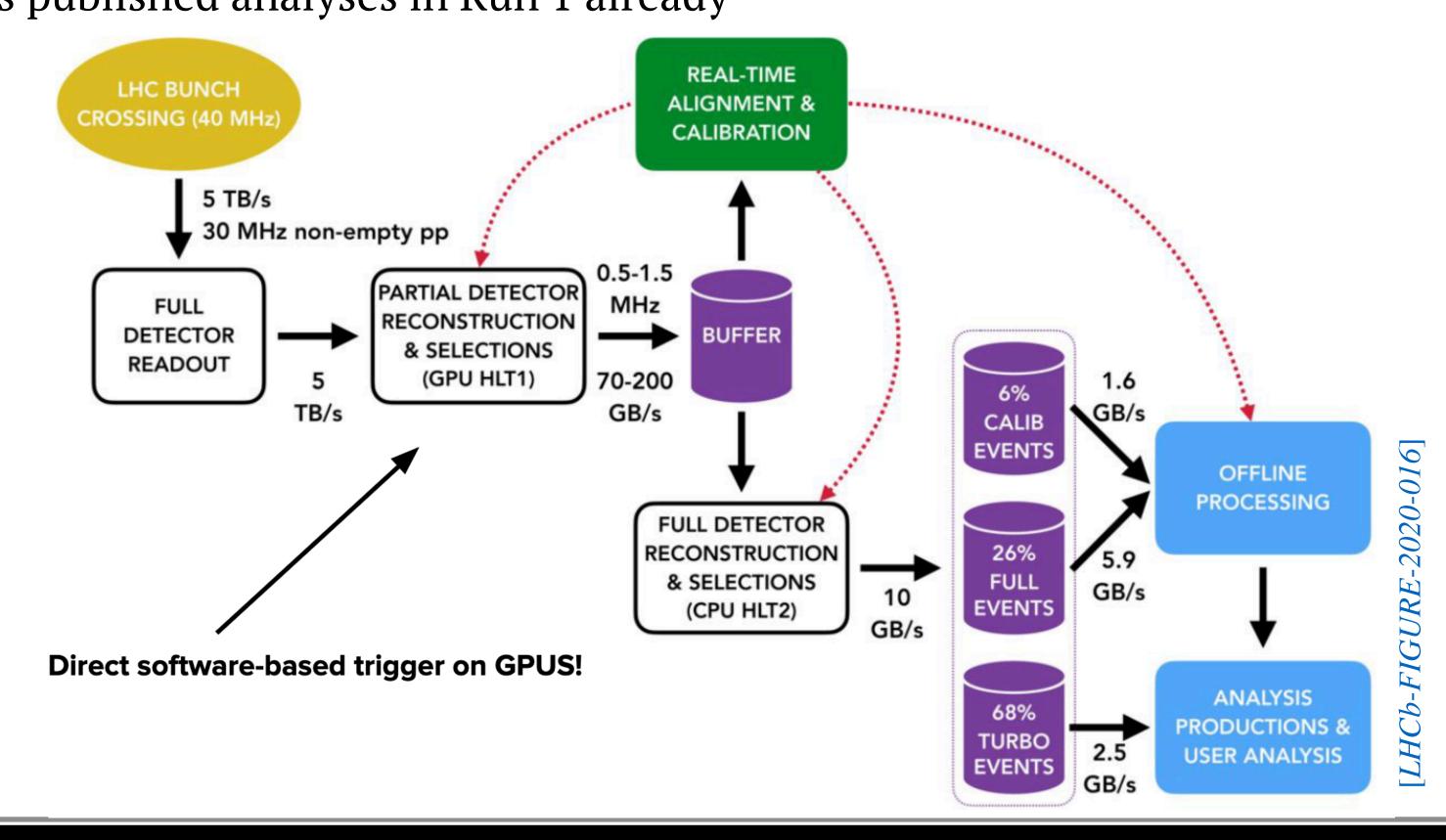
Trigger & Online ops.

• ML-based algorithms (BDT) in inclusive particle selections already during Run1 & Run 2 covering the majority of the collaboration's published analyses in Run 1 already

[LHCb-PUB-2011-016, arxiv:1510.00572]

• New paradigm in Run 3 with full software trigger implementation [CERN-LHCC-2018-014; LHCB-TDR-018]

- 326 GPUs reduce incoming data rate from 5 to approximately 0.1 TB/s
- All subdetectors data available at trigger level
- Opened window for ML application (inference) at earliest selection level as possible directly in the online environment



Trigger & Online ops.

