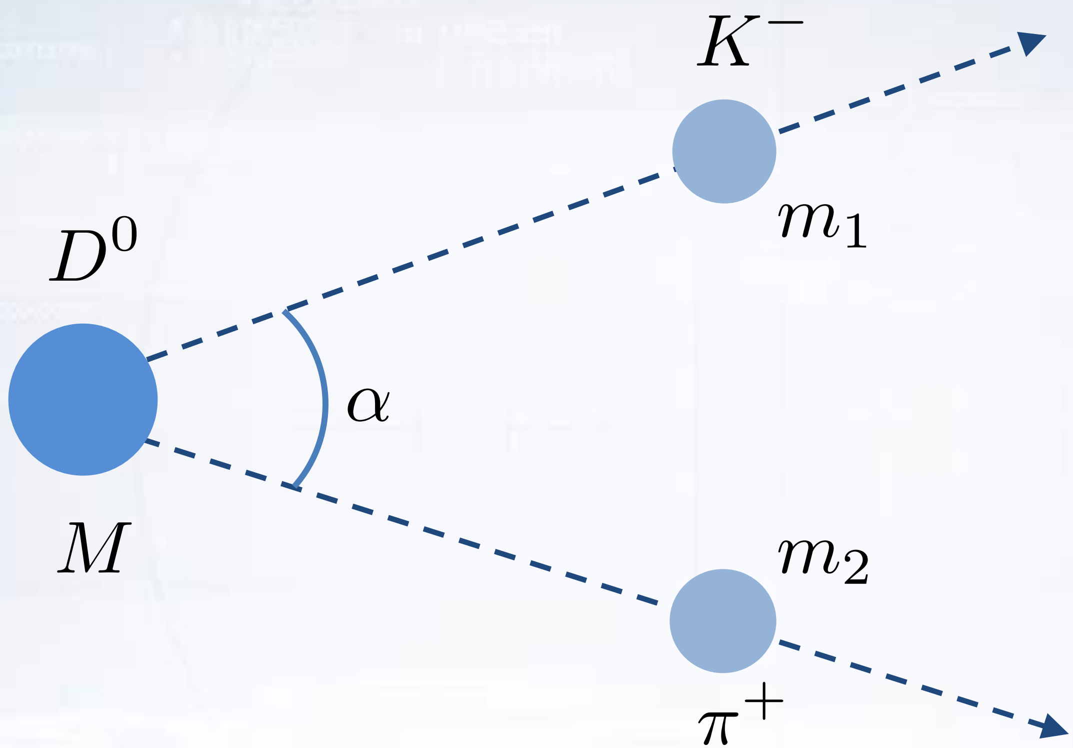
Particle identification

A particle decay



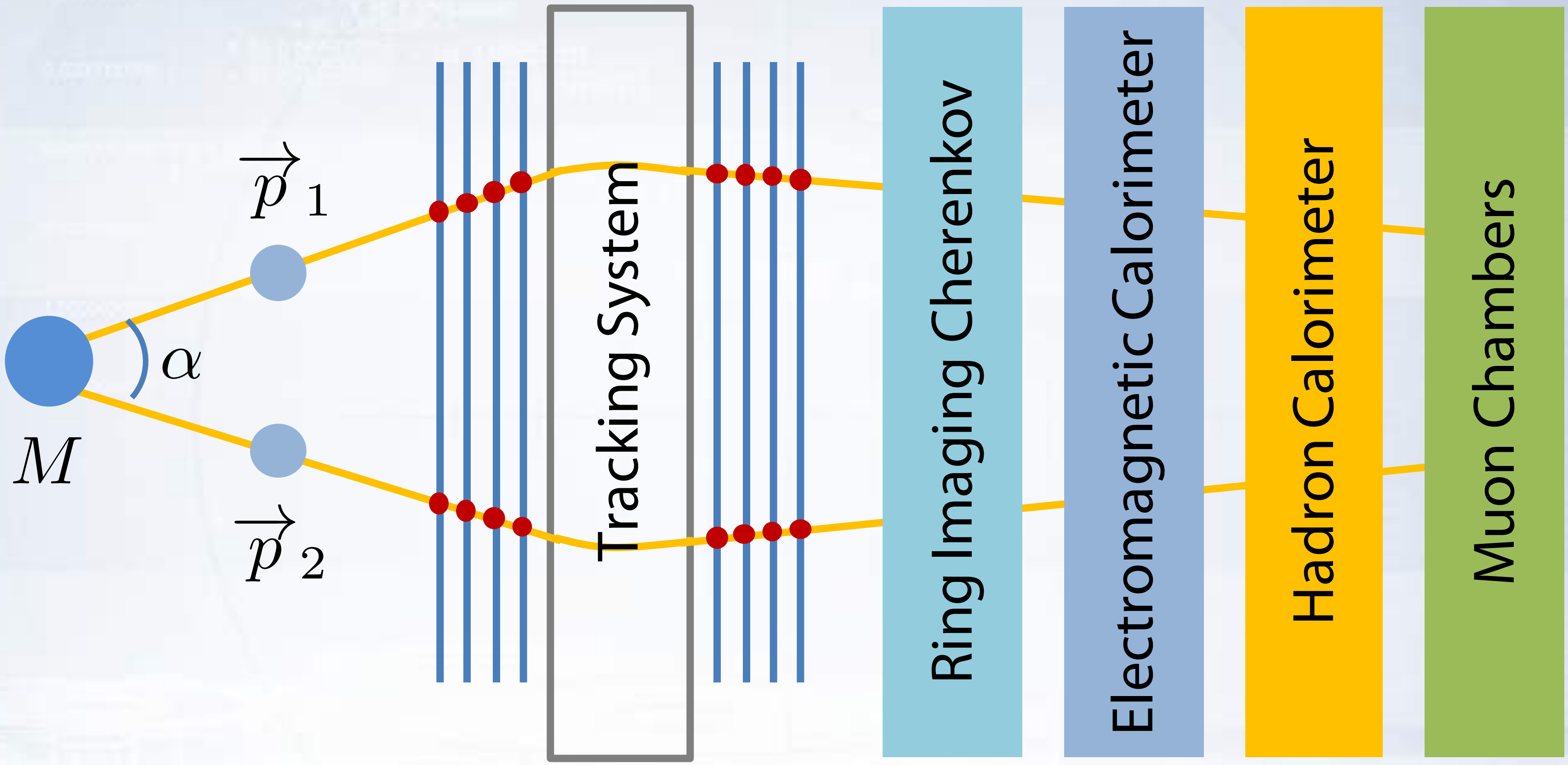
$$E_M = E_1 + E_2$$

$$\vec{p}_M = \vec{p}_1 + \vec{p}_2$$

$$E^2 = p^2c^2 + m^2c^4$$

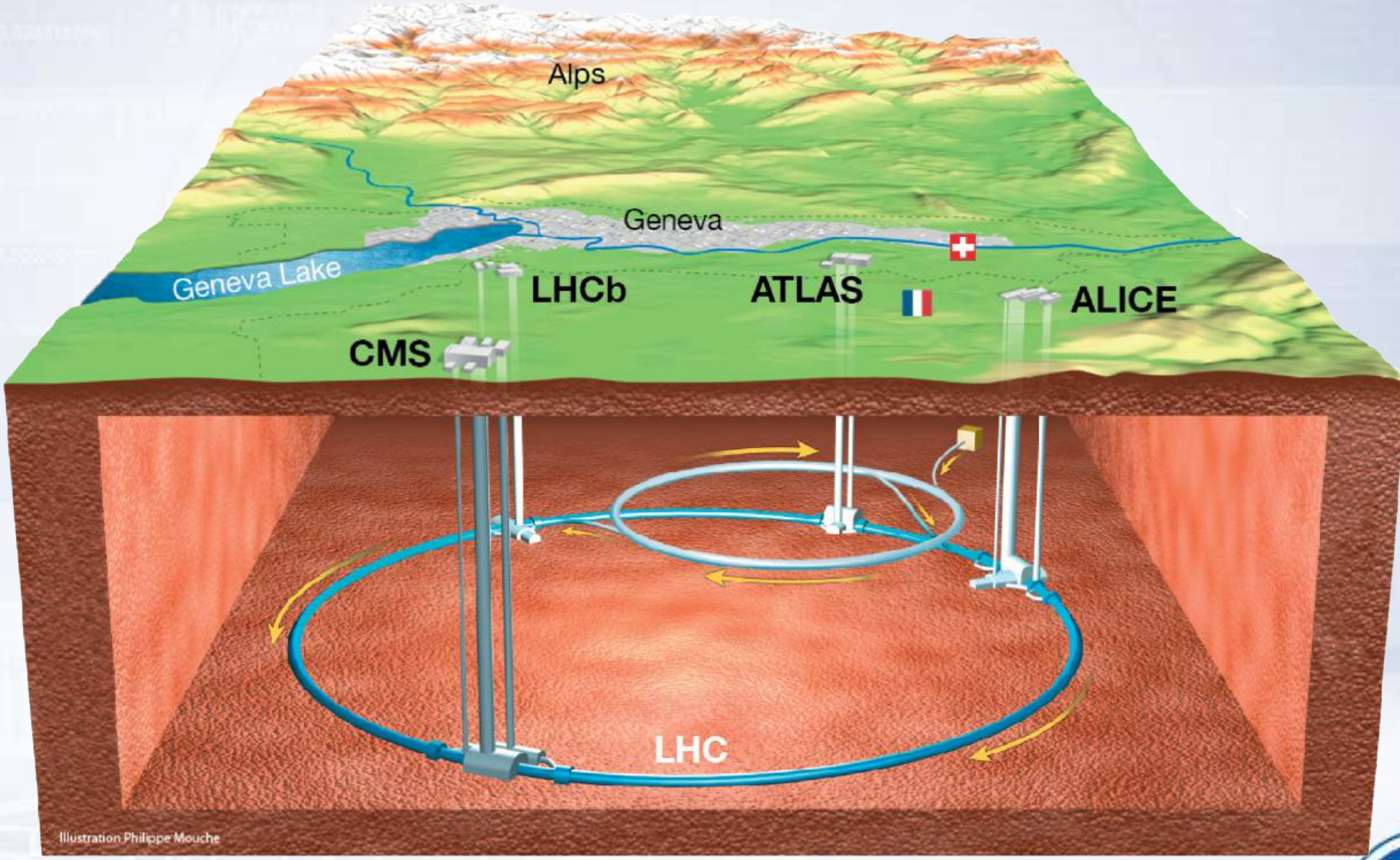
$$M^2 = m_1^2 + m_2^2 + \frac{2}{c^4}(E_1E_2 - p_1p_2c^2\cos\alpha)$$

Particle identification



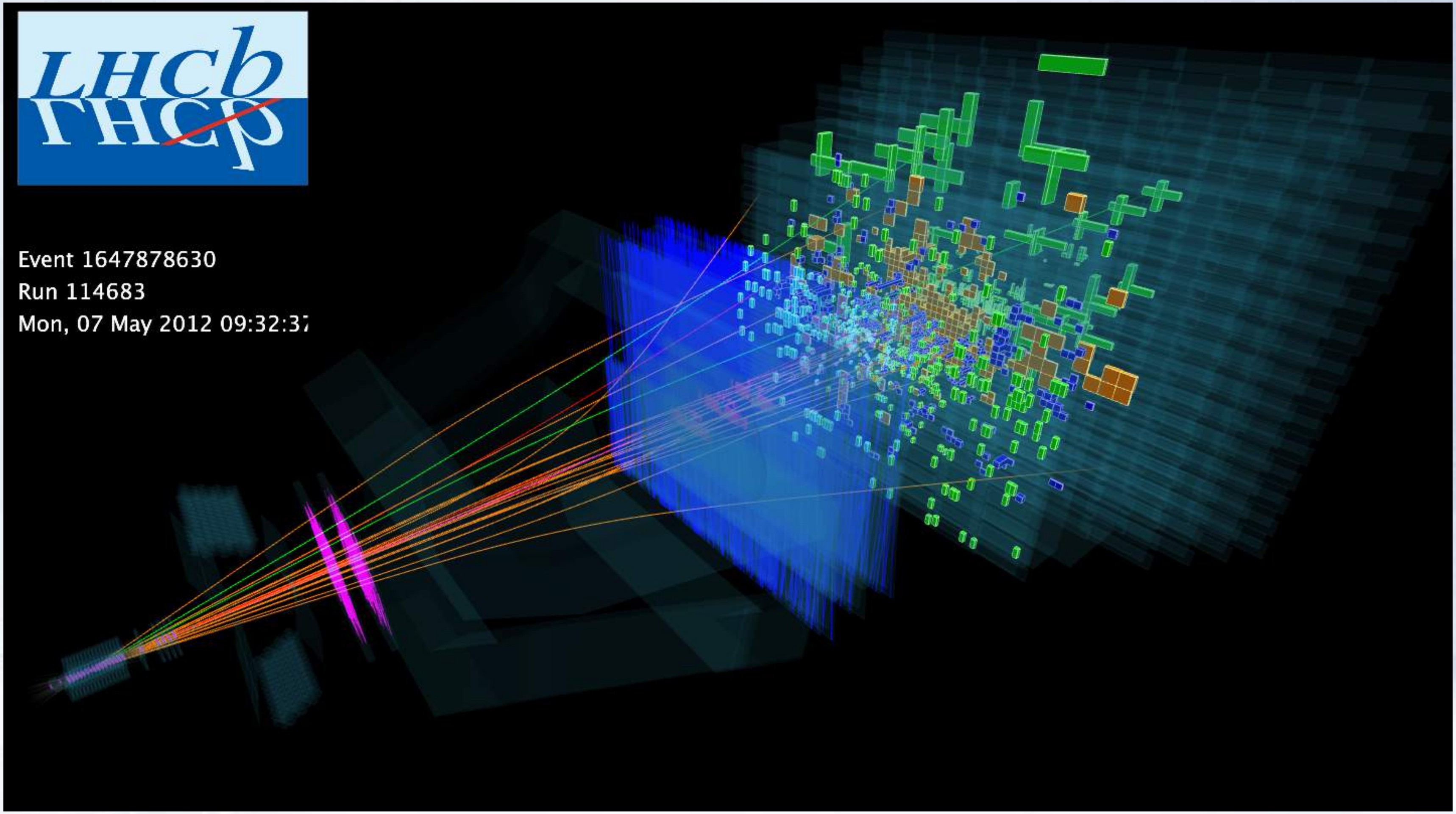
The goal of the **particle identification** (**PID**) is to identify a type of a particle associated with a track using responses from different systems.

LHC experiments



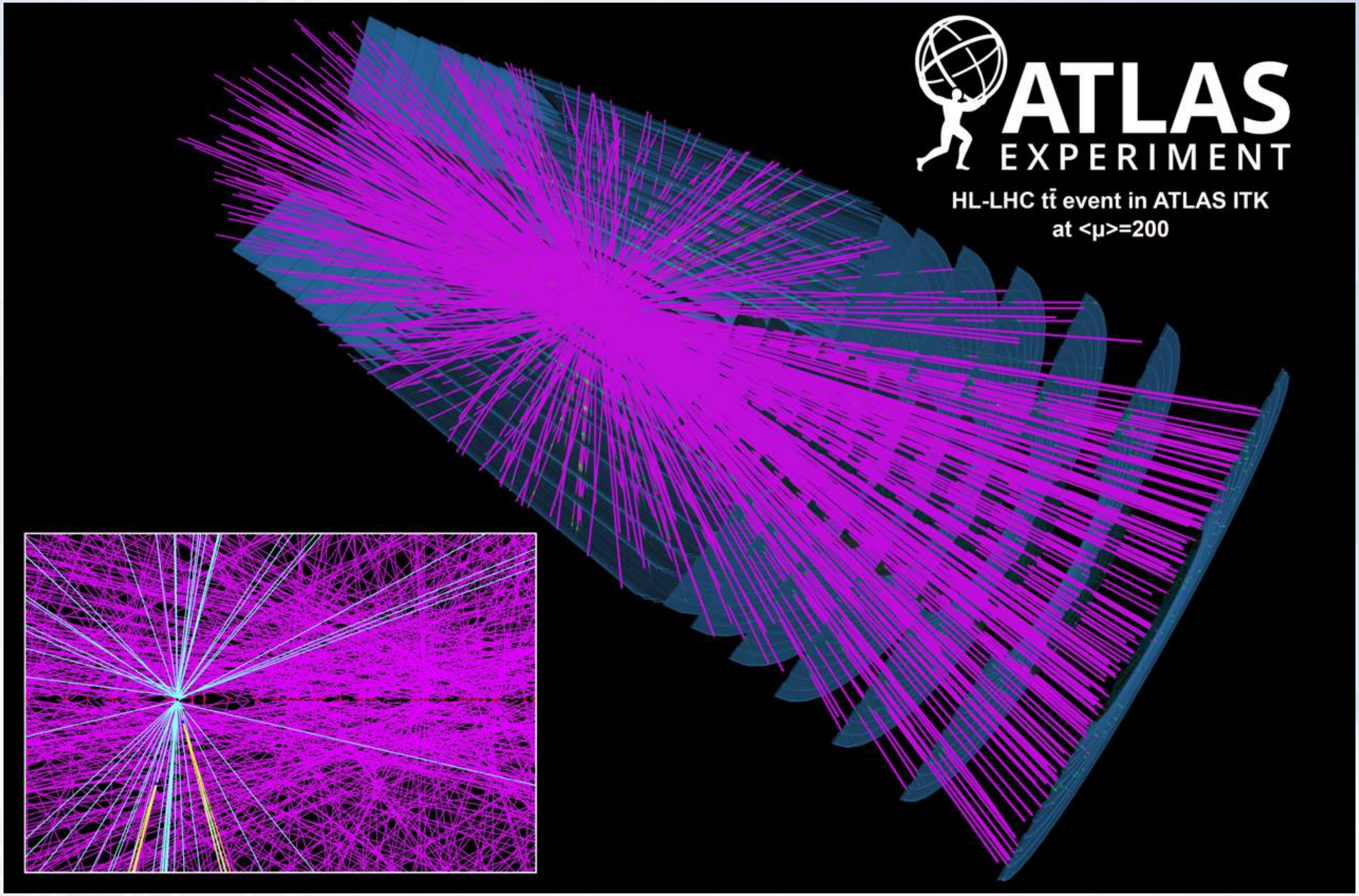
LHC Home / http://lhcathome.web.cern.ch/about

