NATIONAL CENTRE FOR NUCLEAR RESEARCH ŚWIERK

ML solutions for cluster reconstruction in planar calorimeters

WMLQ 2022, Warsaw

by Michał Mazurek

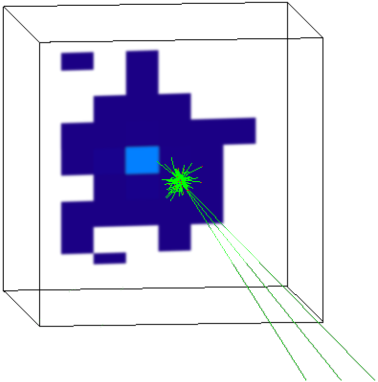
on September 13, 2022

WMLQ2022
13-16 September 2022, Warsaw Poland

Credit: Panorama of Warsaw

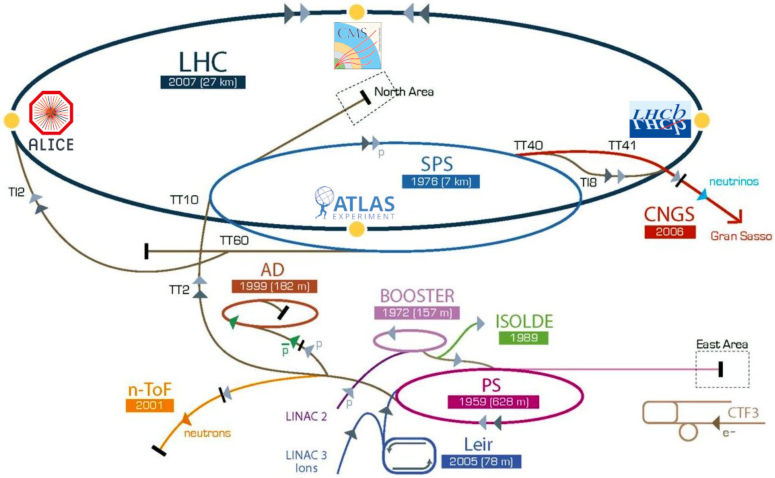
Introduction

- will focus on high-energy physics (HEP) experiments at CERN,
- HEP experiments in a nutshell:
  - a lot of data,
  - data analysis,
  - new discovery,
- data acquisition difficult:
  - high throughput,
  - limited computing resources,



Machine Learning to help! But let's put things into context first...

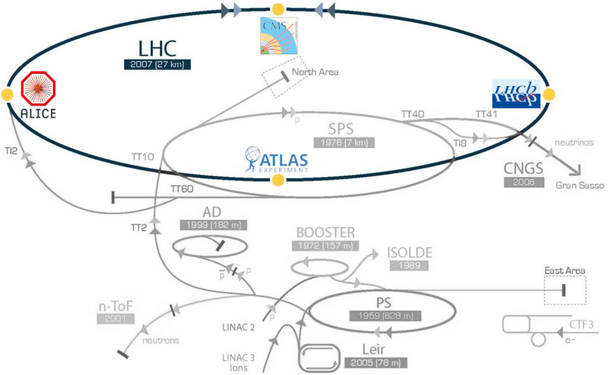
CERN Accelerator Complex



Credit: CERN-GRAPHICS-2019-002

Large Hadron Collider (LHC)

- the largest particle collider in the world
- 27 kilometers in circumference
- registers mainly proton-proton collisions, sometimes heavy-ion collisions
- first collisions in 2010,
- currently during Run 3 of data taking,
- 13.6 TeV center-of-mass collision energy,
- 4 large particle detectors: ALICE, ATLAS, CMS, LHCb



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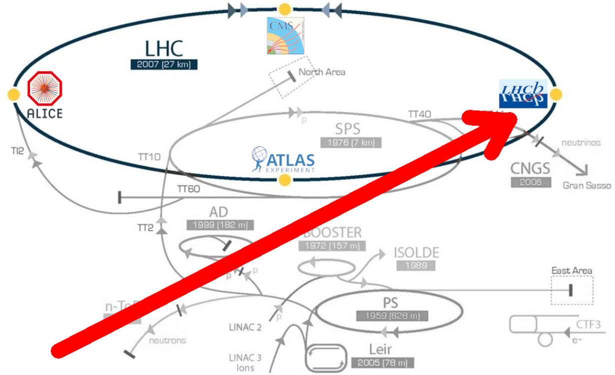
Let's see what's inside!
LHCb for example...