Several on-going efforts to implement ML algorithms inside LHCb online system

- High-throughout Graph Neural Network track reconstruction at LHCb: [talk@CTD2023]
 - **Track reconstruction** in the Velo (high-granularity tracking system)
 - Using GNN pipeline is based on the work of the Exa.TrkX collaboration

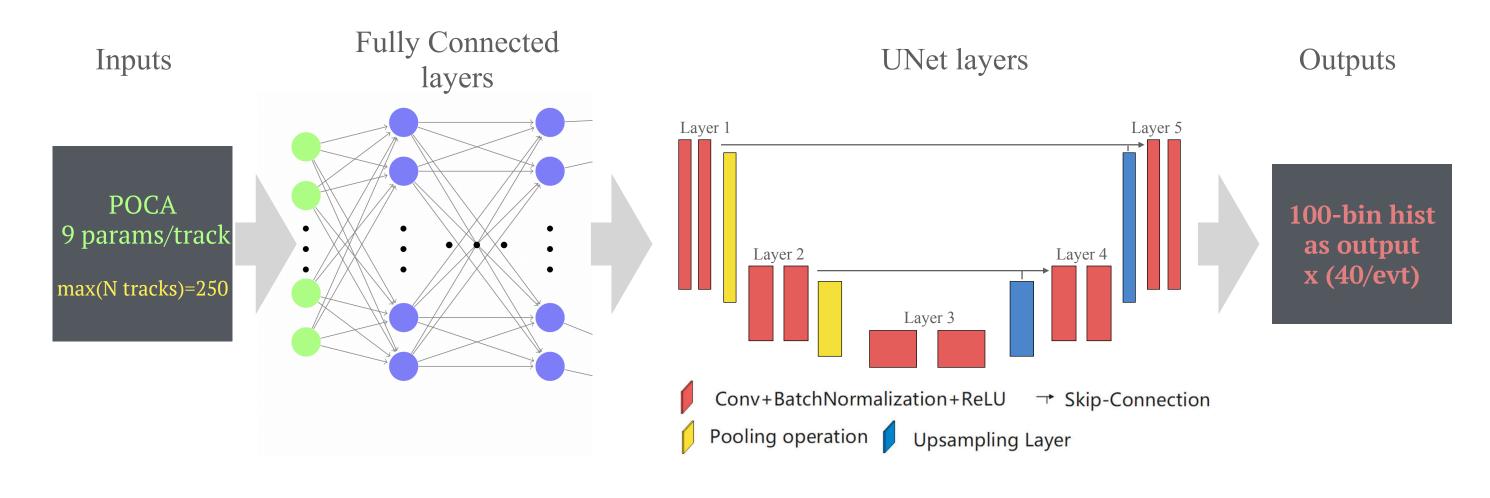


- Training performed using **PyTorch** on **local ressources** (LIP6 Paris Sorbonne Université)
- Inference on low-level features
- High parallelization over hits / edges \Rightarrow adapted to GPUs
- Very promising preliminary physics performances
- On-going R&D to run inference on GPUs in Allen (HLT1)
 - → what throughput on HLT1 GPU farm (identify potential bottlenecks for future upgrades)
 - → study the possibility to extend approach to full detector

Trigger & Online ops.

Several on-going efforts to implement ML algorithms inside LHCb online system

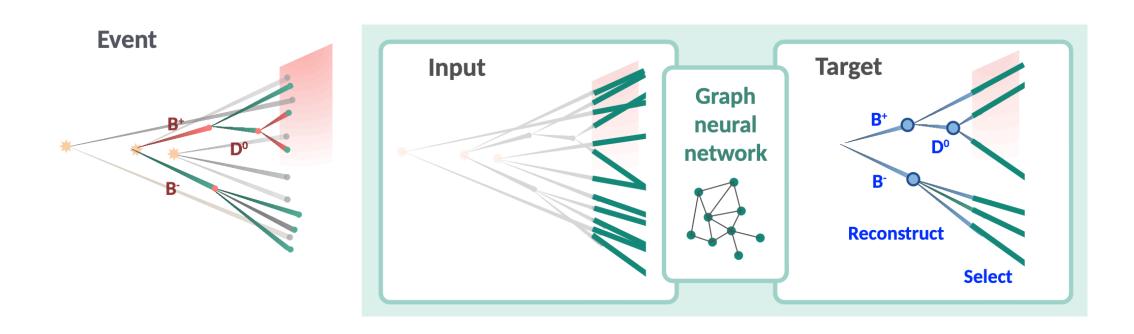
- DNN for finding primary vertices in pp collisions at the LHC: [talk@CHEP2023, arxiv:2309.12417]
 - Identify PV positions from tracks low-level features
 - High parallelization over tracks / events ⇒ adapted to GPUs
 - Non trivial hybrid MLP + CNN architecture
 - Common training platform for LHCb and ATLAS
 - Training performed using **PyTorch** on **local ressources** (University Cincinnati)
 - Very promising preliminary physics performances
 - On-going R&D to run inference for LHCb on GPUs in Allen (HLT1)