LHCb event example



LHCb / http://clangenb.web.cern.ch/clangenb/

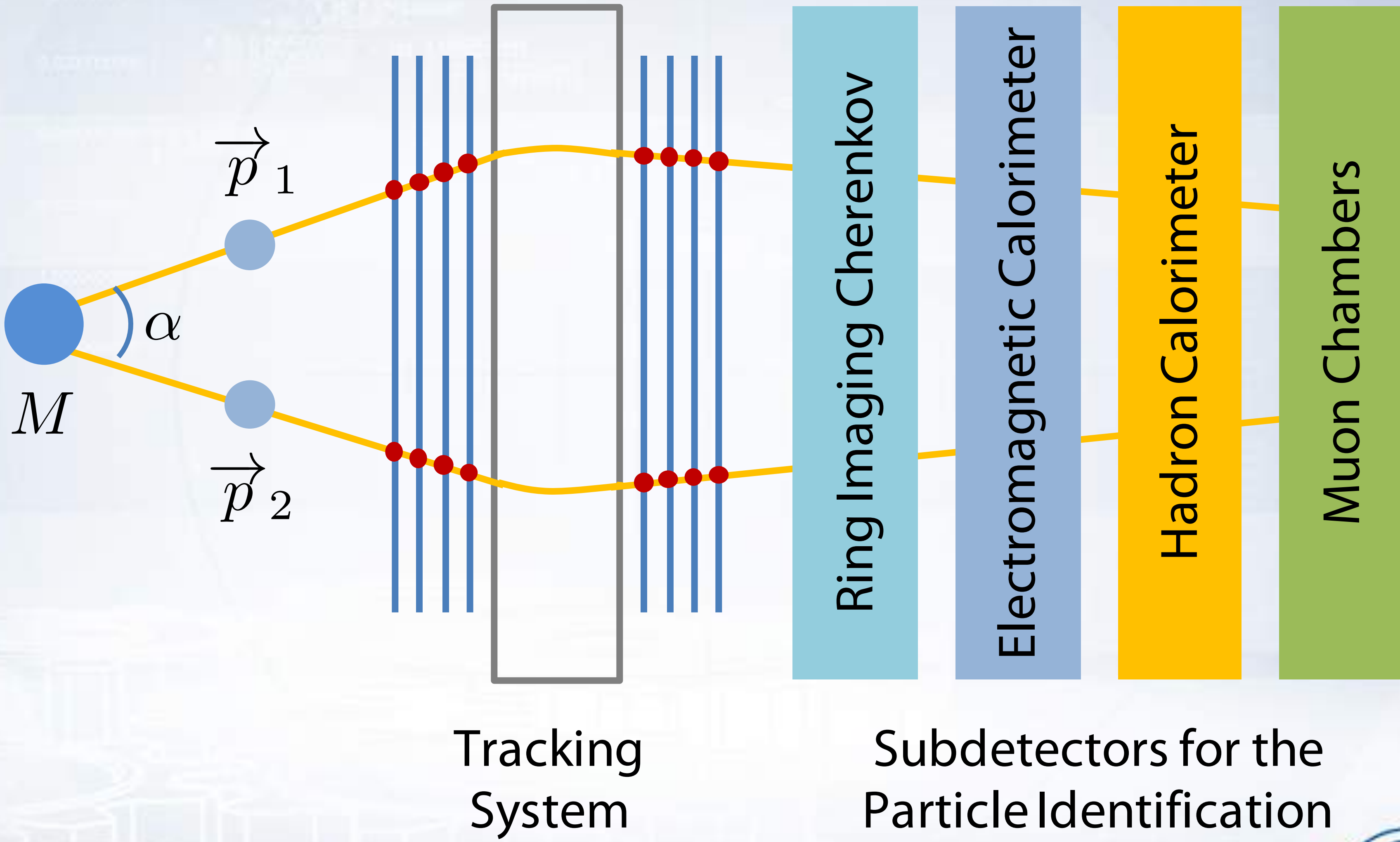
ATLAS event example



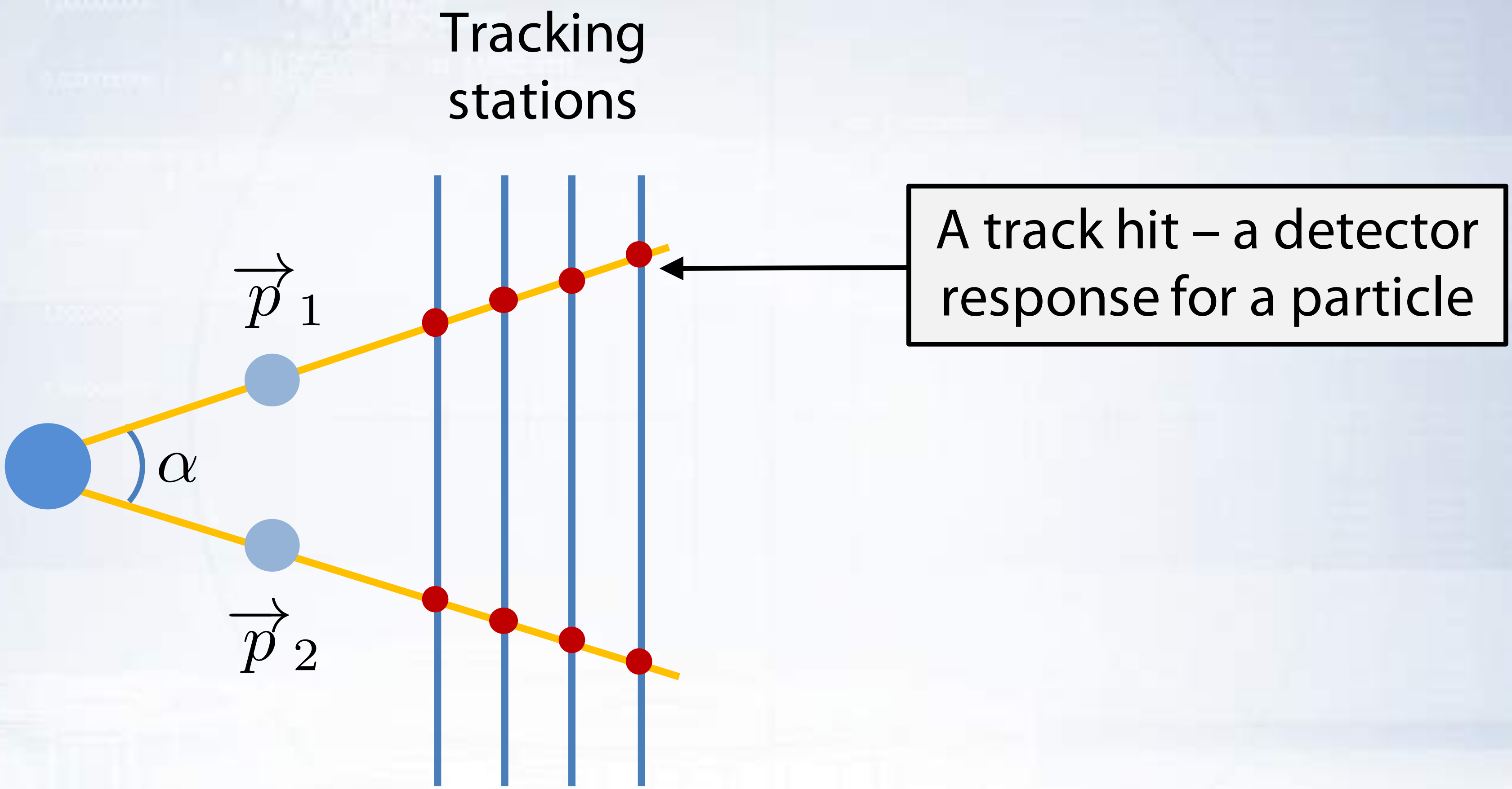
PaulLaycock, https://twiki.cern.ch/twiki/bin/view/AtlasPublic/UpgradeEventDisplays

Tracking system

Particle identification

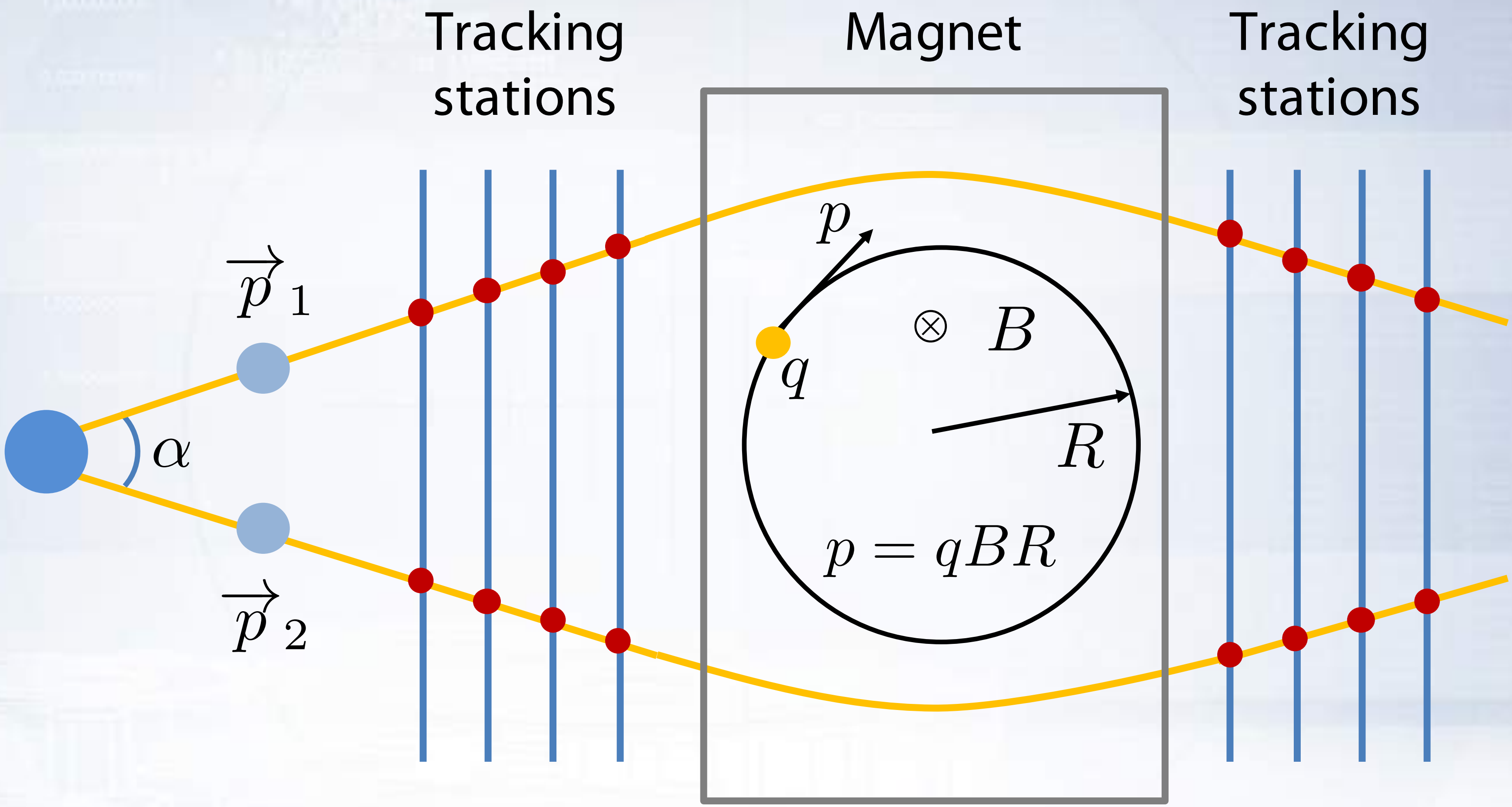


Tracking system



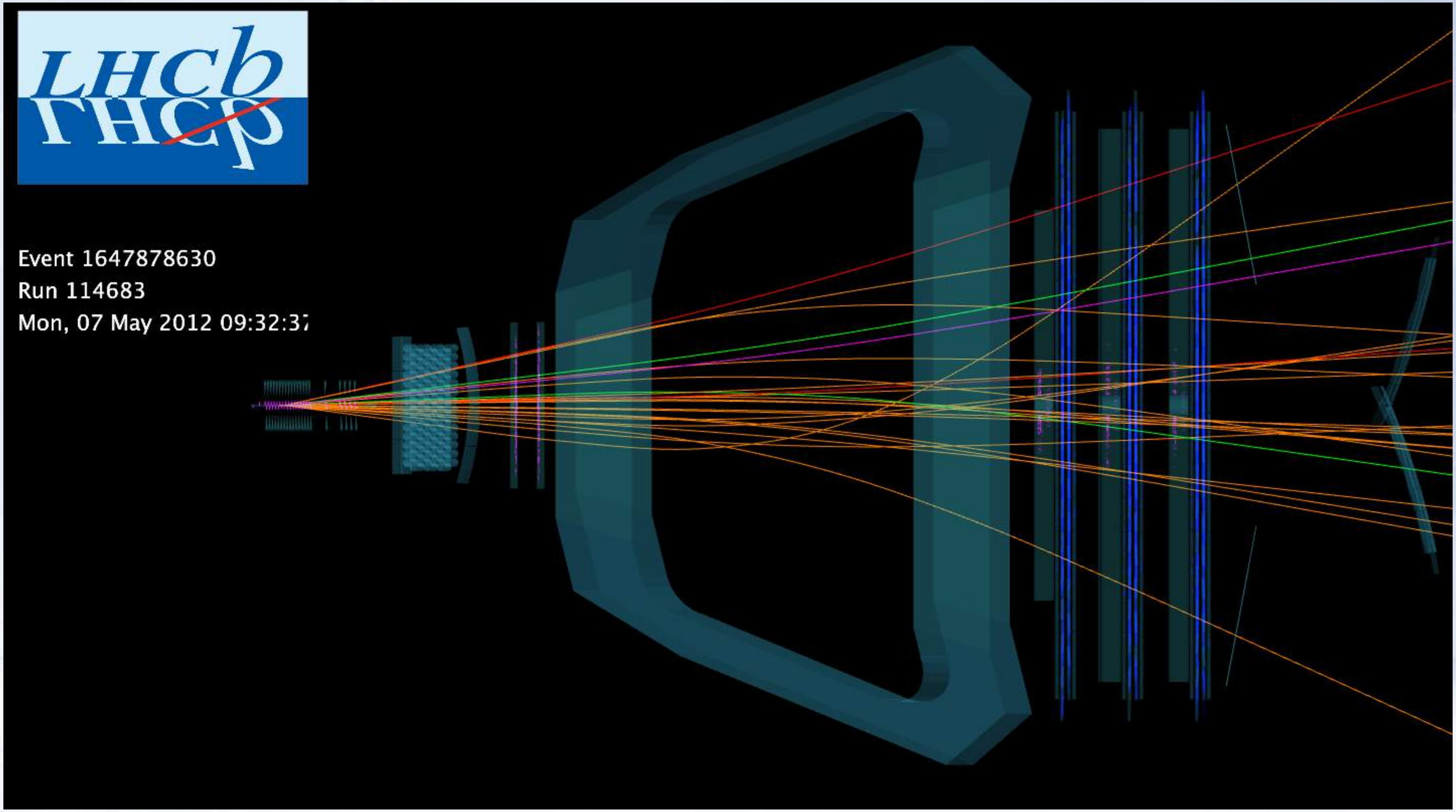
Hits allows to reconstruct particle tracks and estimate α.
Track pattern recognition – recognition of particle tracks among set of hits in the detector.

Tracking system



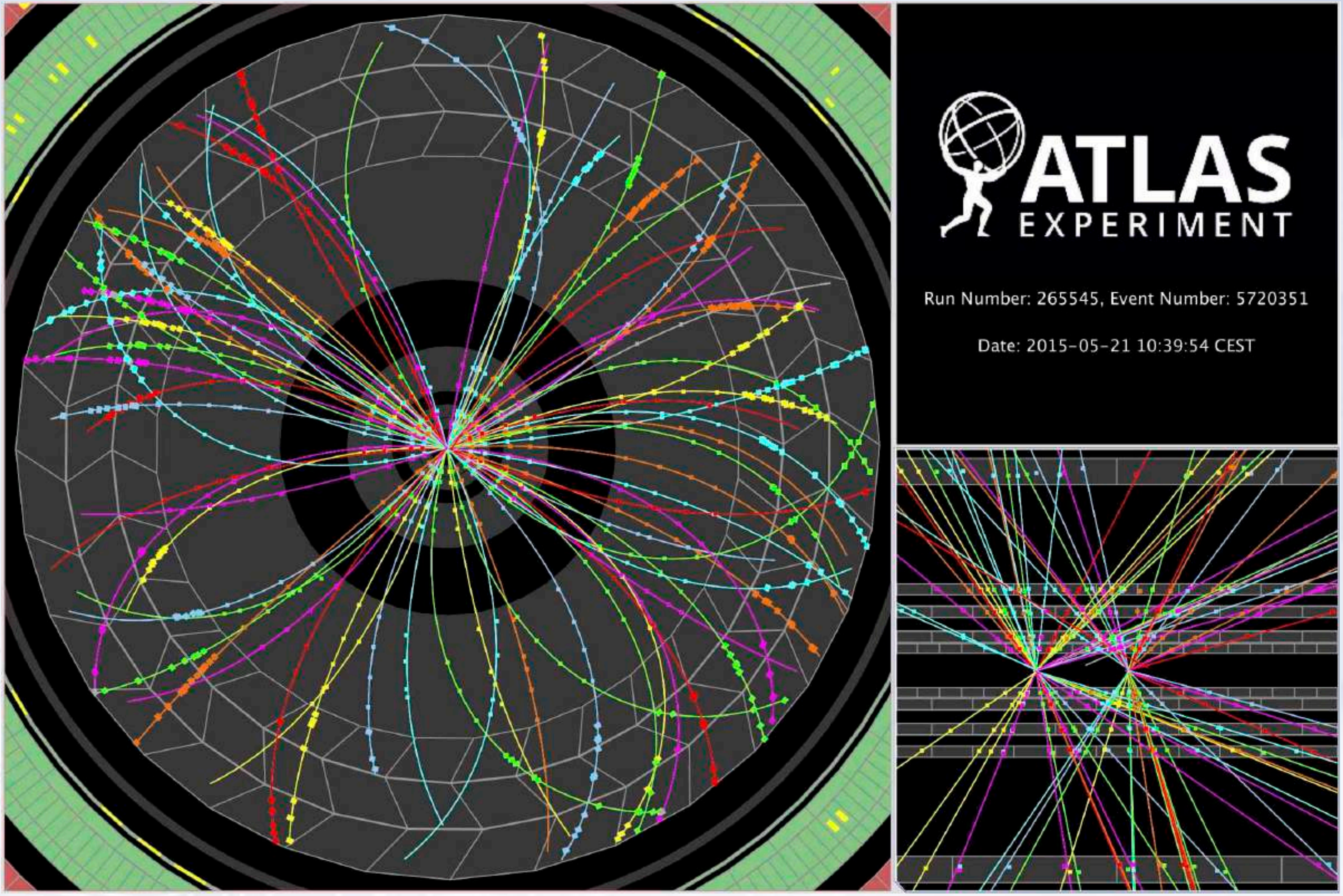
Magnetic field deflects charged particles and allows to estimate particle momentum. Tracking stations are needed to estimate the deflection.

LHCb tracking system



LHCb / http://clangenb.web.cern.ch/clangenb/

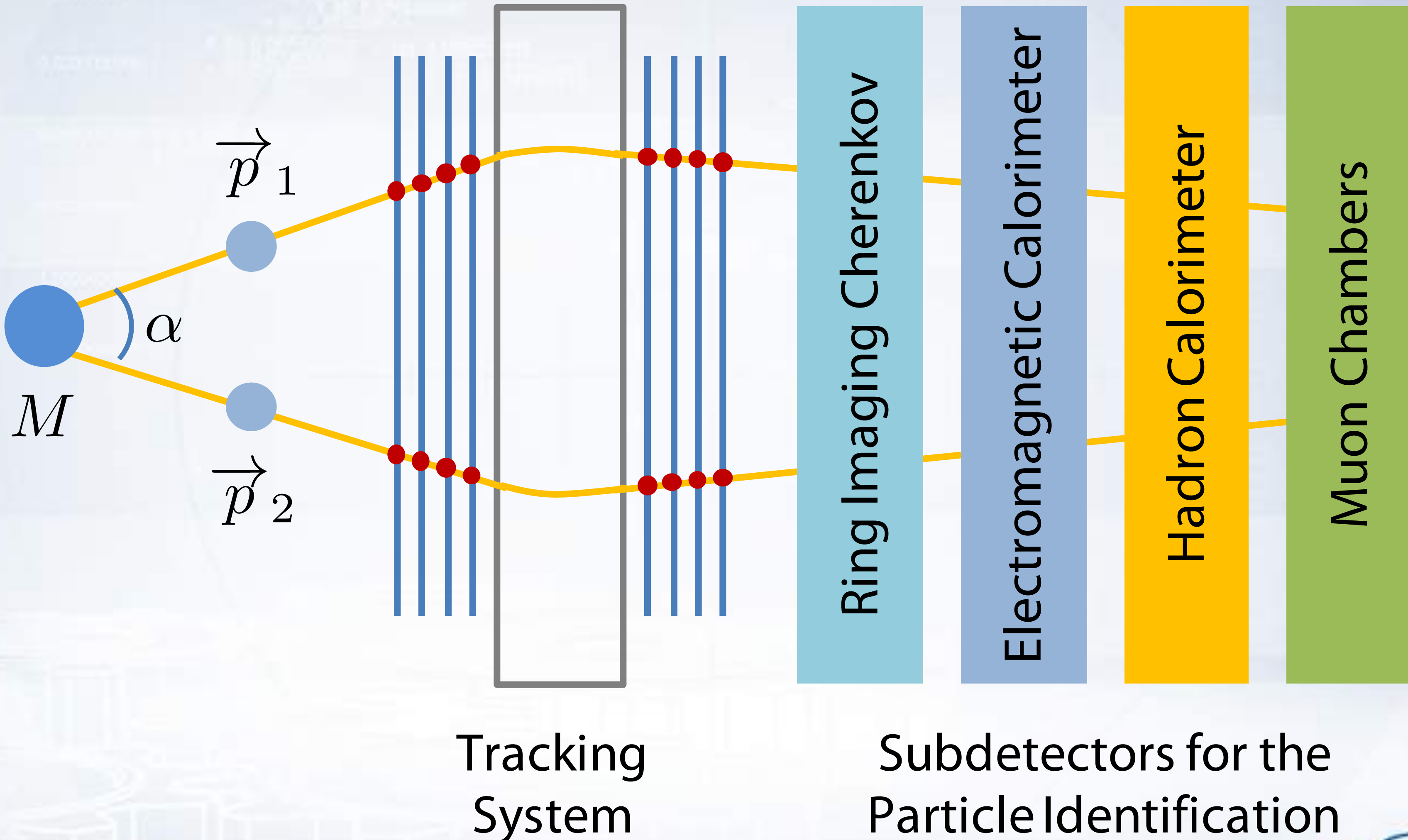
ATLAS tracking system



PaulLaycock, https://twiki.cern.ch/twiki/bin/view/AtlasPublic/EventDisplayRun2Collisions