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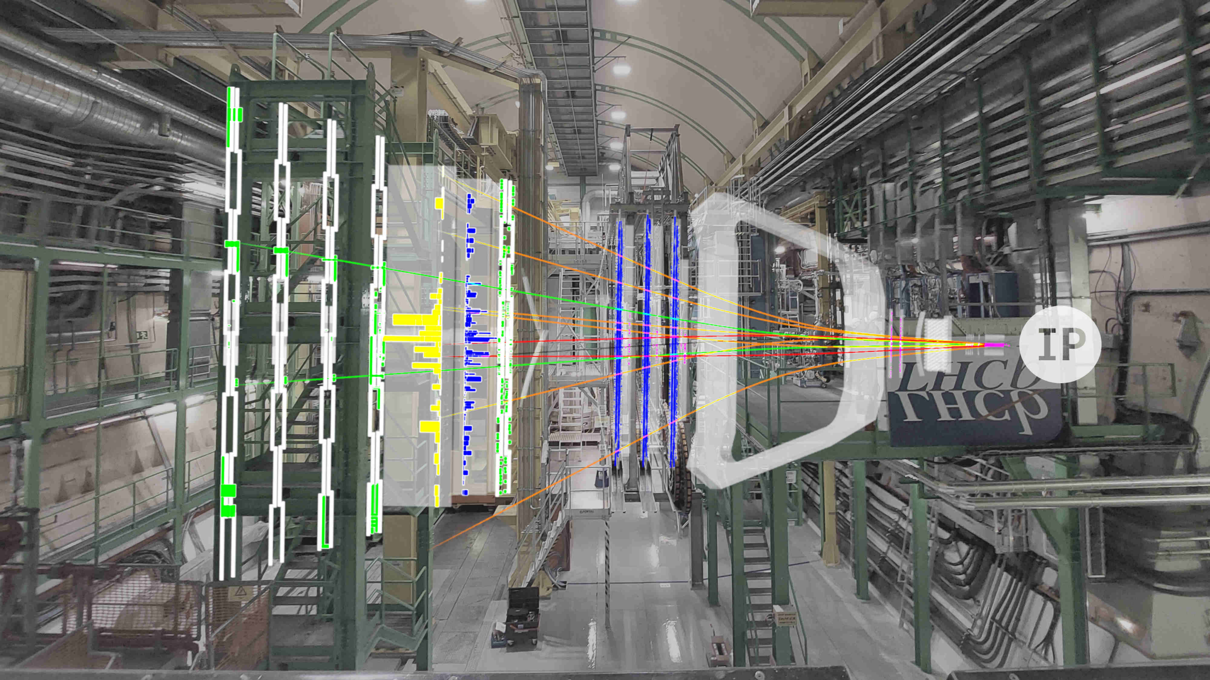
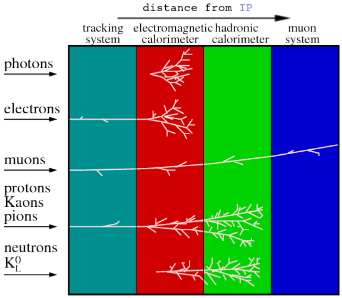
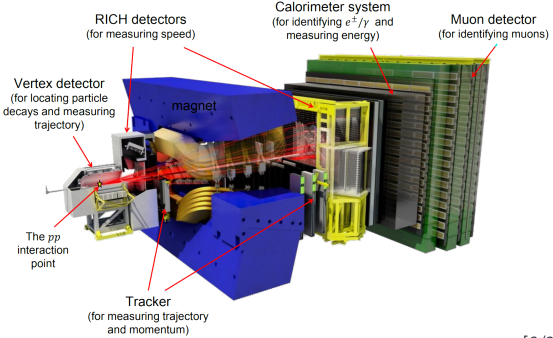