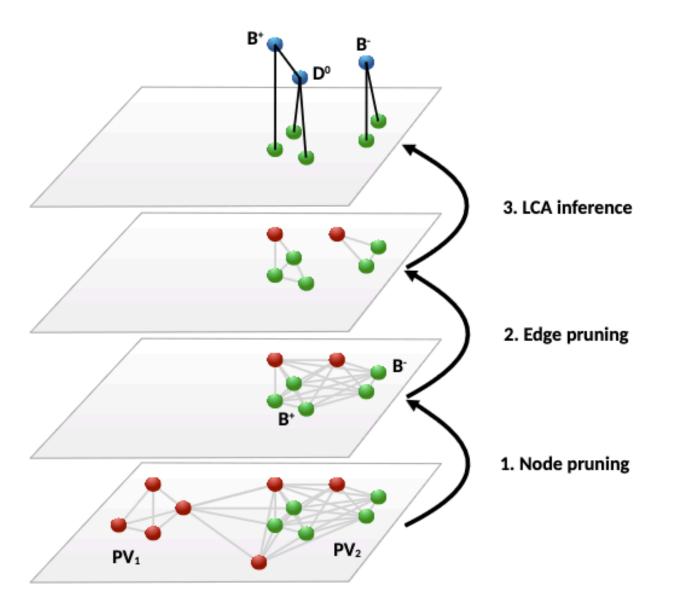
Trigger & Online ops.

Several on-going efforts to implement ML algorithms inside LHCb online system

- Graph Neural Network for Full Event Interpretation at LHCb [talk@CHEP2023, arxiv:2304.08610]
 - Proof of concept: Reduction of event size by a holistic one-go analysis of the full event



- Training performed using **TensorFlow**
- Ongoing detailed performance and timing studies
- Resources for model training were difficult to obtain:
 Lack of adequate ressources @CERN (training over several days)
 - → Finally used *Future SOC Lab* cluster with docker containers for librairies

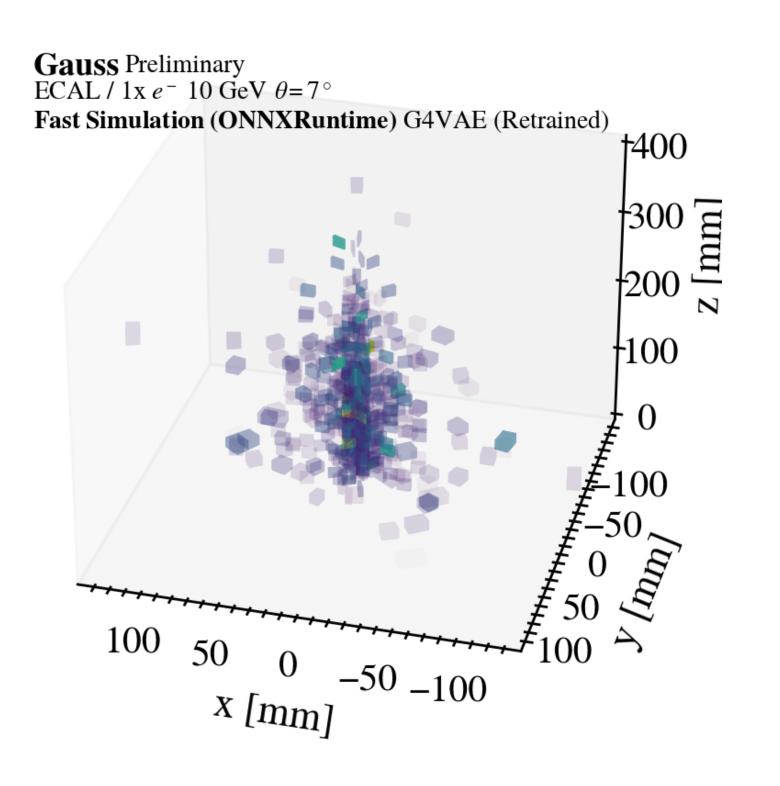


Simulation

Computing resources too limited to use GEANT detailed simulation for the large simulated samples needed!

