MACHINE LEARNING APPLICATION IN THE SEARCH FOR A MAGNETIC MONOPOLE IN ATLAS

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ATLAS EXPERIMENT

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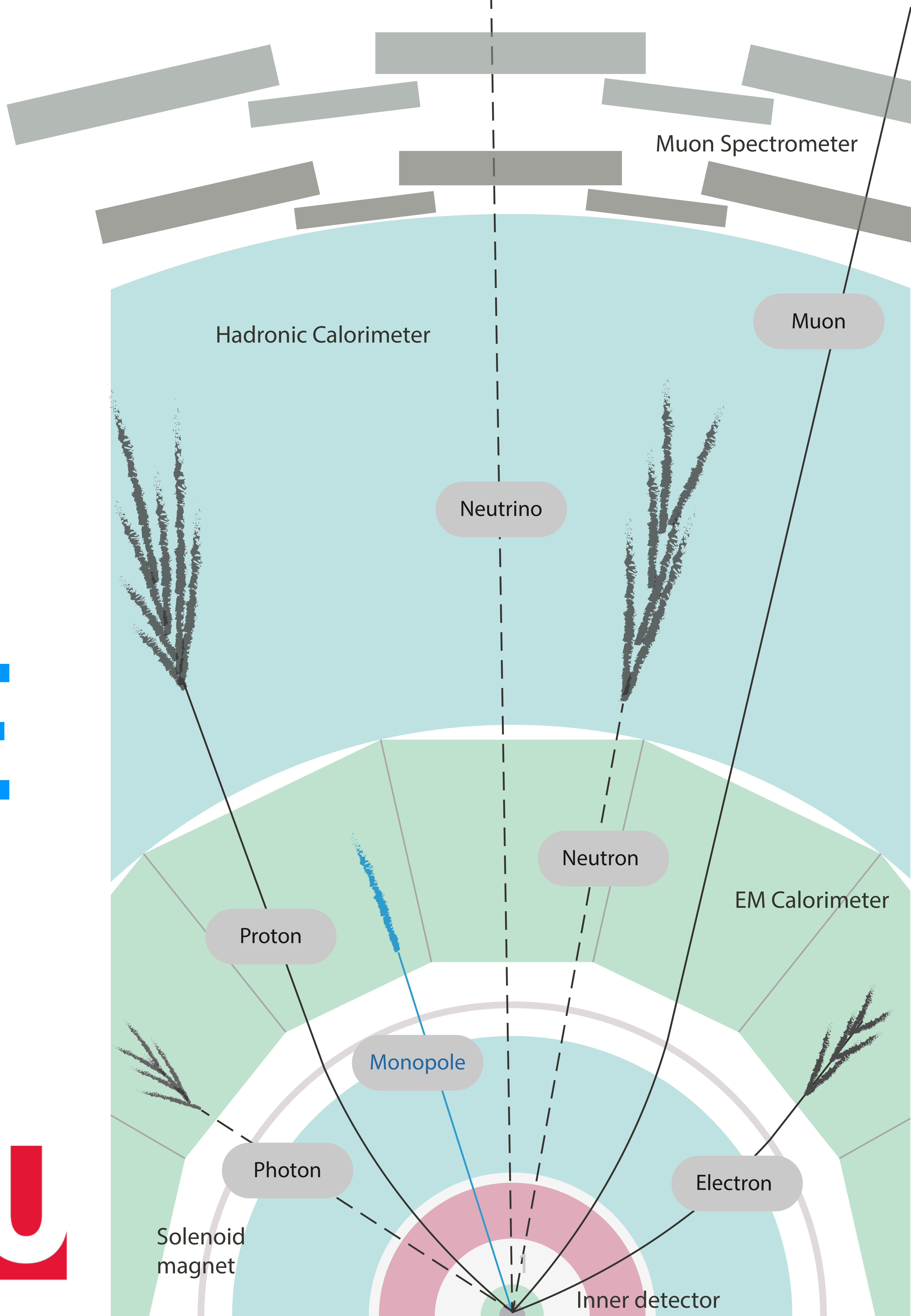


OVERVIEW – TL;DR

- Search for magnetic monopoles in the ATLAS detector
- Pileup conditions in Run 2 affect the discriminating power of one of our signal selection variables
- Random Forest Classifier introduced in the hopes of increasing signal efficiency
- This results in improvement for higher mass monopoles, but reduced signal efficiency in lower mass monopoles

MOTIVATION

- Dirac Magnetic Monopoles (Quantum electrodynamics) [see Dirac]:
  - ➤ Explain electric charge quantization
  - ➤ Symmetry (electric-magnetic fields) in Maxwell's equations

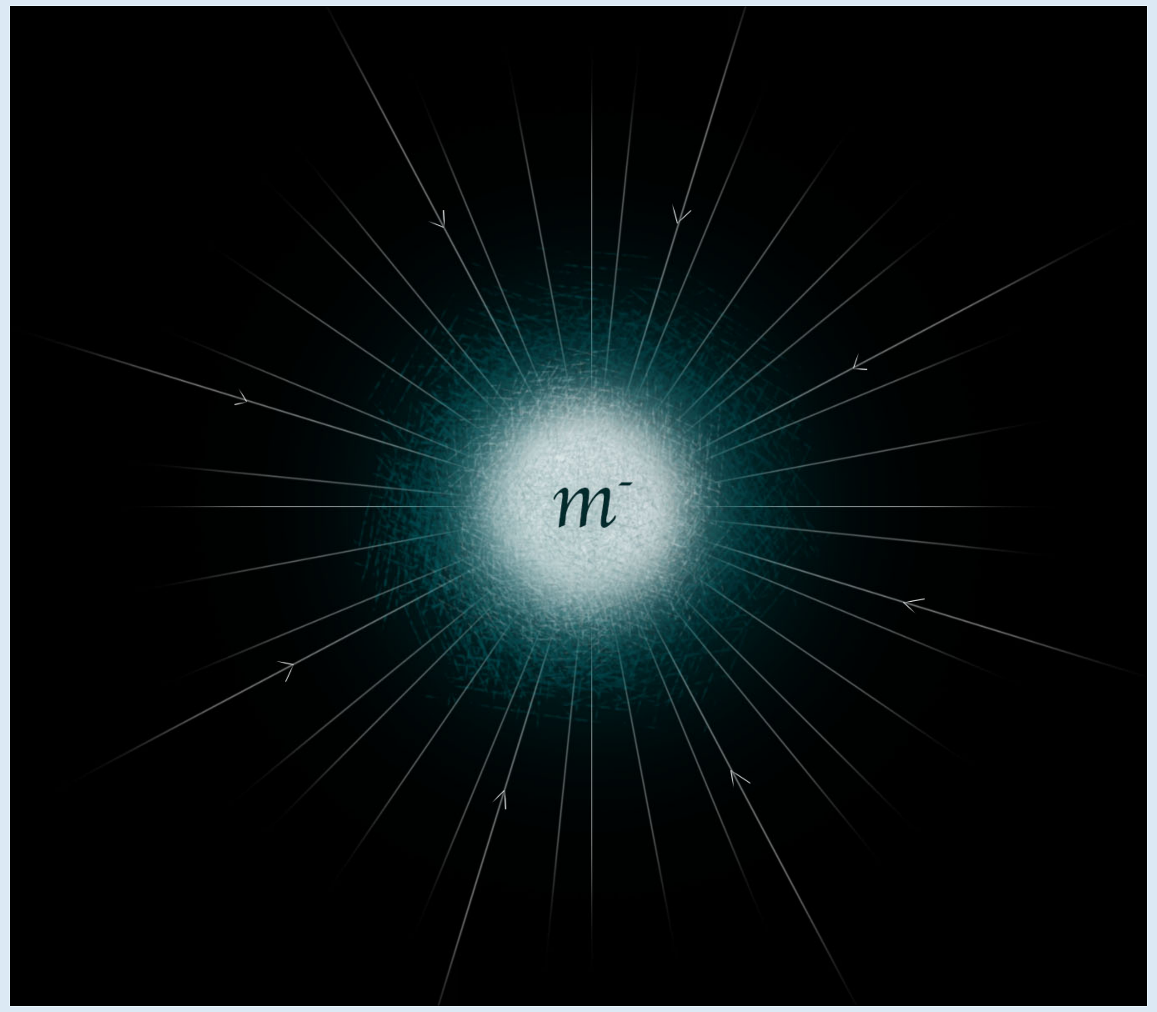
$$\nabla \cdot \mathbf{E} = \frac{\rho_e}{\epsilon_0} \qquad \nabla \cdot \mathbf{B} = \mu_0\, \rho_m$$

$$\nabla \times \mathbf{E} = -\mu_0 \left(\mathbf{j_m} + \frac{\partial \mathbf{B}}{\partial t} \right)$$

$$\nabla \times \mathbf{B} = \epsilon_0 \mu_0 \left(\mathbf{j_e} + \frac{\partial \mathbf{E}}{\partial t} \right)$$

$$\frac{q_m q_e}{\hbar c} = \frac{N}{2}$$

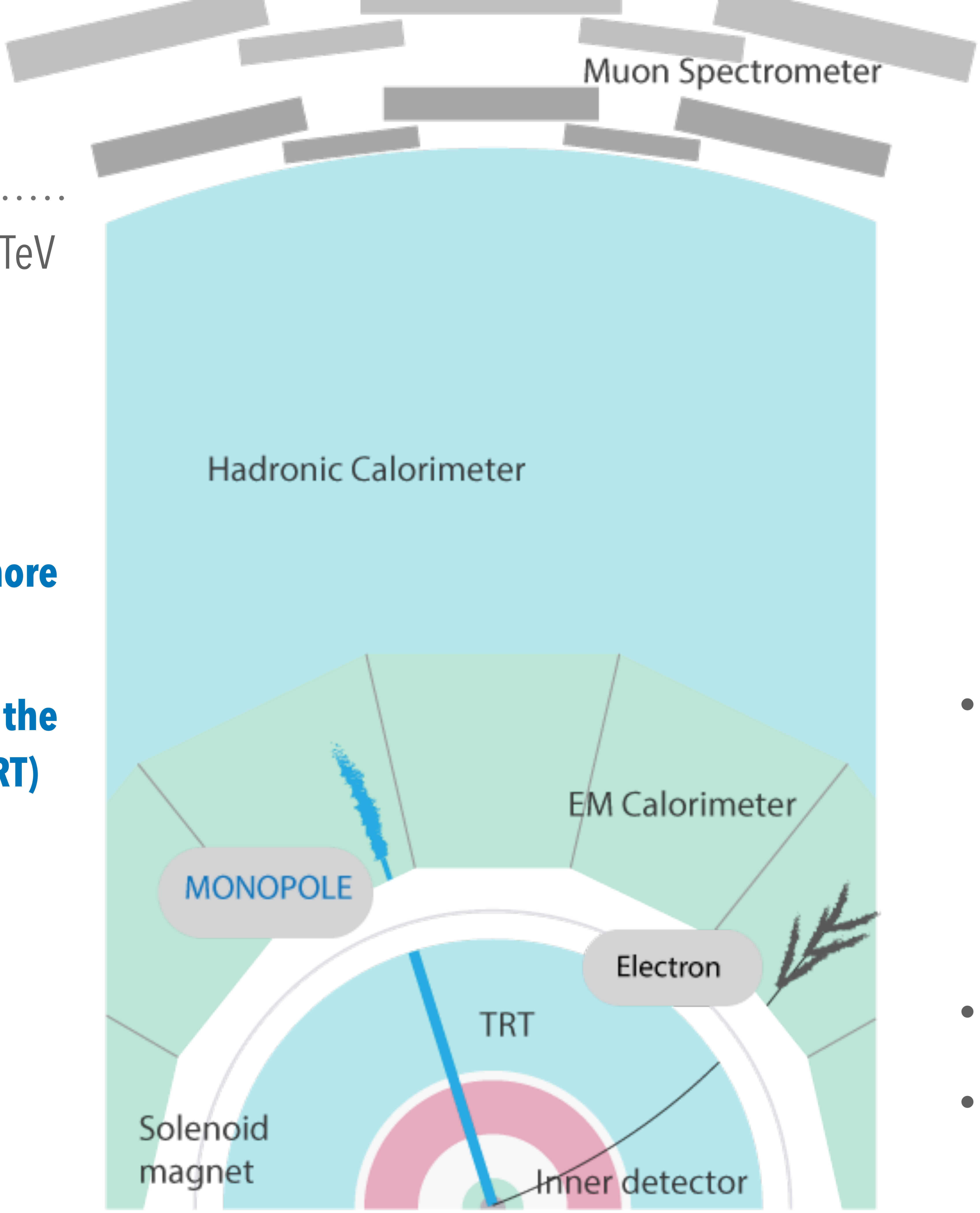
$$q_m = N g_D e c \qquad g_D = \frac{1}{2\alpha} = 68.5$$



