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

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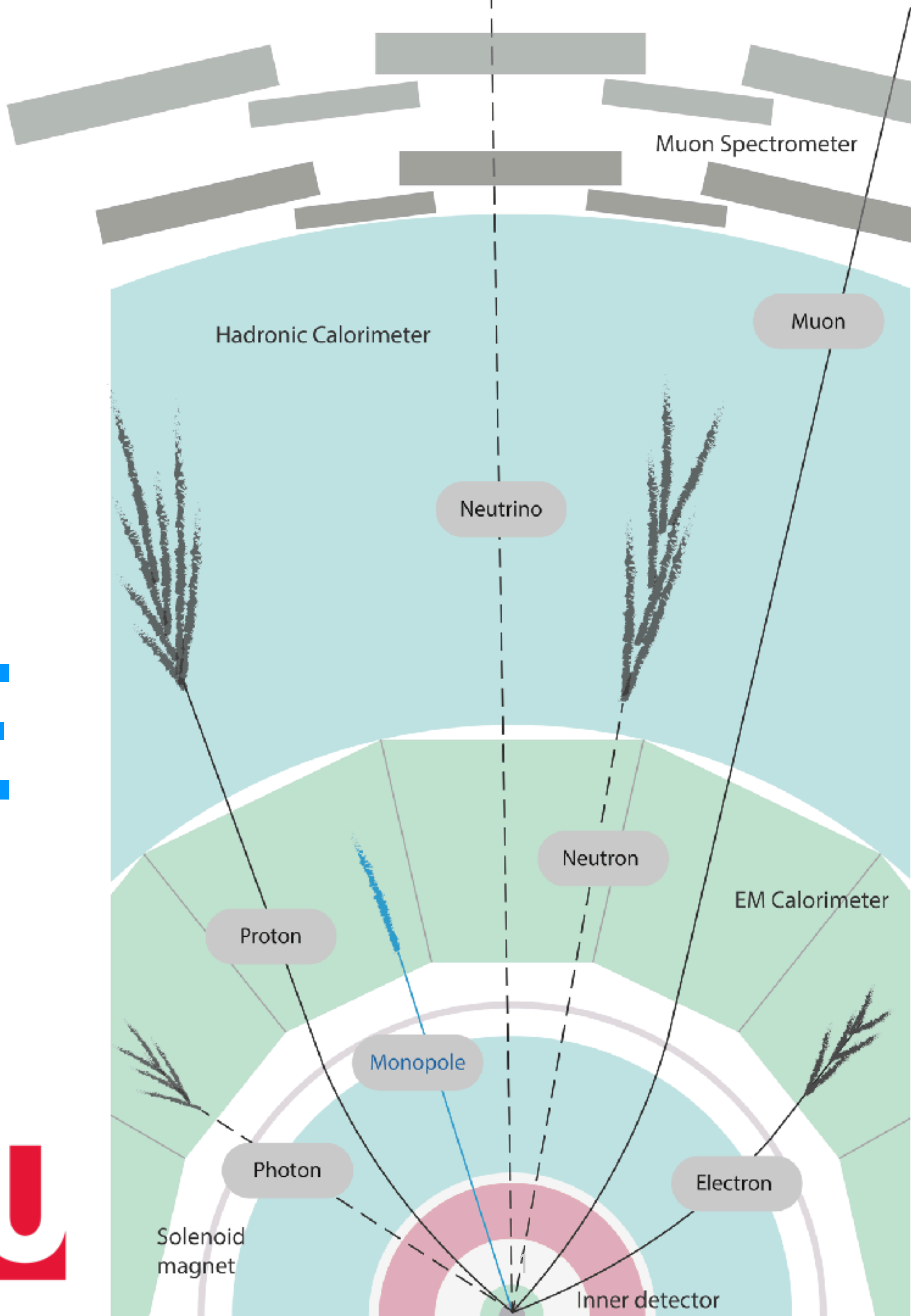
ATLAS EXPERIMENT

PhysRevLett.124.031802

YORK UNIVERSITÉ UNIVERSITY



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

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

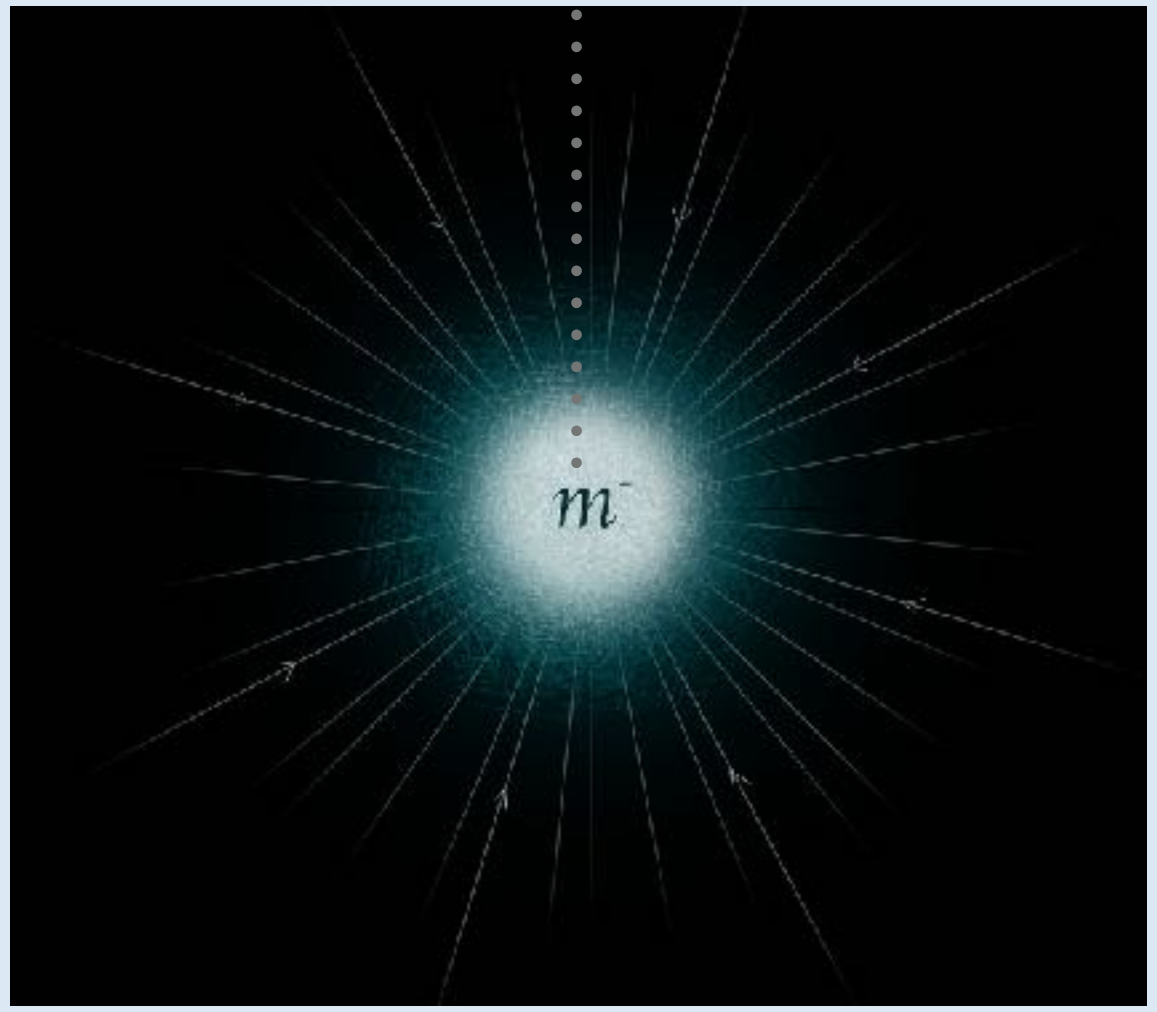
$$\nabla \times \mathbf{E} = -\mu_0\left(\mathbf{j_m} + \frac{\partial \mathbf{B}}{\partial t}\right)$$

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

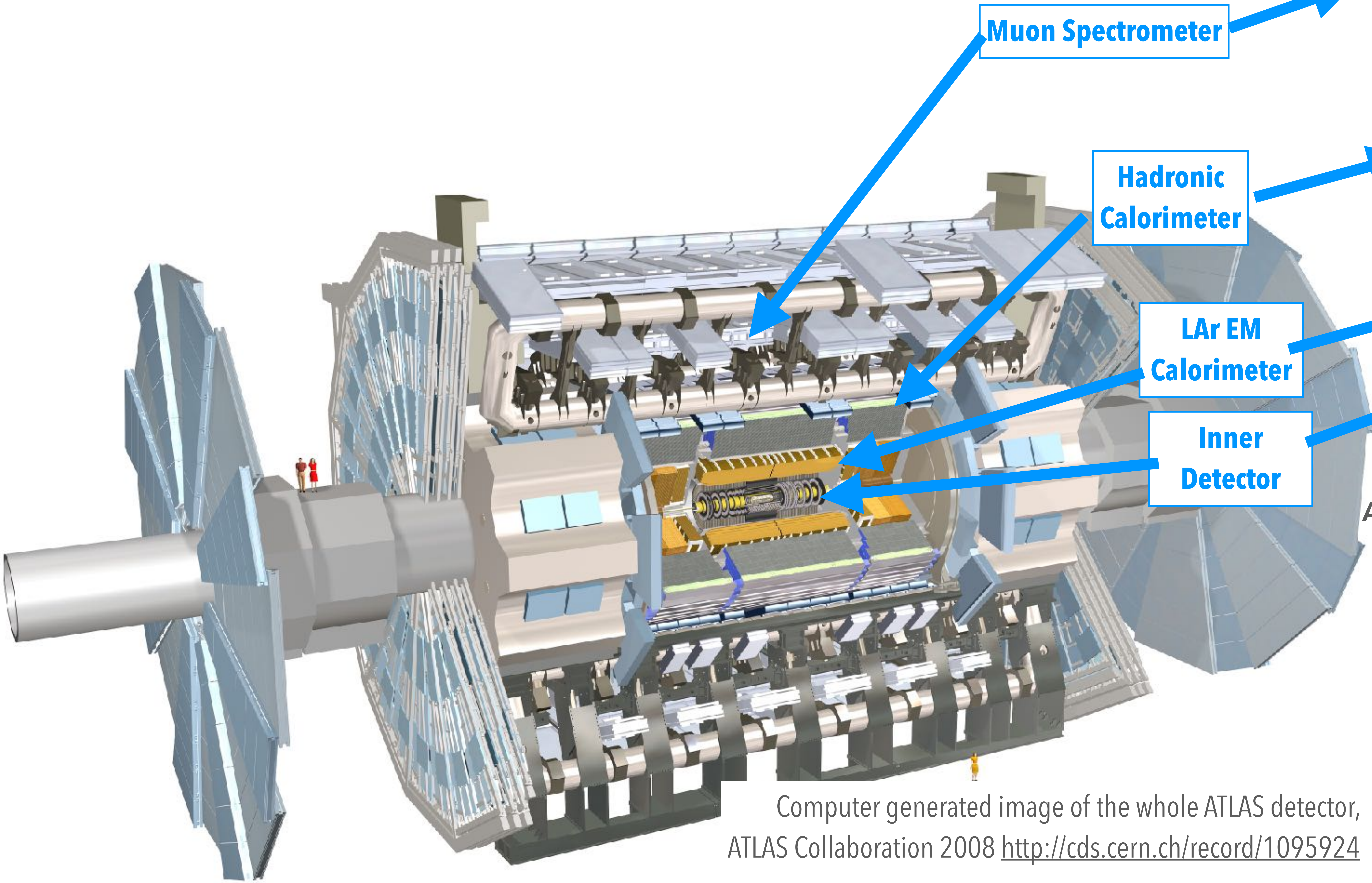
Dirac string is unobservable if:

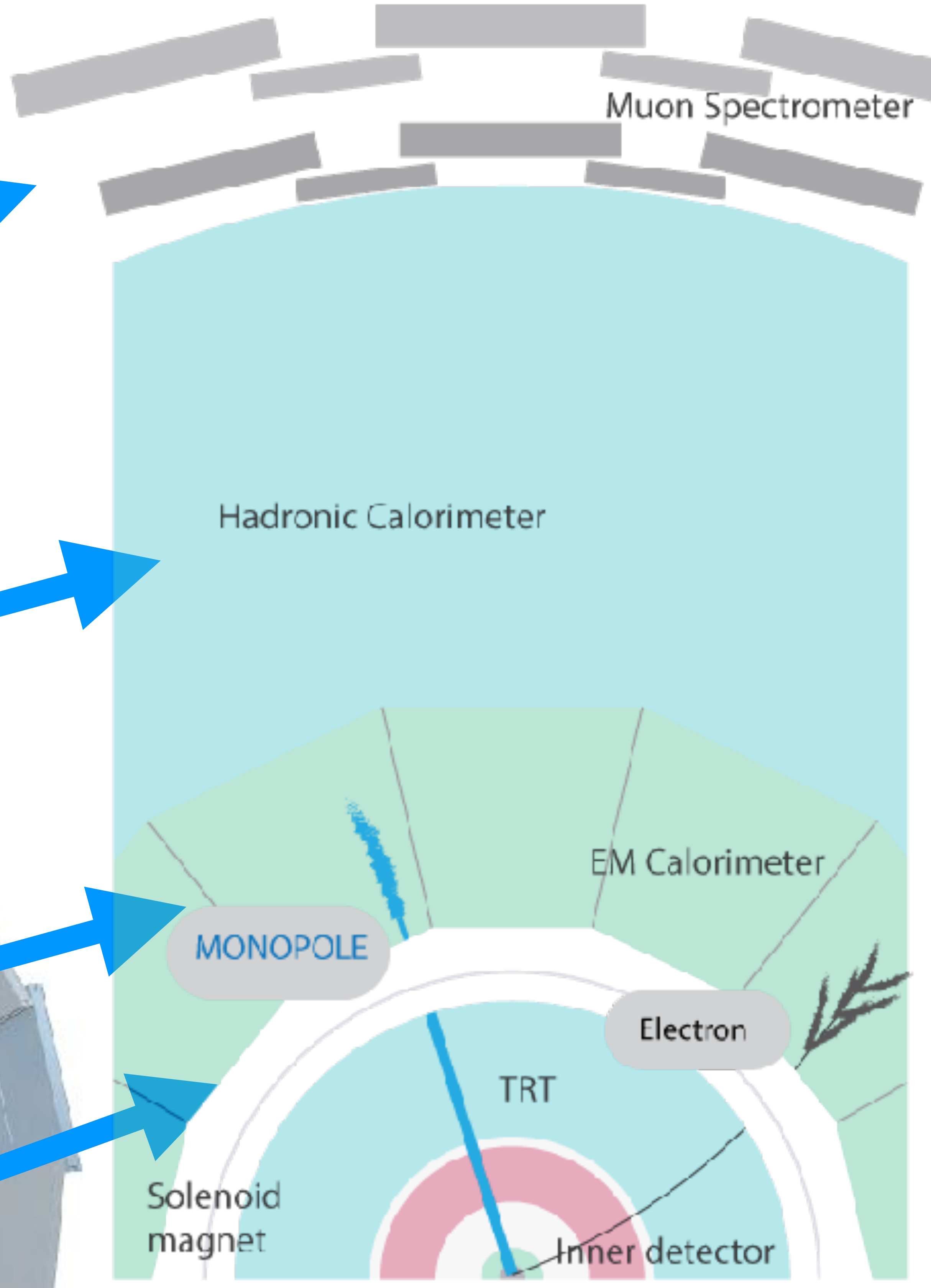
$$\frac{q_m q_e}{\hbar c} = \frac{N}{2}$$

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



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



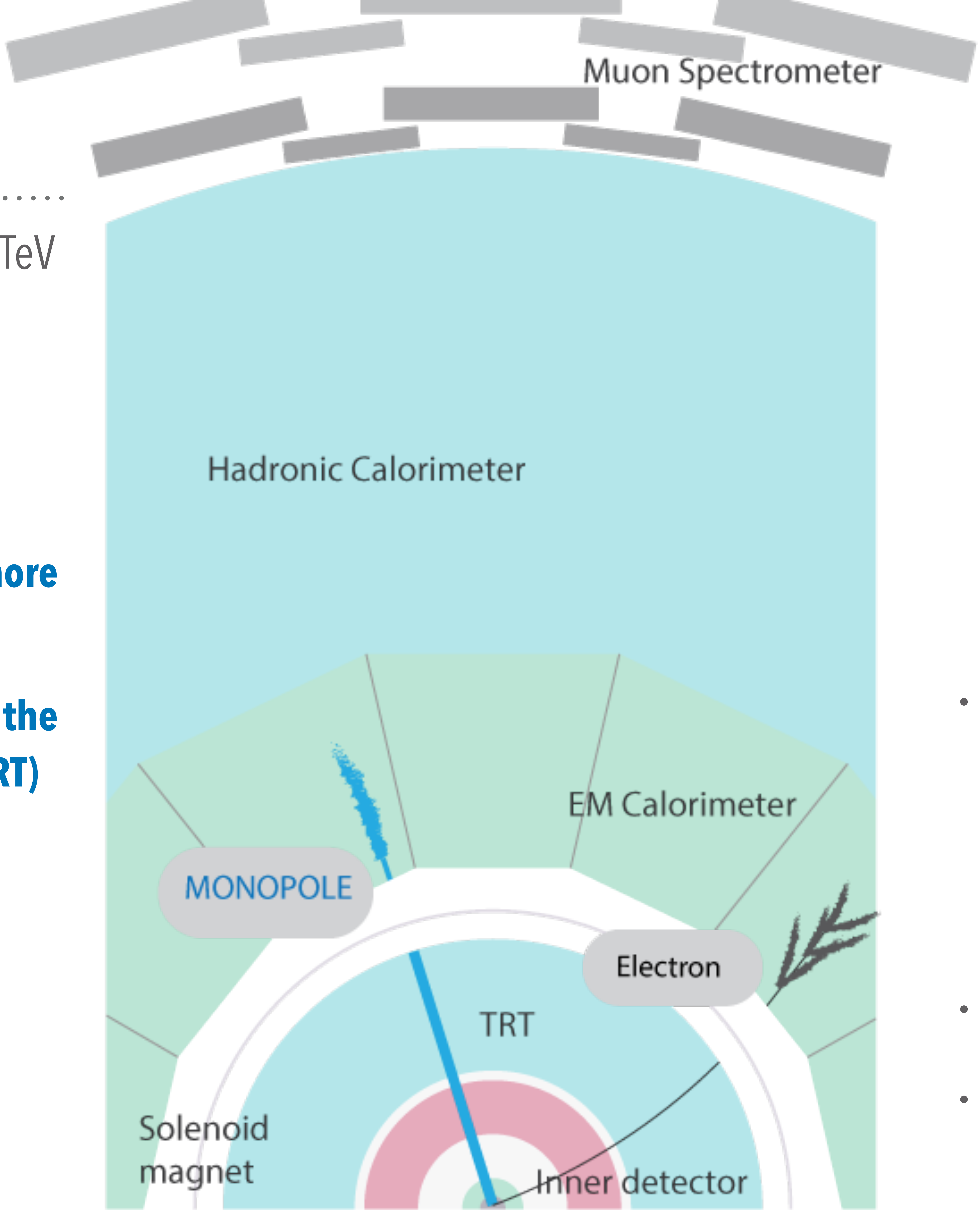


ATLAS DETECTOR SCHEMATIC IN THE r-
plane

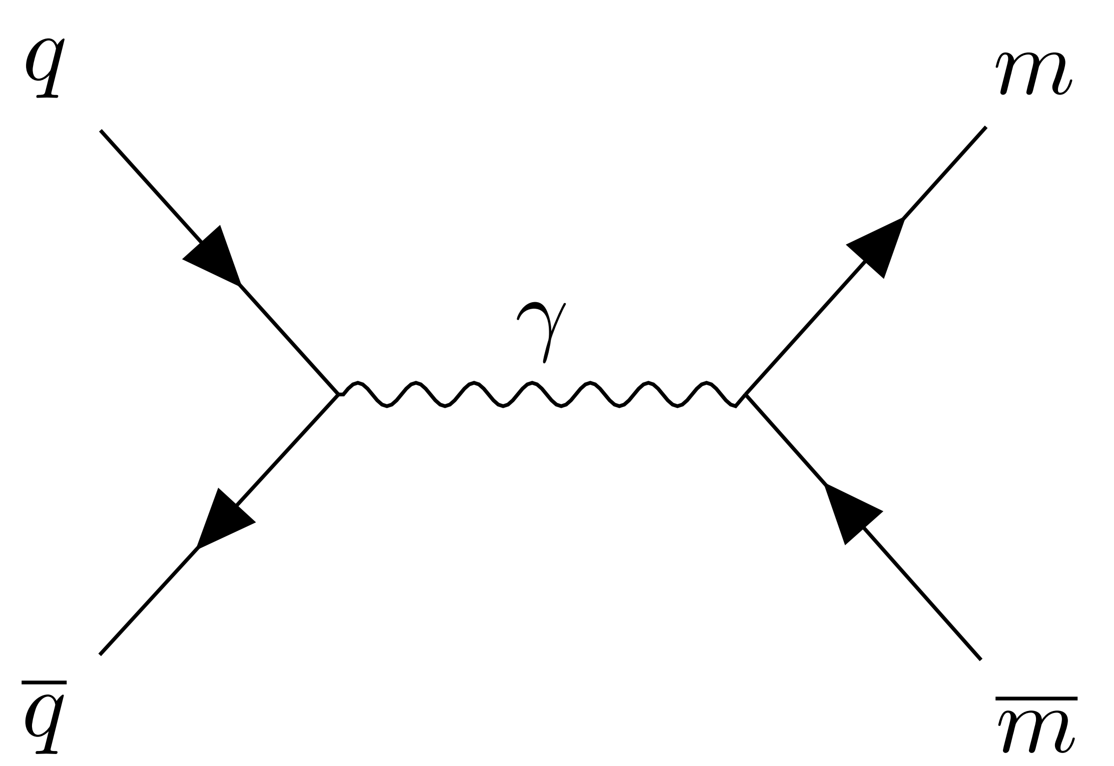
Computer generated image of the whole ATLAS detector, ATLAS Collaboration 2008 http://cds.cern.ch/record/1095924

METHOD

- **ATLAS detector**: LHC (Run 2) 13 TeV pp collisions, 137 fb^{-1}
  - ➤ $m_m < 4$ TeV
- **Ionization** of the medium
  - ➤ Energy loss ∝ charge^2 **~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**

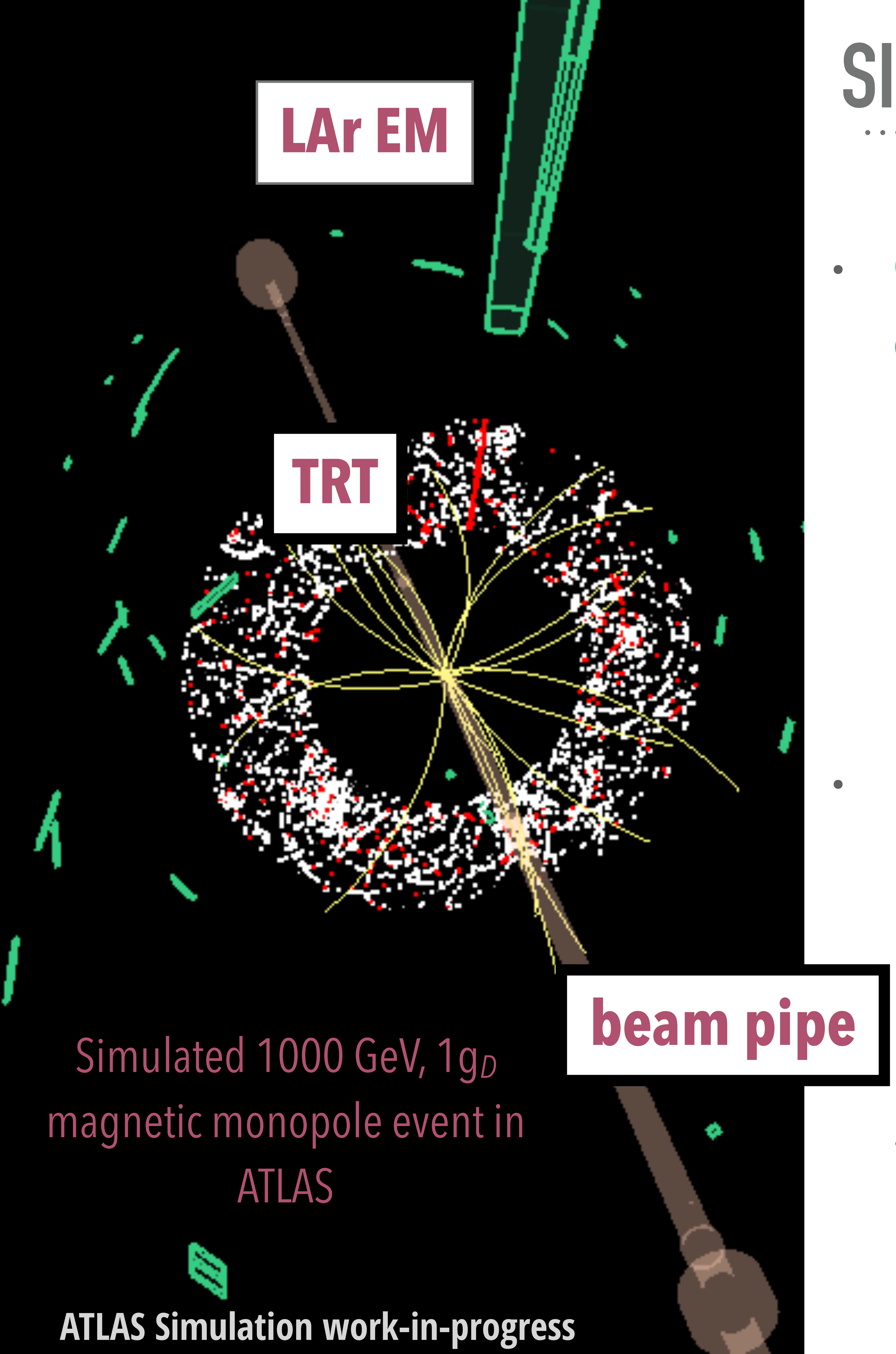


ATLAS DETECTOR SCHEMATIC IN THE r-Φ plane



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.