- Fast simulation: Replace Geant4 simulation with ML-generated output in specific area of the detector
 - Typically calo shower generation with GANs [talk@CHEP2019]

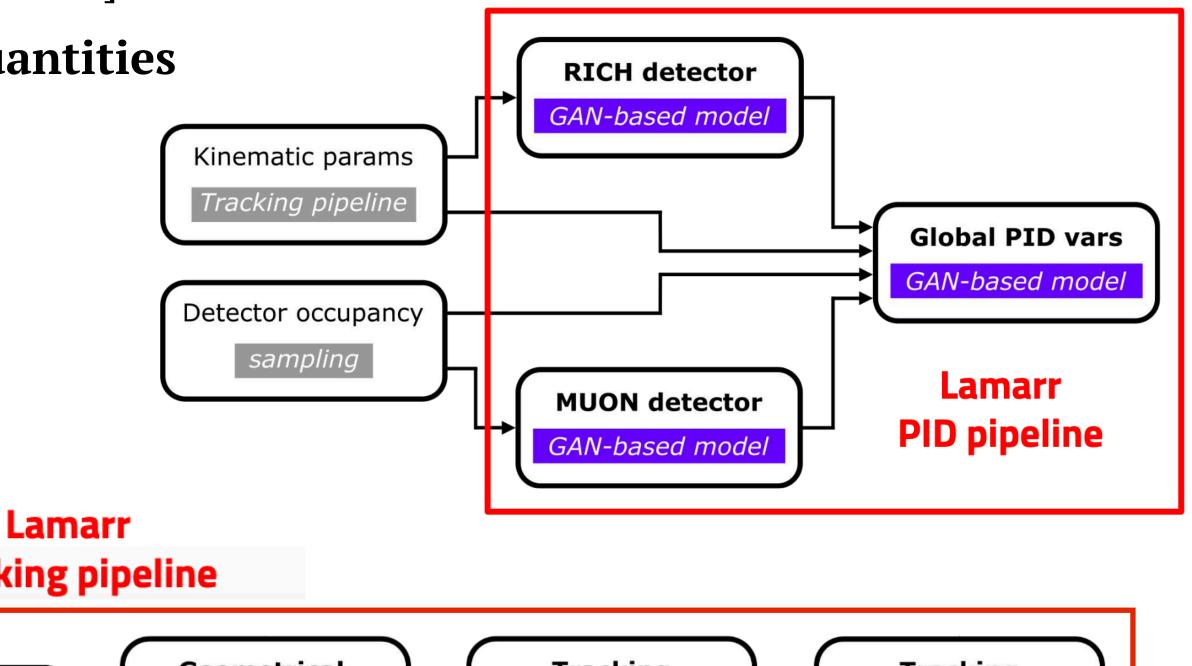
 → Energy deposit generation \Rightarrow same pipeline as data-taking
 - Similar efforts among HEP experiments [CaloChallenge workshop]
 - **Geant4/CERN-SFT initiative** to train on experiment-independent datasets to compare various models objectively: VAEs, GANs, Diffusion models, Normalizing Flows [talk@EP-SFT meeting]
 - LHCb/Gaussino add the infrastructure and retrain on the target geometry [talk@CHEP2023]
 - <u>Challenges</u>: maintainability, large models, complex inference & retraining infrastructure
 - **Desiderata**: training accessible from different institutes

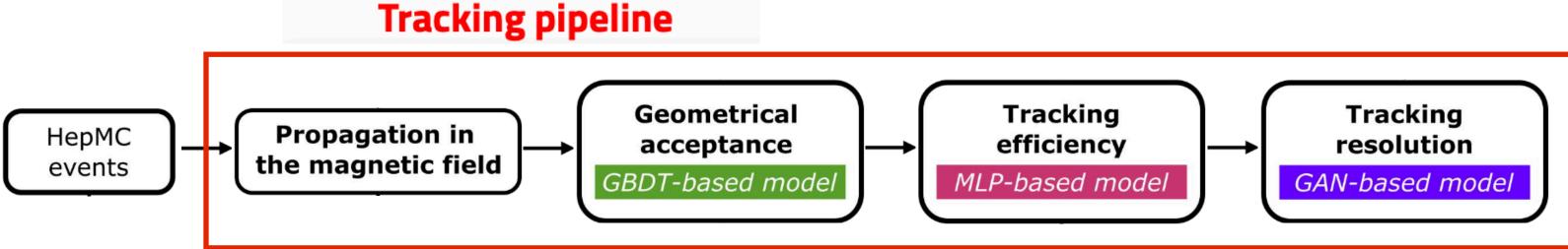


Simulation

Computing resources too limited to use GEANT detailed simulation for the large simulated samples needed!