IP
LHCb

Anatomy of HEP detectors

- large magnet provides a strong magnetic field,
- tracking stations provide track coordinates used to measure the momentum of particles,
- RICH (Rich Imaging Cherenkov) sub-detectors determine particle identities,
- electromagnetic and hadronic calorimeters measure the amount of energy deposited,
- muons get identified in muon stations





Credit: arXiv:1101.3276

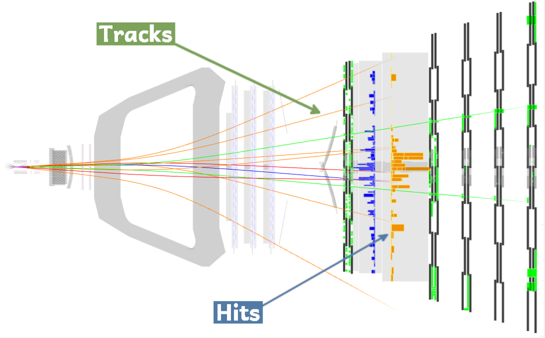
Data objects in HEP

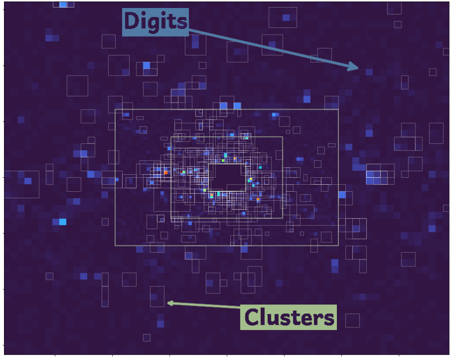
Low-level objects, produced by

- the detector,
- Monte Carlo simulations,

High-level objects, inferred in

- reconstruction software,
- data analysis,

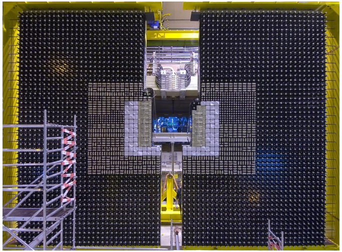




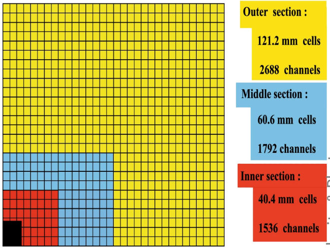
Clusters are specific objects created in calorimeters...

Electromagnetic calorimeter (ECAL) in LHCb

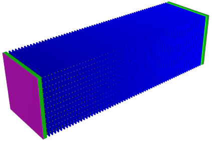
- designed to measure the energy of $e^{\pm}$ and γ,
- captures showers of secondary particles,
- sandwich-like structure,
- 66 alternating lead and scintillator layers plus plastic and steel plates,
- consist of 3 modules with different granularity



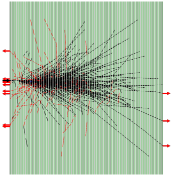
Front view on ECAL



Granularity of ECAL modules



ECAL stack of scintillator and lead plates

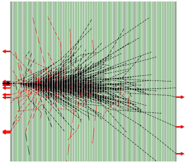


Example of a shower produced by a photon in ECAL (side view)

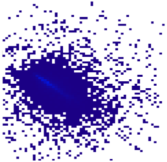
Credit: Stack, Granularity & Photo

Cluster reconstruction in LHCb

What really happens



What is observed



0.3	0.6	0.2			
1.3	4.8	1.2	0.7	0.2	
	0.9		3.1	0.7	

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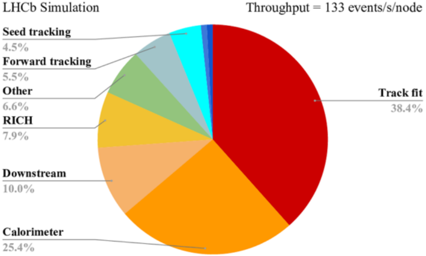
	0.9		3.1	0.7	