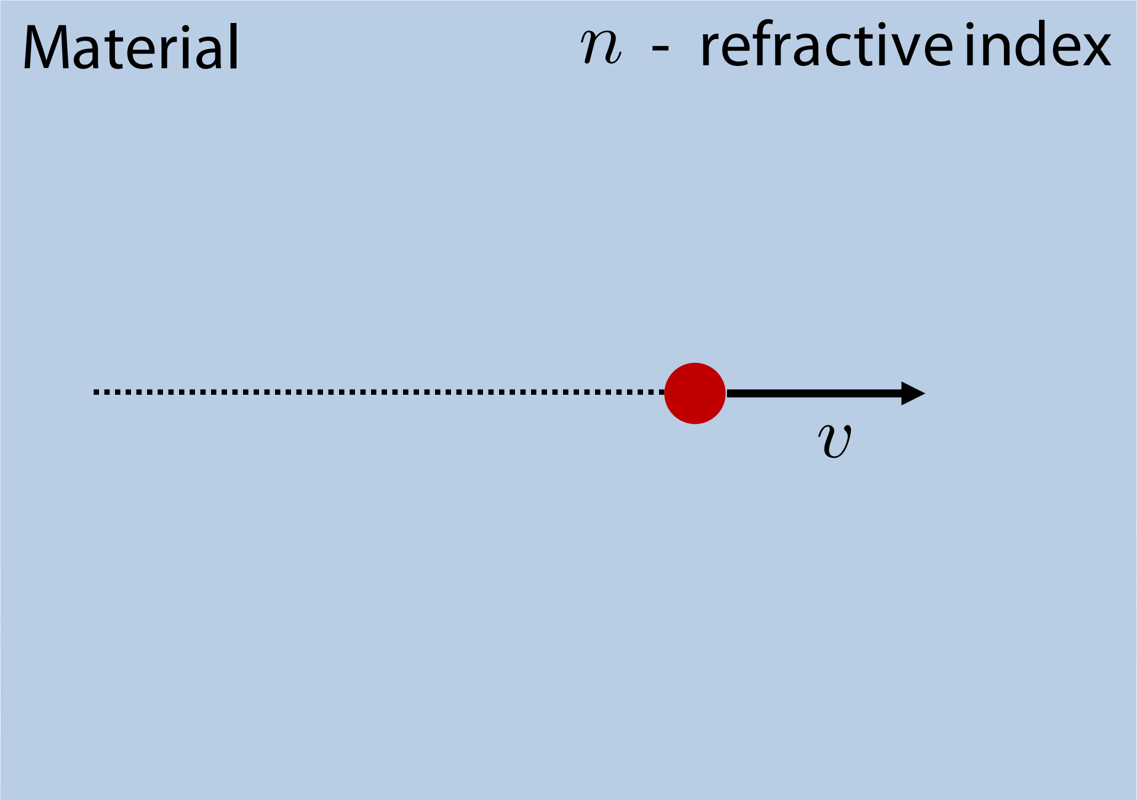
Ring Imaging Cherenkov (RICH) detector

Particle identification



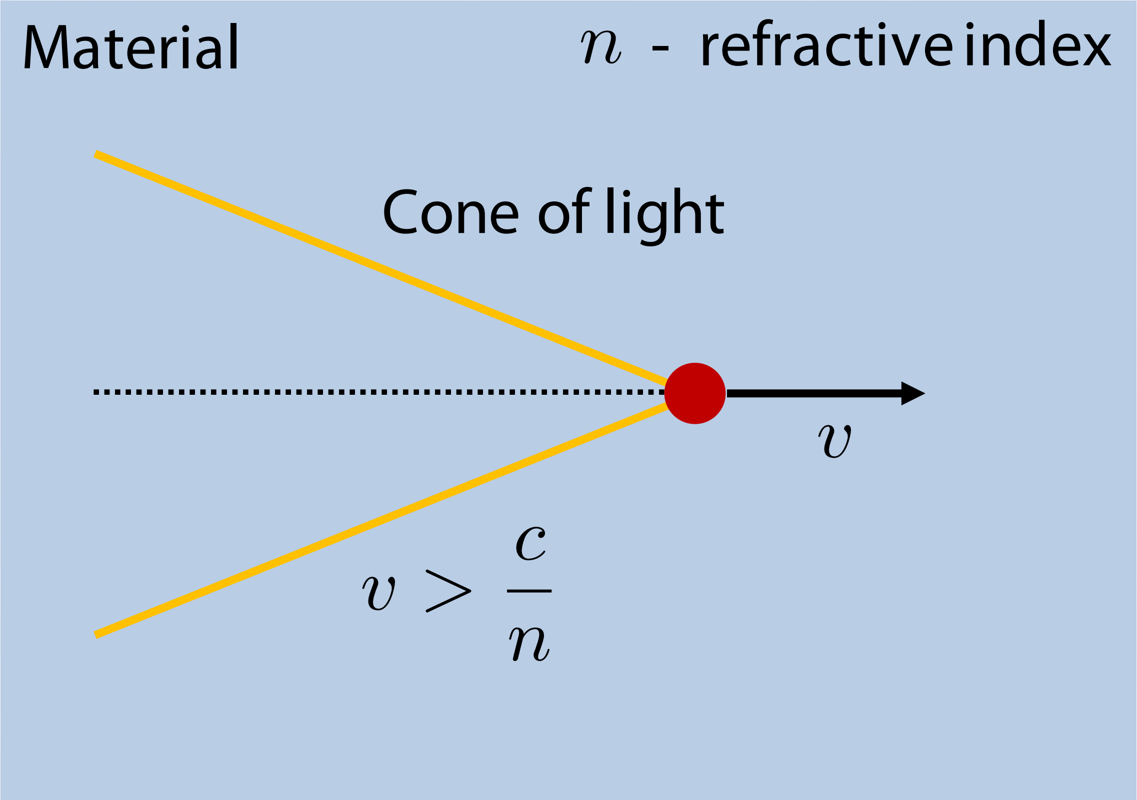
Ring Imaging Cherenkov (RICH) detector

RICH detector is based on Cherenkov radiation effect:



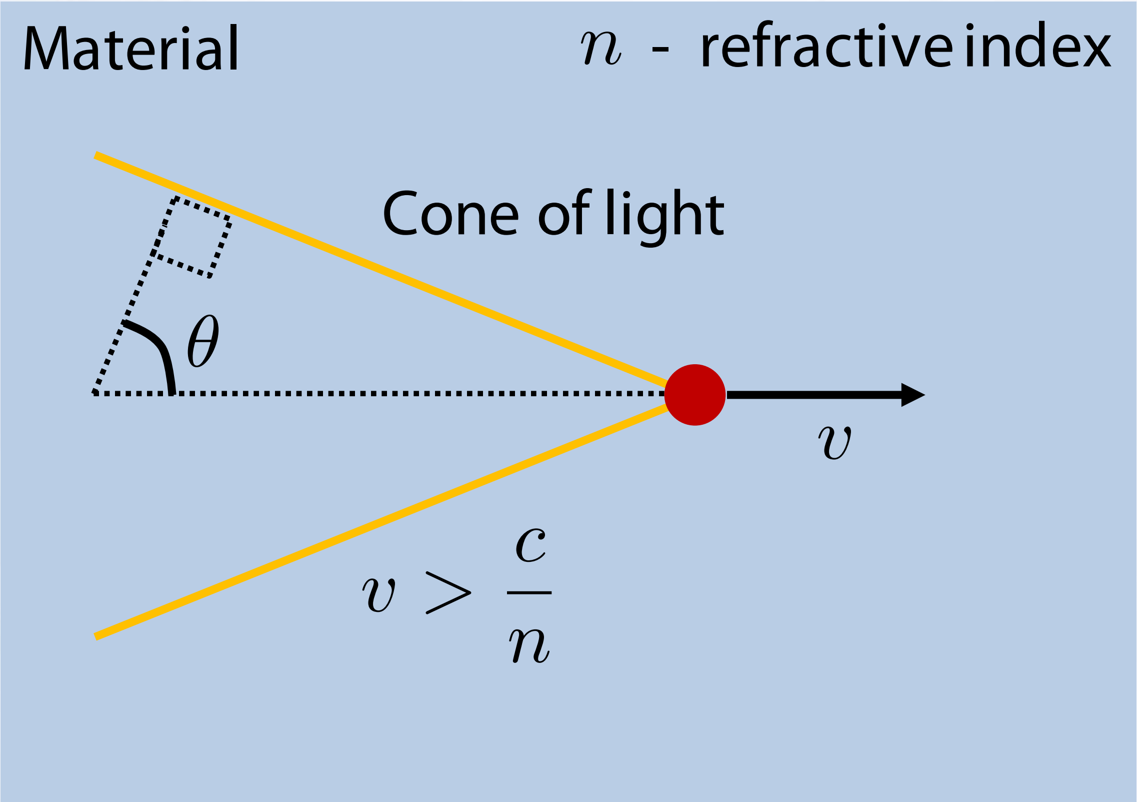
Ring Imaging Cherenkov (RICH) detector

RICH detector is based on Cherenkov radiation effect:



Ring Imaging Cherenkov (RICH) detector

RICH detector is based on Cherenkov radiation effect:



$$\cos\theta = \frac{1}{n\beta}$$

$$\beta = \frac{v}{c}$$

Ring Imaging Cherenkov (RICH) detector

Momentum of a particle:

$$p = \frac{mc\beta}{\sqrt{1-\beta^2}}$$

Then

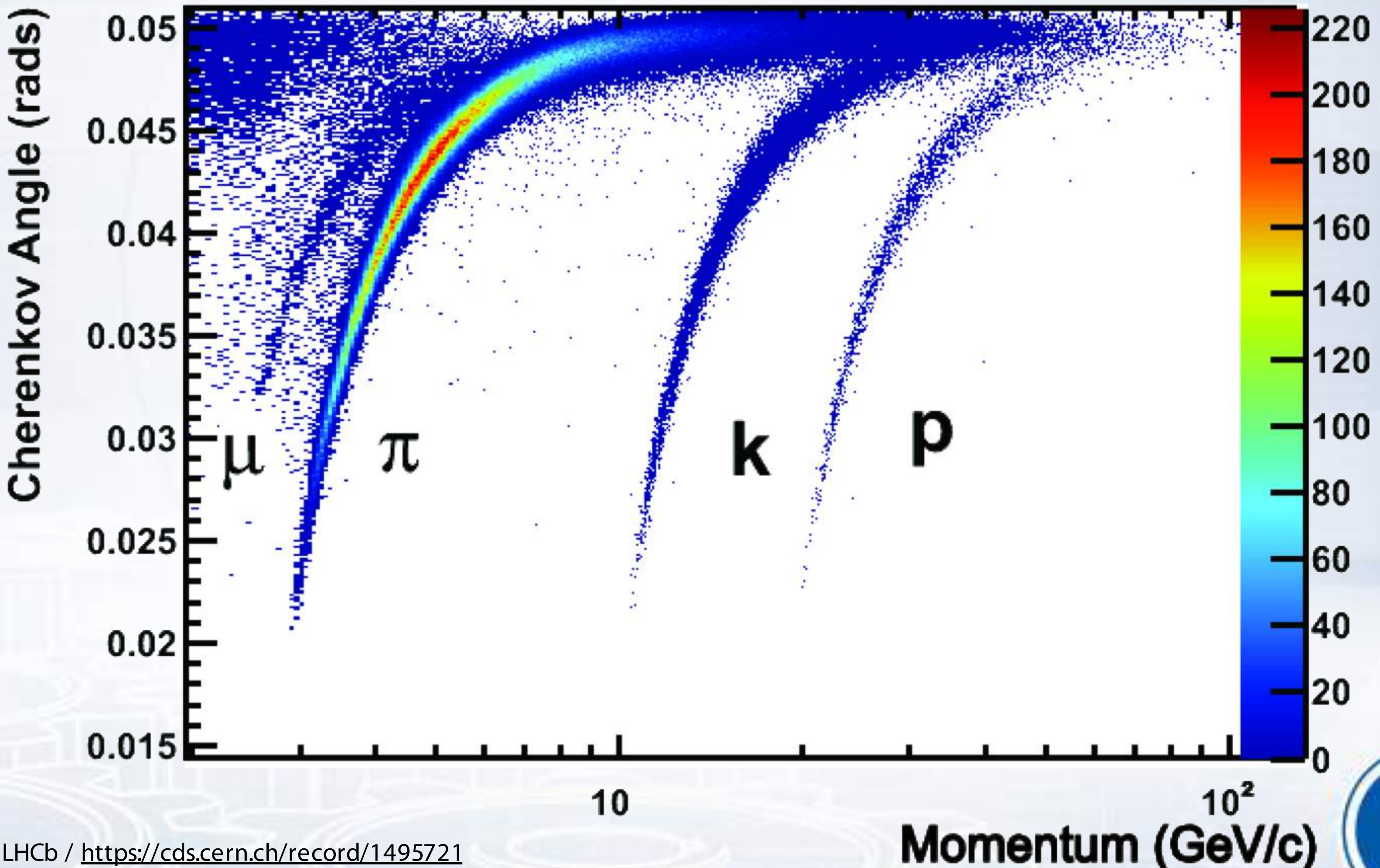
$$\beta = \frac{p}{\sqrt{p^2+m^2c^2}}$$

Cherenkov emission angle takes form:

$$\cos\theta = \frac{1}{n\beta} = \frac{\sqrt{p^2+m^2c^2}}{np}$$

Ring Imaging Cherenkov (RICH) detector

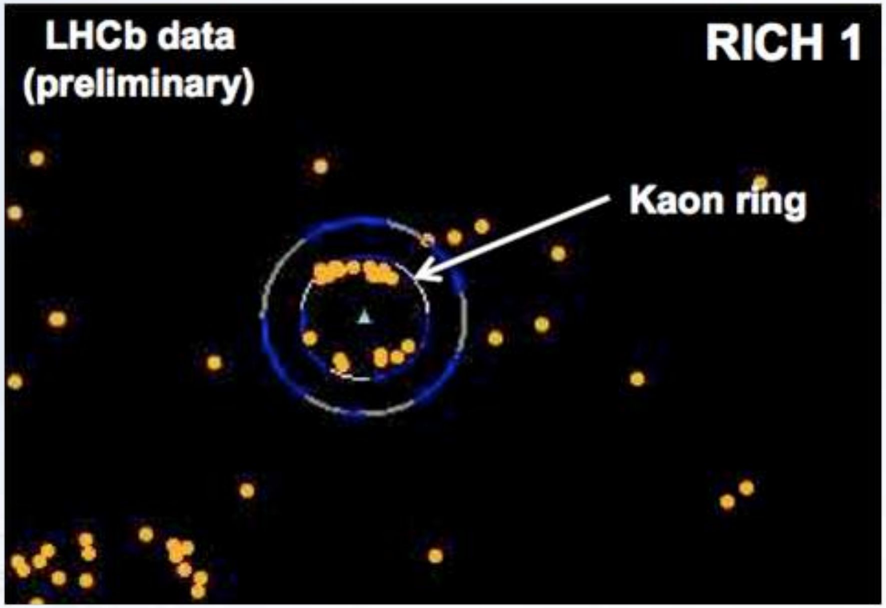
Reconstructed Cherenkov angle as a function of track momentum:



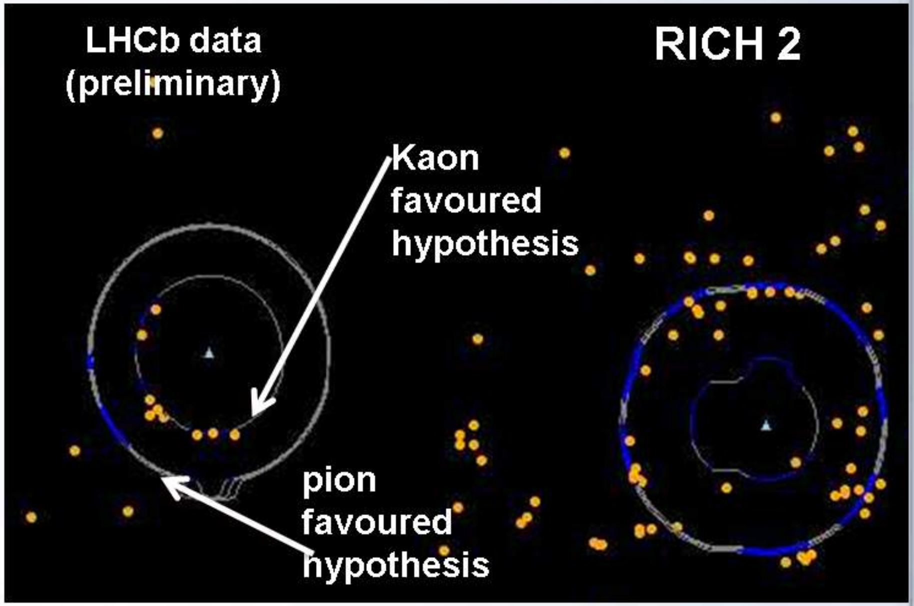
LHCb / https://cds.cern.ch/record/1495721

Ring Imaging Cherenkov (RICH) detector

How it looks in the LHCb RICH detectors:



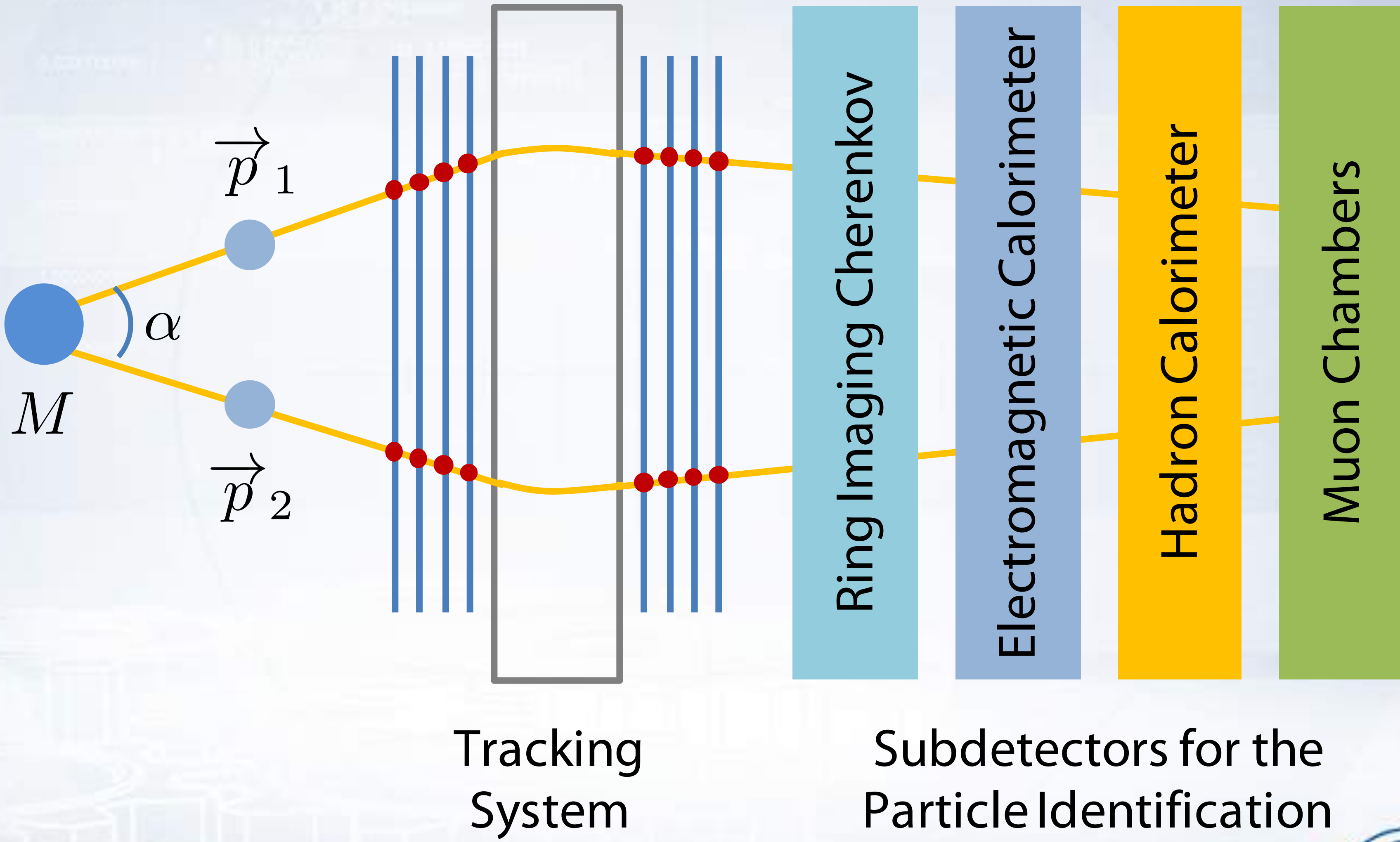
LHCb / https://inspirehep.net/record/857115/plots



LHCb / https://inspirehep.net/record/857115/plots

Calorimeters

Particle identification



Electromagnetic calorimeter

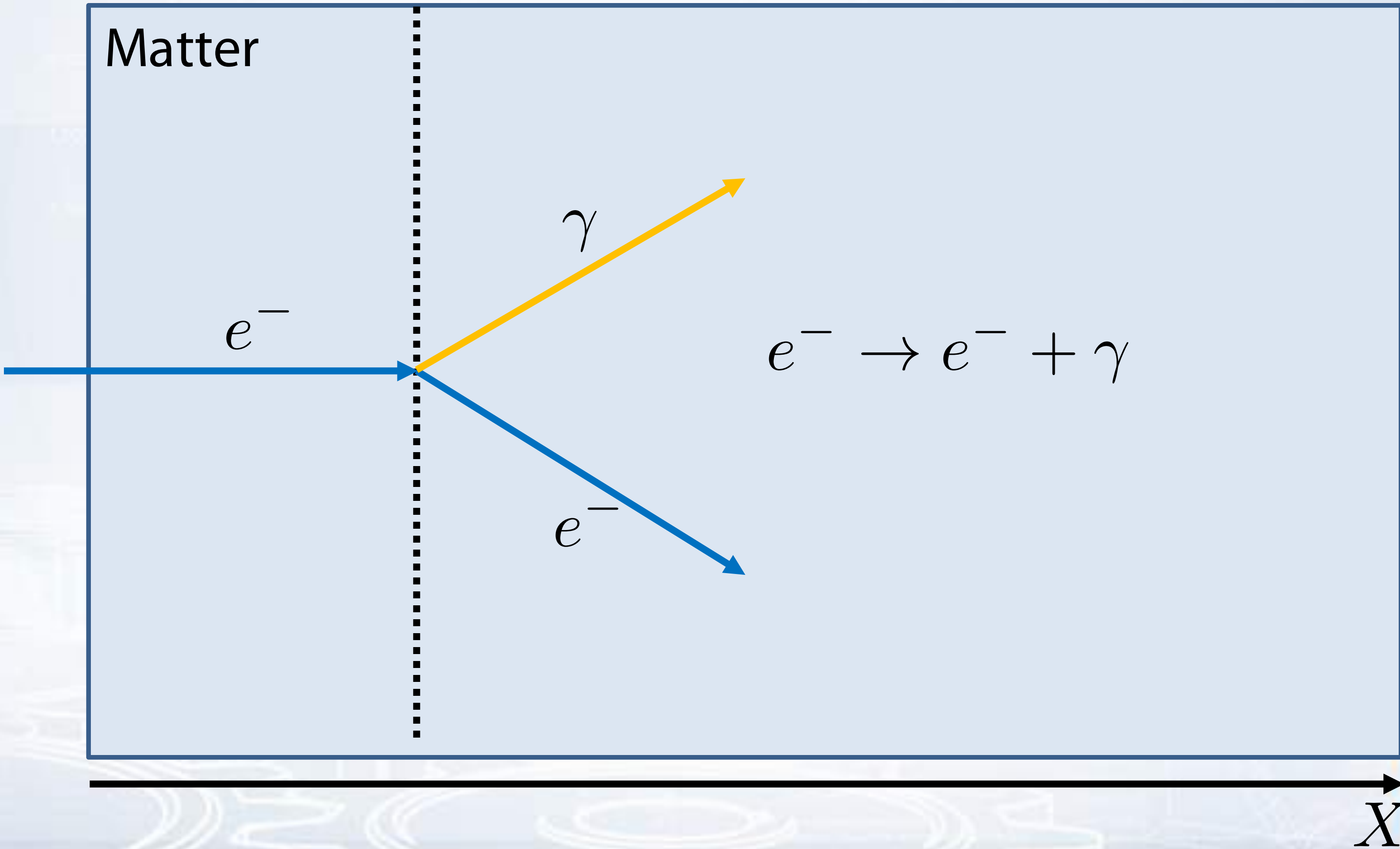
The calorimeter system is designed to measure particles energy.