- Ultra-fast simulation: LAMARR [talk@CHEP2023]
 - ML models used to generate reconstructed quantities (instead of energy deposit like for e.g. in GANs)
 - Scalar features \Rightarrow much smaller models
 - Inference on CPU possible, but using GPU would allow high parallelization!
 - **Pipeline of multiple ML models** is needed: GBDT, MLP, GAN, RNN, transformer...





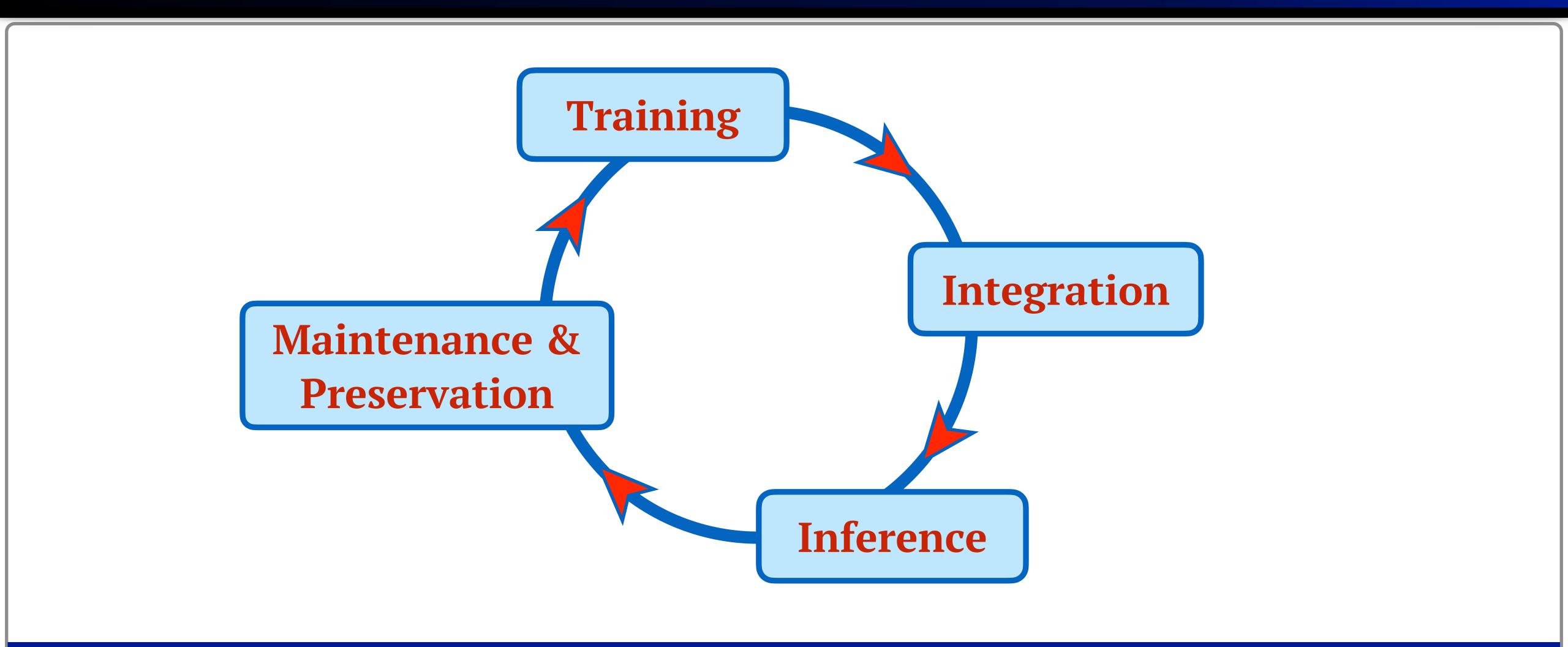
Particle ID

Flavour tagging

- ML-based algorithms used already for many years in general performance tools
 - PID classification: [*Int. J. Mod. Phys. A 30, 1530022 (2015*)]
 - FT algorithm: **MLP** [arxiv:1602.07252], **BDT** [Eur.Phys.J.C 77 (2017) 4, 238]
- Recent developments to improve robustness & performances
 - PID classification: Robust Neural Particle Identification Models [arxiv:2212.07274]
 - FT algorithm: Fast inclusive flavo(u)r tagging at LHCb [talk@CHEP2023]