Cellular Automaton:

- find local maxima,
- tags cells in the neighbourhood,
- resolve overlapping cells,

Graph clustering[1]:

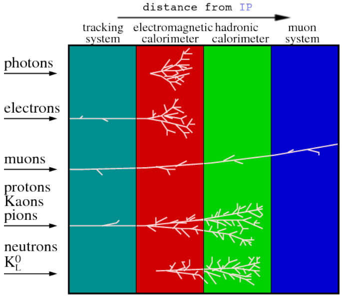
- vertices: digits
- edges: digit to the source,
- optimization from graph theory,
- improved computation complexity,



Credit: LHCb-FIGURE-2020-007 & LHCb-2001-123

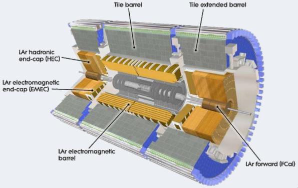
[1] paper by N. Valls et al. will be published soon

Other LHC experiments and their calorimeters



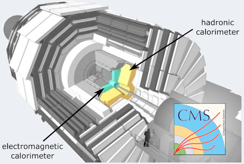
ATLAS

- liquid argon:
  - electromagnetic barrel,
  - electromagnetic end-cap,
  - hadronic end-cap,
- tile calorimeters:
  - hadronic barrel,



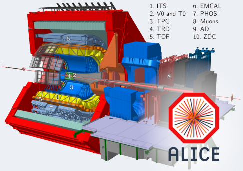
CMS

- EM barrel & endcap
- hadronic barrel & endcap
- high-granular upgrade



ALICE

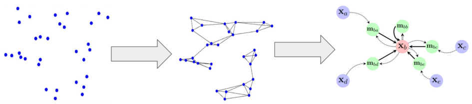
- only EM calorimeter,
- hadronic addition planned for future upgrades



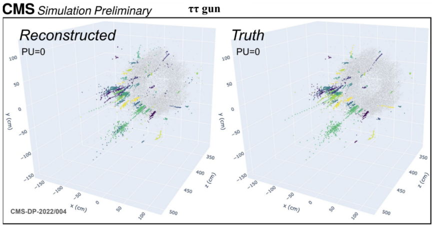
Credit: ATLAS, CMS & ALICE

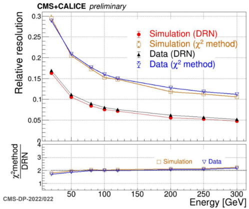
S. Rotham et al., ICHEP 2022
J. Kiesler, arXiv:2002.03605

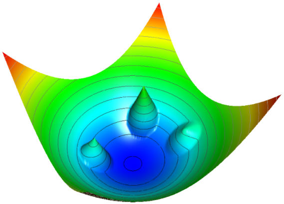
Selected machine learning topics



- **Framework:** graph neural networks
  - hits as a point cloud,
  - construct a graph by drawing edges between k nearest neighbour of each hit,
  - perform 'message passing' to allow information flow along graph edges, comparison for ECAL and the new HGCAL,
- **Method:** Object condensation
  - assumption: every single entity can represent features of the whole object when accumulated,
  - loss: attractive and repulsive terms,
  - adaptable to any input: images, point clouds, etc.