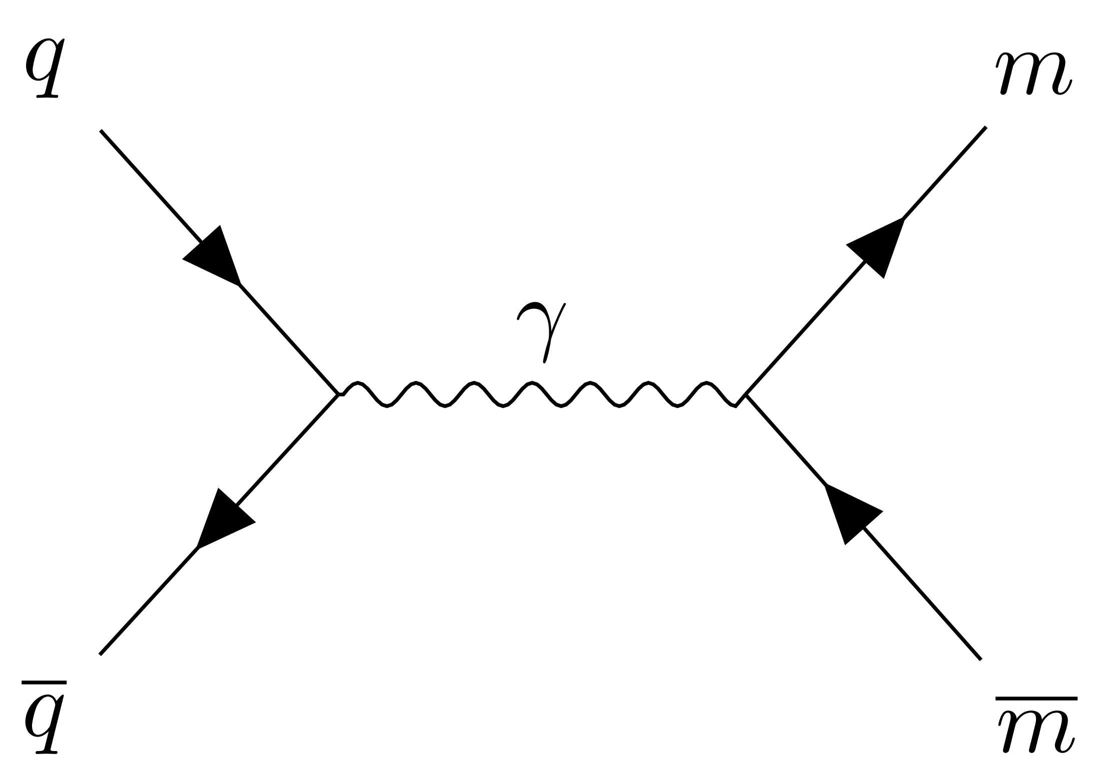
- Magnetic monopole: Fundamental particle with magnetic charge "q_m"
- Static source of radial magnetic field.
- Stable due to magnetic charge conservation.

METHOD

- **ATLAS detector**: LHC (Run 2) 13 TeV pp collisions, ~130 fb[-1]
  - ➤ m_m< 4 TeV
- **Ionization** of the medium
  - ➤ Energy loss ∝ charge² **~4700 x more ionizing than proton!**
  - ➤ **Many large energy deposits in the Transition Radiation Tracker (TRT)**
  - ➤ **Stops before muon system, mostly before Hadronic Calorimeter**
  - ➤ **Monopoles don't produce a shower in ATLAS LAr EM Calorimeter**



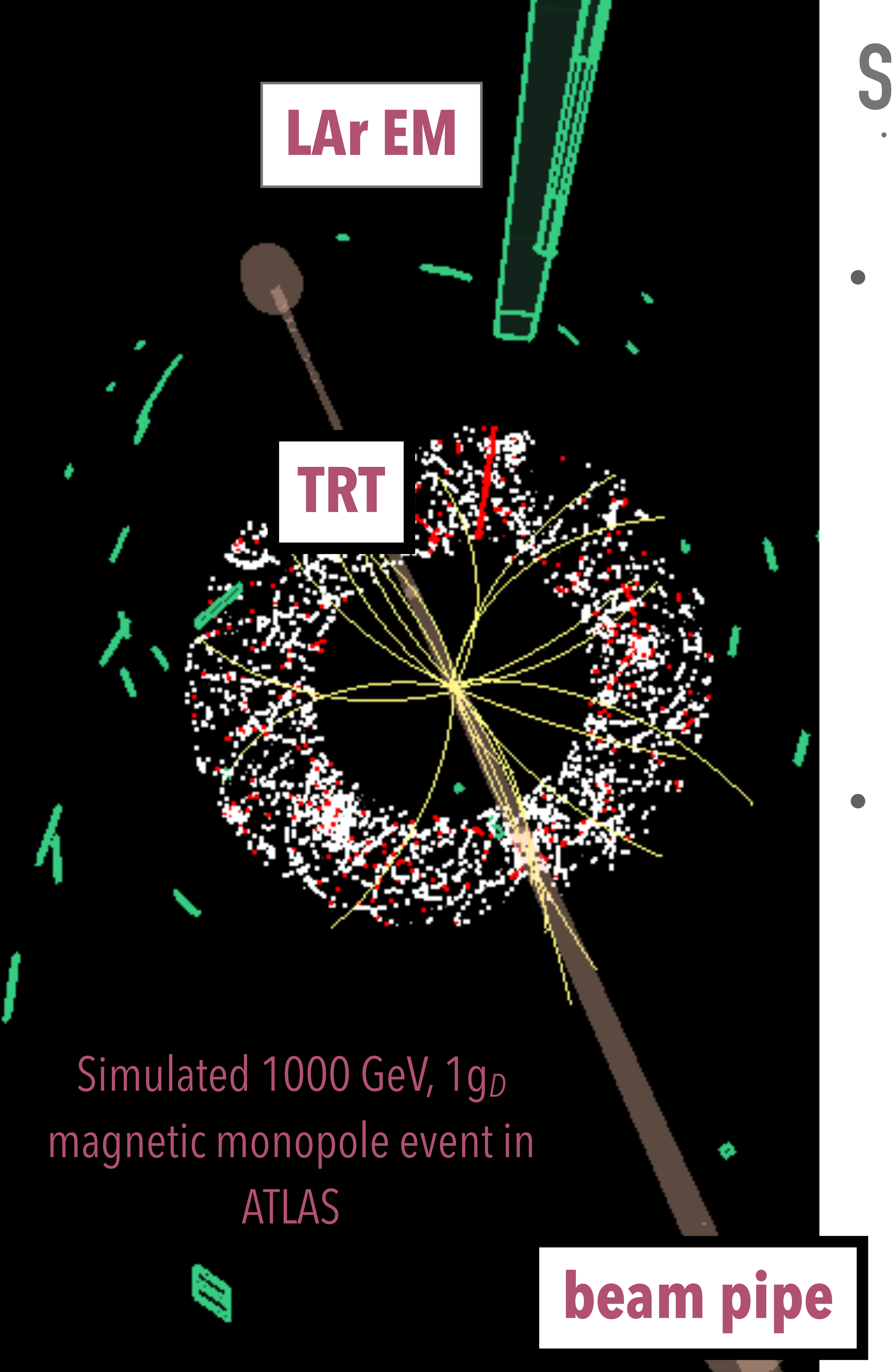
ATLAS DETECTOR SCHEMATIC IN THE r-Φ plane



Feynman-like diagrams for Drell-Yan magnetic monopole pair production.

- **Drell-Yan (DY)** pair production dictates kinematic distributions and predicted cross sections.
  - ➤ **Spin 0 and 1/2** monopoles
- Monopole: **$|g|$ = 1 g_D, 2 g_D**
- Masses considered: Between 0.2 and 4 TeV.

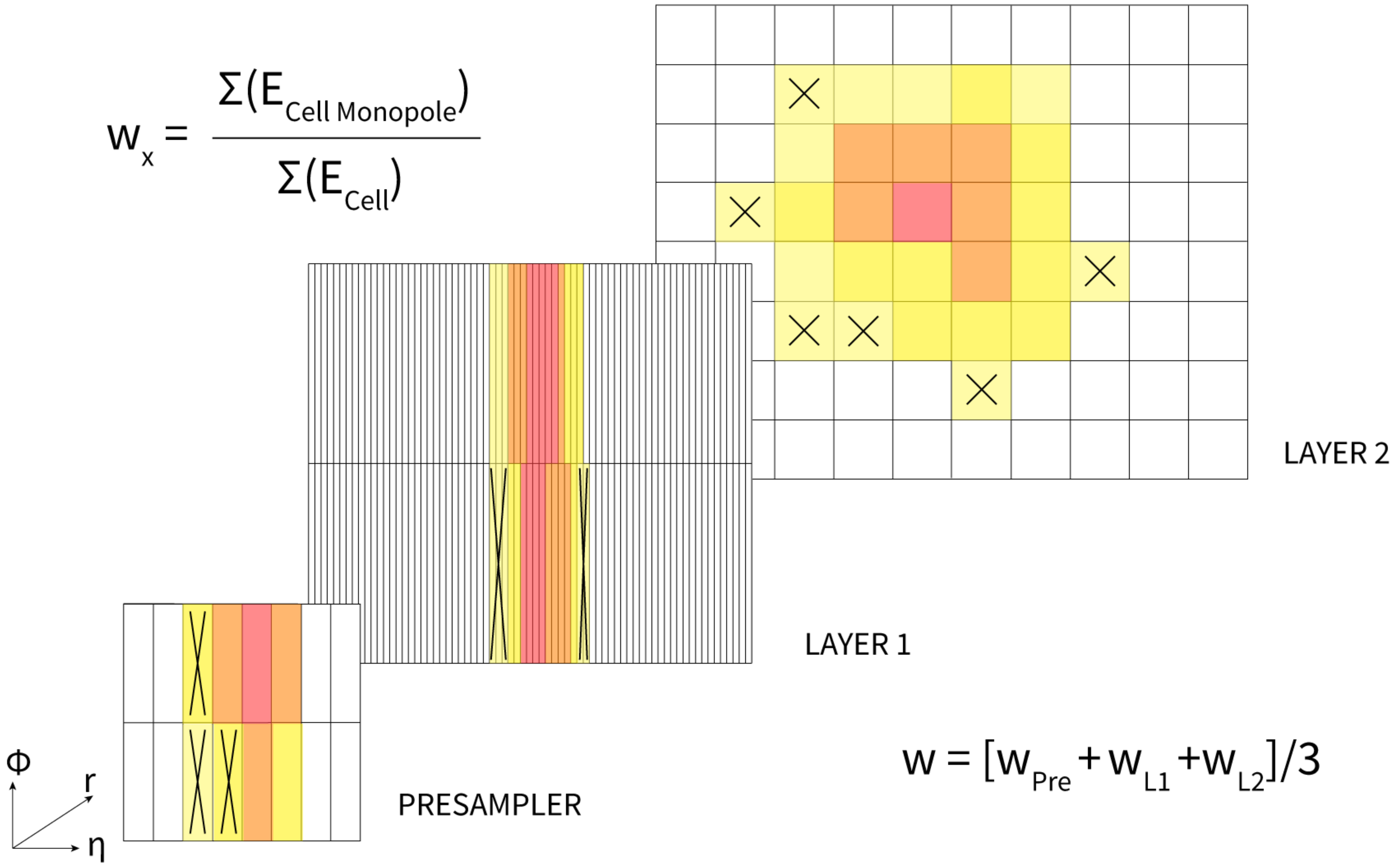
SIGNAL DISCRIMINATING VARIABLES:



Simulated 1000 GeV, 1g_D magnetic monopole event in ATLAS

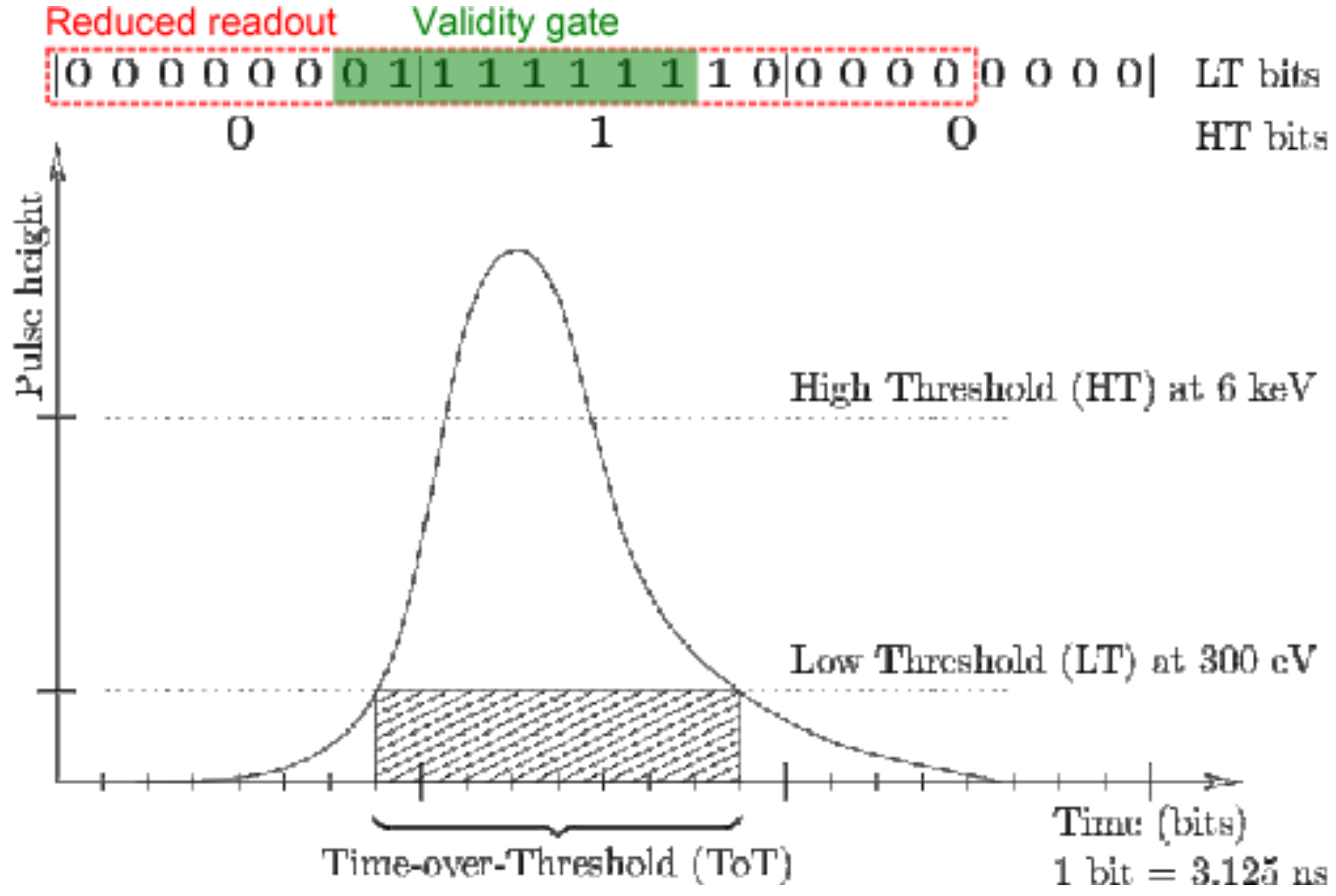
- **Concentrated high energy** deposition in the LAr EM calorimeter.

w



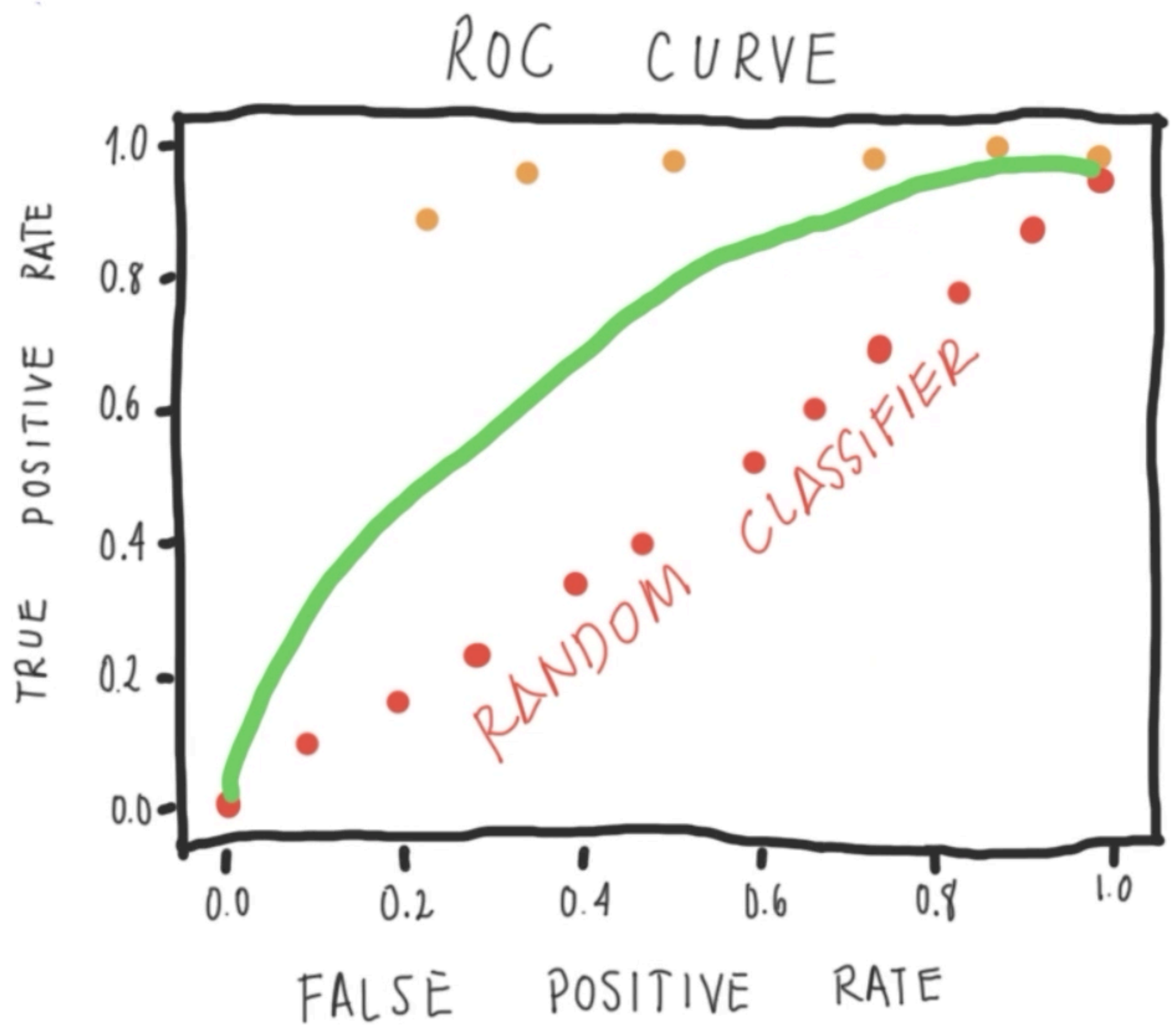
- Many large energy deposits in the TRT observed as **TRT High Threshold hits**