Analysis

- Plethora of techniques and models applied throughout the LHCb analysis landscape
 - Typically simple models (BDT) thanks to the inherent high signal/background ratio in LHCb's environment
 - Developed and using fitters on GPU to perform fits on millions of events (e.g. charm analyses)



Efficient and sustainable exploitation of ML/DL presents challenges at various steps

Common solutions among CERN collaborations is paramount!

Training

- Currently most of the ML/DL trainings performed using resources available at local institutes/national facilities
 - Models still relatively small (compared to industry)
 - SWAN system found to have some limitations (e.g. long trainings)
 - Need robust & flexible pipelines for updated trainings, especially for production applications
- Multi-GPU batch system support would be beneficial
 - Hyperparameters optimisation (lunch hundreds of trainings with different configuration)
 - Distributed computation (e.g. GAN shower generation for simulation)
 - Requires CUDA-enabled software packages available: ONNXRuntime, PyTorch, Tensorflow, VTK, ROOT, PyCUDA, cupy

Integration

- Integration of ML/DL models in software is not straightforward
 - Most LCG stacks are not GPU-enabled
 - Most libraries already available in LCG_10Ncuda stacks recent need for additional packages for GNN and multi-GPU processing: cugraph, nccl, cutlass
 - LCG cuda-enabled stacks built with **gcc11**, LHCb production compiler uses **gcc12** [very responsive communication with LCG]
- Expertise from IT (core software engineers with ML expertise)
 - Understanding which models are particularly efficient on which architectures (CPU vs GPU) and why?
 - → Profiling computing resources to make efficient use of models processing data

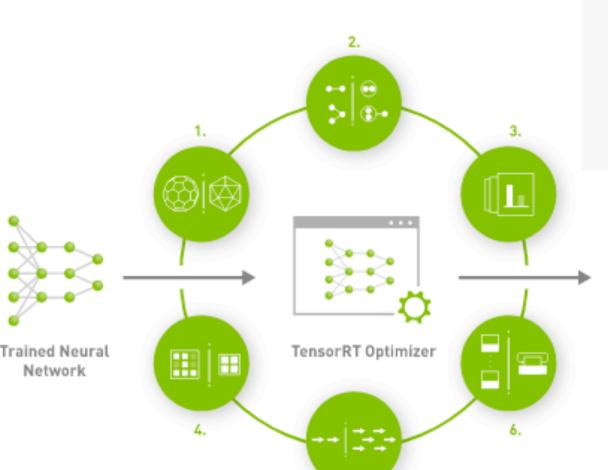
Inference

- Inference (production systems) is currently the main challenge:
 - Needs to be fast, flexible & easily maintainable
 - Standardized ML-model data format: e.g. **ONNX**
 - WIP on generic interface allowing access to desired backends: PyTorch C++ API, ONNXRunTime, TMVA::SOFIE...
 [talk@EP-SFT meeting]



- Inference on **GPUs** (NVIDIA A5000) using **TensorRT**
- Benchmark for a **simple MLP** for ghost track probability 17 features 2 hidden layers (25x20) 1 output





1. Weight & Activation Precision Calibration

Maximizes throughput by quantizing models to INT8 while preserving accuracy

2 Laver & Tensor Fusion

Optimizes use of GPU memory and bandwidth by fusing nodes in a kernel

3. Kernel Auto-Tuning

Selects best data layers and algorithms based on target GPU platform

4. Dynamic Tensor Memory

Minimizes memory footprint and re-uses memory for tensors efficiently

5. Multi-Stream Execution

Scalable design to process multiple input streams in parallel

6. Time Fusion

Optimizes recurrent neural networks over time steps with dynamically generated kernels