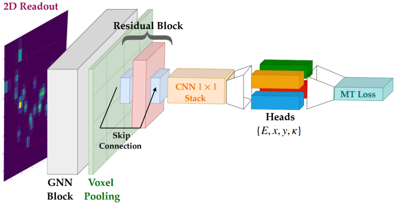


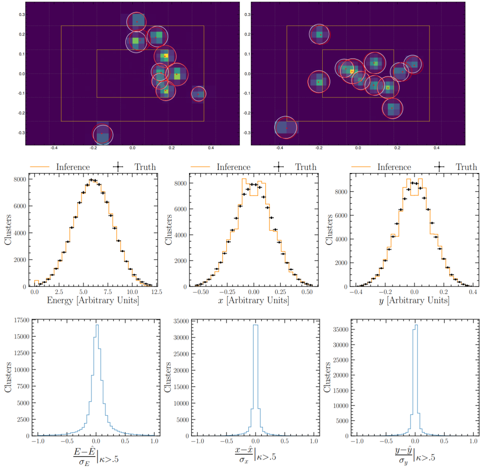


Graph neural networks in planar calorimeters

B. Delaney, PhD thesis

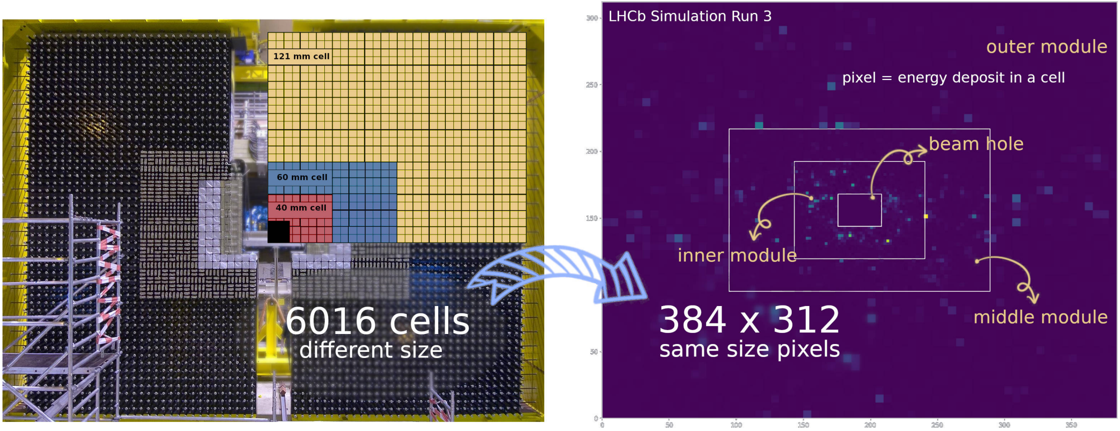
- **LHCb-inspired** toy model,
- **2 main components:**
  - **GNN block**, see digits of a planar calorimeter as elements of a point cloud to tackle the problem of **irregular geometry**,
  - map the output to a **CNN-based framework** to take into account deposits within the receptive field & optimize for inference speed,





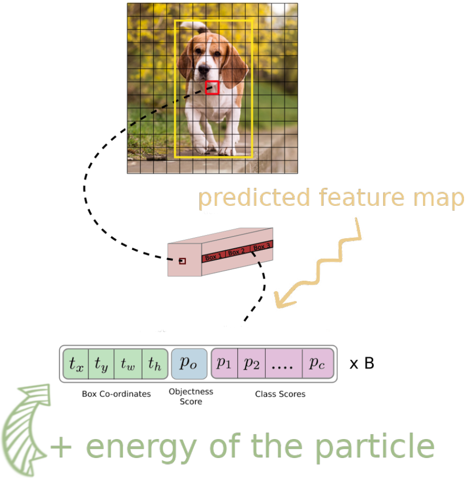
What about plain convolutional neural networks?

Going convolutional: calorimeter as an image *M. Mazurek et al., 4th IML workshop*