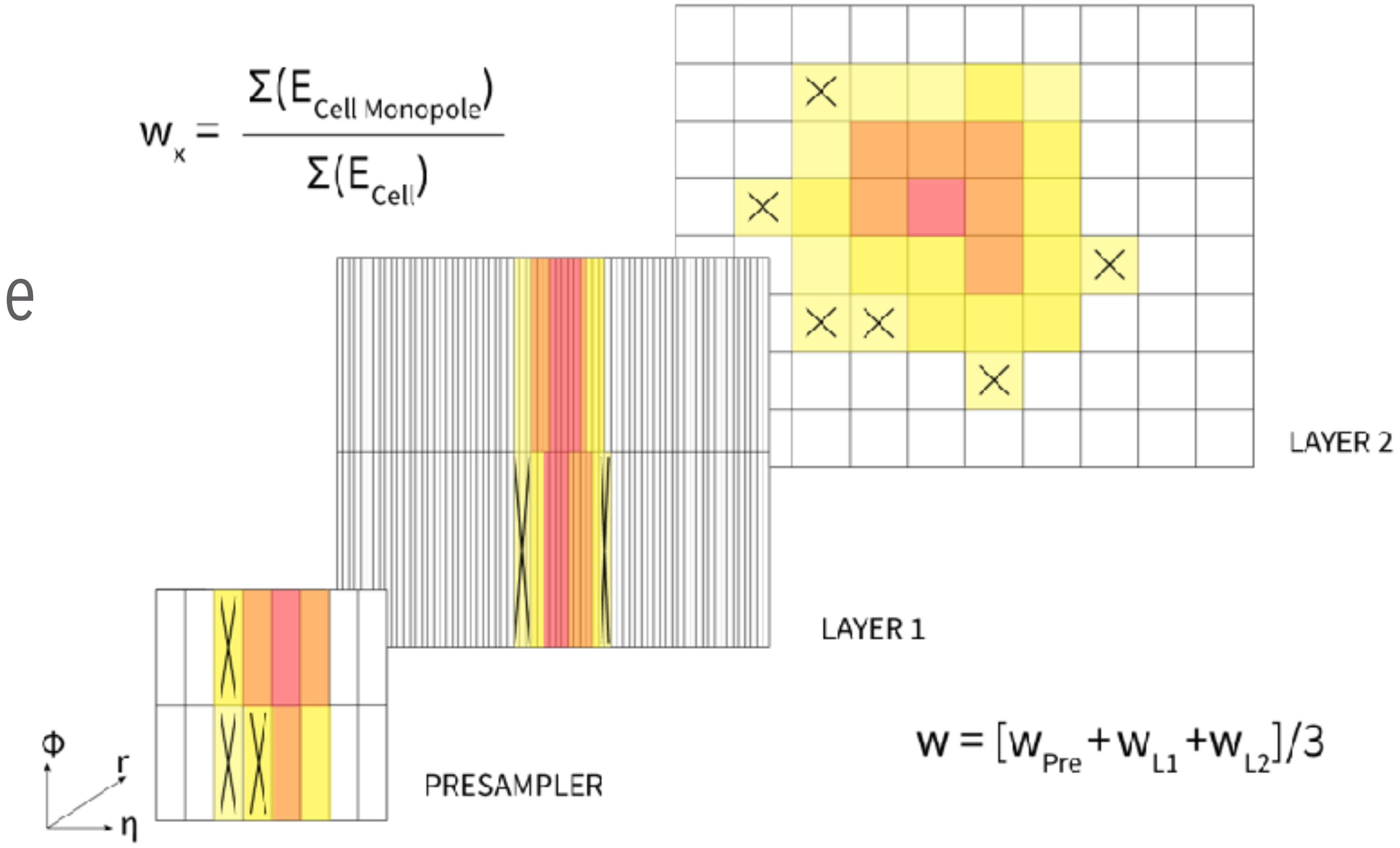


Simulated 1000 GeV, $1g_D$ magnetic monopole event in ATLAS

SIGNAL DISCRIMINATING VARIABLES:

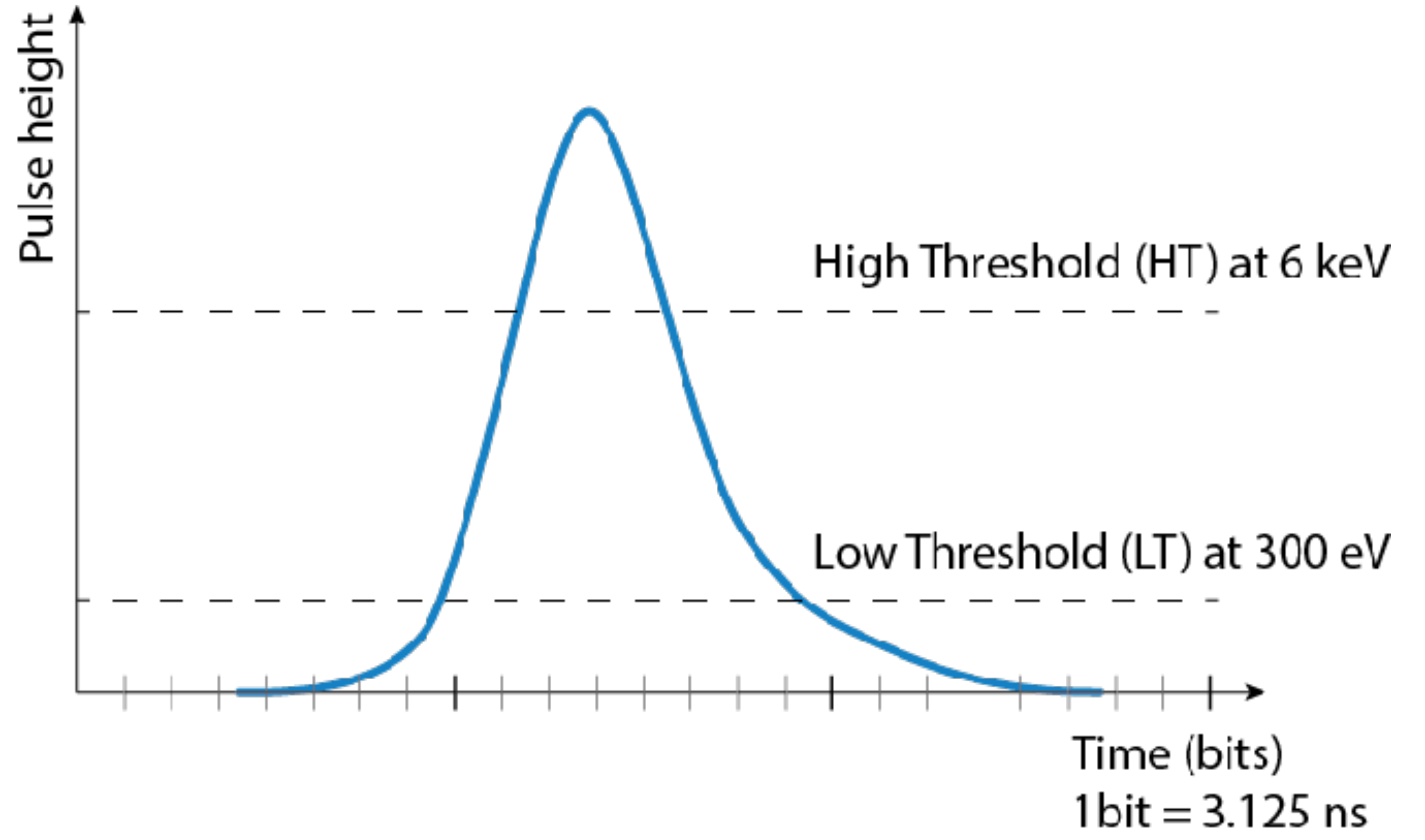
- **Concentrated high energy** deposition in the LAr EM calorimeter.

W



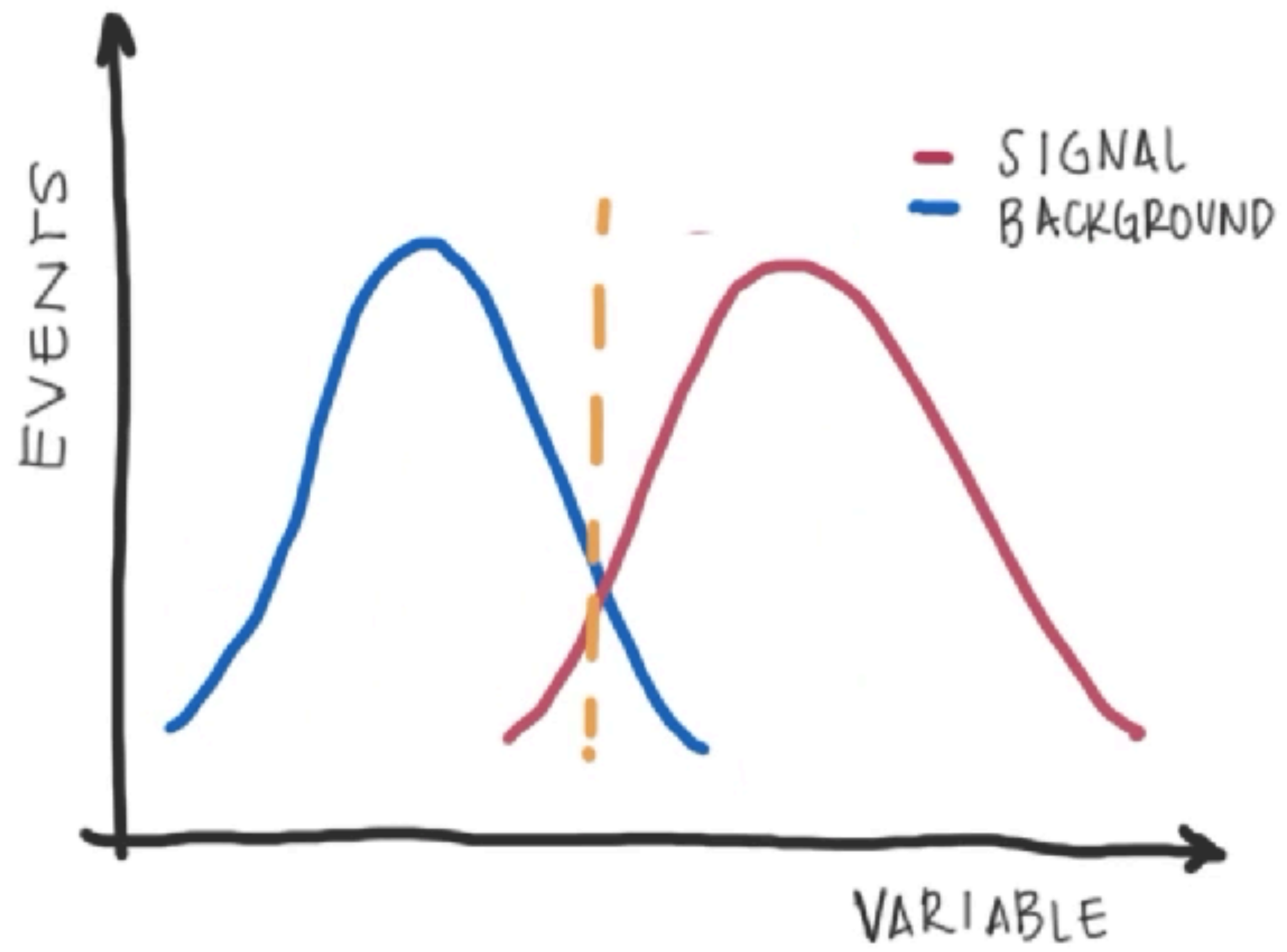
- Many large energy deposits in the TRT observed as **TRT High Threshold hits**