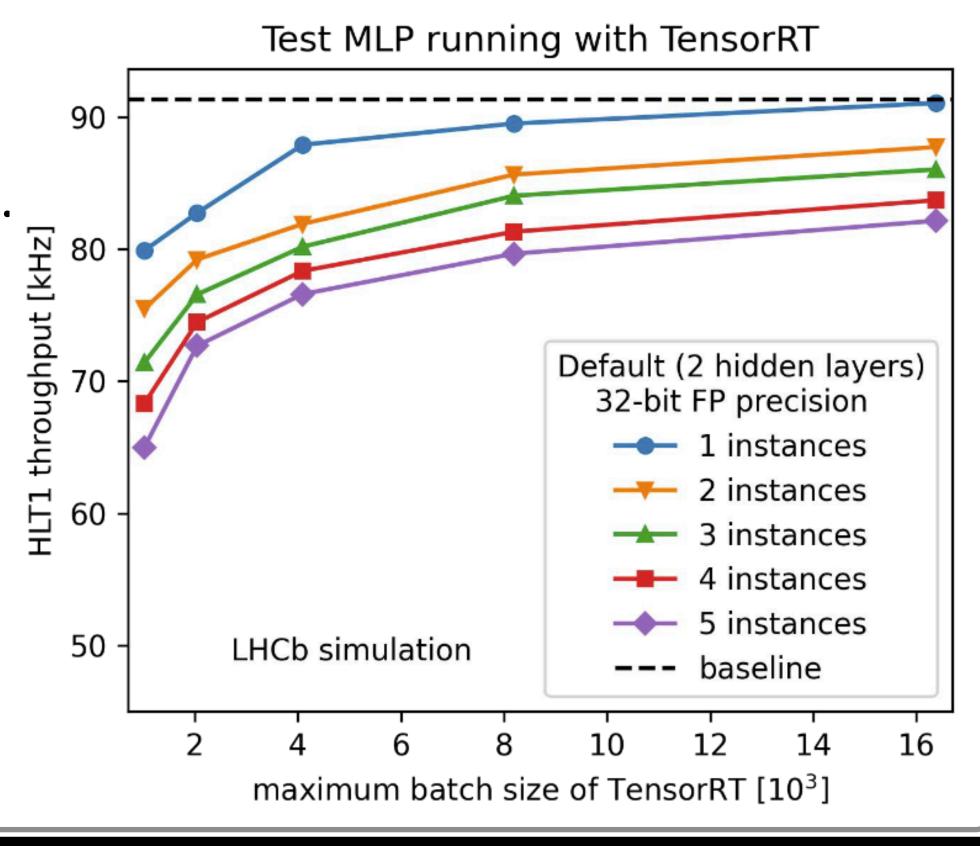
Optimized Inference Engine

Inference

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 [talk@EP-SFT meeting]
- Ongoing developments / studies inside LHCb:

[talk@CHEP2023]

- Tested throughput impact of TensorRT inference
 - → Multiple copies of typical sized MLPs seems to effect throughput in an acceptable way
 - → Promising avenue of having flexible ML reconstruction and selection at the first trigger level