Exploring convolutional frameworks

M. Mazurek et al., 4th IML workshop

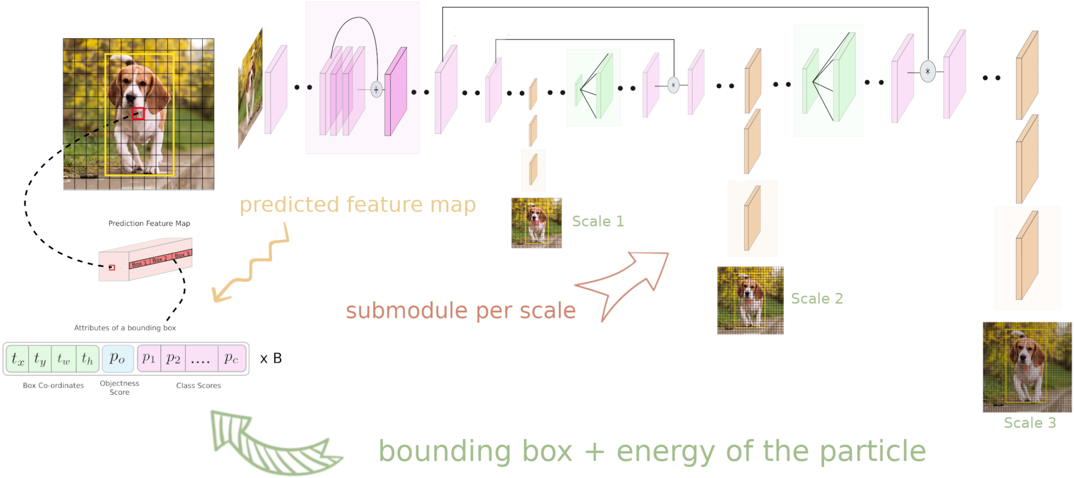


- YOLO = You Only Look Once,
- state-of-the-art, real-time framework,
- mixed classification and regression problem,
- introduces its own, regular grid,
- the backbone is a CNN that produces the feature map,
- the head is responsible for parsing the feature map into the bounding box candidates,
- loss is a linear combination of MSE and CE losses of the bounding box attributes,

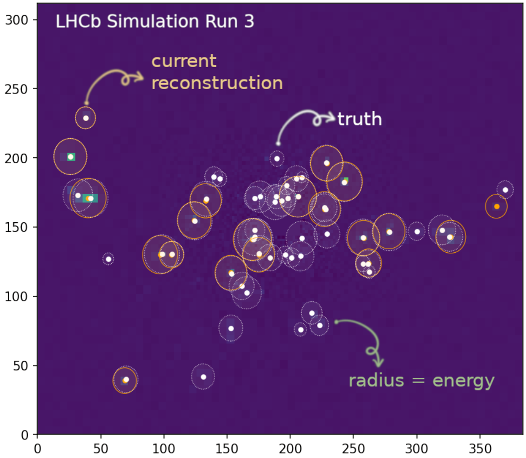
Credit: arXiv:1506.02640

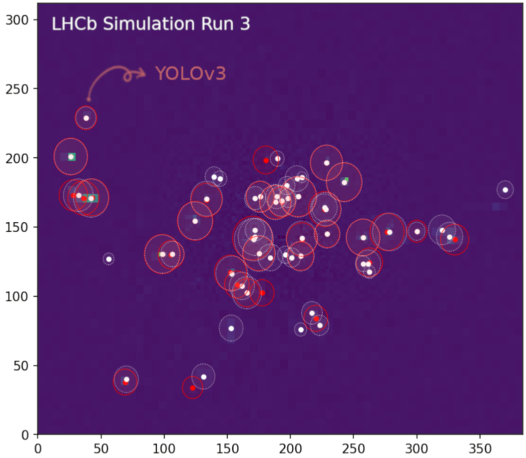
Adapting YOLO to our needs

M. Mazurek et al., 4th IML workshop



Preliminary results



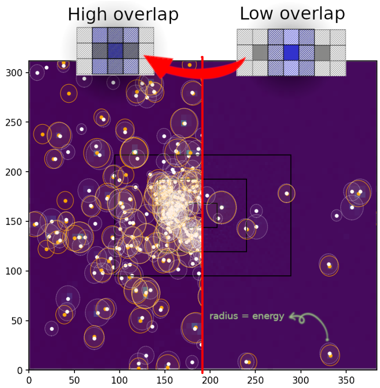


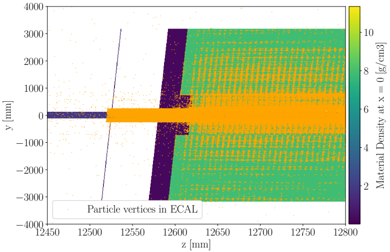
Credit: arXiv:1506.02640

Improving the data

- ML demanding
  - difficult conditions,
  - complex geometry,
  - high throughput and precision required,
  - a lot of hyperparameters to tweak!
- Need for more data
  - required data for ML studies (training & inference) is not always present,
  - the output is optimized for physics reconstruction & analysis,

What if we had more control over the simulations?