Particles interact with matter of the calorimeter and lose energy. The calorimeter measures how much energy the particles lose before they stop.

The **electromagnetic calorimeter** is responsible for measuring the energy of electrons and photons.

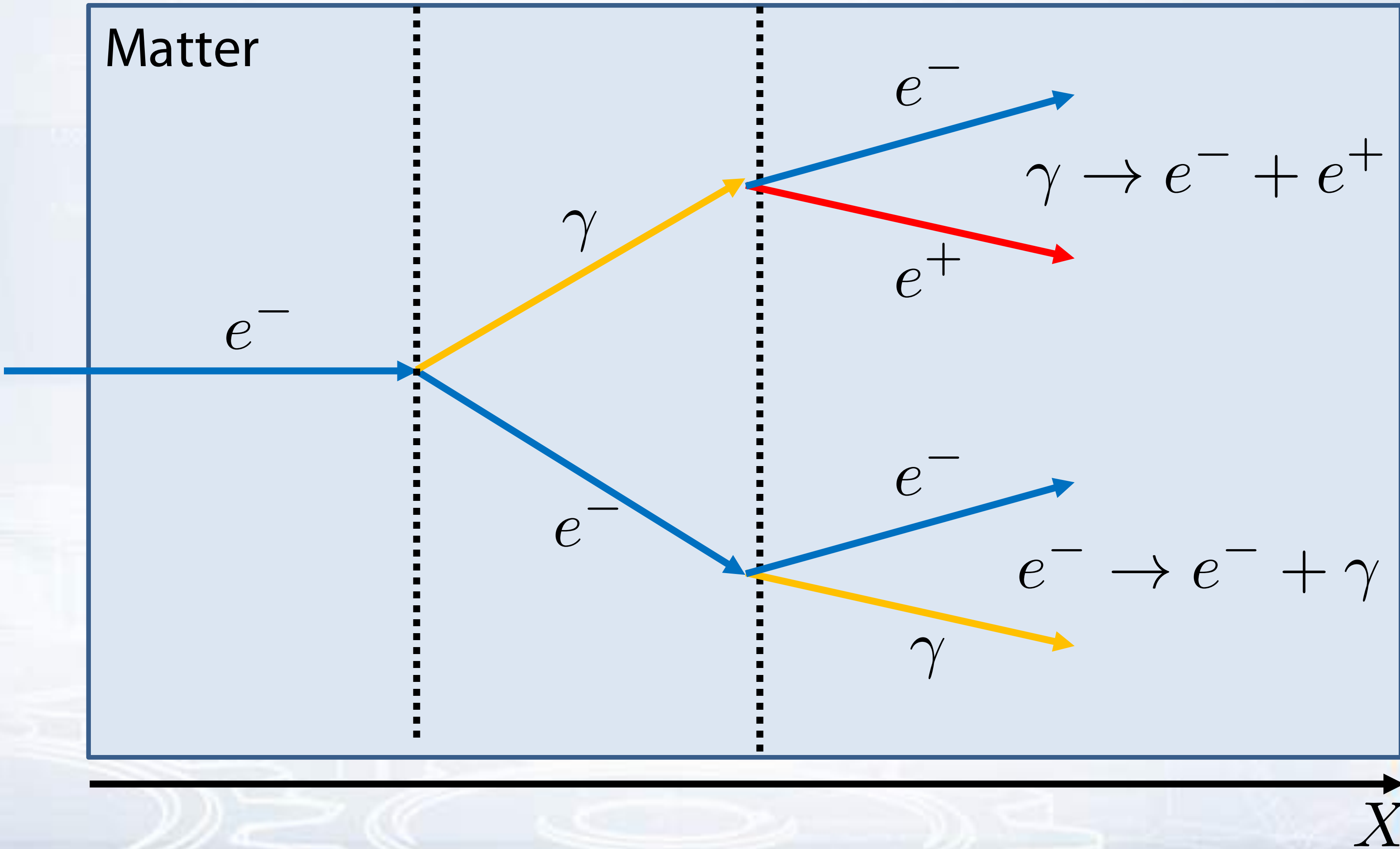
Electromagnetic calorimeter

Interacting with matter an electron emits an photon:



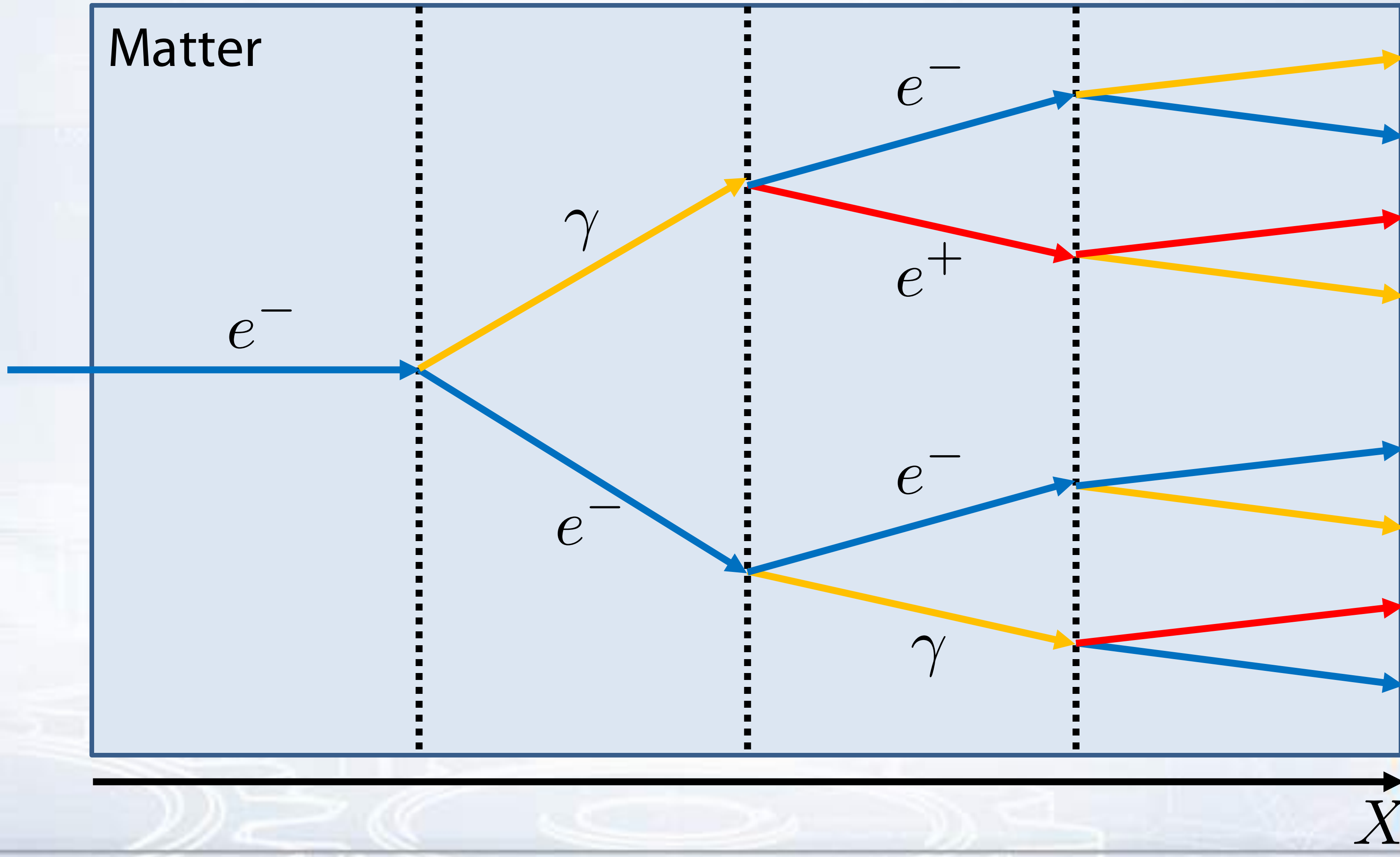
Electromagnetic calorimeter

Interacting with matter an phonon decays into an electron and a positron:



Electromagnetic calorimeter

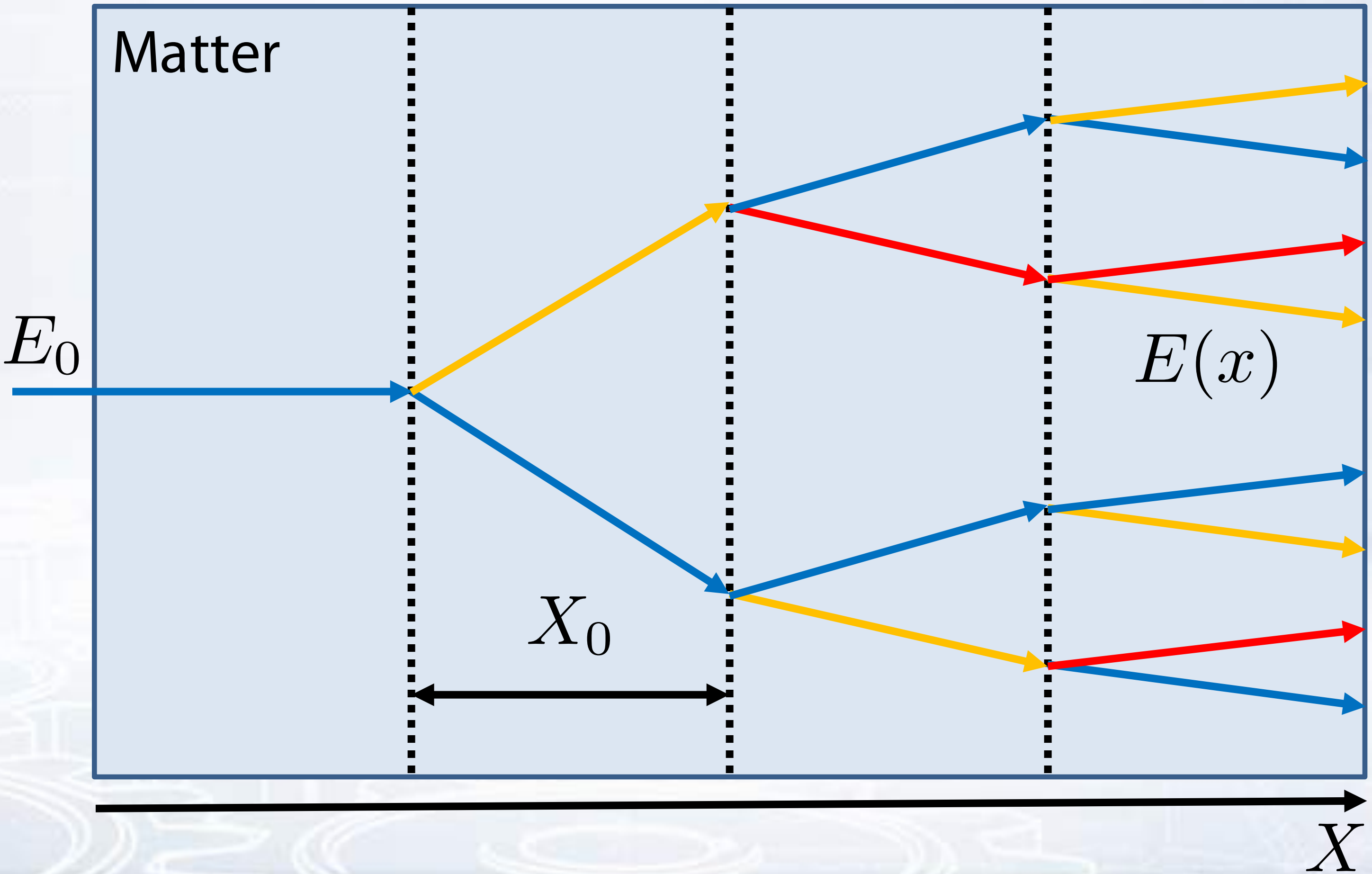
The process repeats creating an **electromagnetic shower**:



Electromagnetic calorimeter

Particle energy is defined as:

$$E(x) \approx E_0 e^{-\frac{x}{X_0}}$$



Electromagnetic calorimeter

Electromagnetic shower grows while the energy of the particles is above the critical value E_C. The shower size X_{max} can be estimated as follow:

$$E_C \approx E_0 e^{-\frac{X_{max}}{X_0}}$$

$$X_{max} \approx X_0 \ln \frac{E_0}{E_C}$$

Electromagnetic calorimeter

Electromagnetic shower grows while the energy of the particles is above the critical value E_C. The shower size X_{max} can be estimated as follow:

$$E_C \approx E_0 e^{-\frac{X_{max}}{X_0}}$$

$$X_{max} \approx X_0 \ln \frac{E_0}{E_C}$$

The total number of particles in the shower is estimated as:

$$N \backsim \frac{E_0}{E_C}$$

Measuring the number of particles allows to determine the energy of the incoming particle. This number is measured by **Scintillation Counters**.

Electromagnetic calorimeter

Matter: creates an electromagnetic shower

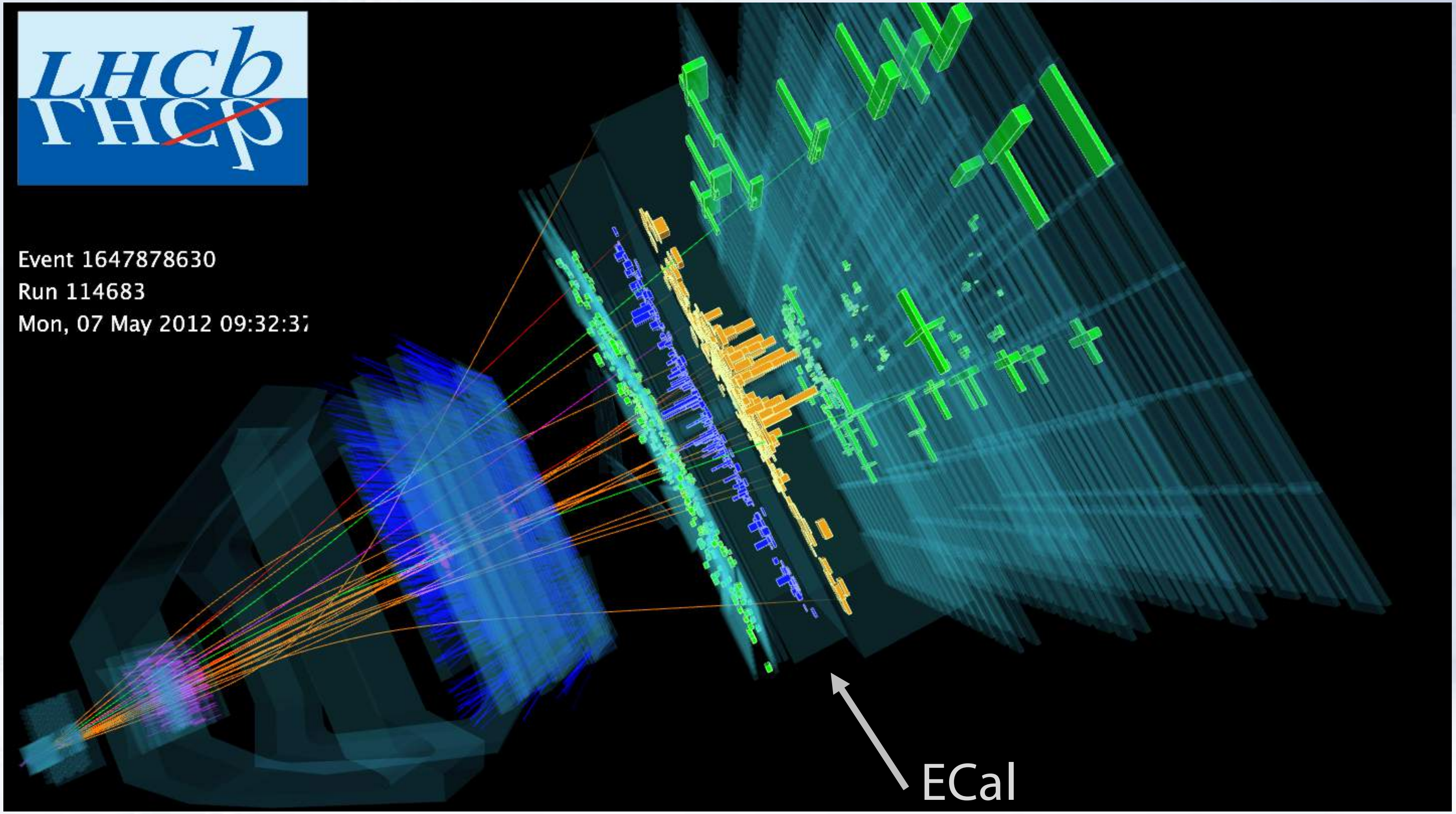
Scintillation Counter: count number of particles in the shower

CMS Ecal / https://cms-docdb.cern.ch/cgi-bin/PublicDocDB/ShowDocument?docid=12030

LHCb electromagnetic calorimeter

Maximilien Brice / http://cds.cern.ch/record/835712

LHCb electromagnetic calorimeter



Maximilien Brice / http://cds.cern.ch/record/835712

Electromagnetic calorimeter

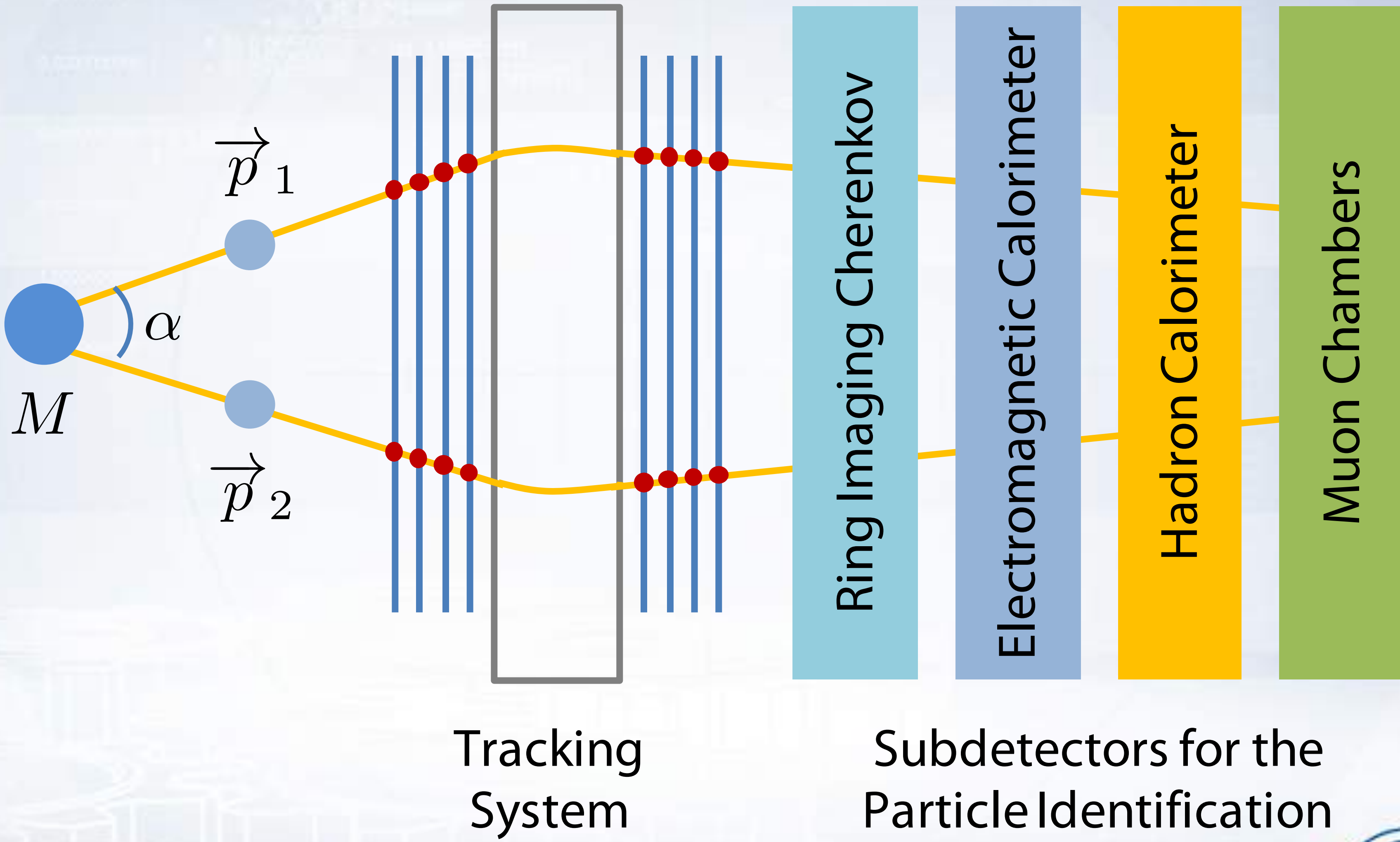
Estimated from this equation.
Identifies a particle.