$$f_{HT} = \frac{HT_{hits}}{HT_{hits} + LT_{hit}}$$



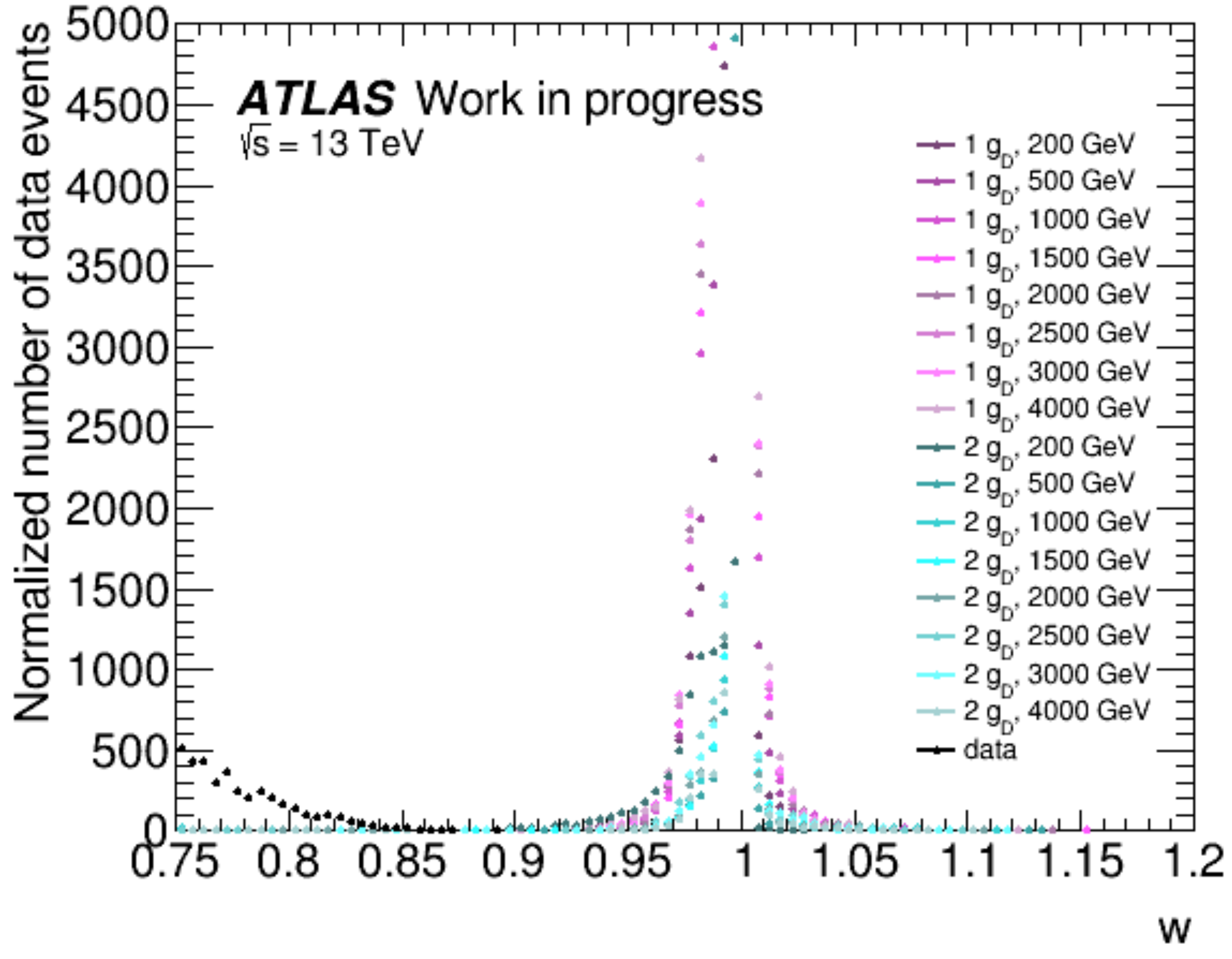
ROC CURVES

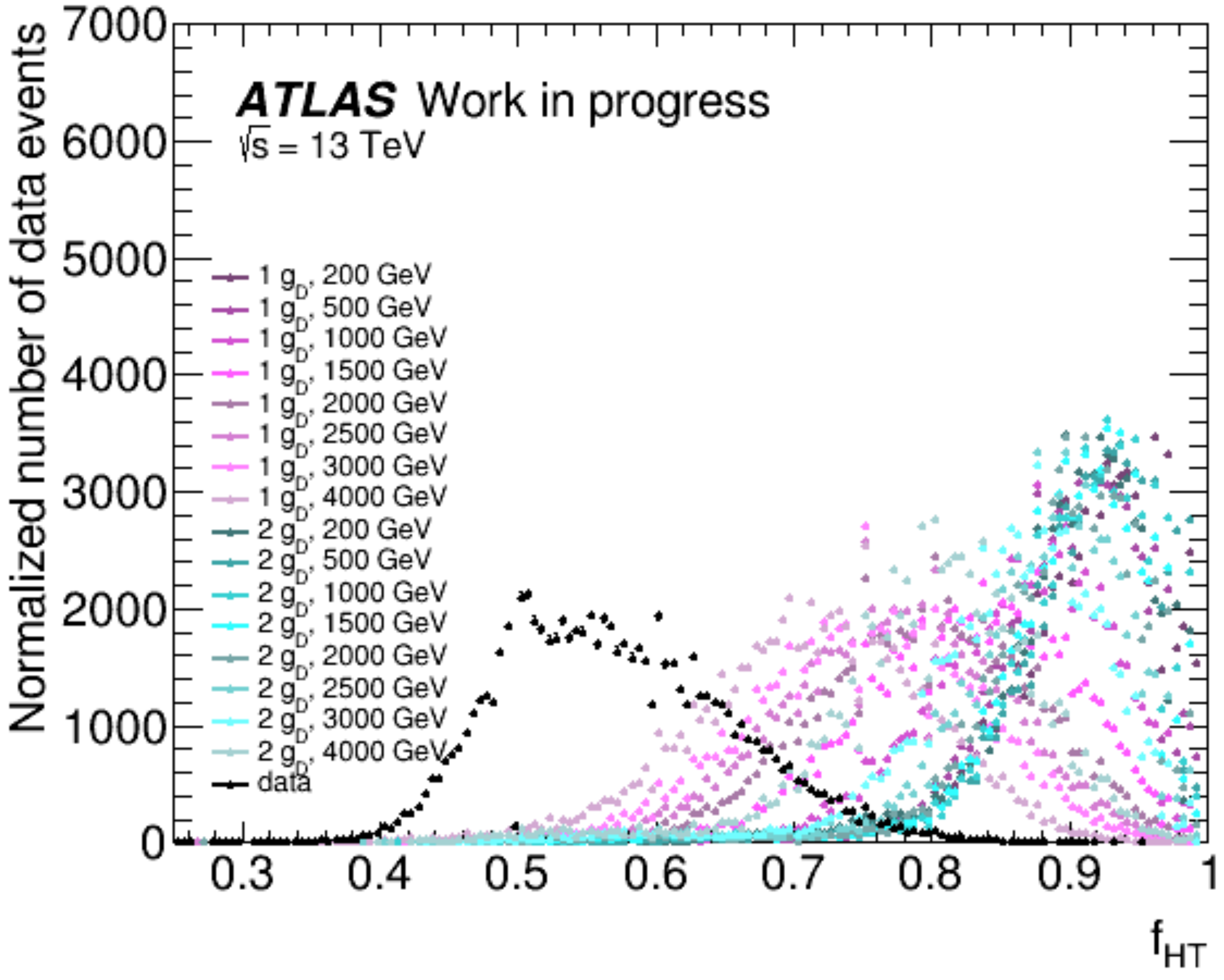
*Receiver Operating Characteristic

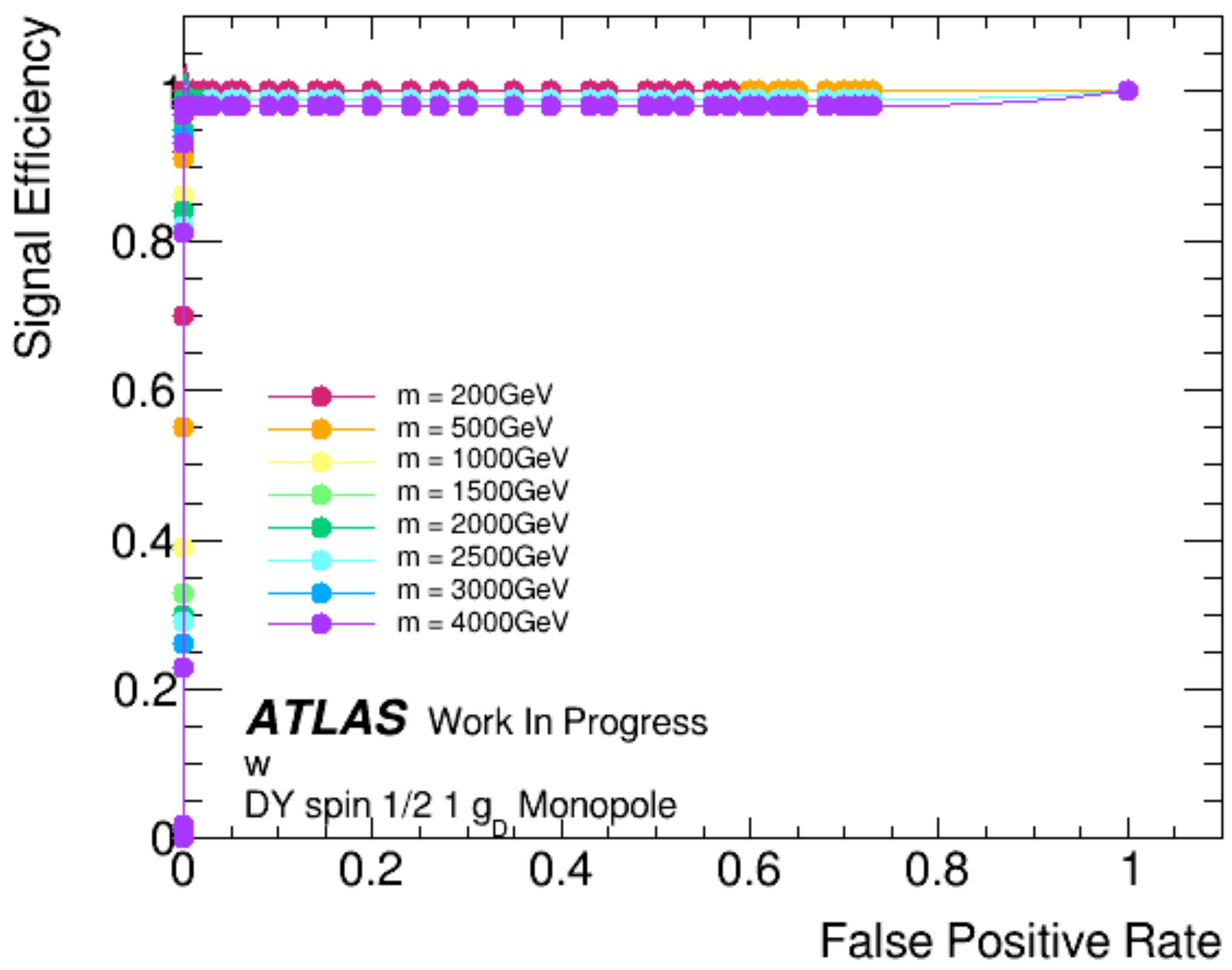


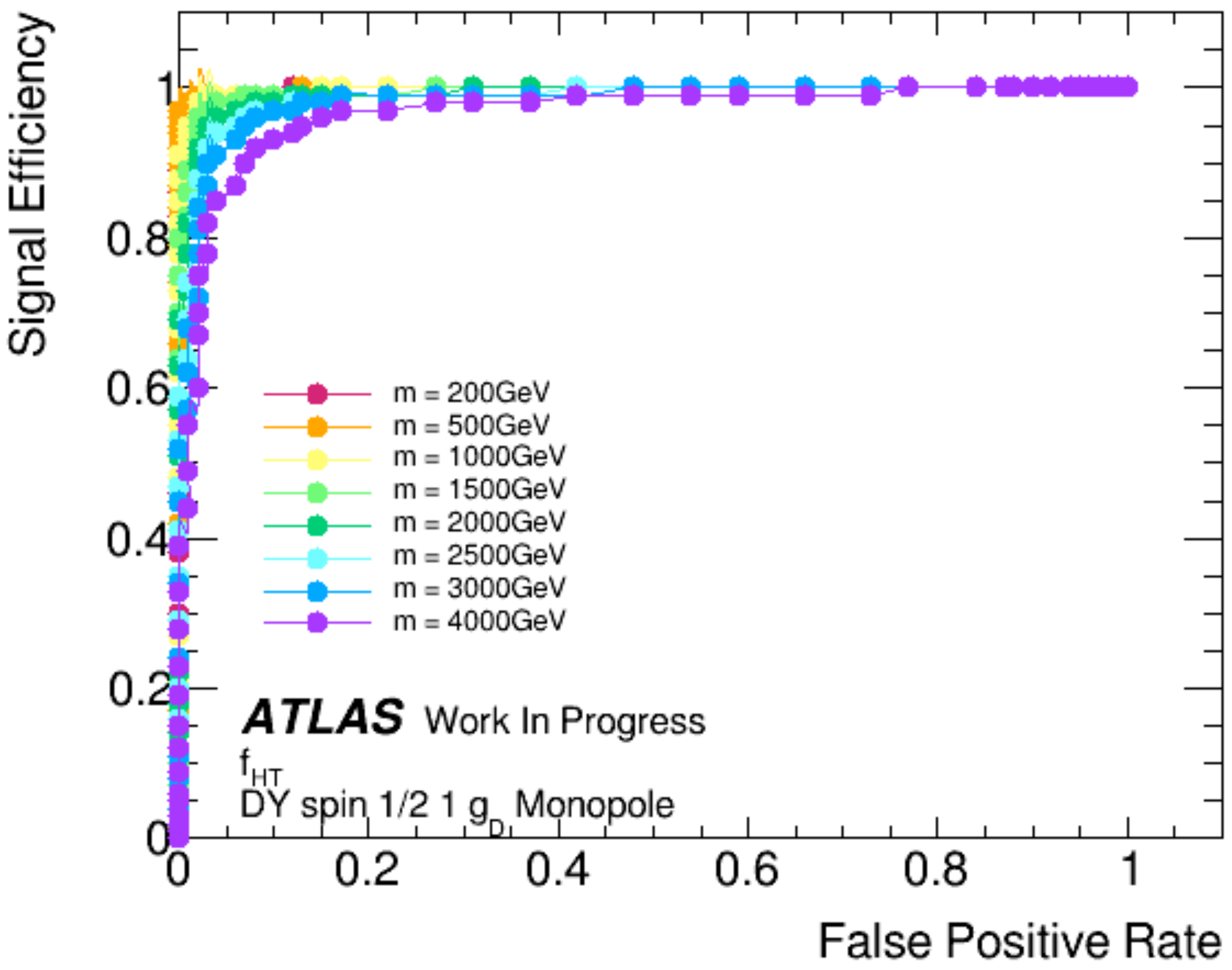
- Balance between signal selection (TPR) and background rejection (FPR)
- Area under the curve (AUC) measures discriminating power