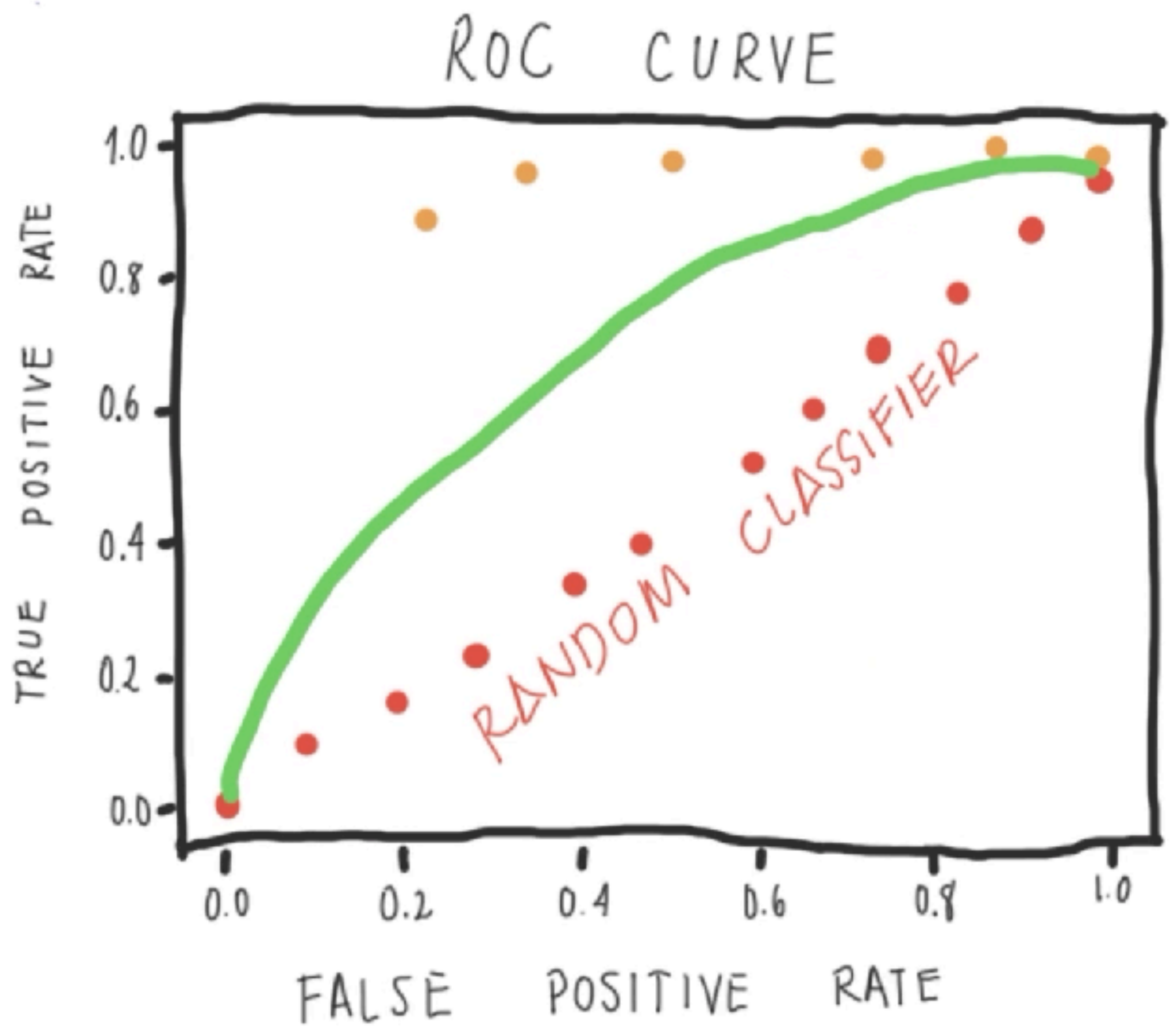
$$f_{HT} = \frac{HT_{hits}}{HT_{hits} + LT_{hit}}$$



ROC CURVES

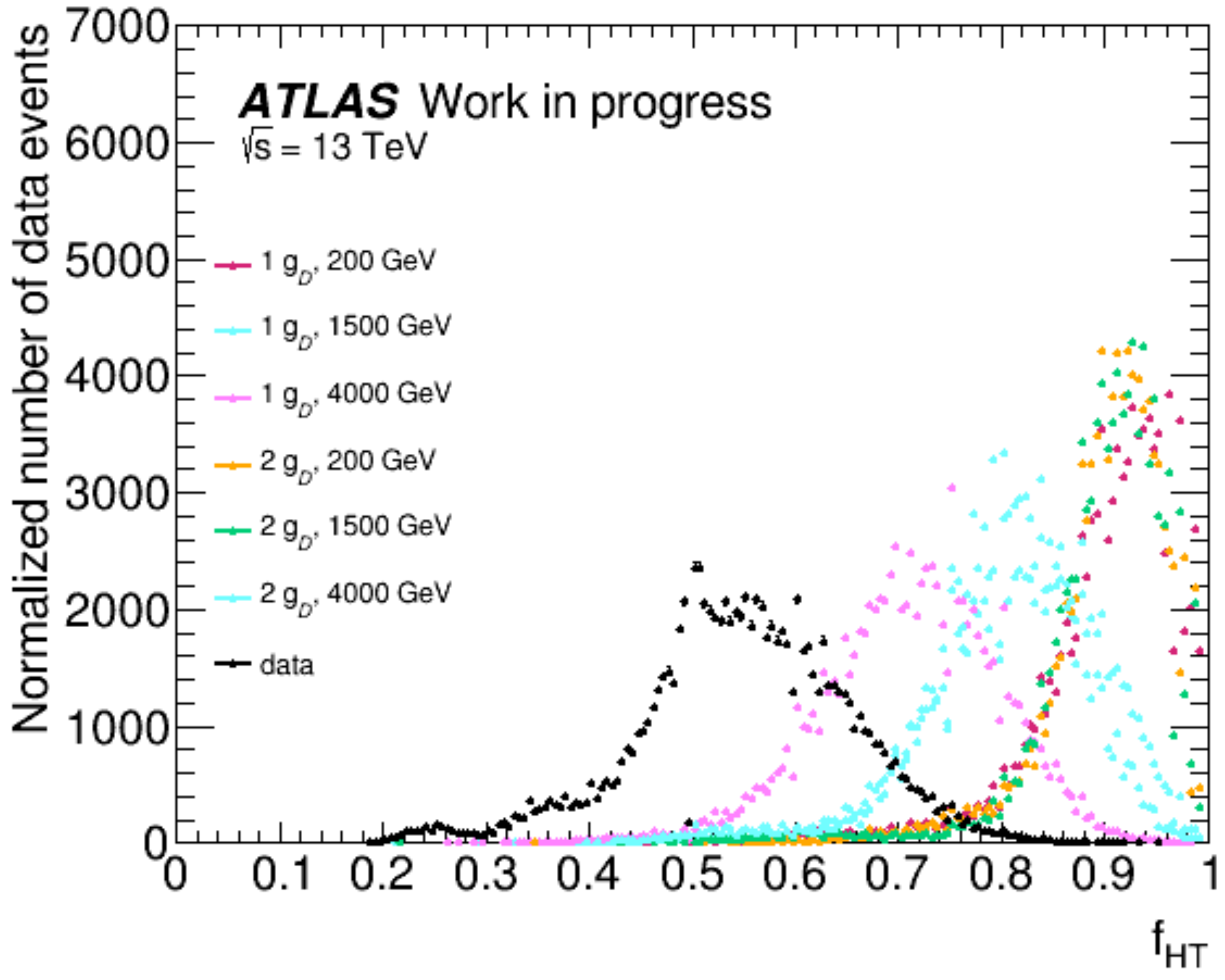
*Receiver Operating Characteristic

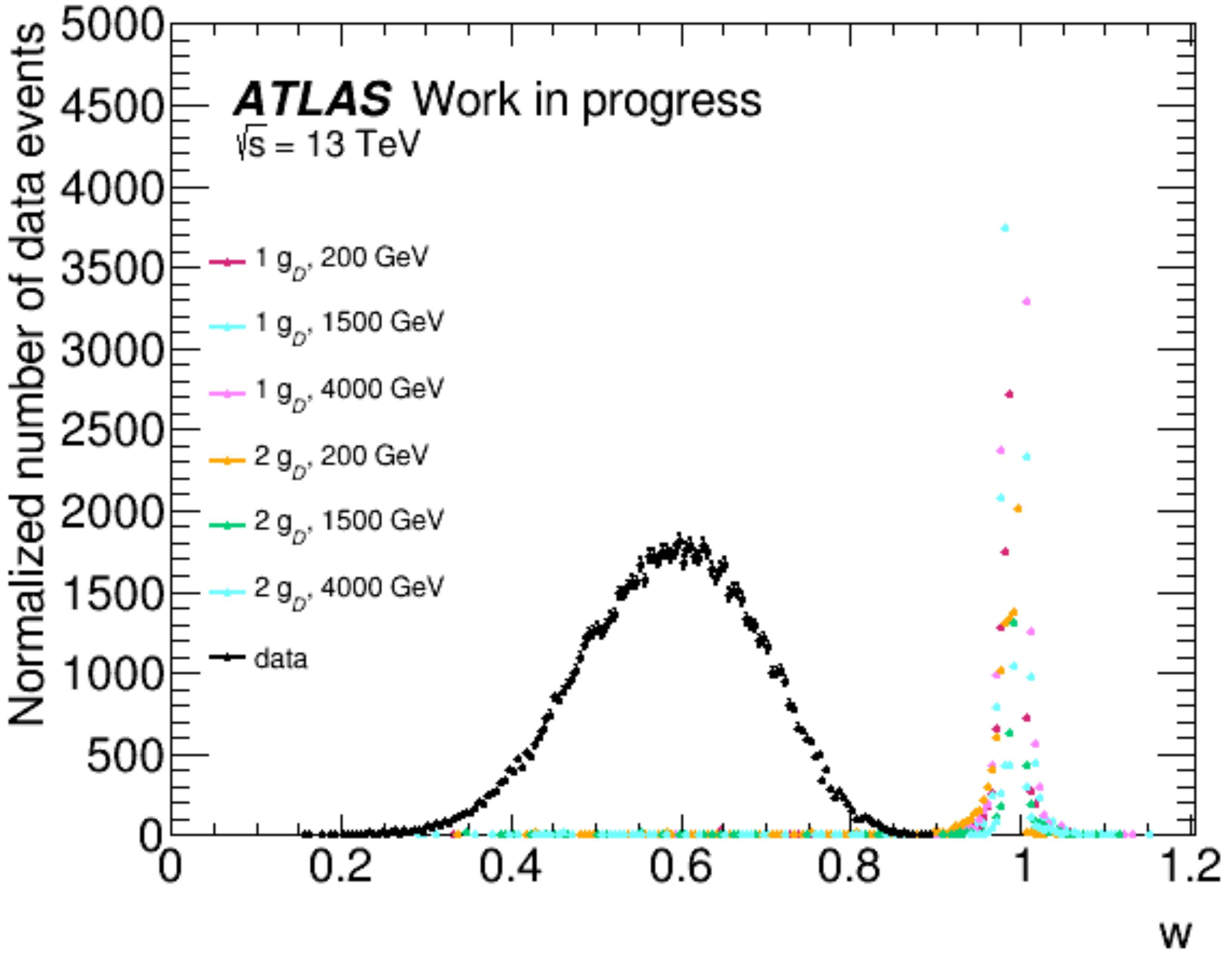




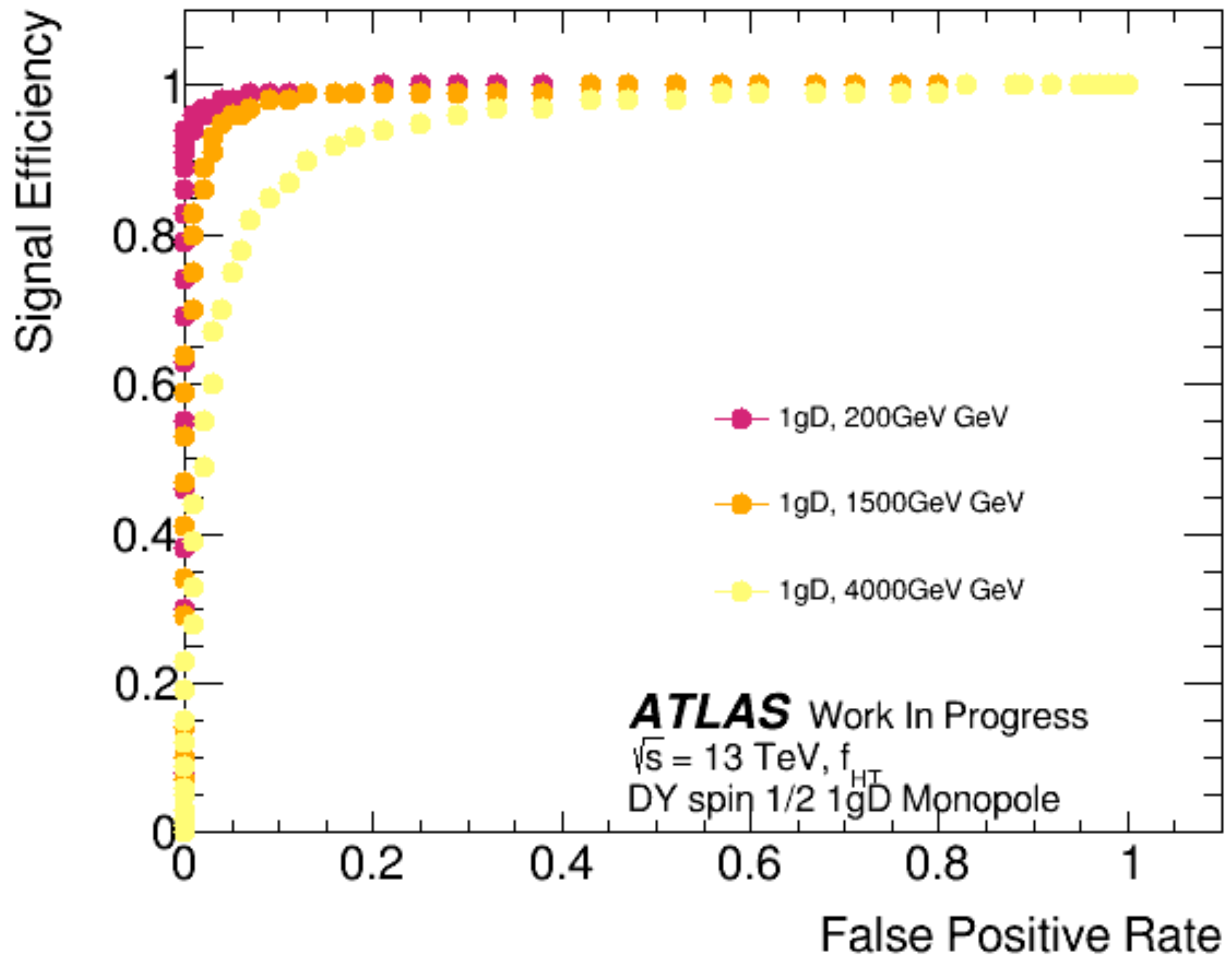
- Balance between signal selection (TPR) and background rejection (FPR)
- Area under the curve (AUC) measures discriminating power