Measured in the
calorimeter

$$E^2 = p^2c^2 + m^2c^4$$

Measured in the
tracking system

Particle identification

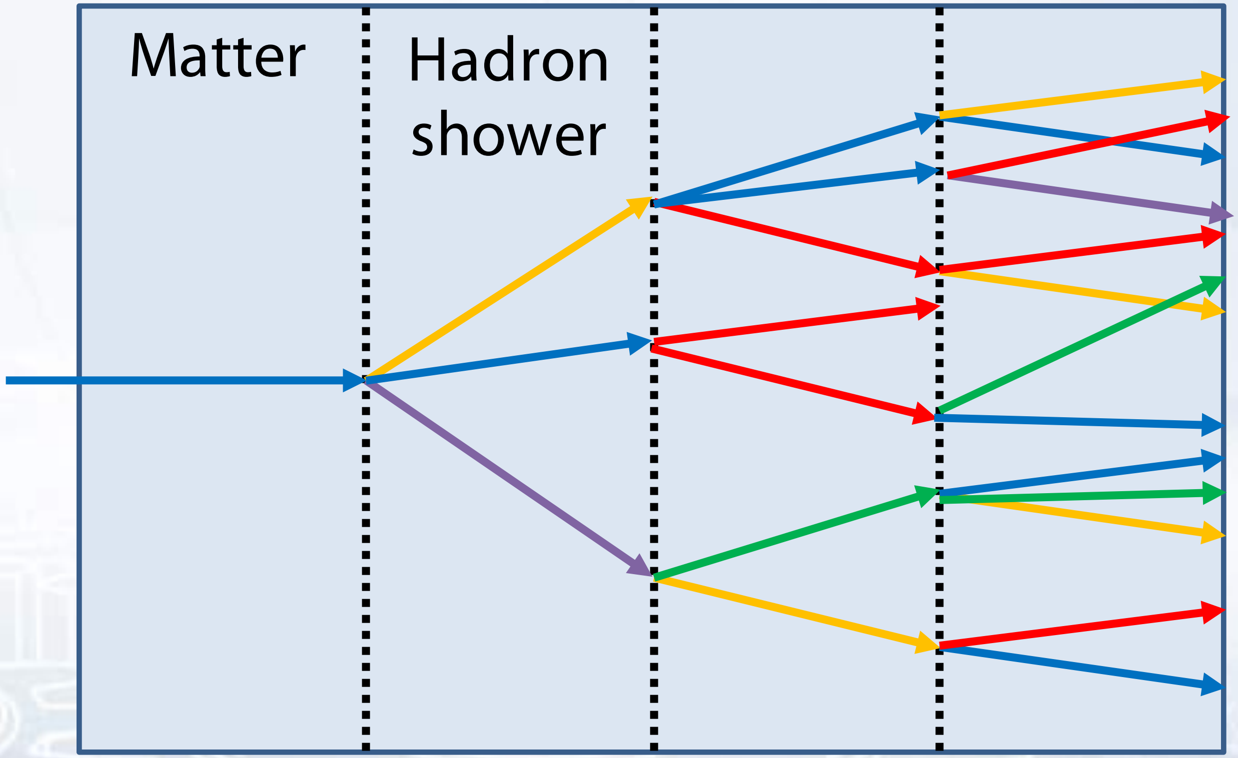


Hadron calorimeter

The **hadron calorimeter** is responsible for measuring the energy of protons, neutrons and other particles containing quarks.

Hadron calorimeter

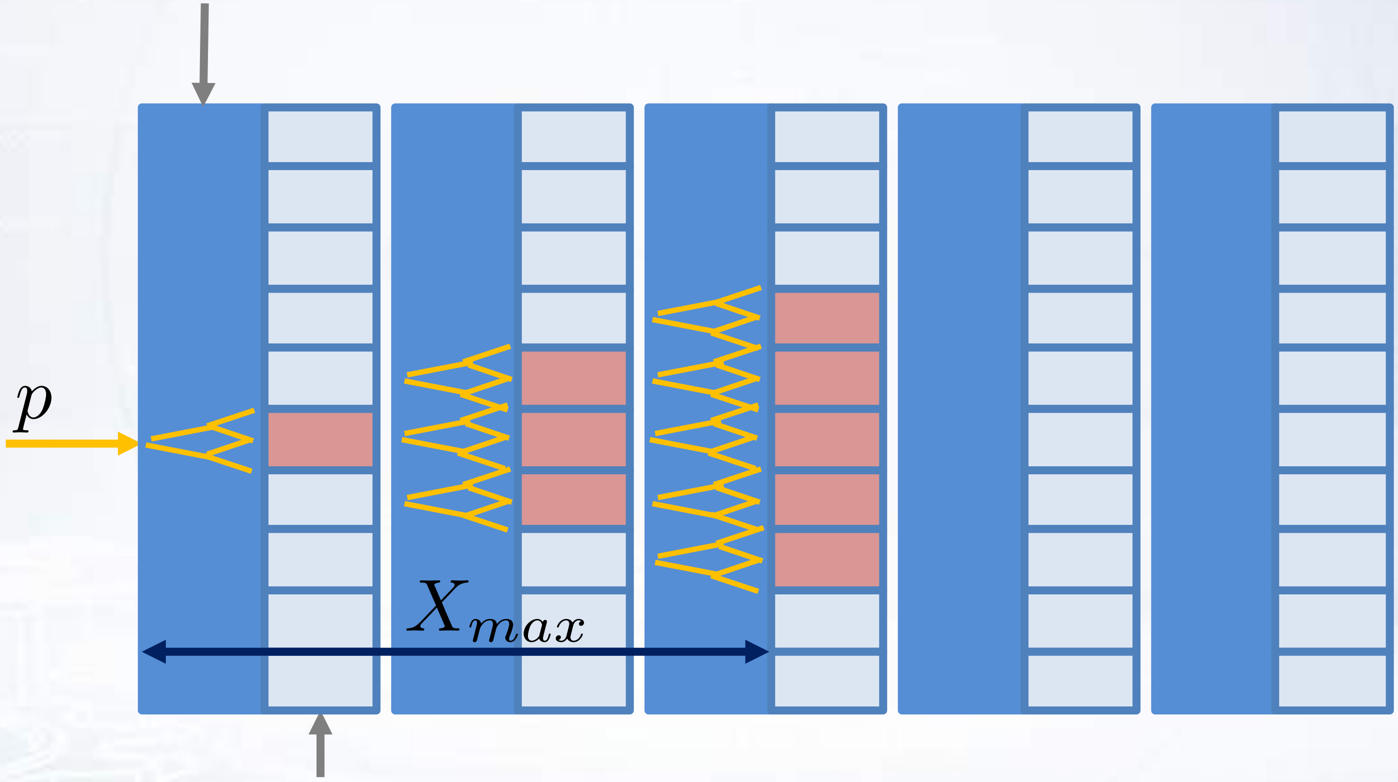
- The **hadron calorimeter** is similar to the electromagnetic calorimeter.
- But a particle produces a **hadronic shower** due to interactions with the nuclei of matter atoms.
- The shower consists of a large number of different particle types.



Hadron calorimeter

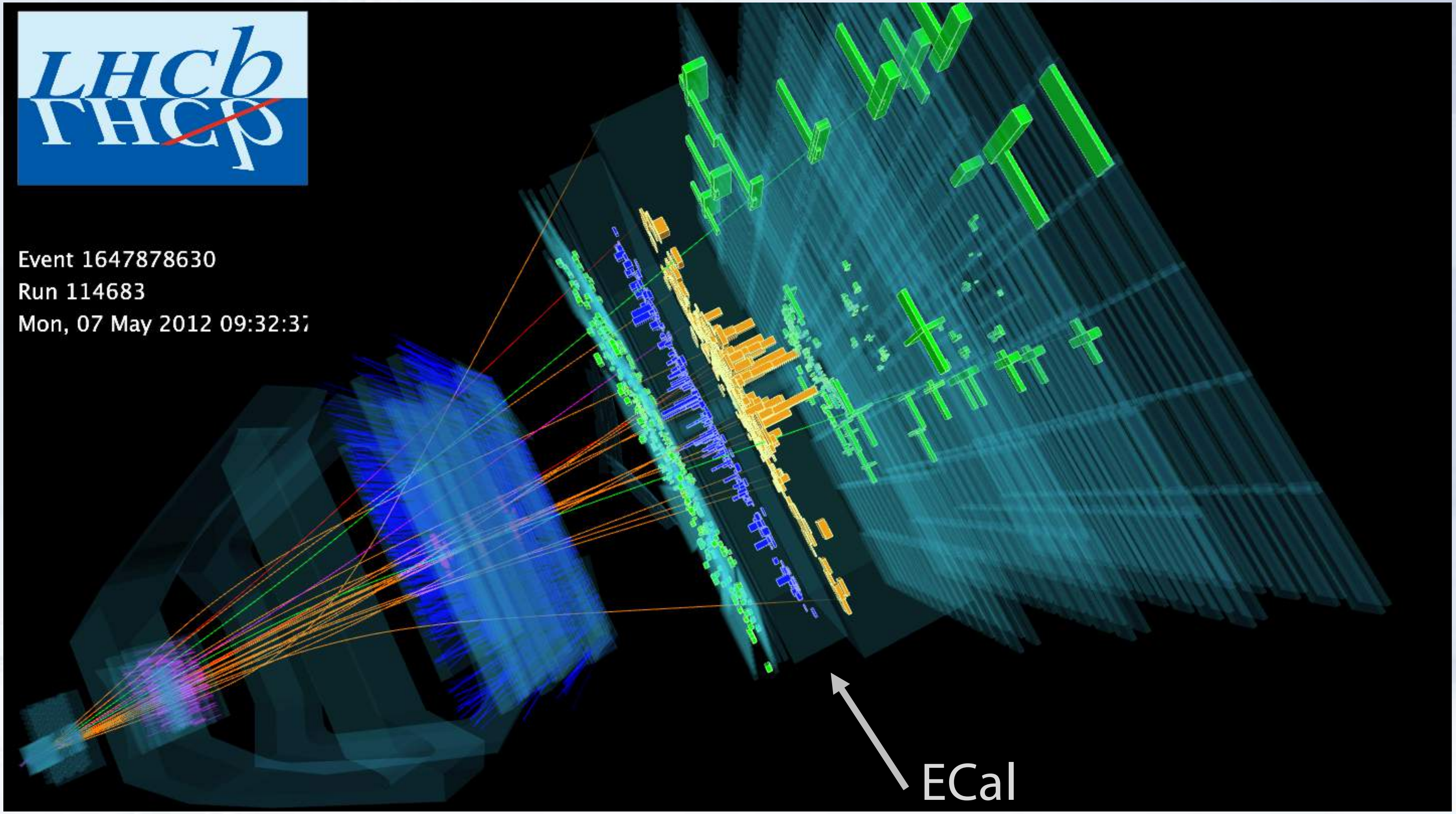
The hadron calorimeter composition:

Matter: creates an hadronic shower



Scintillation Counters: counts number of particles in the shower

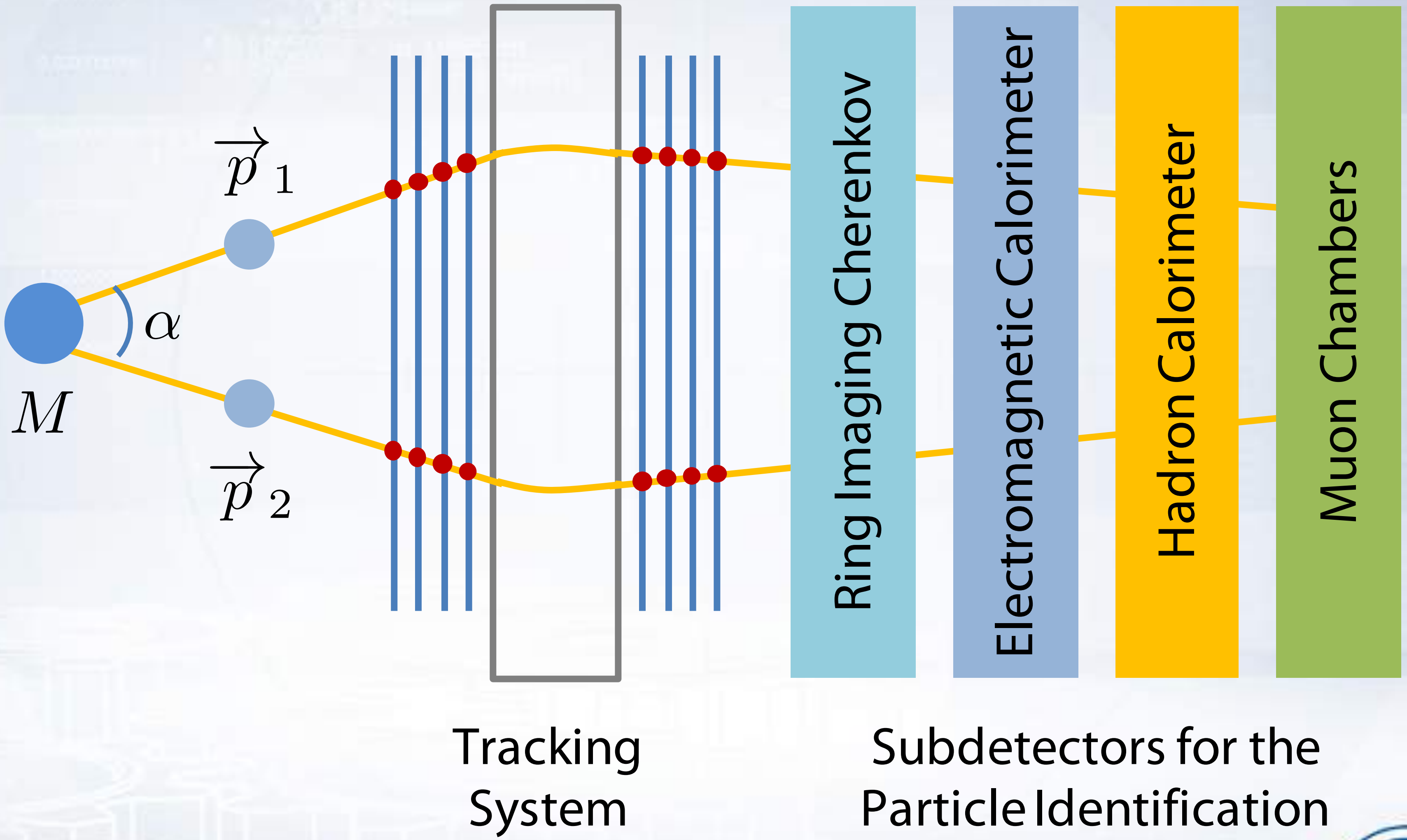
LHCb electromagnetic calorimeter



LHcb / http://clangenb.web.cern.ch/clangenb/

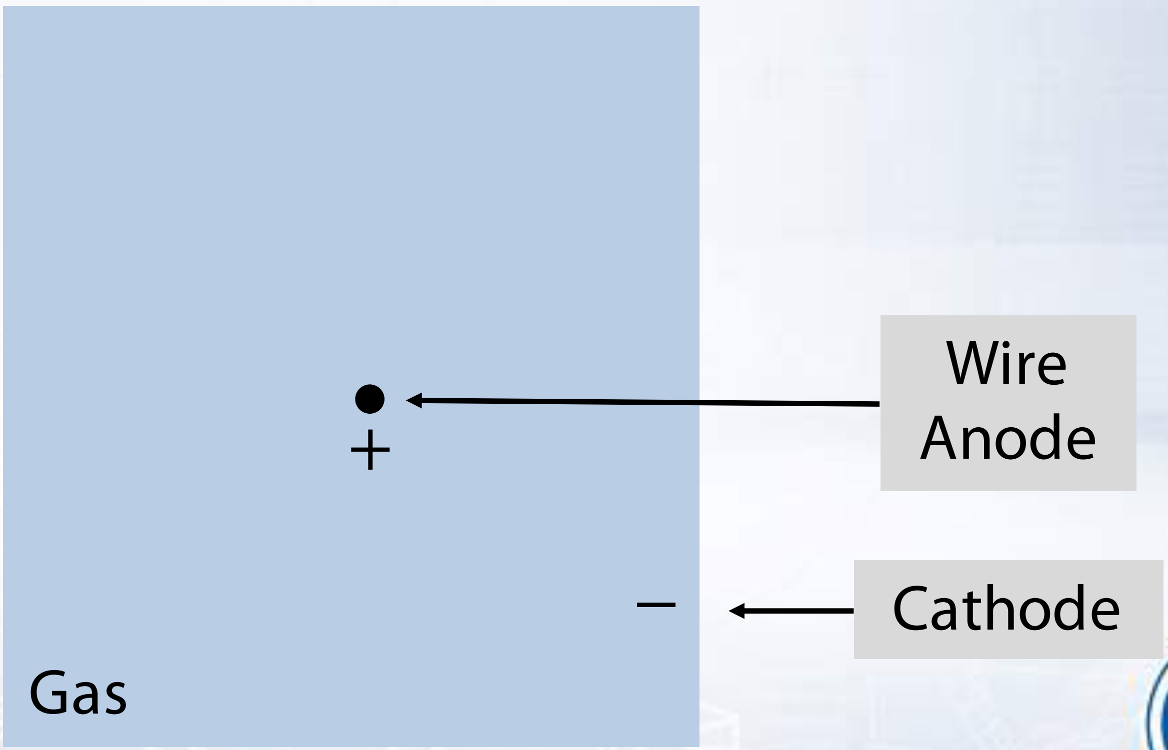
Muon system

Particle identification



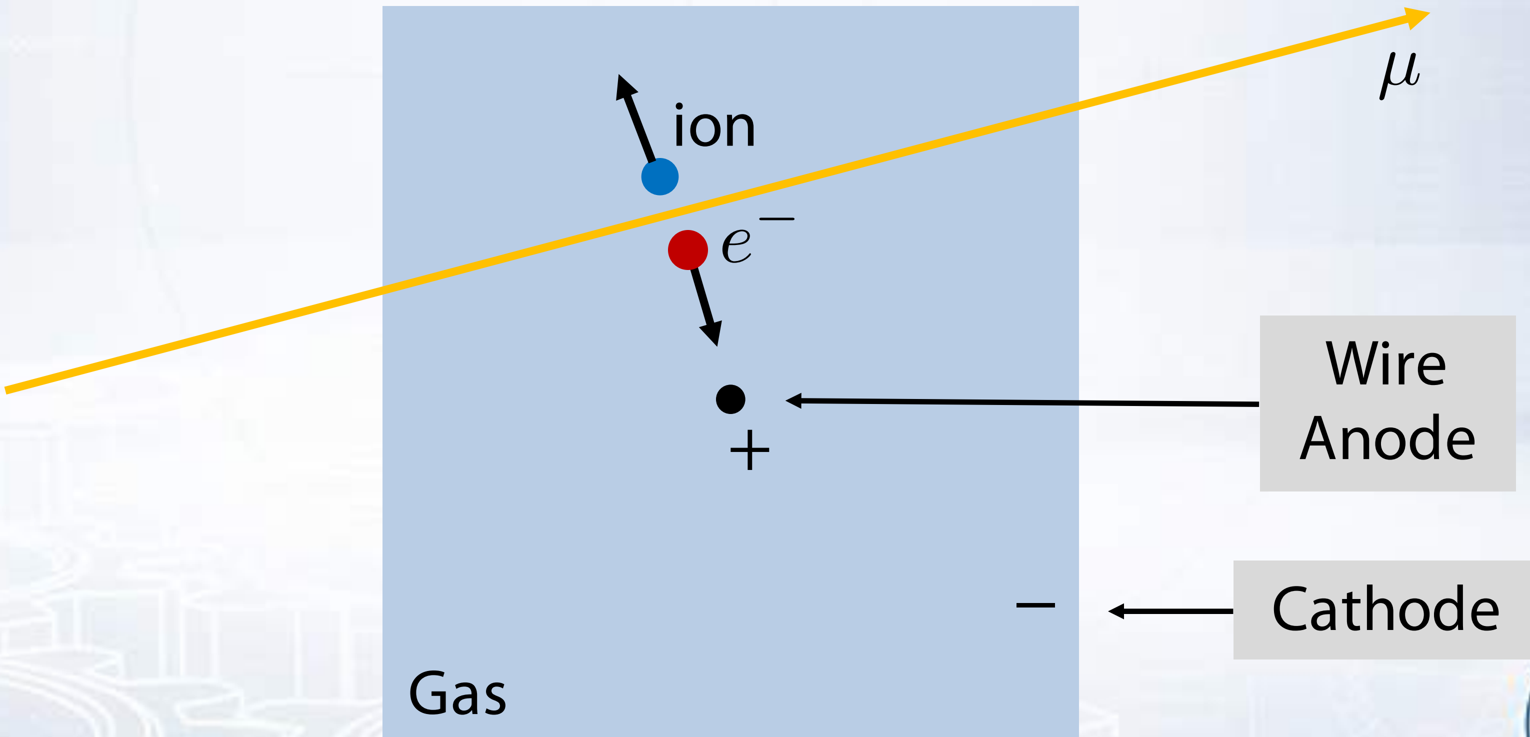
Muon chambers

- A muon chamber is filled with gas and has a wire inside.
- Voltage is applied between the wire (anode) and the chamber walls (cathode).