W AND F_{HT} DISCRIMINATING POWER

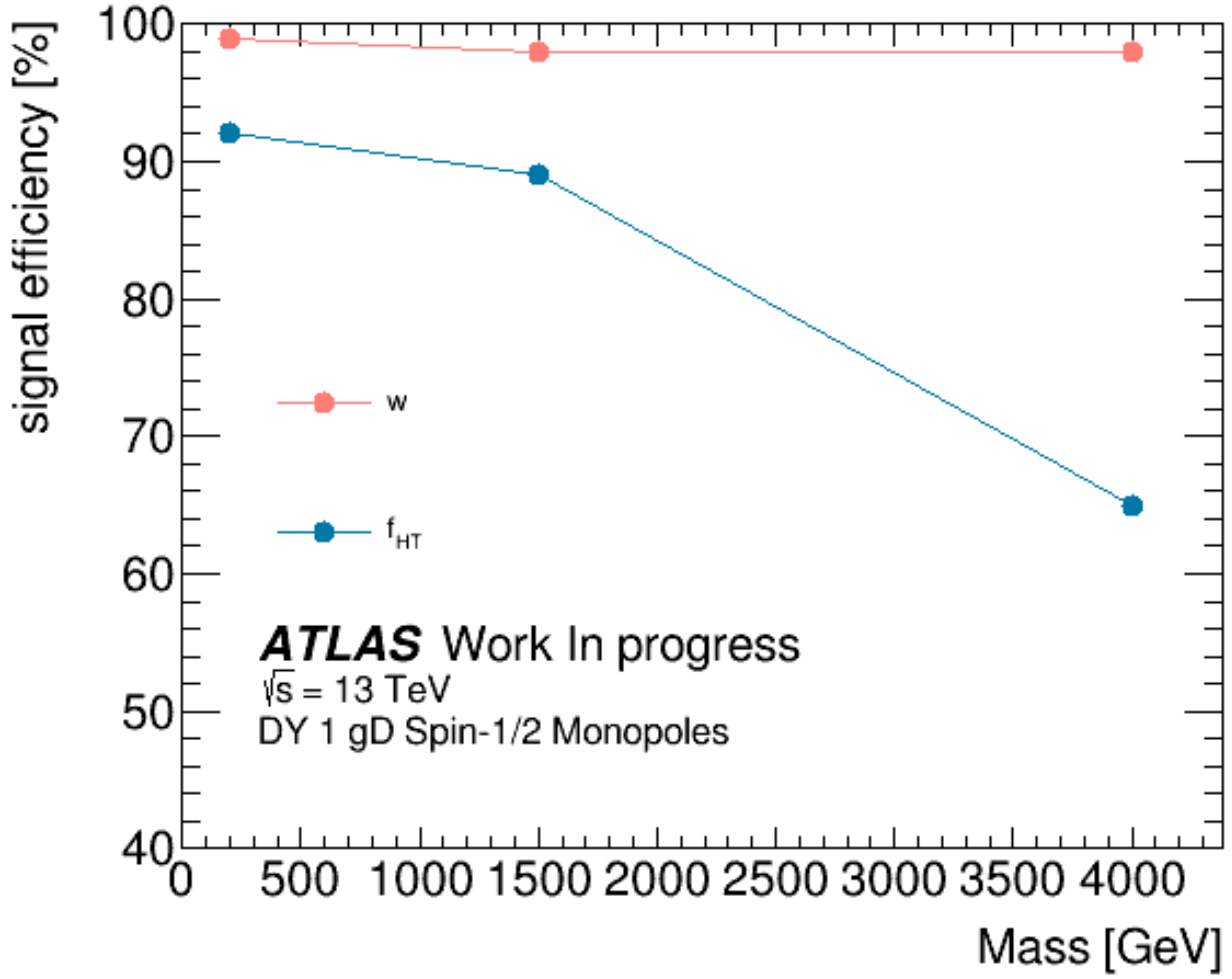






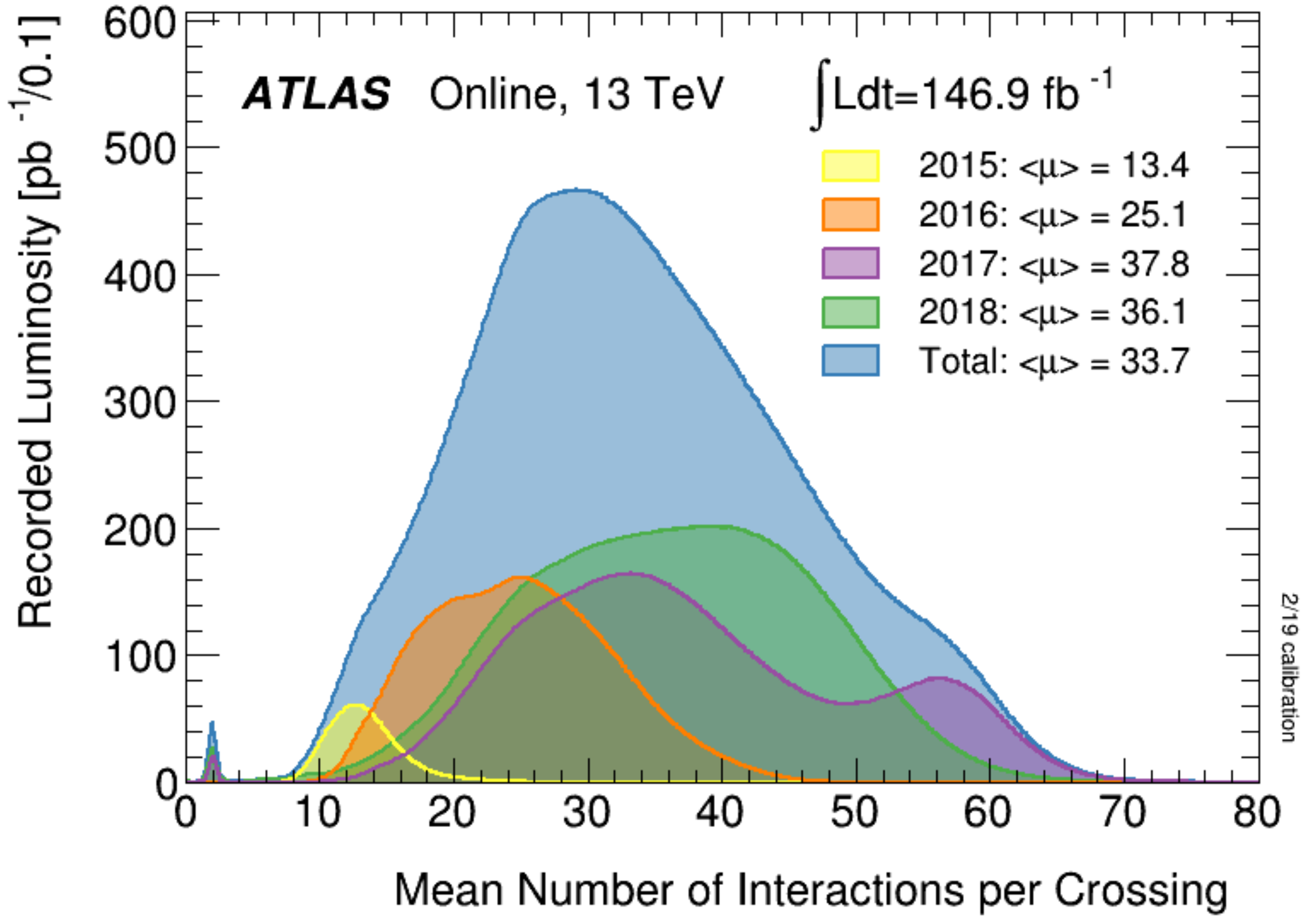


- *w* has almost ideal discriminating power!
- The larger the mass, the less we are able to discriminate using f_{HT}

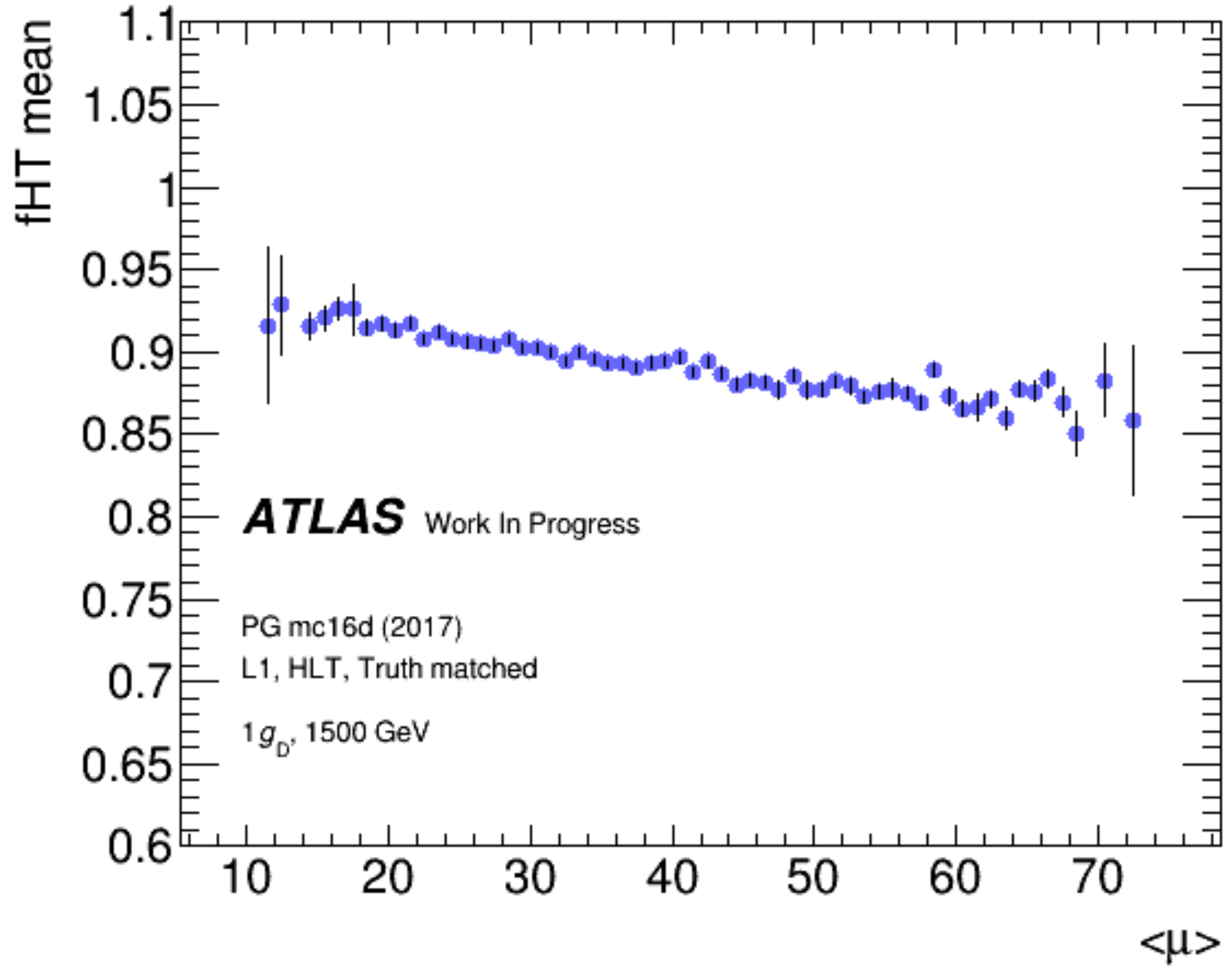


F_{HT} – TRT PILEUP PROBLEM

- Increased number of interactions per bunch-crossing
  - ➤ More low threshold hits
- **f_{HT} decreases as a function of the mean number of interactions per bunch crossing <μ>**
- Introducing alternative methods to quantify high-threshold hits

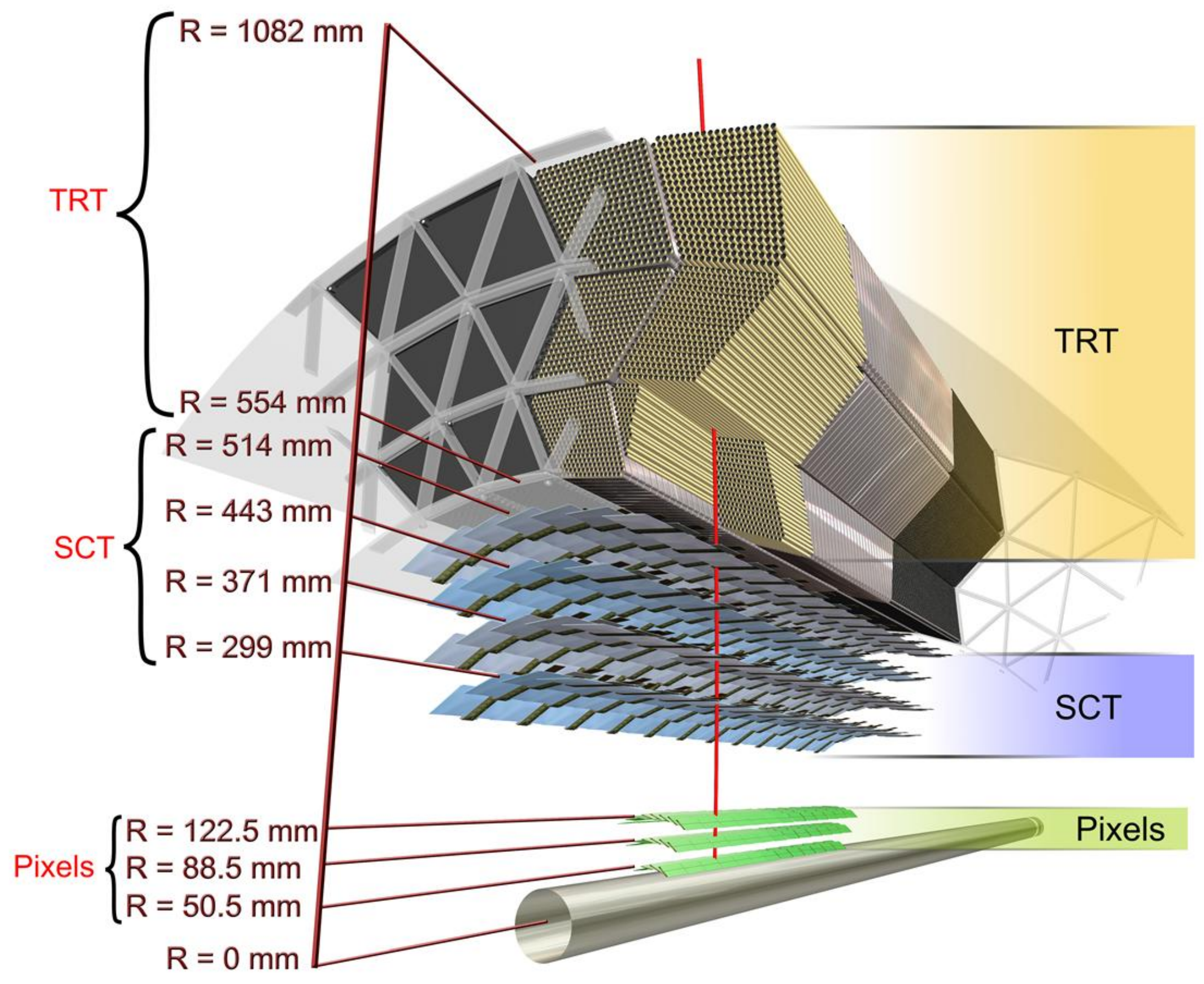


Luminosity-weighted distribution of the mean number of interactions per crossing for p-p collisions [see ATLAS Twiki]



f_{HT} IMPROVEMENT THROUGH RANDOM FOREST CLASSIFIER

- Train a random forest (RF) classifier on a pair of sections called "roads" (one signal, one background) of the TRT for the same event
- Consider only TRT-barrel events