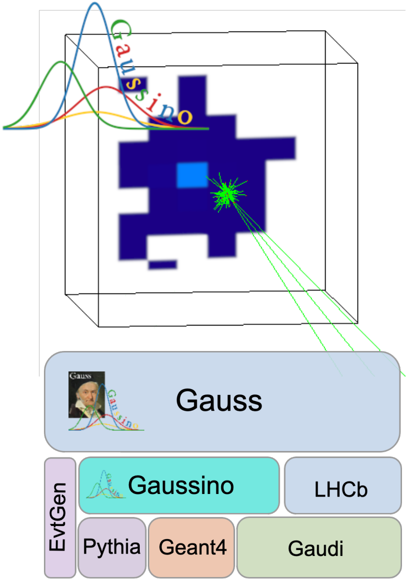




Getting more from simulations

- **Gaussino**
  - new core experiment-independent simulation framework,
  - complete generation & detector transport phase,
  - created by extracting experiment-independent components from LHCb simulation framework,
  - ideal test bed for new developments,

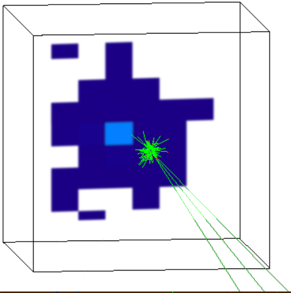
see more in Gaussino's documentation

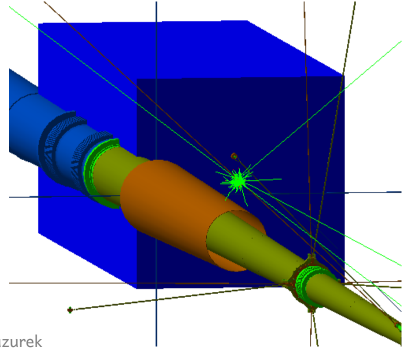


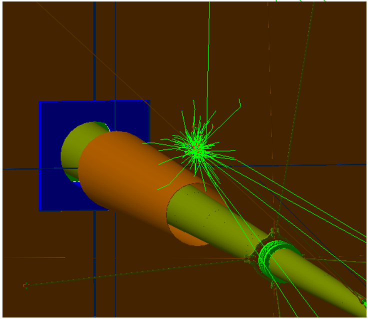
Credit: LHCb-TDR-017

Incremental approach

- Generic toy model
- Toy model in the experiment's environment
- Real detector

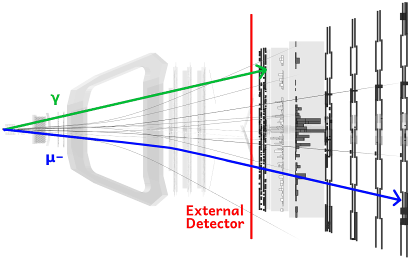


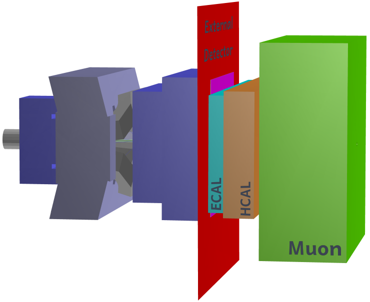




Adding more volumes

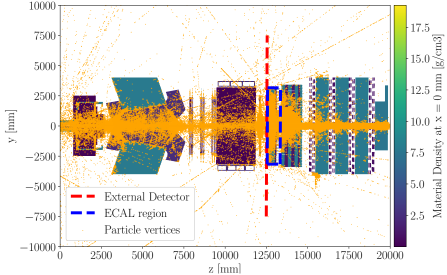
- An abstract, external detector can be used as a collector of the required information at any position in the detector.
- A built-in mechanism can take care of potential volume overlaps by placing extra volumes in parallel geometries.