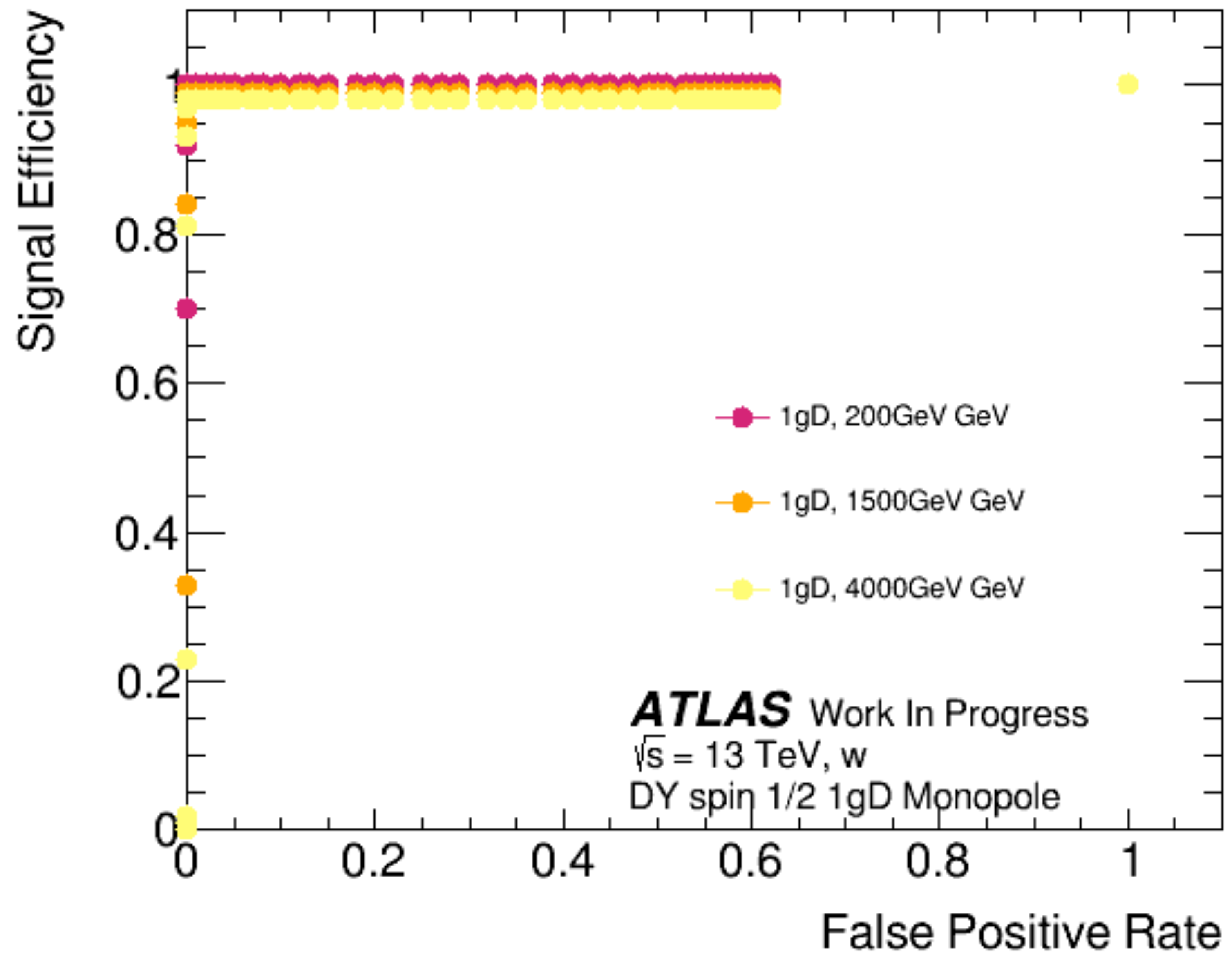
W AND F_{HT} DISCRIMINATING POWER

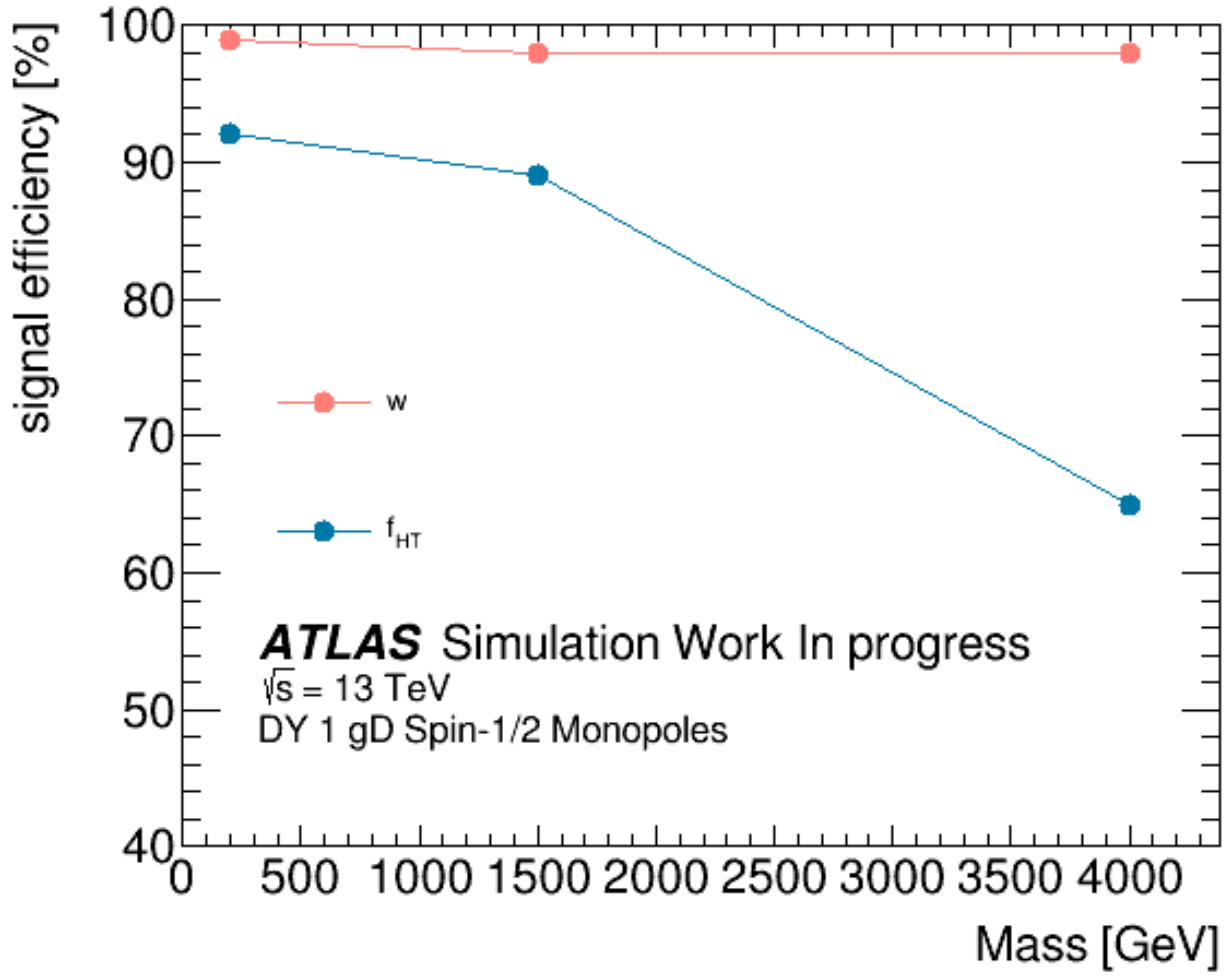




- w has almost ideal discriminating power!
- The larger the mass, the less we are able to discriminate using f_{HT}