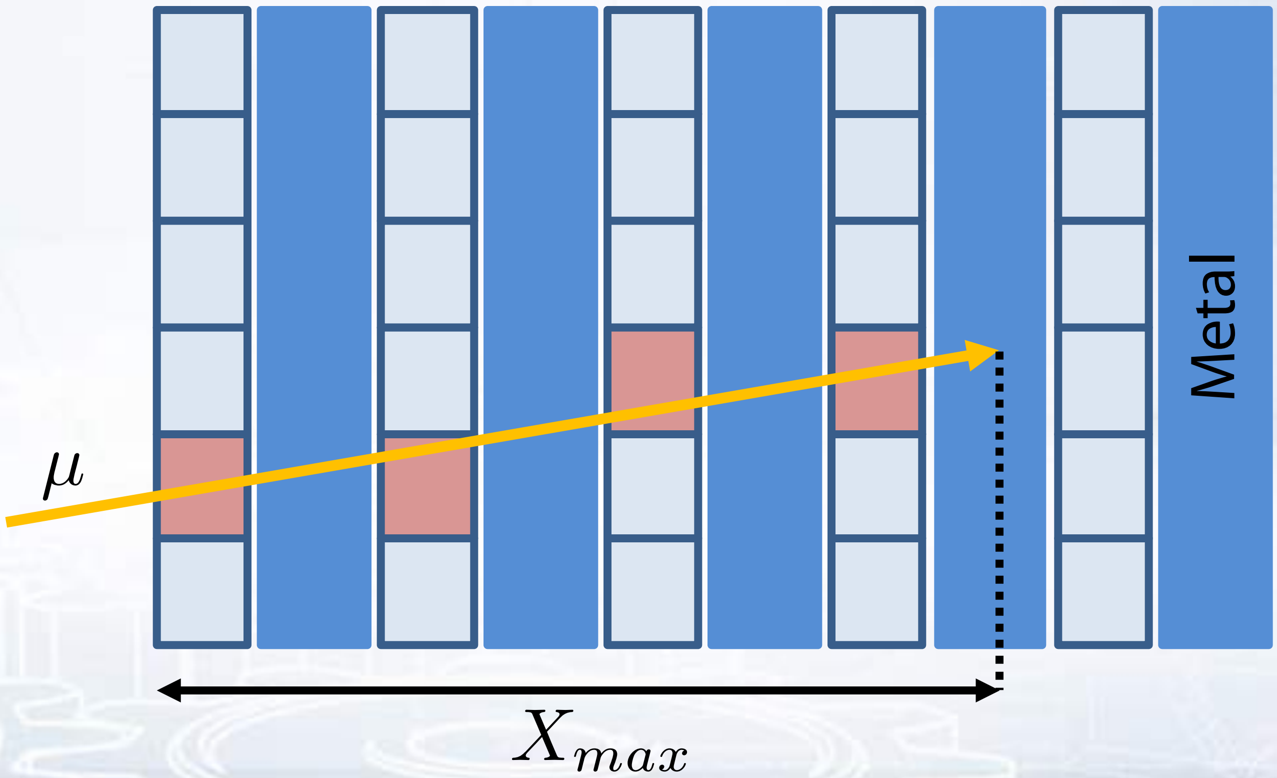
Muon chambers

- A muon passes through the gas and ionizes it.
- Due to the electrostatic field inside the chamber, ions go to the cathode, electrons go to the anode. This creates signal in the chamber that detects the muon.

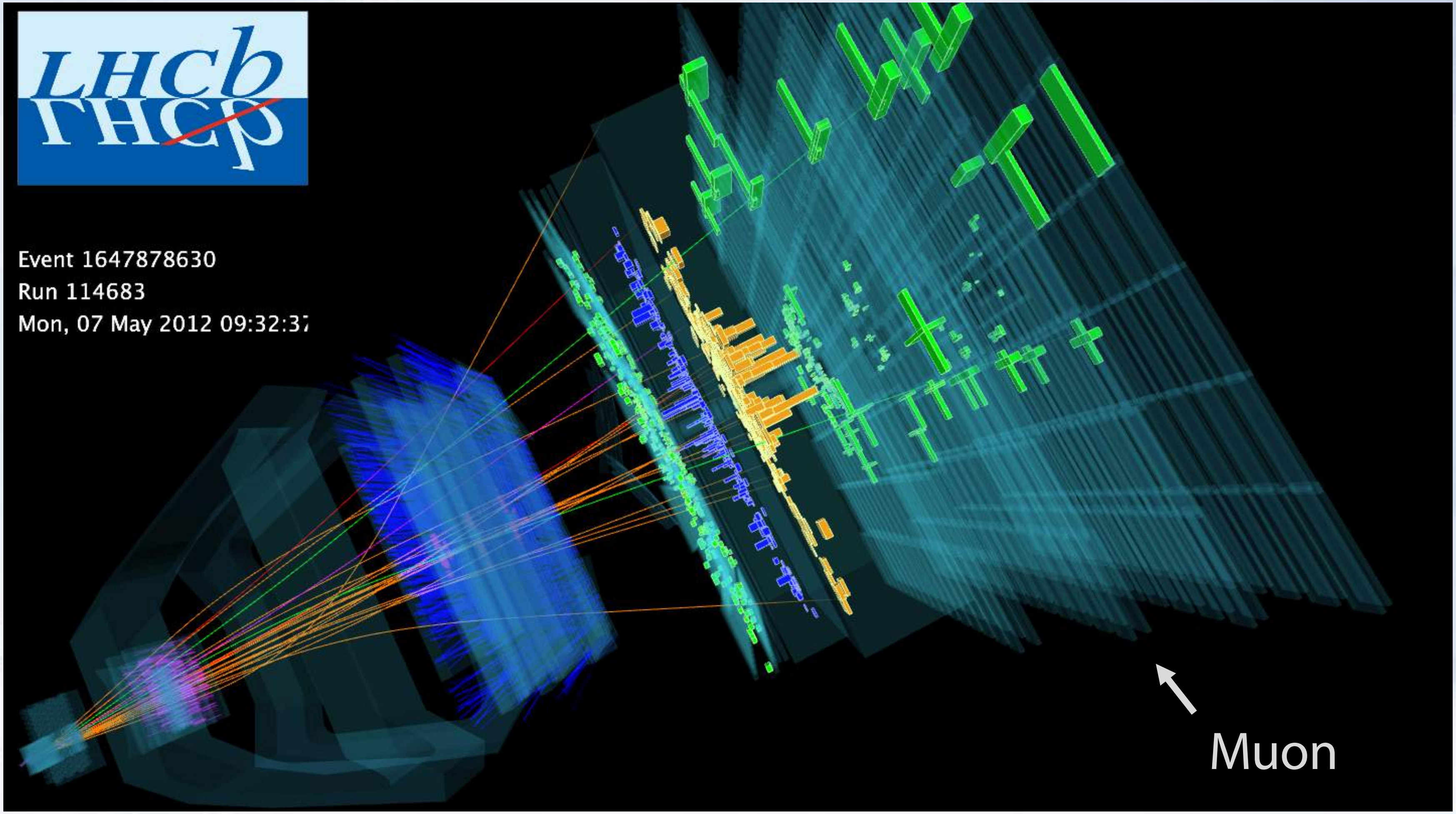


Muon chambers

- A muon system has several layers of muon chambers with layers of metal between them.
- The goal of the metal is to stop muons.
- The larger X_{max} the higher muon energy.

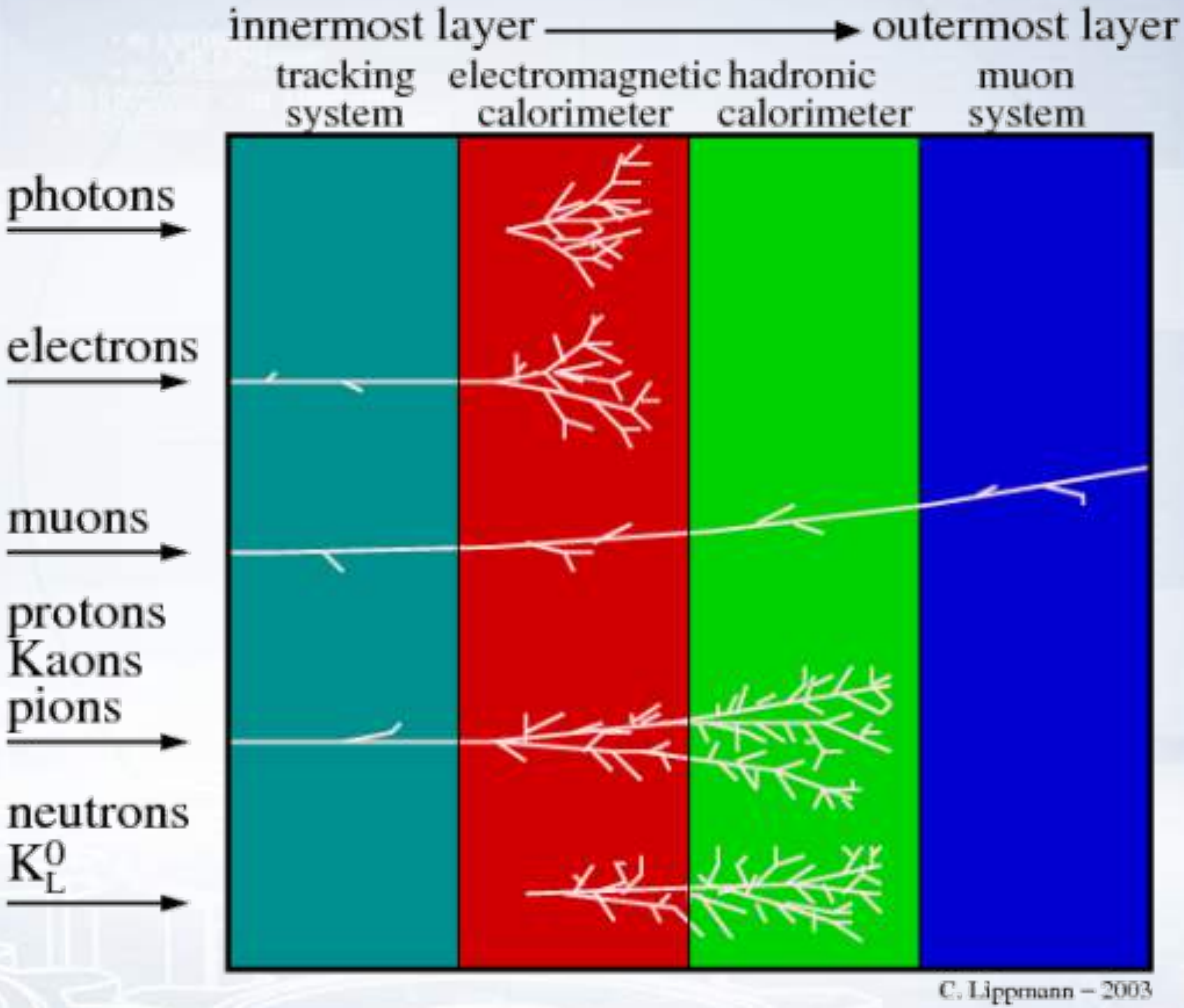


LHCb muon system



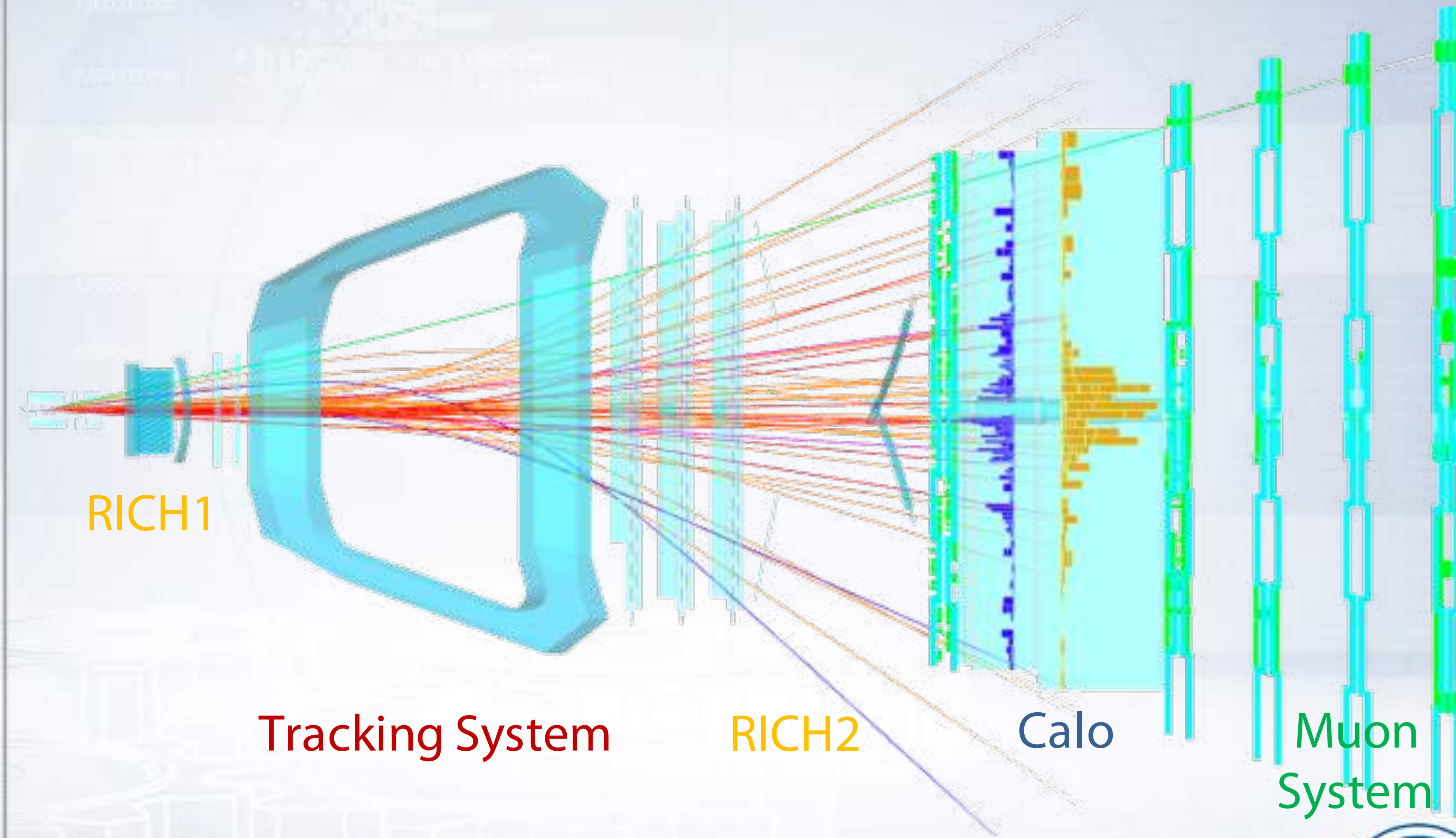
LHcb / http://clangenb.web.cern.ch/clangenb/

Particle identification overview

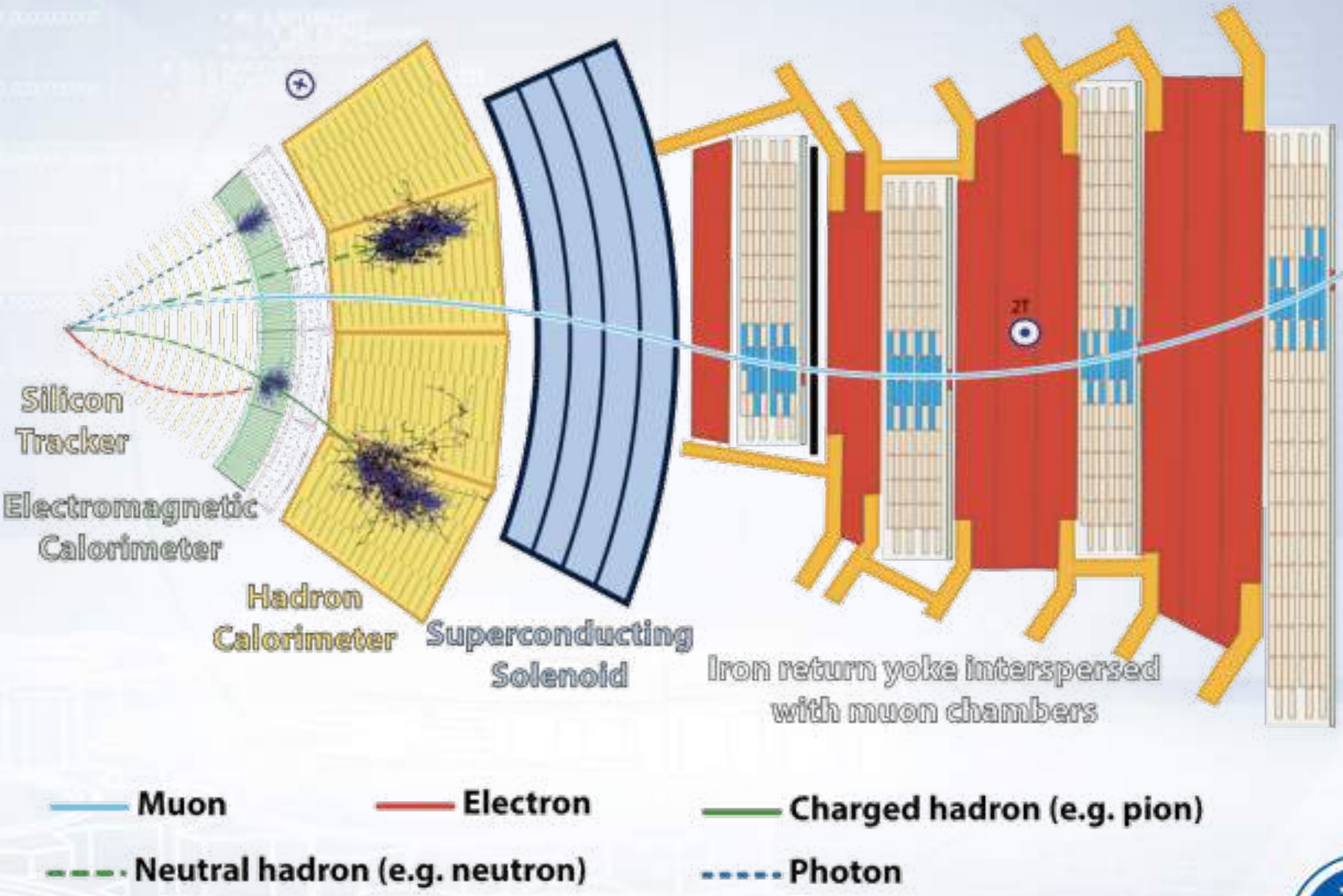


Lippmann / https://inspirehep.net/record/884672/plots

LHCb detector



CMS detector



CMS / https://cds.cern.ch/record/2120661

Machine learning in particle identification

Problem statement

The goal of the **particle identification** (**PID**) is to identify a type of a particle associated with a track using responses from different subdetectors (detector systems).

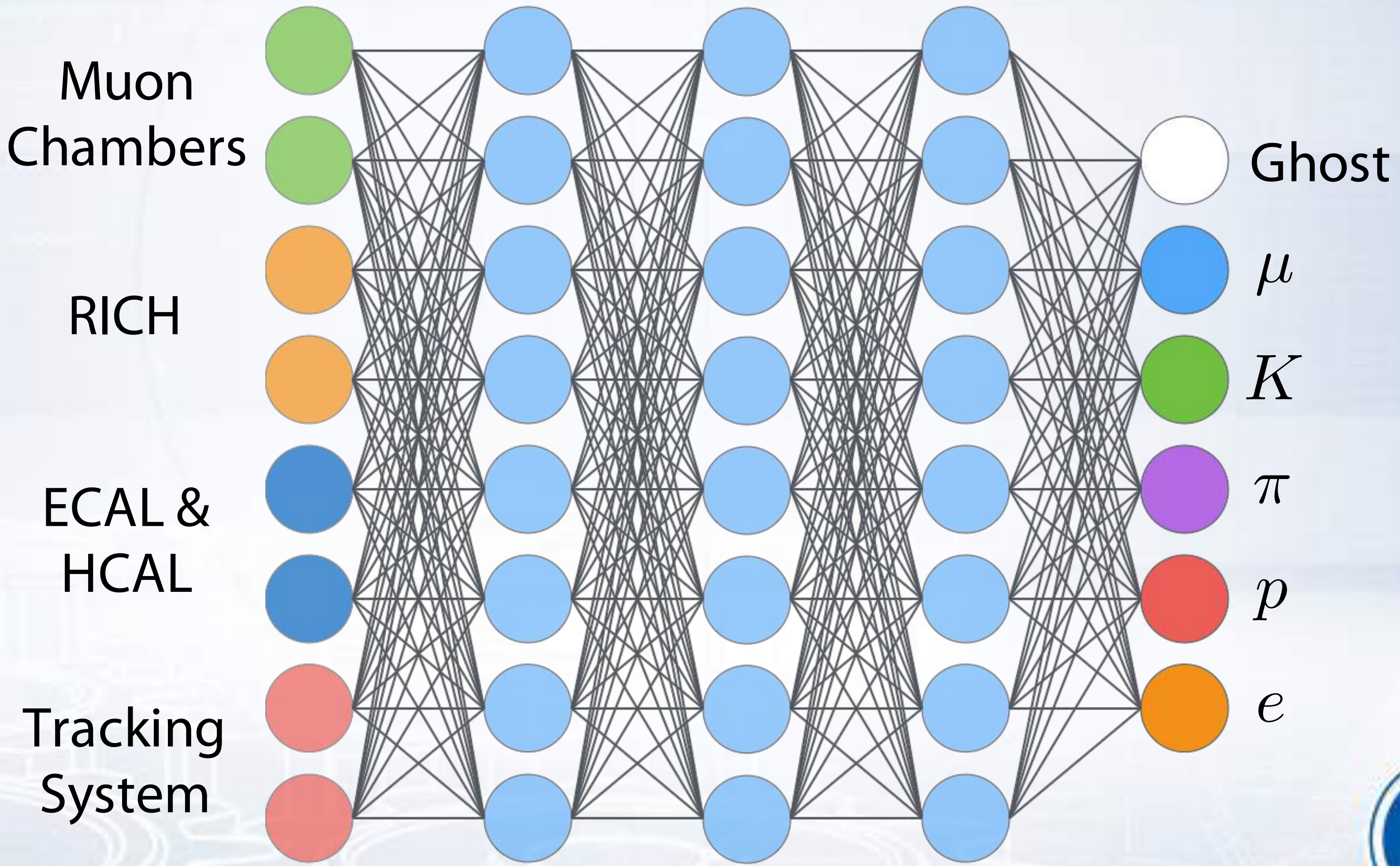
There are 5 particle types: Electron (e), Proton (p) , Kaon (K), Pion (π), Muon (μ).