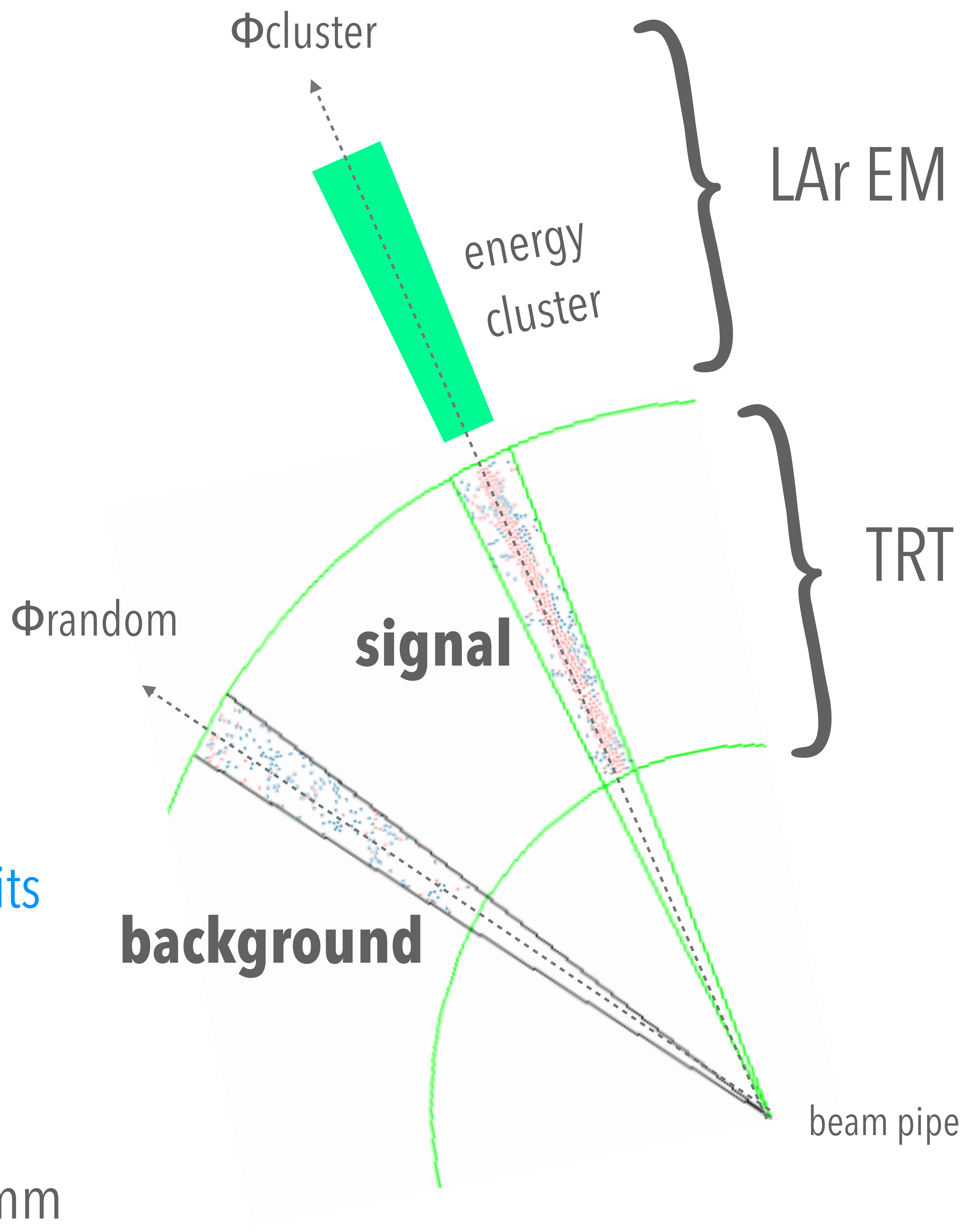
ATLAS Inner Detector barrel r-Φ slice

Features

- 2D representation of HT hits, LT hits and empty straws.

Labels

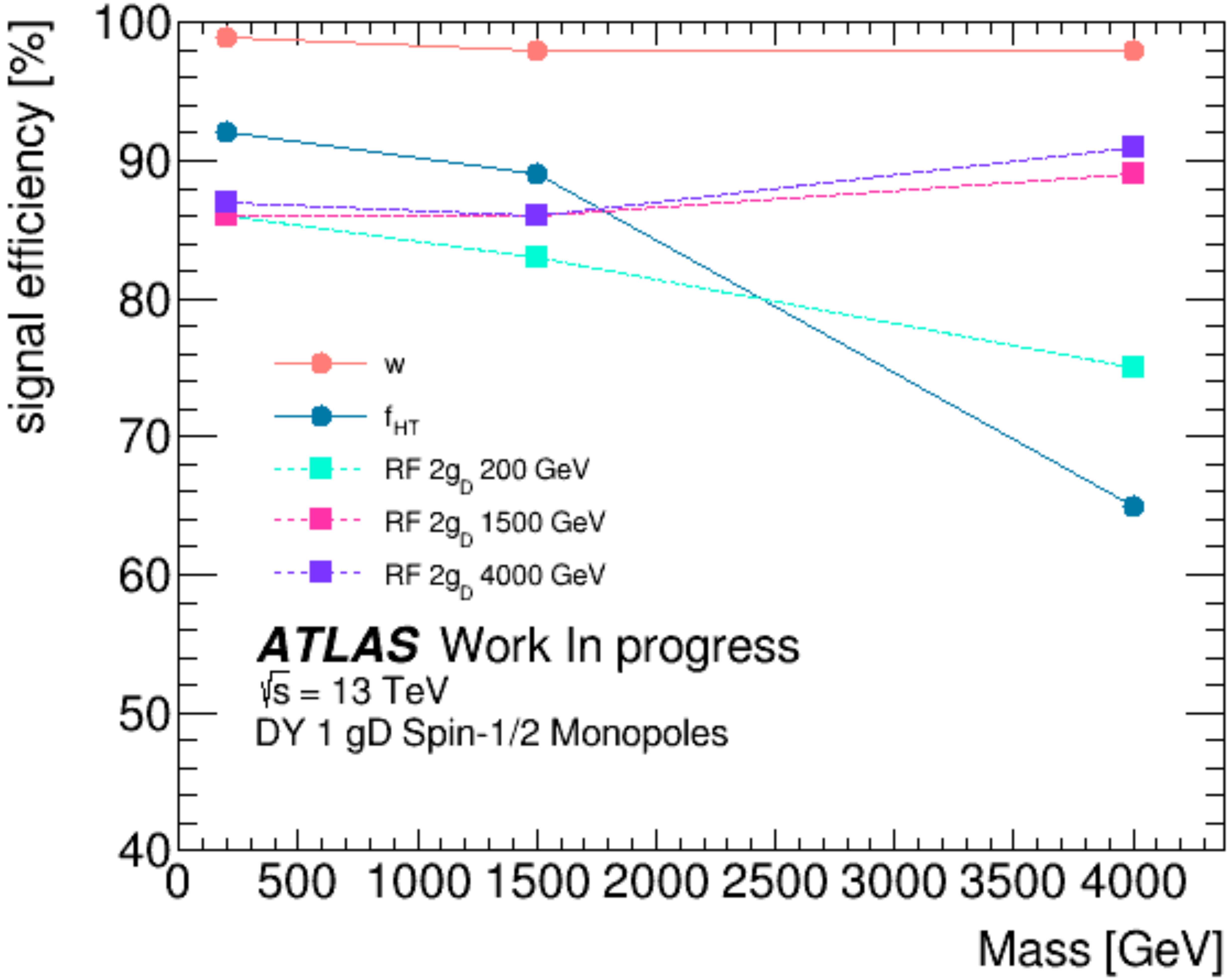
- **signal** = section |Φcluster| < 4mm
- **background** = section |Φrandom| < 4mm



Sections of TRT hits in r-Φ plane

Results

- Training and testing on limited Monte Carlo Drell-Yan samples of different masses and charges ($2g_D$)
  - Less than 5% variability on results
  - Same trends
  - No under or overfitting of the model (Train-Test score difference < 6%)
- Area Under the Curve > 0.95 shows great discriminating power of the Random Forest classifier
- We quantify the loss or gain of signal efficiency using the Random Forest classifier, large masses benefit from it, while small and mid range do not



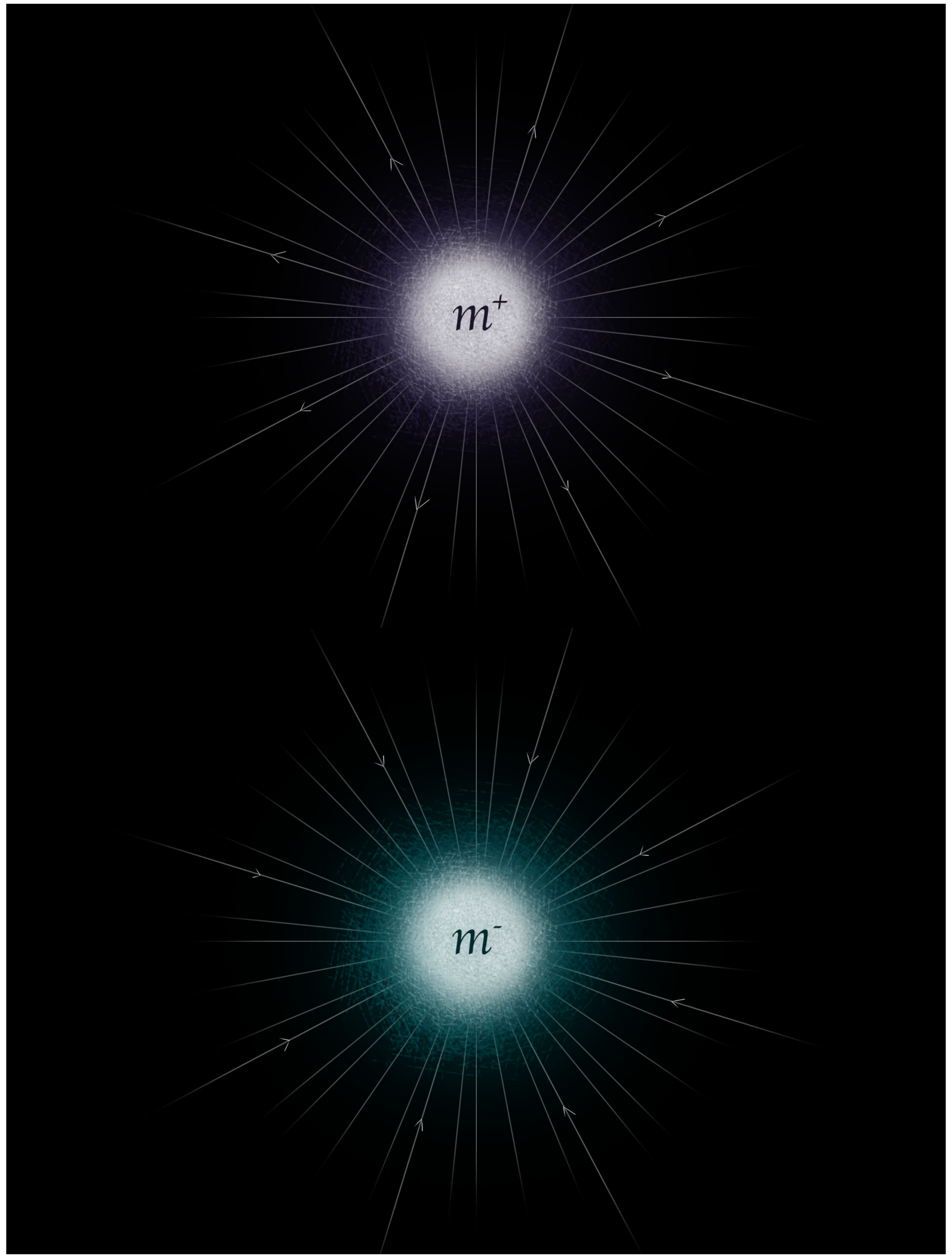
FINAL REMARKS AND OUTLOOK

- We successfully trained a Random Forest Classifier to discriminate TRT roads with monopole-like signals in the TRT
- This classifier improved selection efficiency of preselected Drell-Yan spin 1/2, 1 g_D monopoles of mass 4000 GeV between 10 and 26% percent
- In the future, we will train in a combination of samples of different masses and charges
- We will also test if the classifier performs better at higher $<\mu>$ conditions.

THANK YOU!

BACKUP

MAGNETIC MONOPOLE



- Electric monopole: Fundamental particle with **electric charge "*e*"**.
  - Static source of radial electric field.
- Magnetic monopole: Fundamental particle with **magnetic charge "q_m"**.
  - Static source of radial magnetic field.
  - **No substructure.**
  - **Stable** due to magnetic charge conservation.

SYMMETRY IN MAXWELL'S EQUATIONS

In a sense, Maxwell's equations *beg* for magnetic charge to exist—it would fit in so nicely. And yet, in spite of a diligent search, no one has ever found any.