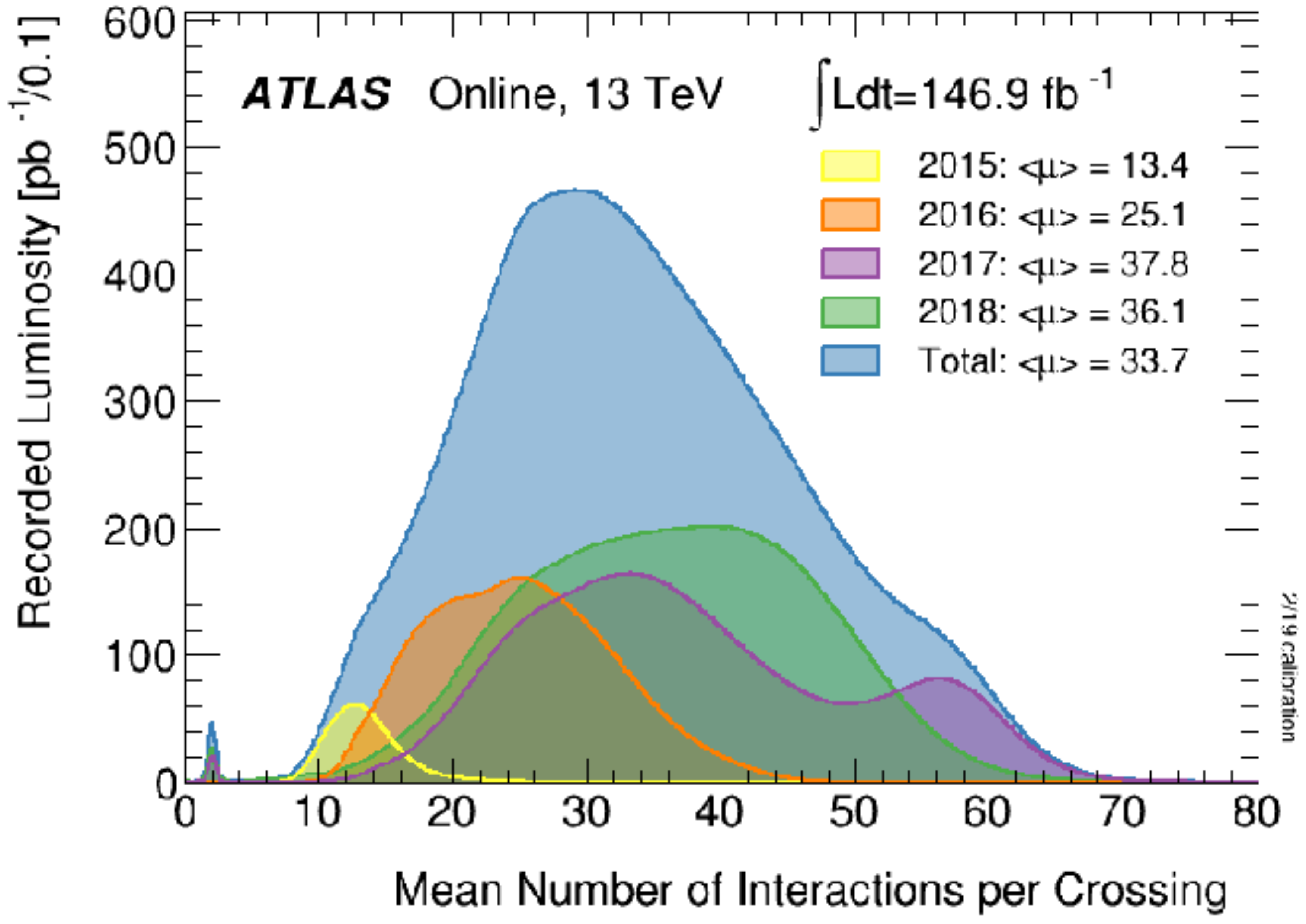




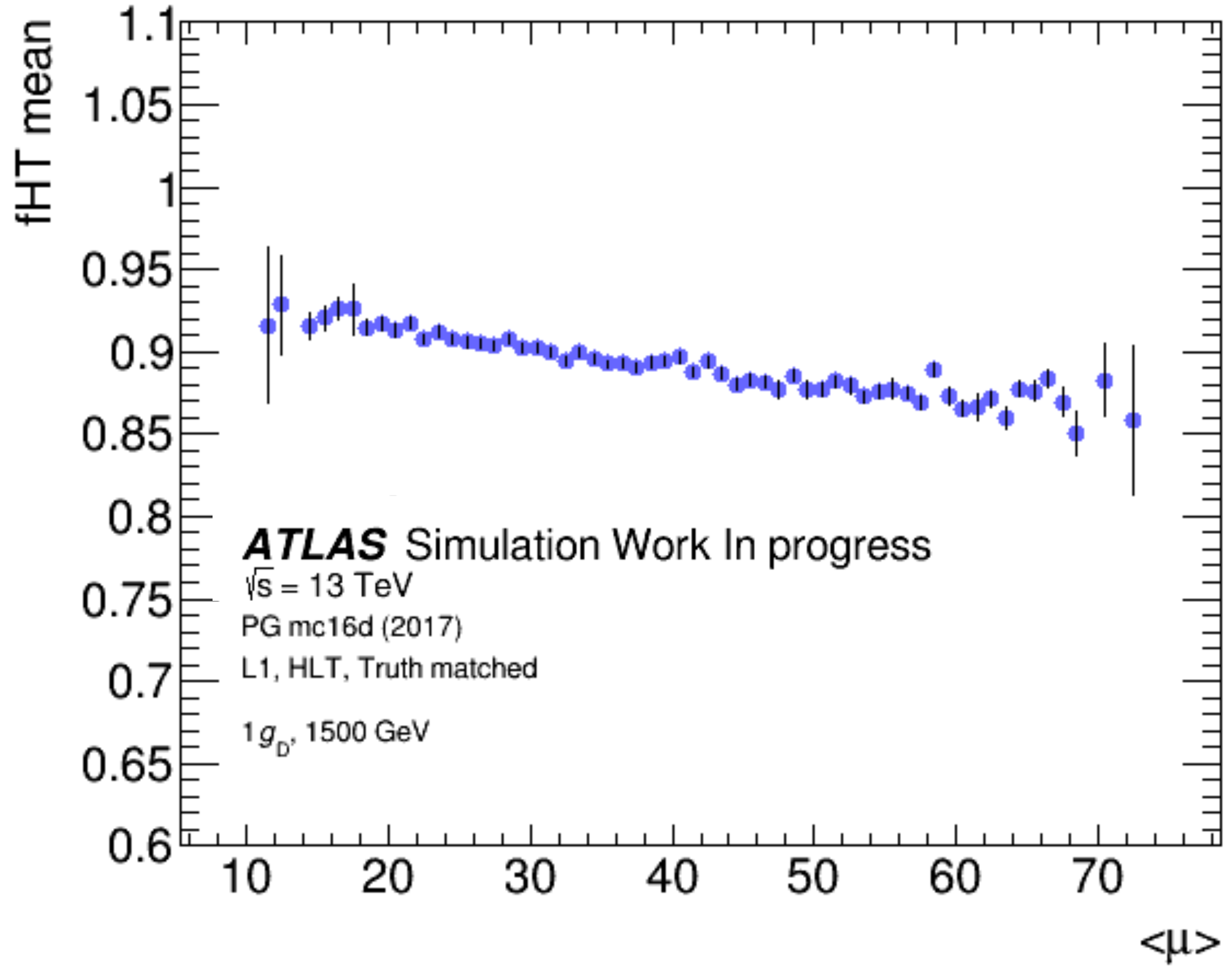


F_{HT} – TRT PILEUP PROBLEM

- 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 $<\mu>$**
- 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

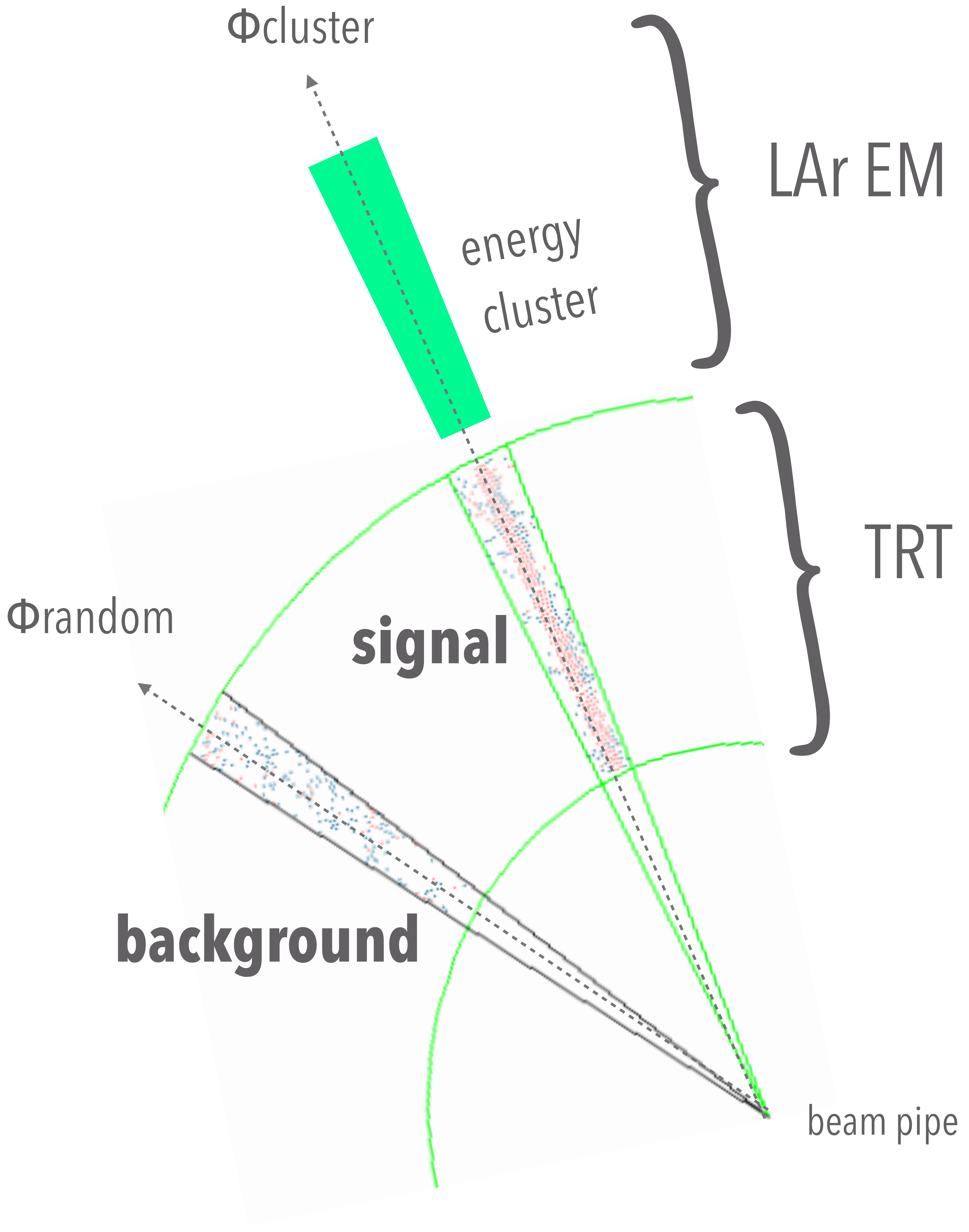
- Train a random forest (RF) classifier on a pair of sections called "roads" (one signal, one background) of the TRT for the same event
- Consider only TRT-barrel events

Features

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

Labels

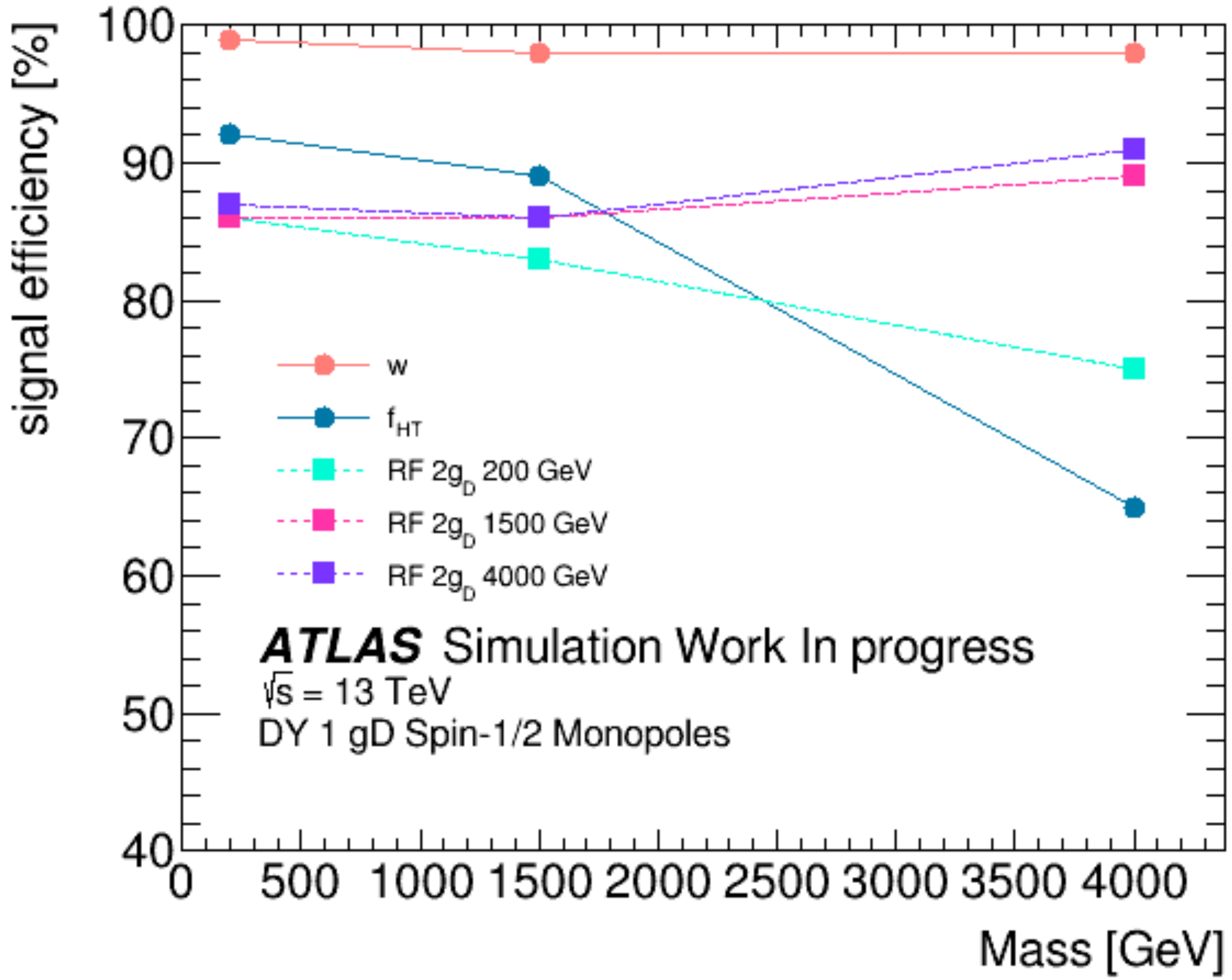
- **signal** = section |Φcluster| < 4mm
- **background** = section |Φrandom| < 4mm



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%
- 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 <μ> conditions.

THANK YOU!