Detector systems:

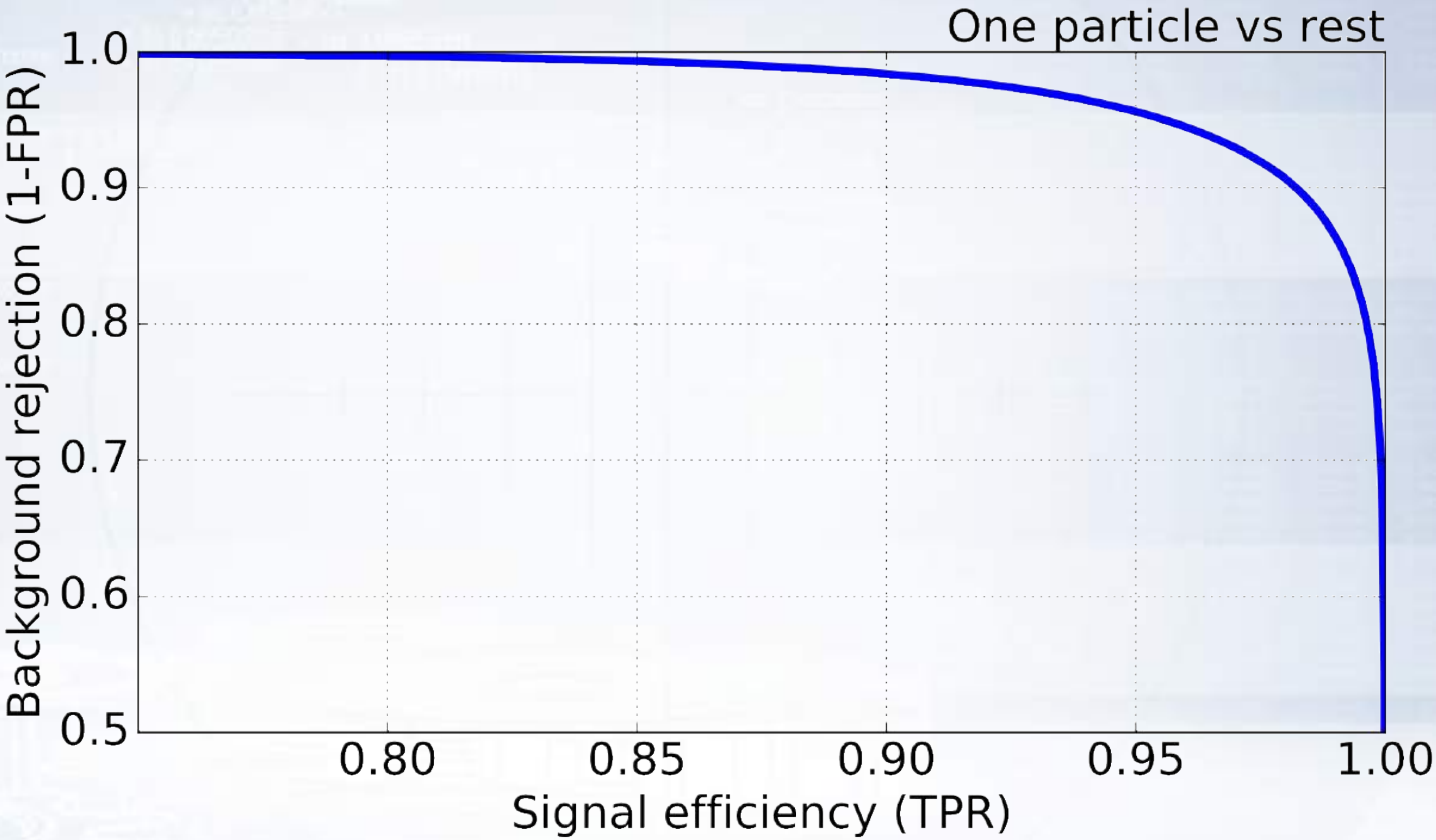
- Tracking system
- Ring Imaging Cherenkov detector (RICH)
- Electromagnetic calorimeter (ECAL)
- Hadron calorimeter (HCAL)
- Muon Chambers

Machine learning in PID

Particle identification is multiclass problem in machine learning:

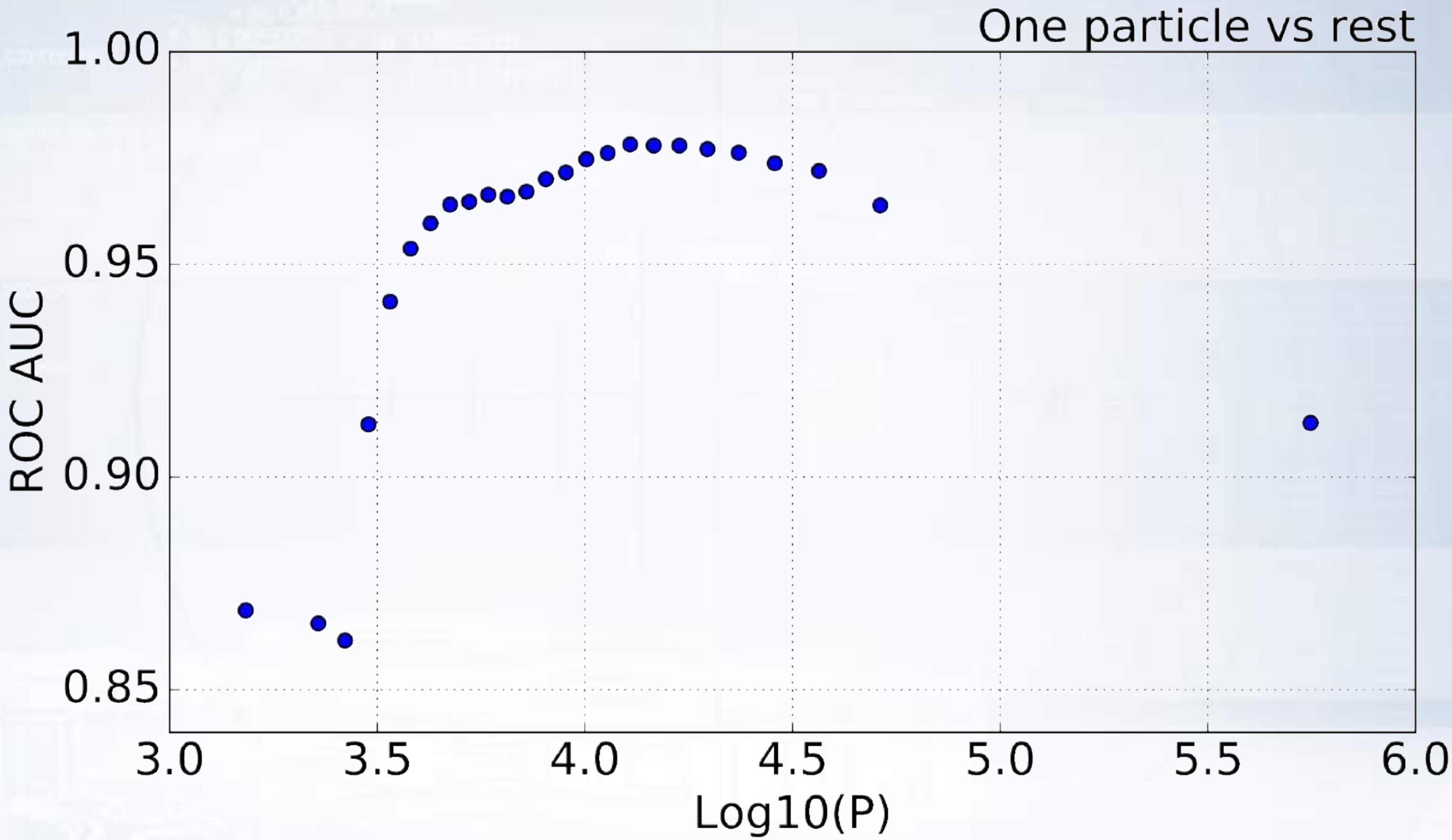


ROC curve in PID



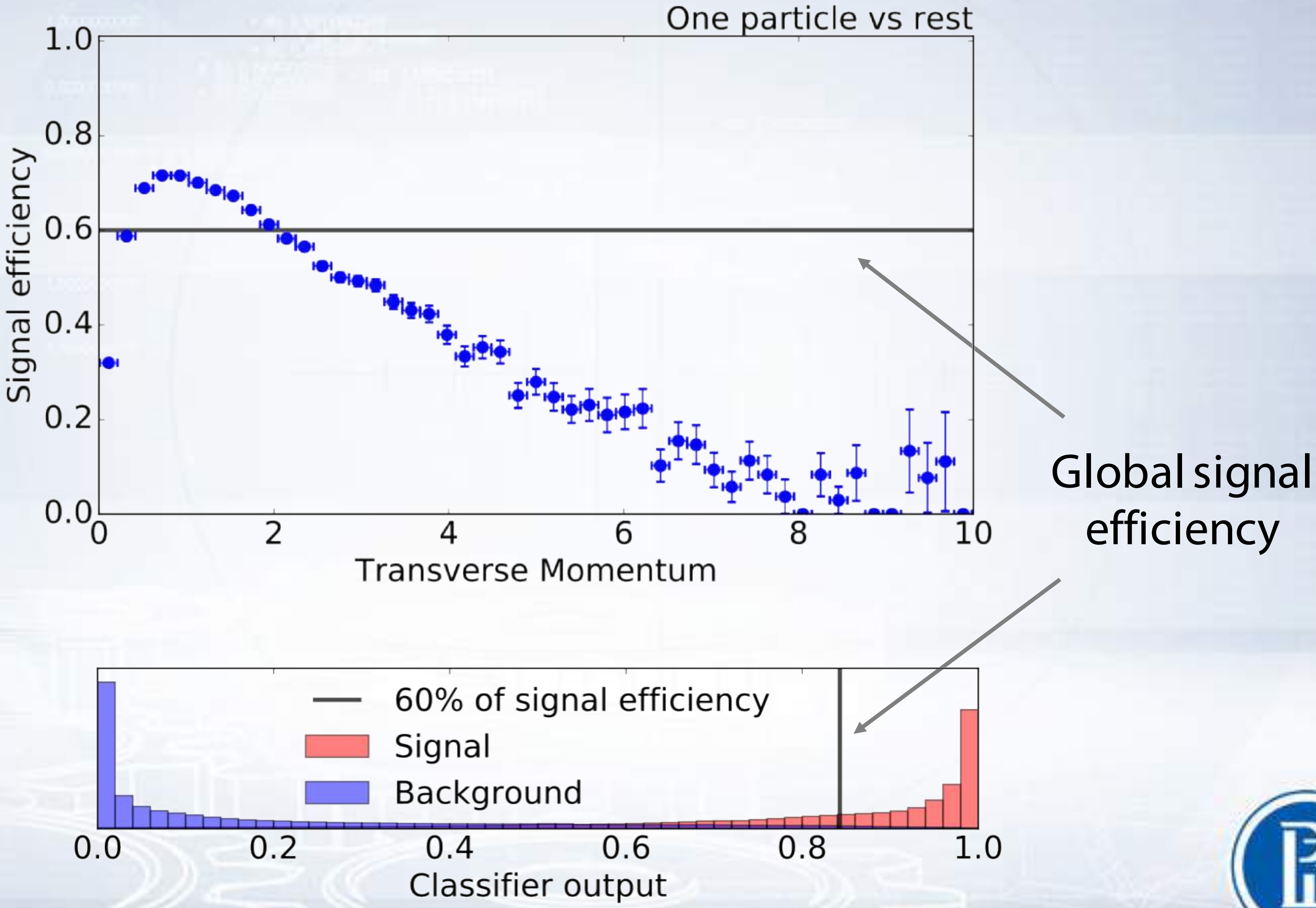
Typical ROC AUC values in PID are 0.90 – 0.995 depending on particle type.

ROC AUC dependencies

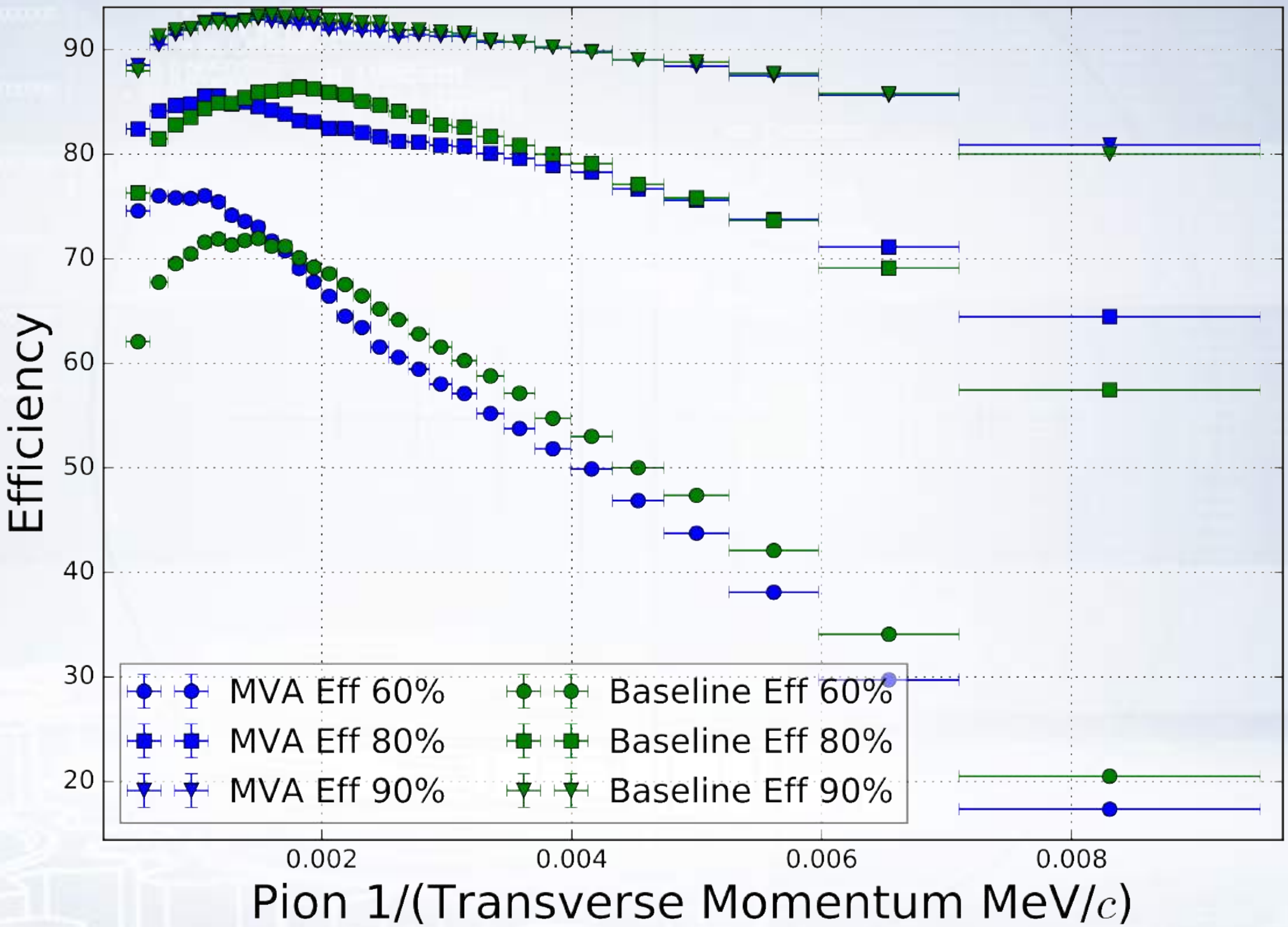


PID quality depends on different particle parameters such as momentum or transverse momentum.

Signal efficiency dependencies



Signal efficiency dependencies



Derkach D. et. al., Machine-Learning-based global particle-identification algorithms at the LHCb experiment, ACAT 2017, Seattle, USA

Uniform Classifiers

Uniform boosting

Consider how to train a boosting over decision trees classifier to provide flat performance on a set of features.

AdaBoost classifier with the following loss function:

$$L_{ada} = \sum_{i=0}^{n} \exp(-\gamma_i s_i)$$

where $\gamma_i \in \{-1, 1\}$ is a true label of an event, s_i is score obtained for each event as the sum of predictions of all trees in the series.

Rogozhnikov A. etc., New approaches for boosting to uniformity, Journal of Instrumentation, Volume 10, March 2015, DOI: 10.1088/1748-0221/10/03/T03002

Uniform boosting

Modify the AdaBoost loss function:

$$L_{ada+flat} = L_{flat} + \alpha L_{ada}$$

where

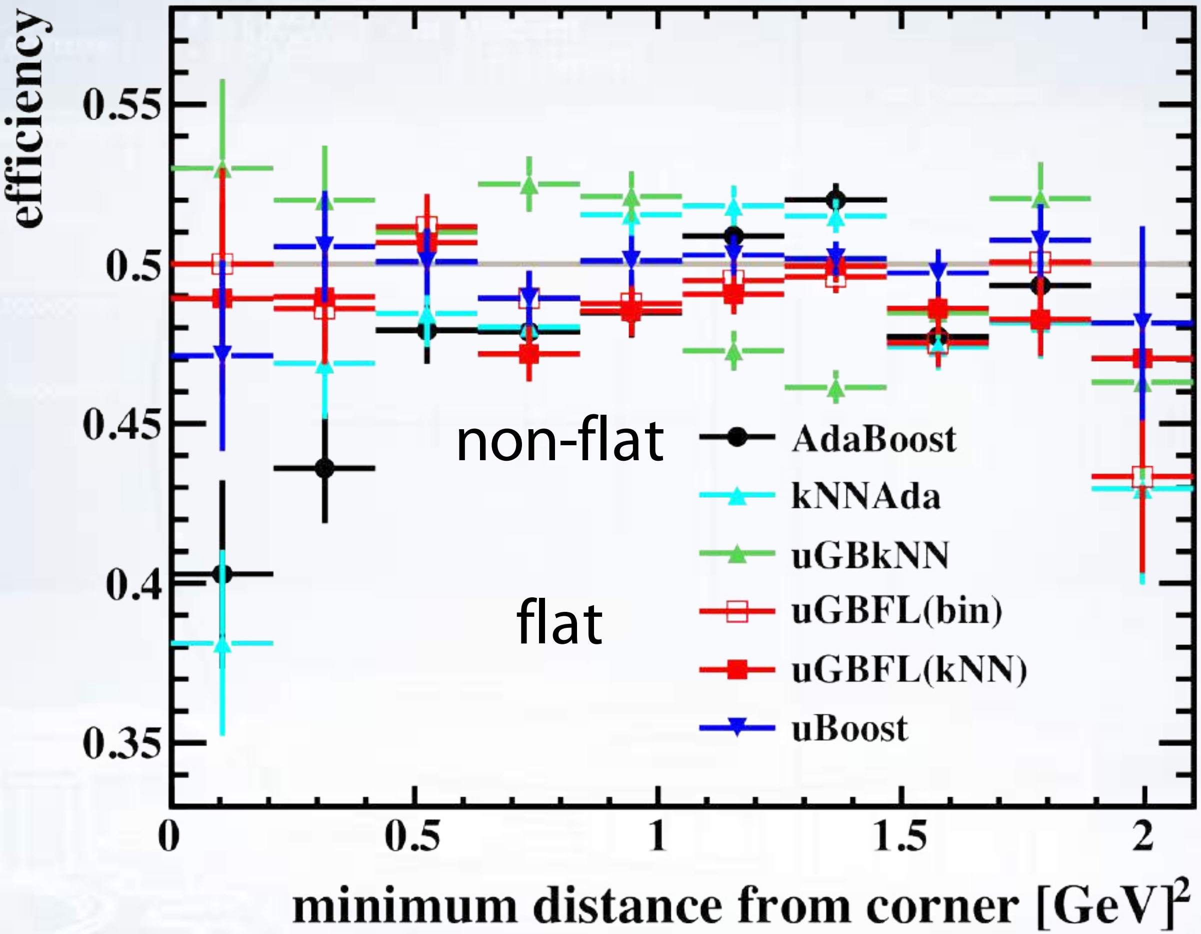
$$L_{flat} = \sum_b w_b \int |F_b(s) - F(s)|^2 ds$$

where w_b is the fraction of signal events in a bin b, $F_b(s)$ is the cumulative distribution of the classifier output in the bin, $F(s)$ is the global cumulative distribution of the classifier output.