- Griffiths "Introduction to Electrodynamics" p.338

Monopole "Free"

$$\nabla \cdot \mathbf{E} = \frac{\rho_e}{\epsilon_0}$$

$$\nabla \cdot \mathbf{B} = 0$$

$$\nabla \times \mathbf{B} = \epsilon_0 \mu_0 \left(\mathbf{j_e} + \frac{\partial \mathbf{E}}{\partial t} \right)$$

$$\nabla \times \mathbf{E} = -\mu_0 \frac{\partial \mathbf{B}}{\partial t}$$

With Magnetic charge

$$\nabla \cdot \mathbf{E} = \frac{\rho_e}{\epsilon_0}$$

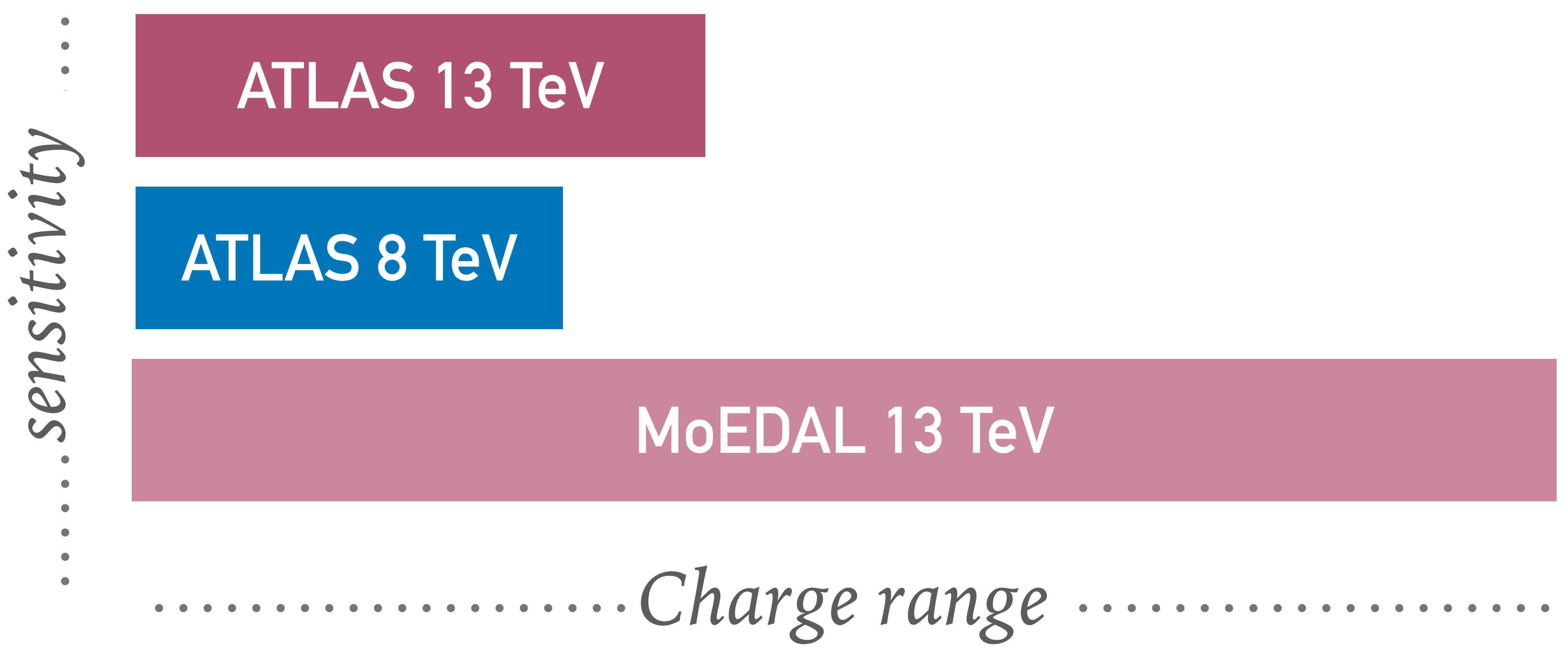
$$\nabla \cdot \mathbf{B} = \mu_0 \rho_m$$

$$\nabla \times \mathbf{B} = \epsilon_0 \mu_0 \left(\mathbf{j_e} + \frac{\partial \mathbf{E}}{\partial t} \right)$$

$$\nabla \times \mathbf{E} = -\mu_0 \left(\mathbf{j_m} + \frac{\partial \mathbf{B}}{\partial t} \right)$$

RELEVANCE OF THIS STUDY

- Magnetic Monopole has not been observed.
- LHC might be producing them.
- We have data: ATLAS experiment collects valuable "all purpose" data.
- Complements other Dirac Magnetic Monopole searches:



HIGHLY IONIZING PARTICLES

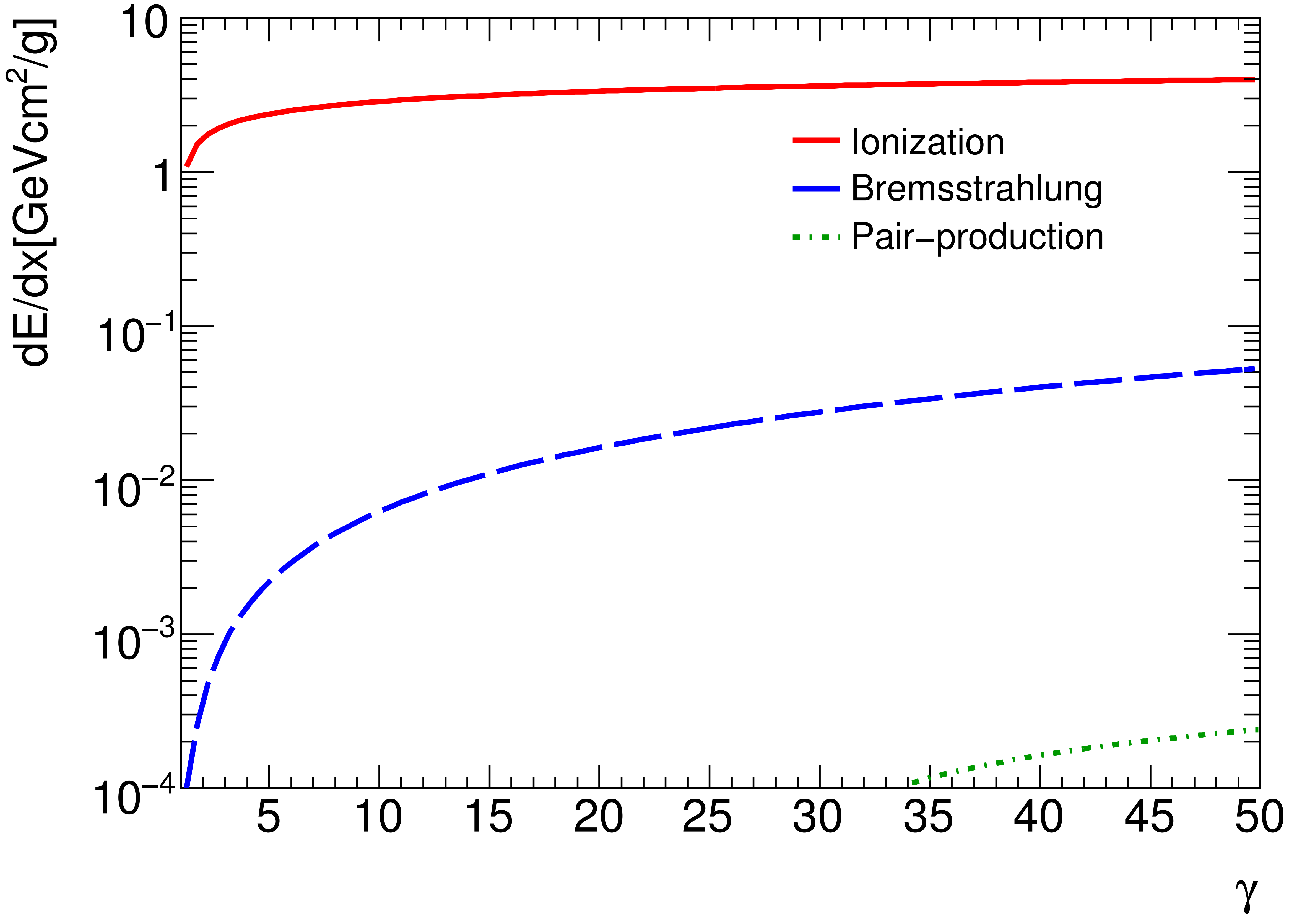
$$-\frac{dE}{dx} = \frac{4\pi e^4 z^2 N_e}{m_e c^2 \beta^2}\left[\ln\left(\frac{2m_e c^2\beta^2\gamma^2}{I}\right) - \beta^2 - \frac{\delta}{2})\right]$$

HECOs: Bethe-Bloch

$$-\frac{dE}{dx} = \frac{4\pi e^2 g^2 N_e}{m_e c^2}\left[\ln\left(\frac{2m_e c^2\beta^2\gamma^2}{I}\right) + \frac{k(g)}{2} - \frac{1}{2} - \frac{\delta}{2} - B(g))\right]$$

Magnetic Monopoles: Bethe-Ahlen see Ahlen et al.

- Electrons in the presence of a magnetic monopole would experience an interaction proportional to gβ
- Bremsstrahlung energy losses go as 1/M, where M is the mass of the monopole (~TeV)
- Pair production is less likely due to the kinematics of these monopoles (γ < 10)



Energy loss per unit distance as a function of the Lorentz factor for a 1g_D 1500 GeV monopole in LAr.