BACKUP

HIGHLY IONIZING PARTICLES

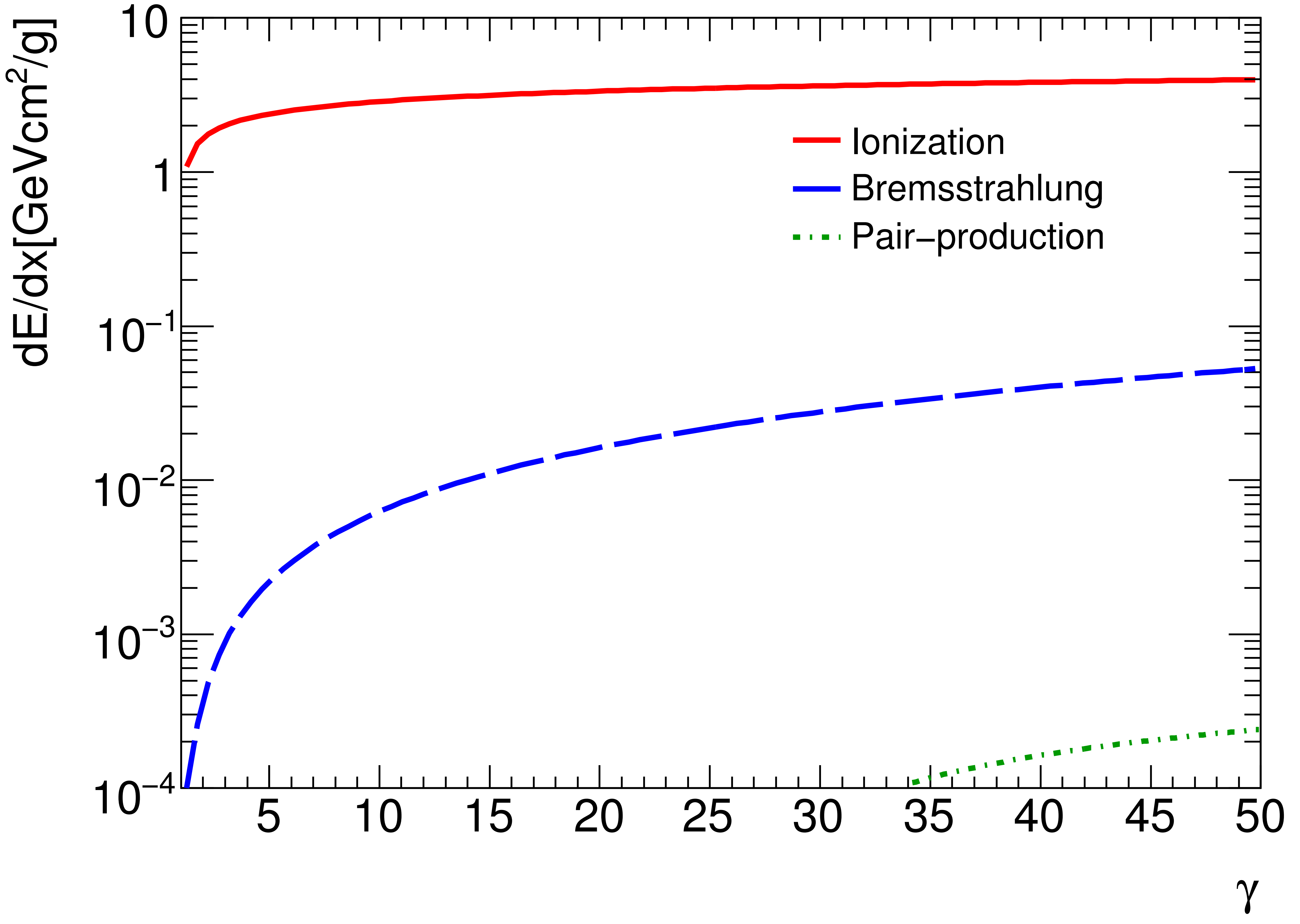
$$-\frac{dE}{dx} = \frac{4\pi e^4 z^2 N_e}{m_e c^2 \beta^2}\left[\ln\left(\frac{2m_e c^2\beta^2\gamma^2}{I}\right) - \beta^2 - \frac{\delta}{2})\right]$$

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. Palacino, Gabriel.

BREMSSTRAHLUNG

Bremsstahlung

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

Ionization

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

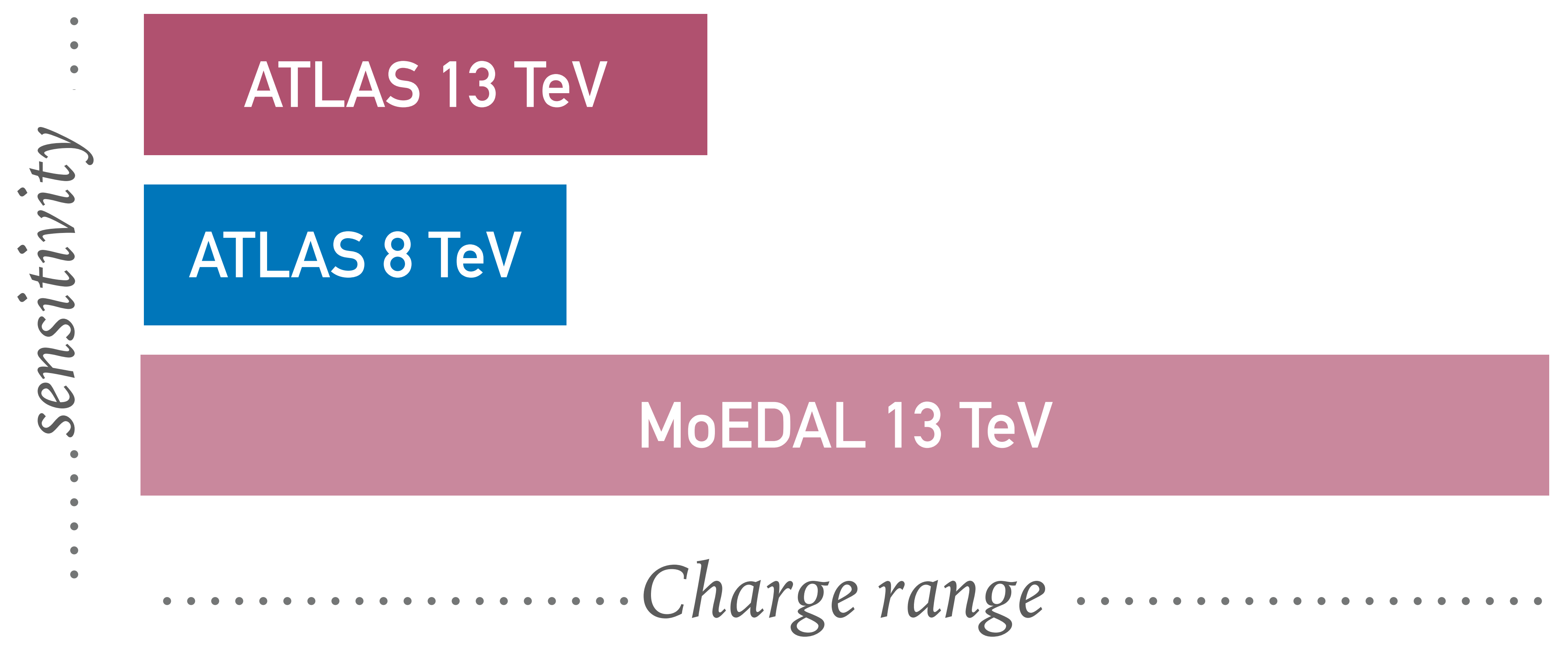
$$-\frac{dE_{rad}}{dE_I} \approx \frac{4g^2Z}{3\pi\hbar c}\frac{m_e}{m} \approx 10^{-3}$$

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

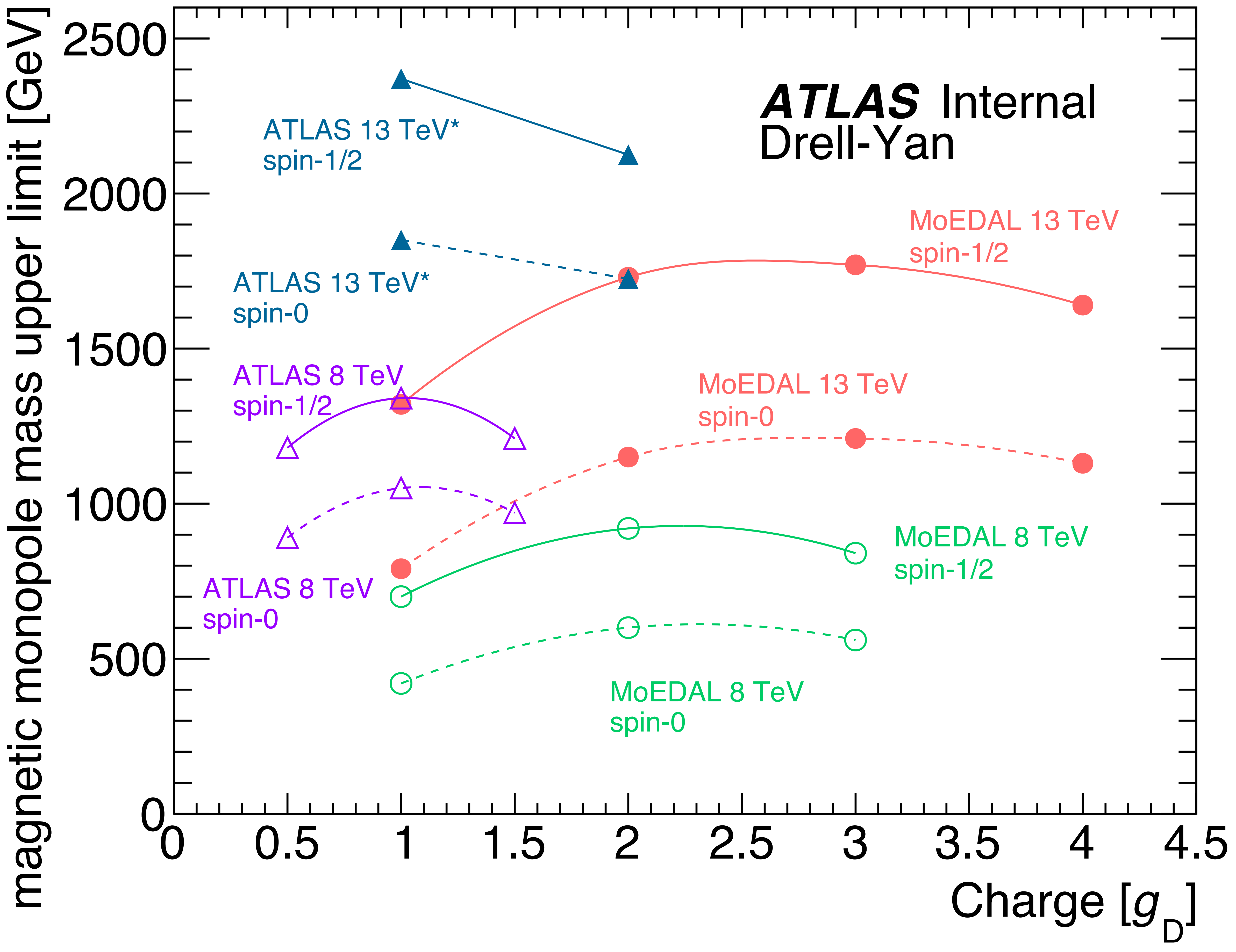
$$\frac{m_e}{m} \approx 10^{-7}$$

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:



RECENT MONOPOLE SEARCHES AT THE LHC



MoEDAL: *"exposed to […] proton-proton collisions at the LHCb interaction point […] searching for induced persistent currents"*

PhysRevLett.123.021802

Full Run 2 (13 TeV)

JHEP08(2016)067

Full Run 1 (8 TeV)