For the flat classifier efficiency $L_{flat} \to 0$

Rogozhnikov A. etc., New approaches for boosting to uniformity, Journal of Instrumentation, Volume 10, March 2015, DOI: 10.1088/1748-0221/10/03/T03002

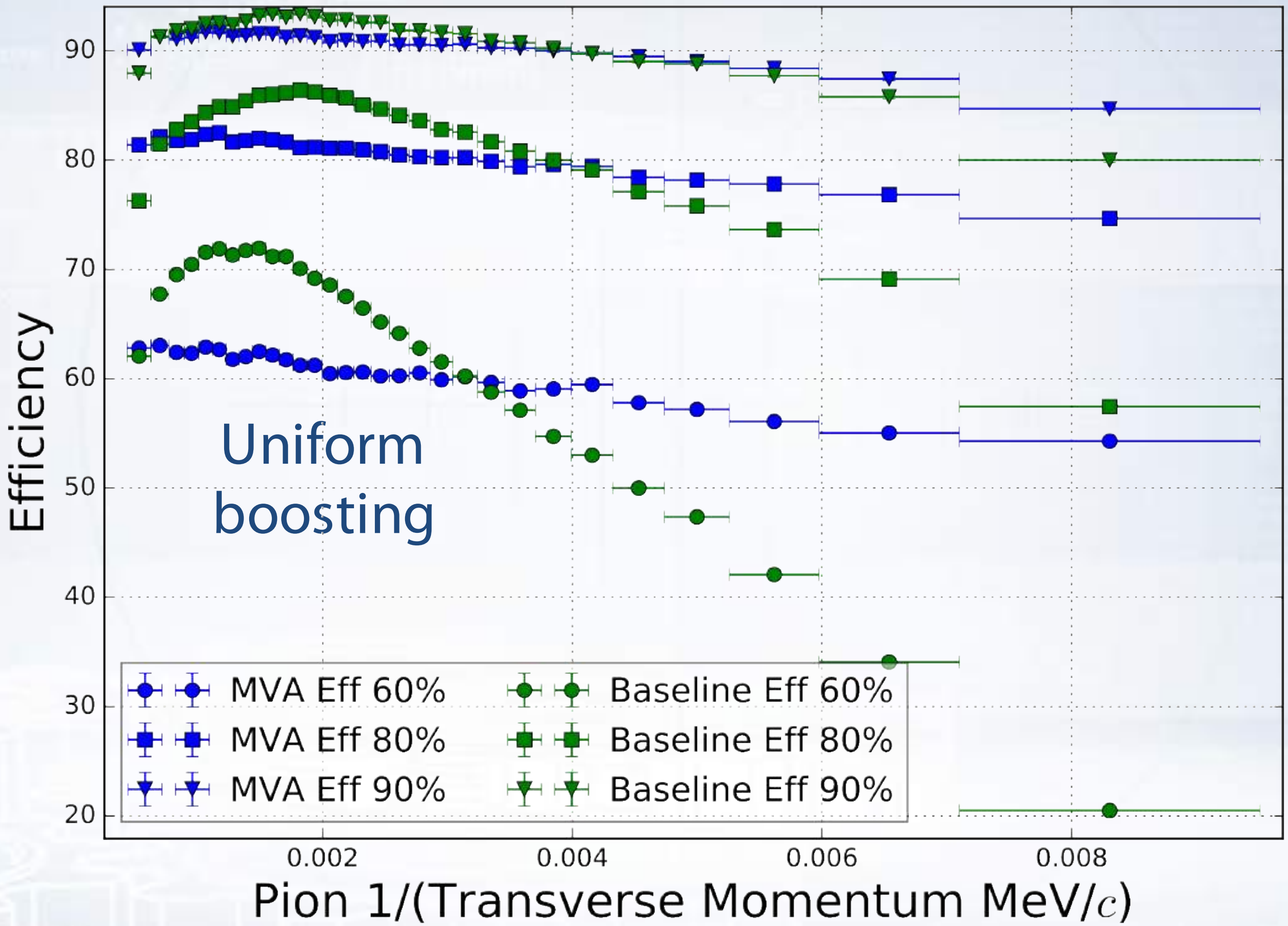
Uniform boosting



Global signal efficiency is 50%

Rogozhnikov A. etc., New approaches for boosting to uniformity, Journal of Instrumentation, Volume 10, March 2015, DOI: 10.1088/1748-0221/10/03/T03002

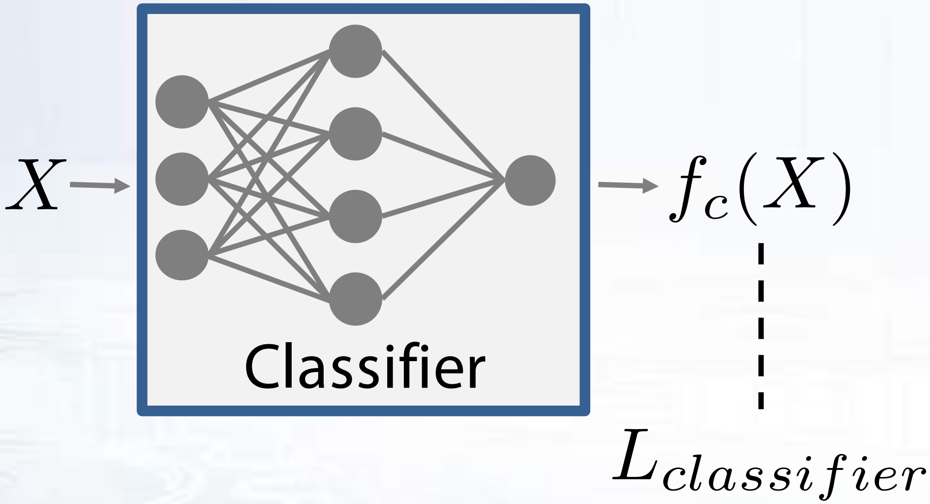
Uniform boosting



Derkach D. et. al., Machine-Learning-based global particle-identification algorithms at the LHCb experiment, ACAT 2017, Seattle, USA

Decorrelation using adversarial NN

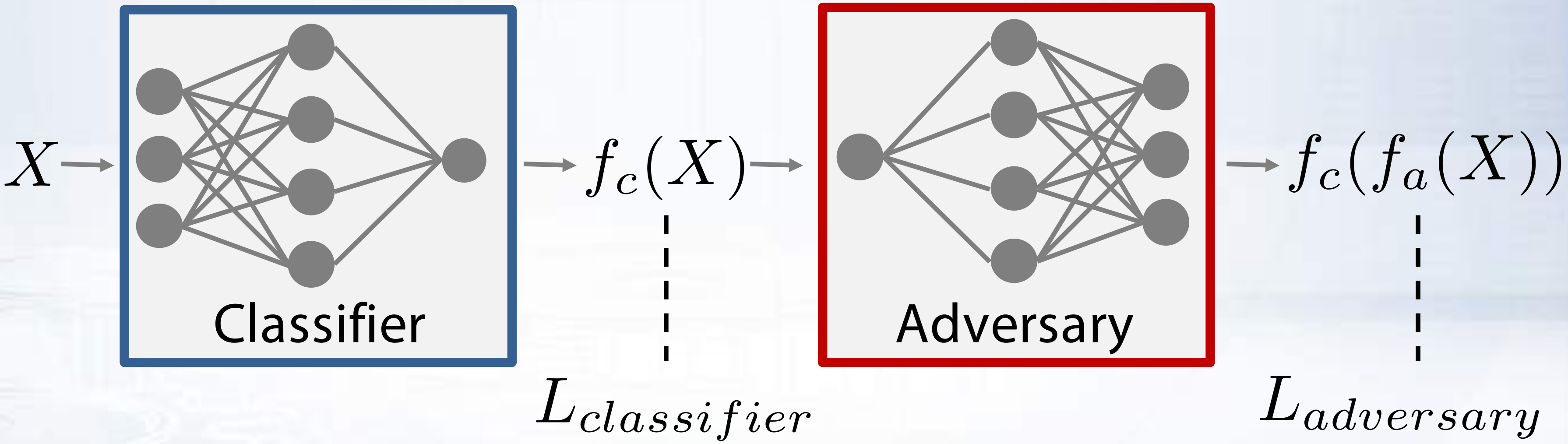
Classifier is trained to identify particle type. It returns score (probability) particle belong to a type.



Shimmin C. et. al., Decorrelated Jet Substructure Tagging using Adversarial Neural Networks, Phys. Rev. D 96, 074034 (2017), DOI:10.1103/PhysRevD.96.074034

Decorrelation using adversarial NN

Adversary is trained to predict particle parameter such as momentum, mass and other. The parameter is predicted using multiclassification problem.



Shimmin C. et. al., Decorrelated Jet Substructure Tagging using Adversarial Neural Networks, Phys. Rev. D 96, 074034 (2017), DOI:10.1103/PhysRevD.96.074034

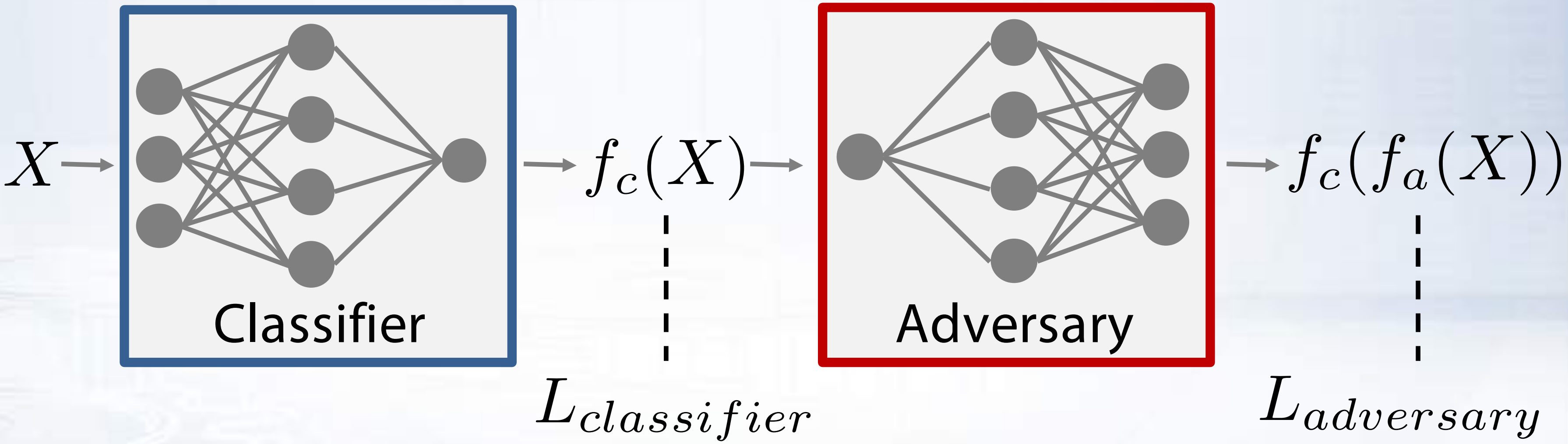
Decorrelation using adversarial NN

To provide flat output of the classifier minimize concurrently two loss functions:

$$L_{adversary}$$

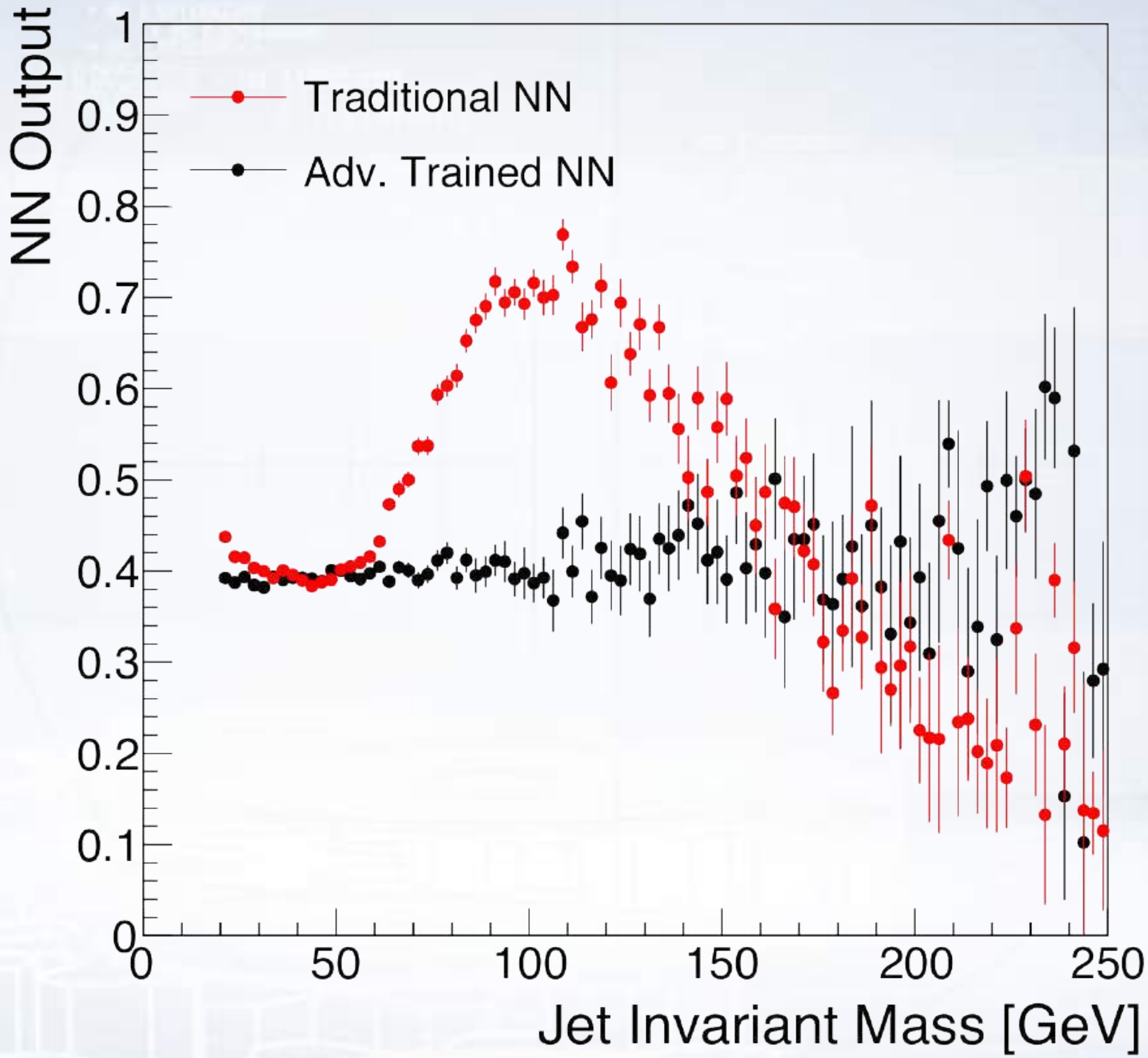
and

$$L = L_{classifier} - \lambda L_{adversary}$$



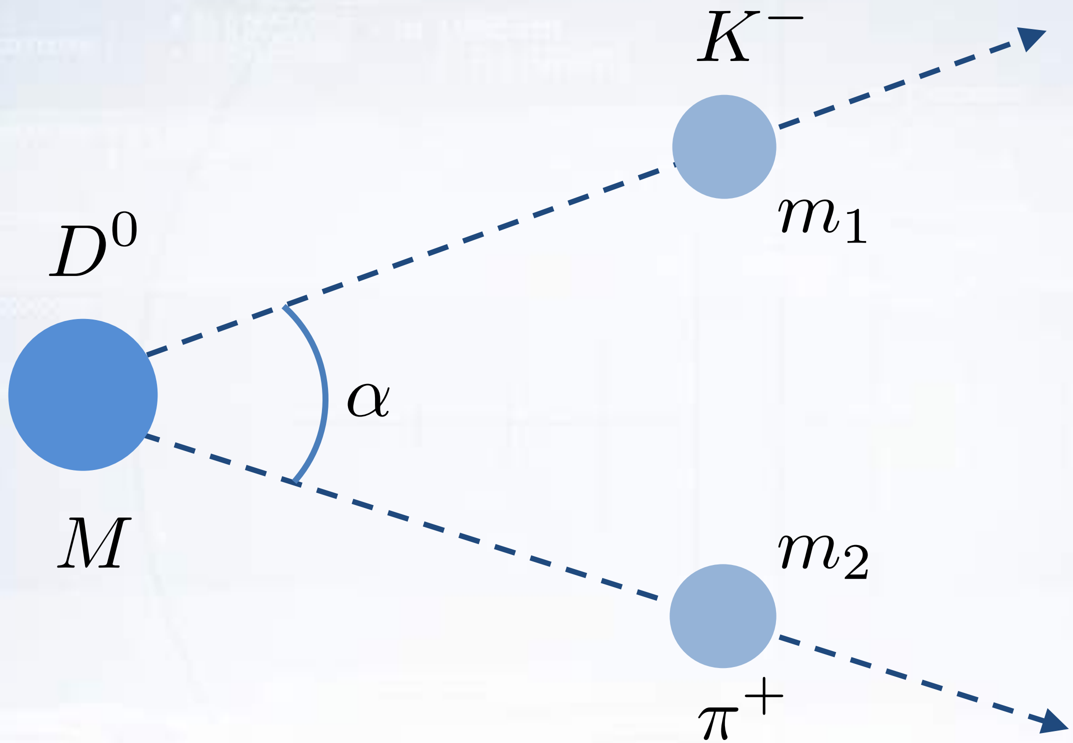
Shimmin C. et. al., Decorrelated Jet Substructure Tagging using Adversarial Neural Networks, Phys. Rev. D 96, 074034 (2017), DOI:10.1103/PhysRevD.96.074034

Decorrelation using adversarial NN



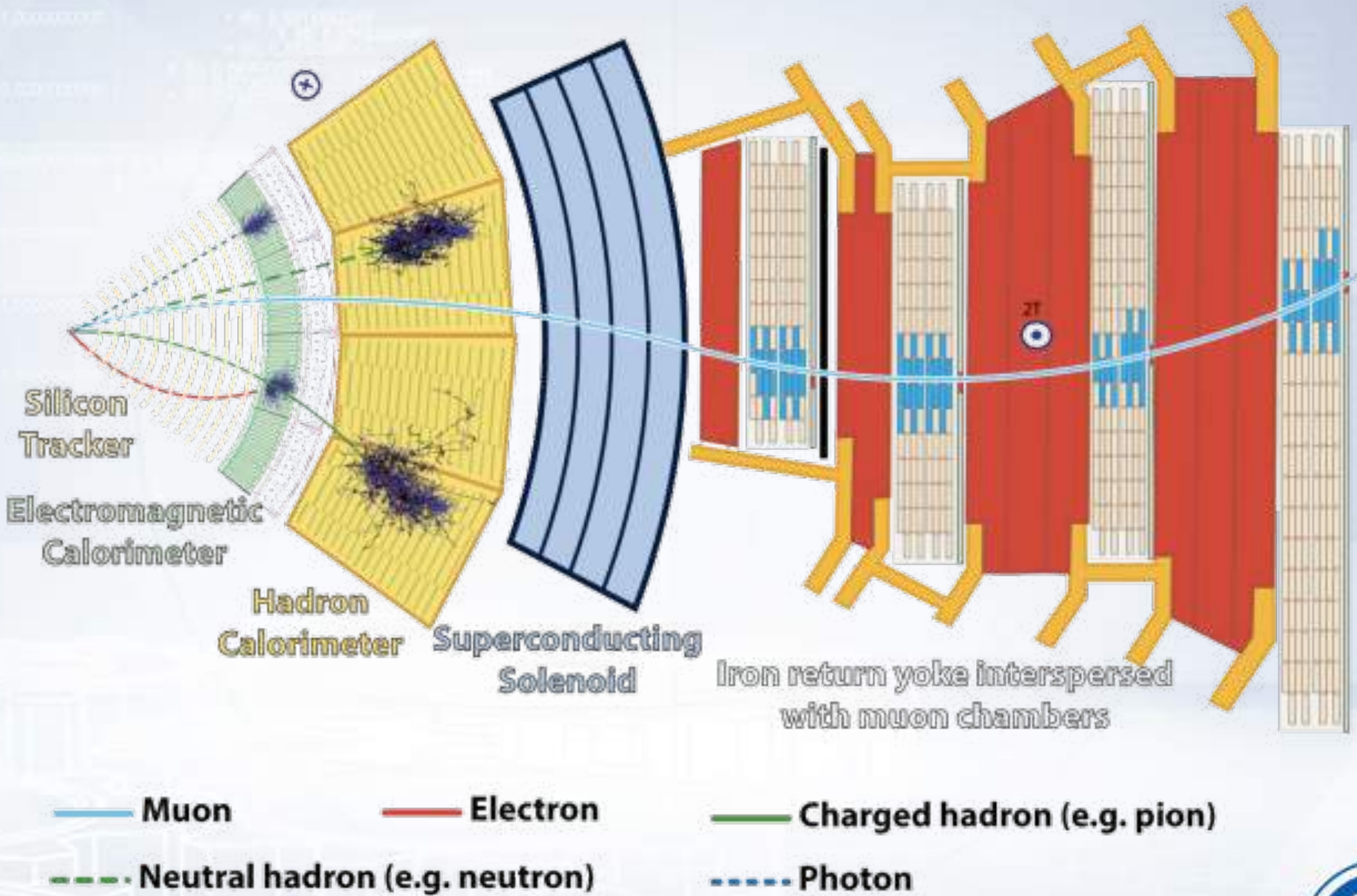
Shimmin C. et. al., Decorrelated Jet Substructure Tagging using Adversarial Neural Networks, Phys. Rev. D 96, 074034 (2017), DOI:10.1103/PhysRevD.96.074034

Summary



$$M^2 = m_1^2 + m_2^2 + \frac{2}{c^4}(E_1 E_2 - p_1 p_2 c^2 \cos\alpha)$$

Summary



CMS / https://cds.cern.ch/record/2120661

Summary

Machine Learning cases:

- Particle tracks pattern recognition among detector hits
- Combining recognized tracks into vertices
- Particle momentum estimation
- Ring image recognition in RICH subdetectors
- Particle energy estimation and neutral particle identification based on calorimeter responses
- Global particle identification based on responses of different subdetectors

References

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