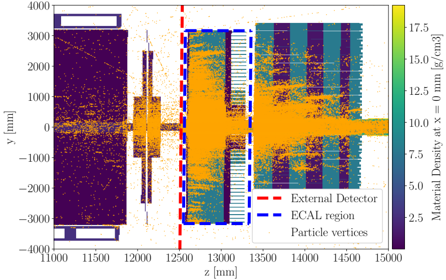


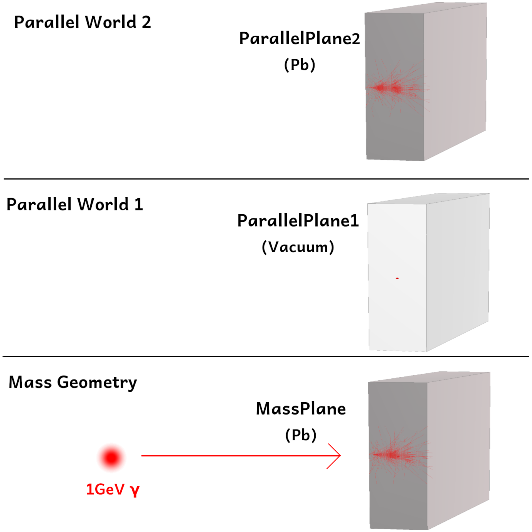


Credit: LHCB-FIGURE-2021-004

Abstract geometry





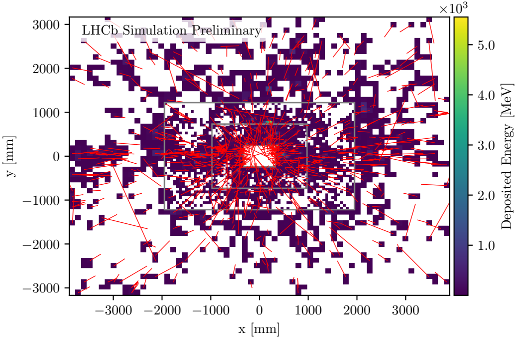


Credit: LHCB-FIGURE-2021-004

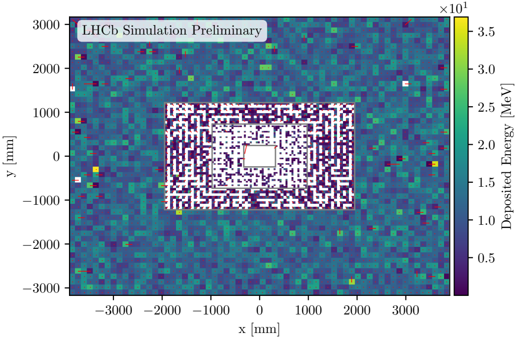
Examples of custom datasets

LHCB-FIGURE-2021-004

external plane (incident particles info) ↔ ECAL hits



Real event sample



Evenly-spaced grid of photons

Credit: LHCB-FIGURE-2021-004

Complete implementation plan

- Toy model part
  - check if the framework is feasible,
  - tweak the hyperparameters of the network on a simplified geometry description in Gaussino,
- Real detector part
  - seamlessly move to the real calorimeter geometry,
  - investigate the effect on performance,
  - compare with the current reconstruction algorithms (using the same comparison tools!),
- Extension part
  - see how the additional information from the network can be used to improve the reconstruction algorithms (e.g. classification of particles),

Summary & Future outlook

- introduced the concept of cluster reconstruction in calorimeters.
- presented some selected solutions in HEP experiments,
- graph & convolutional neural networks in planar calorimeters possible, but difficult!
- showed how recent results in the simulation framework can help to improve the training and understanding of the network,
- complete implementation plan in place!

Thank you!