BREMSSTRAHLUNG

Bremsstahlung

$$-\frac{dE_{rad}}{dx} = \frac{16NZ^2e^2g^4}{3\hbar mc^2}$$

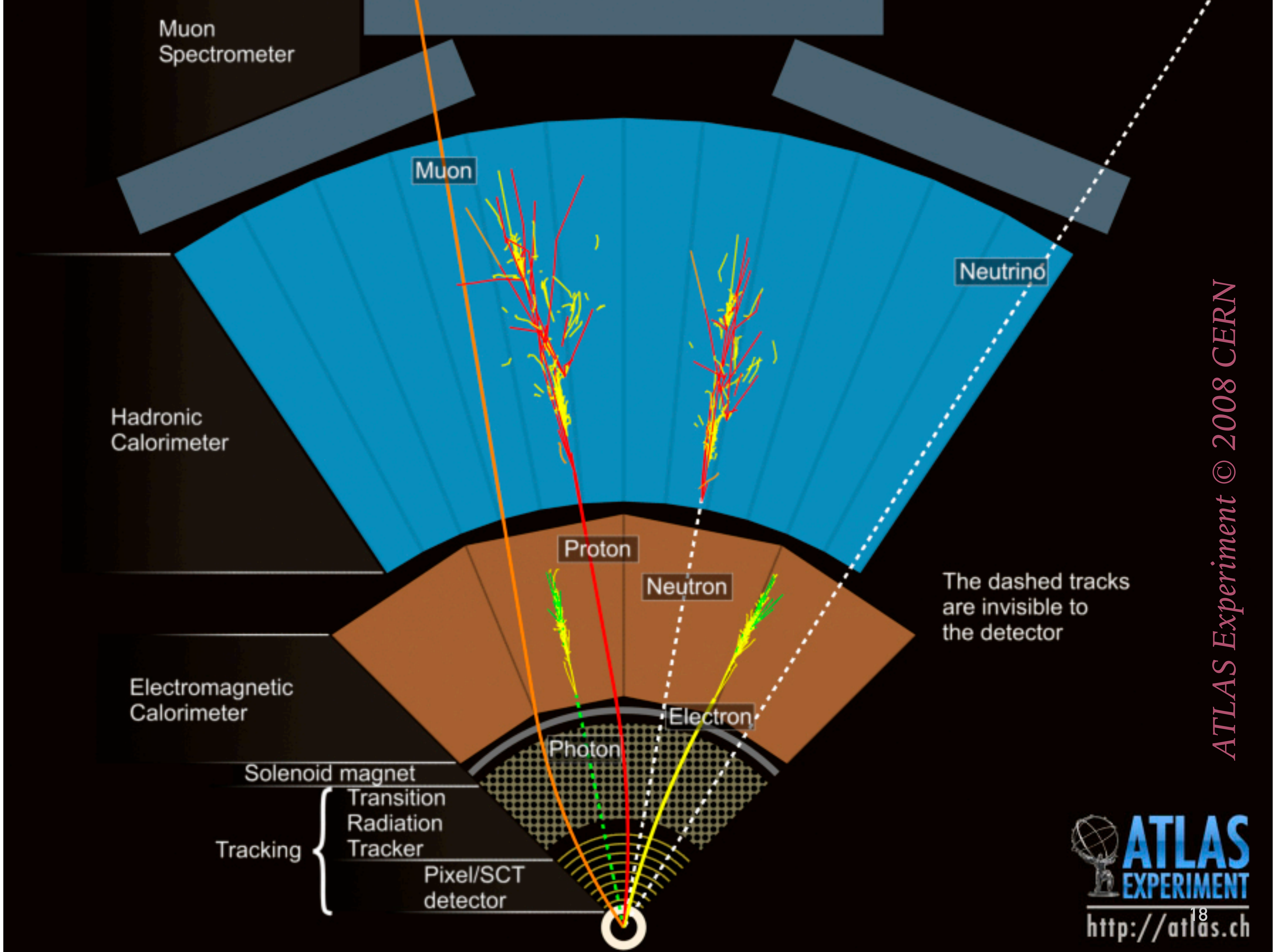
Ionization

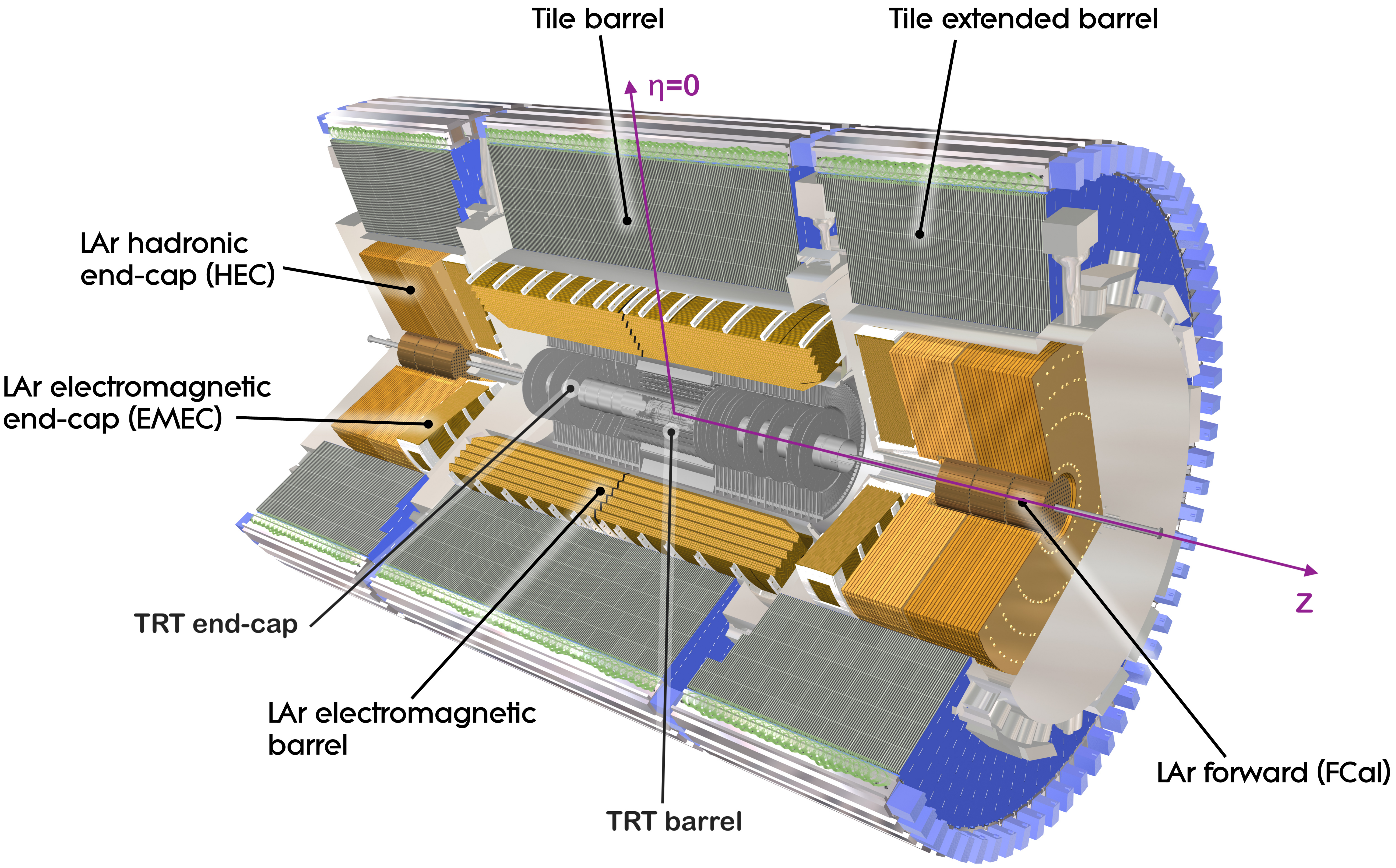
$$-\frac{dE}{dx} = \frac{4\pi e^4 z^2 N_e}{m_e c^2 \beta^2}\left[\ln\left(\frac{2m_e c^2\beta^2\gamma^2}{I}\right) - \beta^2 - \delta/2)\right]$$

$$-\frac{dE_{rad}}{dE_I} \approx \frac{4g^2Z}{3\pi\hbar c}\frac{m_e}{m} \approx 10^{-3}$$

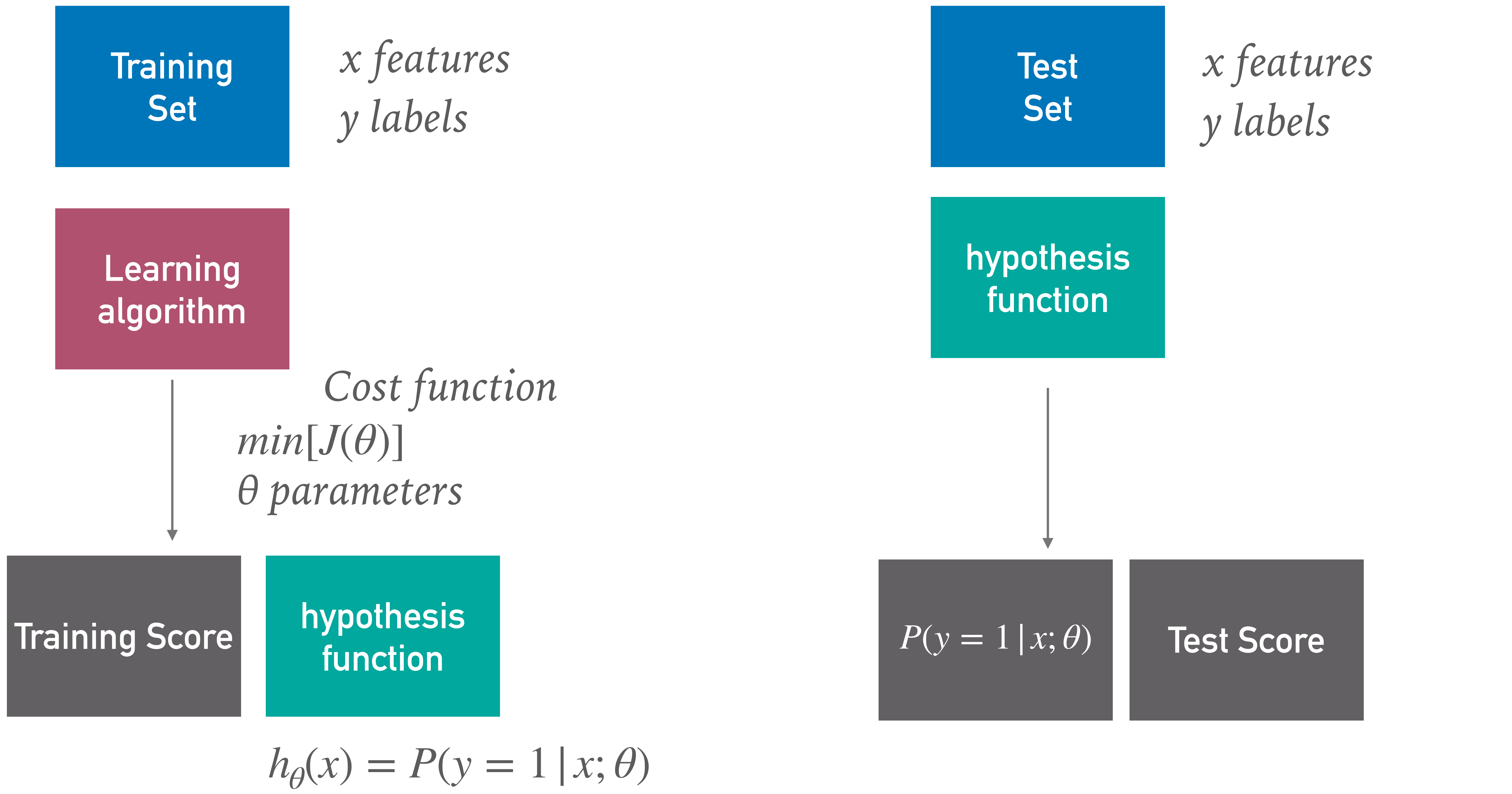
$$\frac{4g^2Z}{3\pi\hbar c} \approx 10^4$$

$$\frac{m_e}{m} \approx 10^{-7}$$


Muon
Spectrometer
Muon
Neutrino
Hadronic
Calorimeter
Proton
Neutron
The dashed tracks
are invisible to
the detector
Electromagnetic
Calorimeter
Electron
Photon
Solenoid magnet
Transition
Radiation
Tracker
Tracking
Pixel/SCT
detector
ATLAS
EXPERIMENT
http://atlas.ch
ATLAS Experiment © 2008 CERN

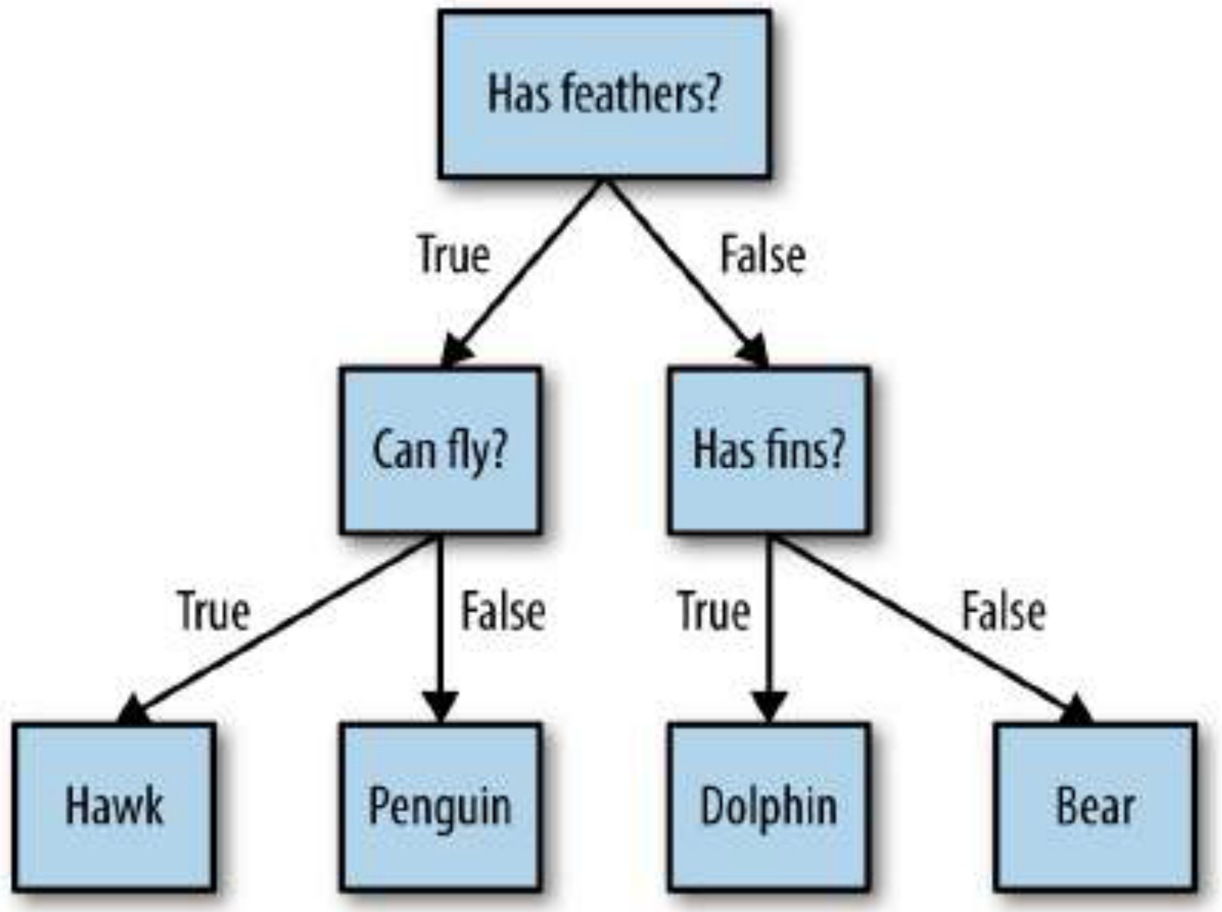

Tile barrel
Tile extended barrel
η=0
LAr hadronic end-cap (HEC)
LAr electromagnetic end-cap (EMEC)
TRT end-cap
LAr electromagnetic barrel
TRT barrel
LAr forward (FCal)
z

SUPERVISED MACHINE LEARNING



RANDOM FOREST CLASSIFIER

- Classifiers learn hierarchy of *if/else* questions leading to a decision. These classifiers can be represented as decision trees
- Ensemble methods combine the prediction of one method to improve generalizability and robustness
  - ➤ averaging: independent training
  - ➤ boosting: sequential training
- Random Forests are an averaging method: the combination of the prediction of multiple individual decision trees introducing two sources of randomness:
  - ➤ Each tree has a random portion of the training data
  - ➤ Each tree "decides" based on a portion of the features
- The resulting predictions are averaged to reduce overfitting.



Decision Tree Classifier. *Copyright ˝2017 Sarah Guido, Andreas Müller.*