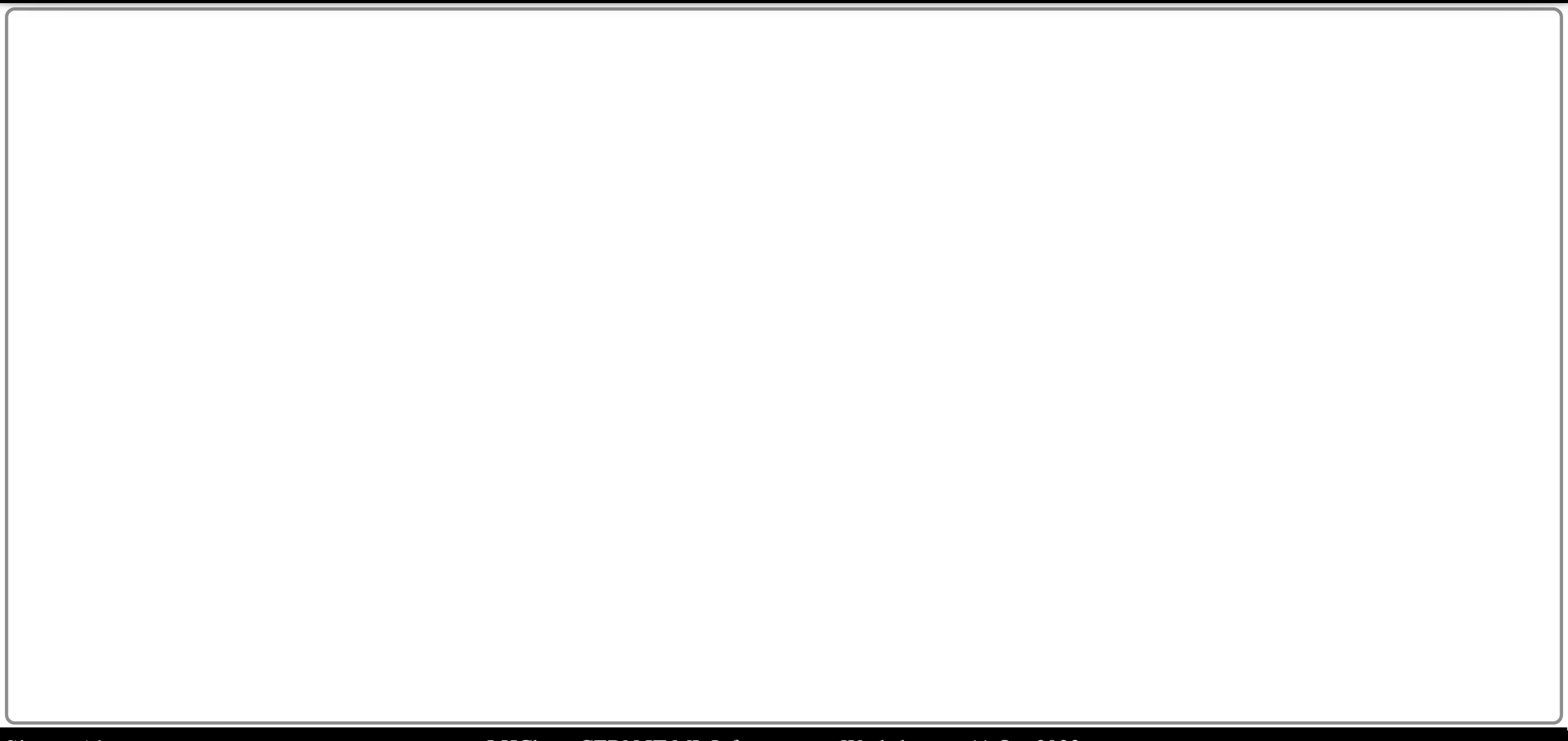
Maintenance & Preservation

- Key aspect that needs to become standard practice
 - Online ML applications need to be well structured with flexible and robust retraining pipelines
- CI/CD system
 - GitLab runners with GPU
 - Pipeline training to make optimal use of resources (e..g. for large models in simulation)
- MLOps
 - Necessity for a **powerful tool** allowing **versioning of model, data and hyperparameters**: **e.g.** *MLFlow* & *Dvc* for versioning of Deep Learning datasets \Rightarrow common storage space like EOS?!
 - Models organisation and fast retraining:
 e.g. Snakemake used for the ultra-fast simulation project

Summary

- Multiple on-going developments of ML/DL in LHCb
 - **Online** (tracks reconstruction, PV finding, trigger) & **Offline** (simulation, performance, analysis)
 - Majority built on **PyTorch** library (few TensorFlow) with **trainings** done using **local resources**
- Currently the main challenges lie in the integration, inference & maintenance
 - Working towards standardization (ONNX) for ML-model data format
 - Effort to enable a generic backend inference interface in LHCb production systems
- Would benefit from collaboration with / support from experts at IT department
 - Large state-of-the-art GPU clusters available for the CERN community
 - Multi-GPU batch system hyperparameter optimisation
 - Integrated MLOps tools model, data & hyperparameters versioning
 - **Profiling expertise** efficient integration and use of models used to process data
 - Maintenance expertise keeping updated versions of the different backend packages

Supplementary material



Supplementary material

• Latest reports on ML applications in LHCb:

Trigger & Online

- Applications of Lipschitz neural networks to the Run 3 LHCb trigger [talk@CHEP2023]
- Graph Neural Networks for Full Event Interpretation at LHCb [talk@CHEP2023, arxiv:2304.08610]
- DNN for finding primary vertices in proton-proton collisions at the LHC [talk@CHEP2023, arxiv:2309.12417]
- High-throughput machine learning inference with NVIDIA TensorRT [talk@CHEP2023]
- High-throughout GNN track reconstruction at LHCb [talk@CTD2023]

Simulation

- The LHCb ultra-fast simulation option, LAMARR [talk@CHEP2023]
- From prototypes to large scale detectors: the Gaussino simulation framework [talk@CHEP2023]

Flavour tagging

- Fast inclusive flavo(u)r tagging at LHCb [talk@CHEP2023]