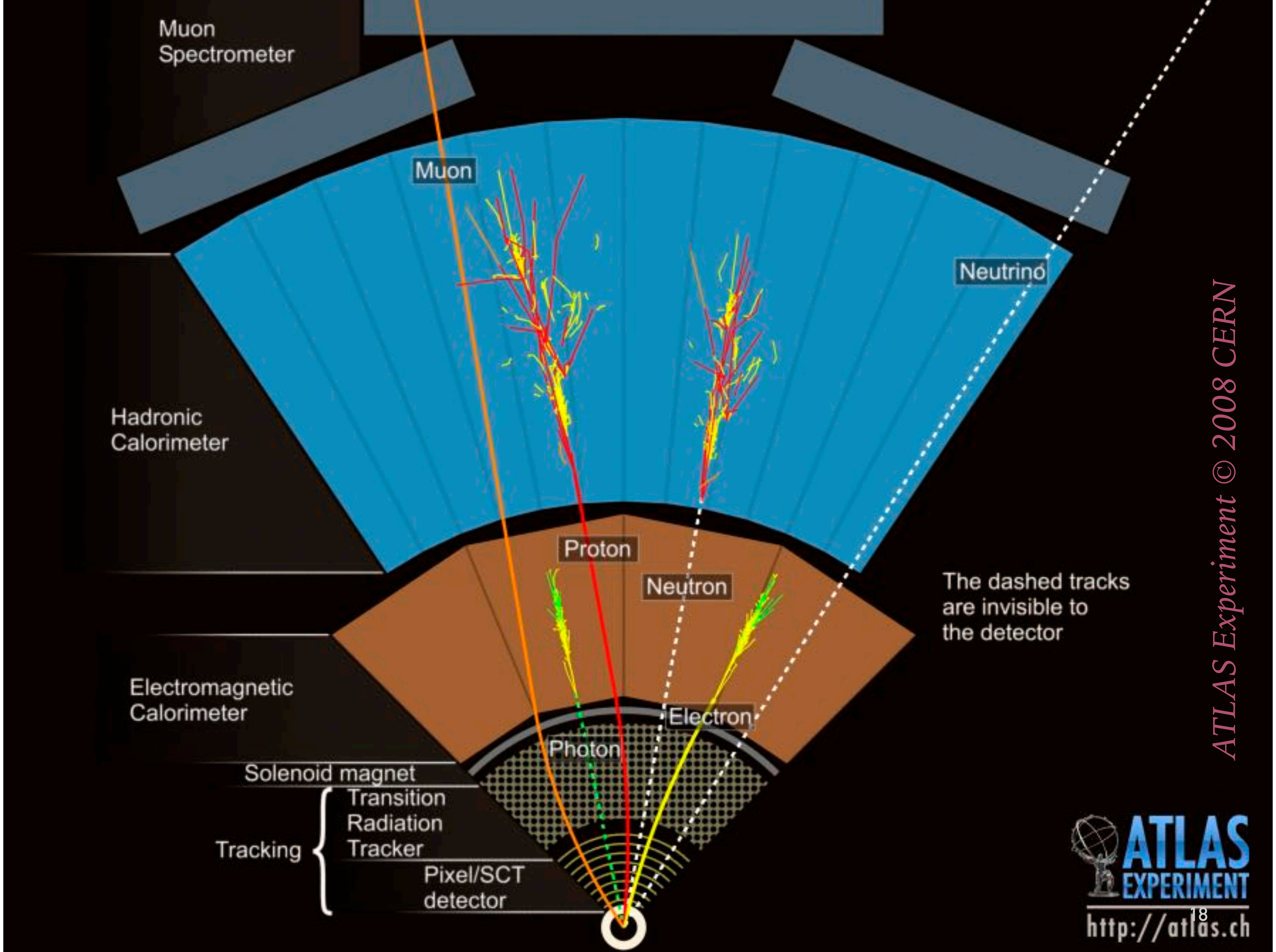
ATLAS: Highly ionizing particle signal

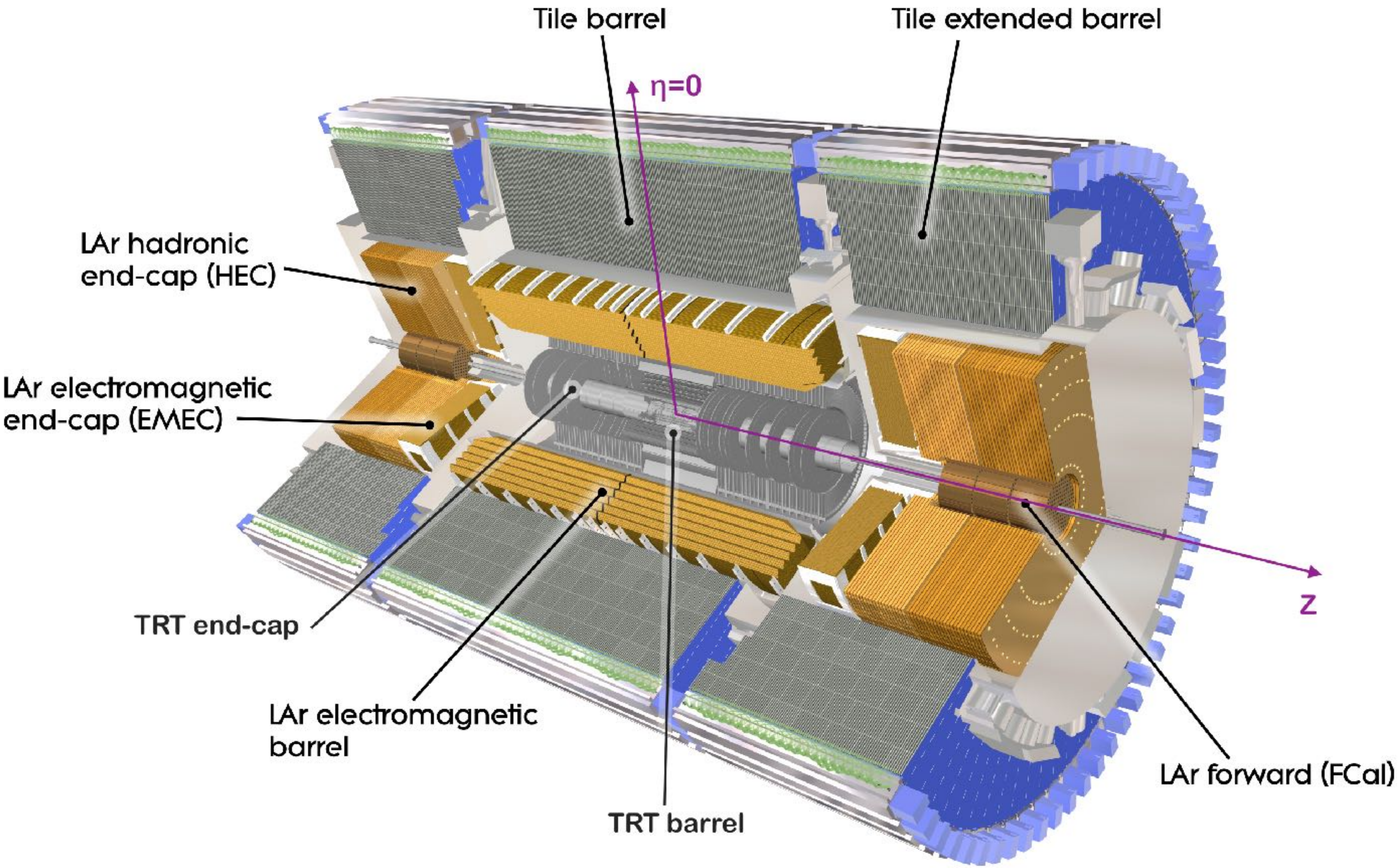
PhysRevLett.124.031802:

Partial Run 2 (13 TeV) analysis

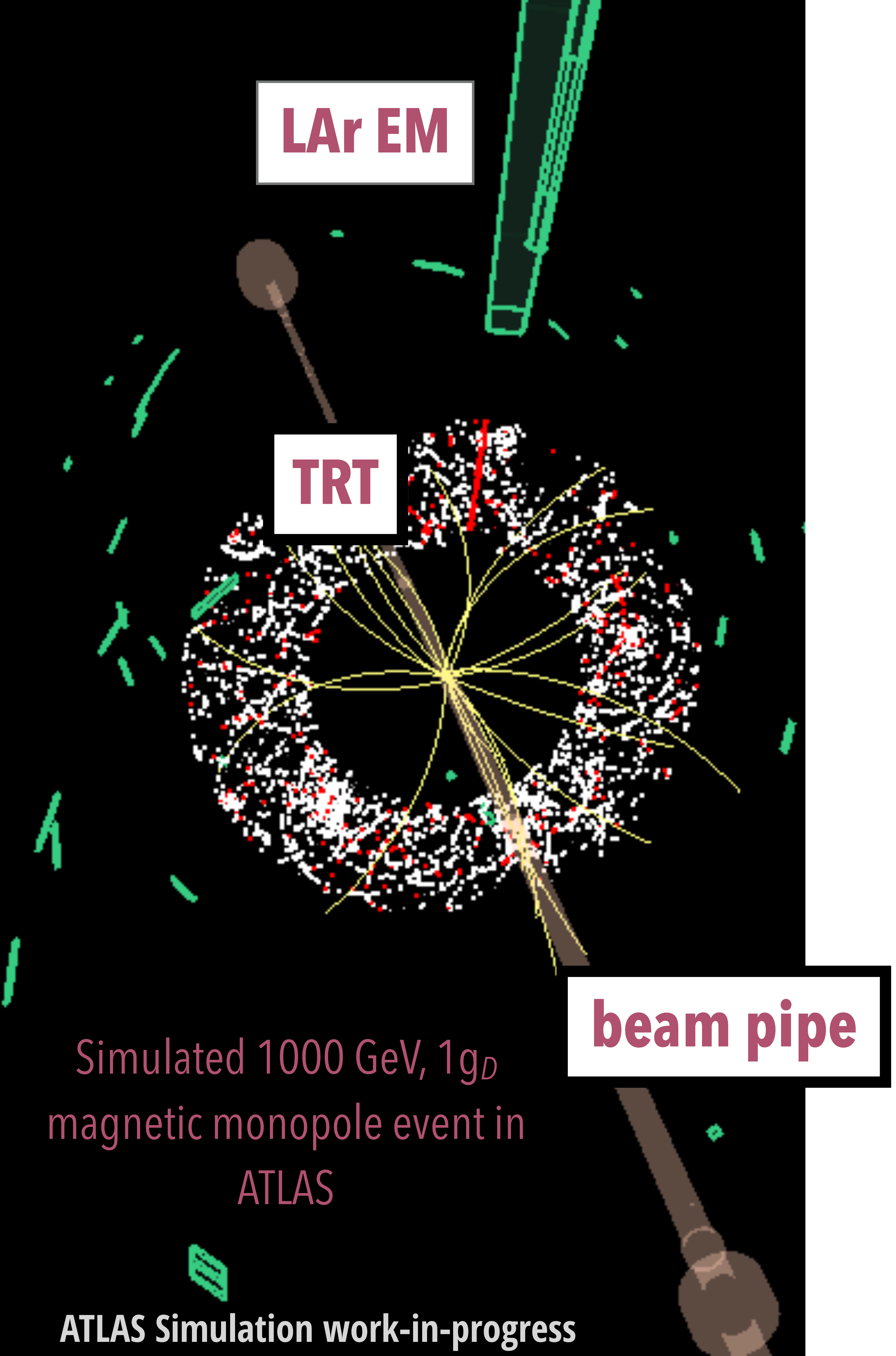
PhysRevD.93.052009

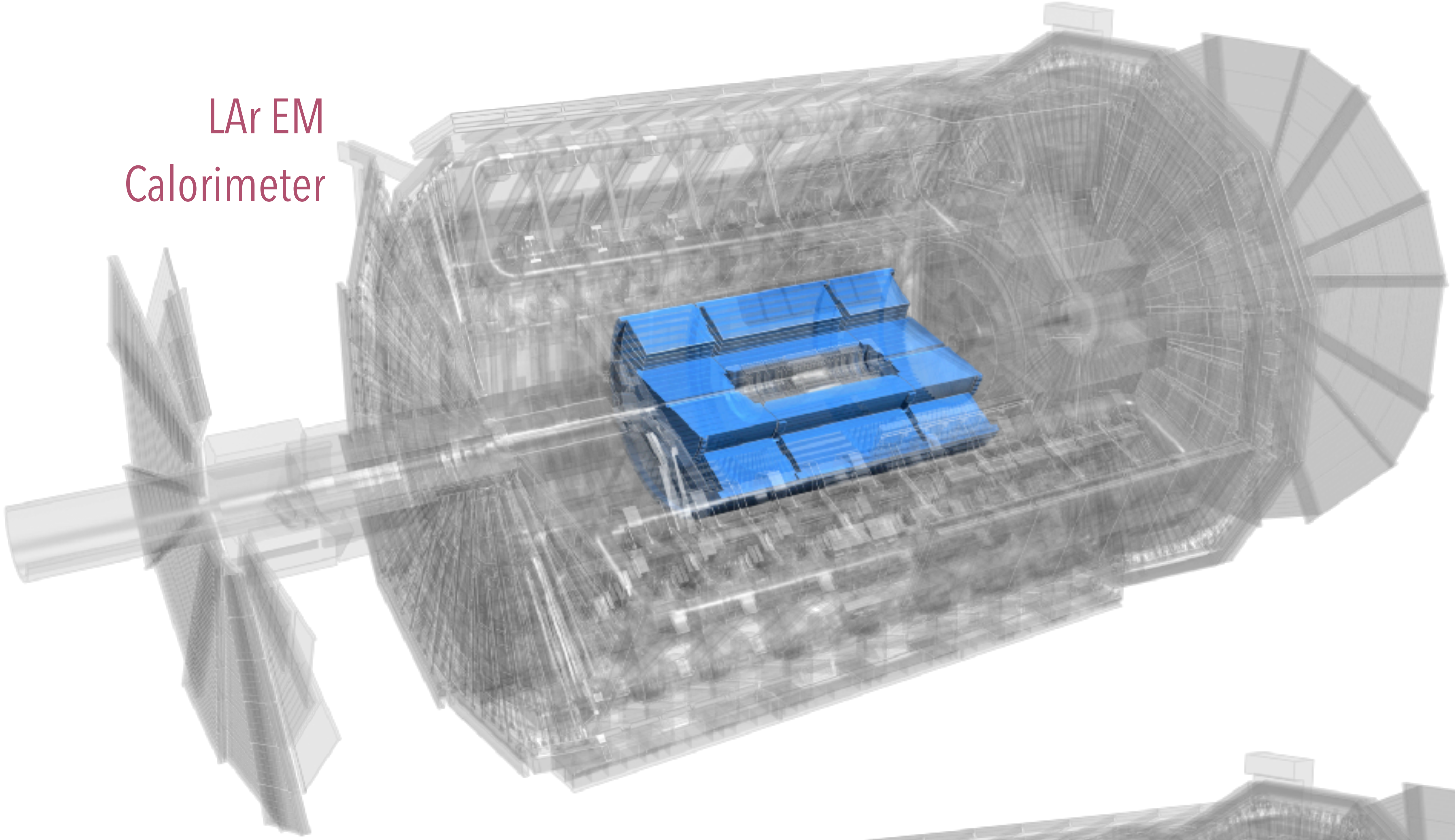
Full Run 1 (8 TeV)

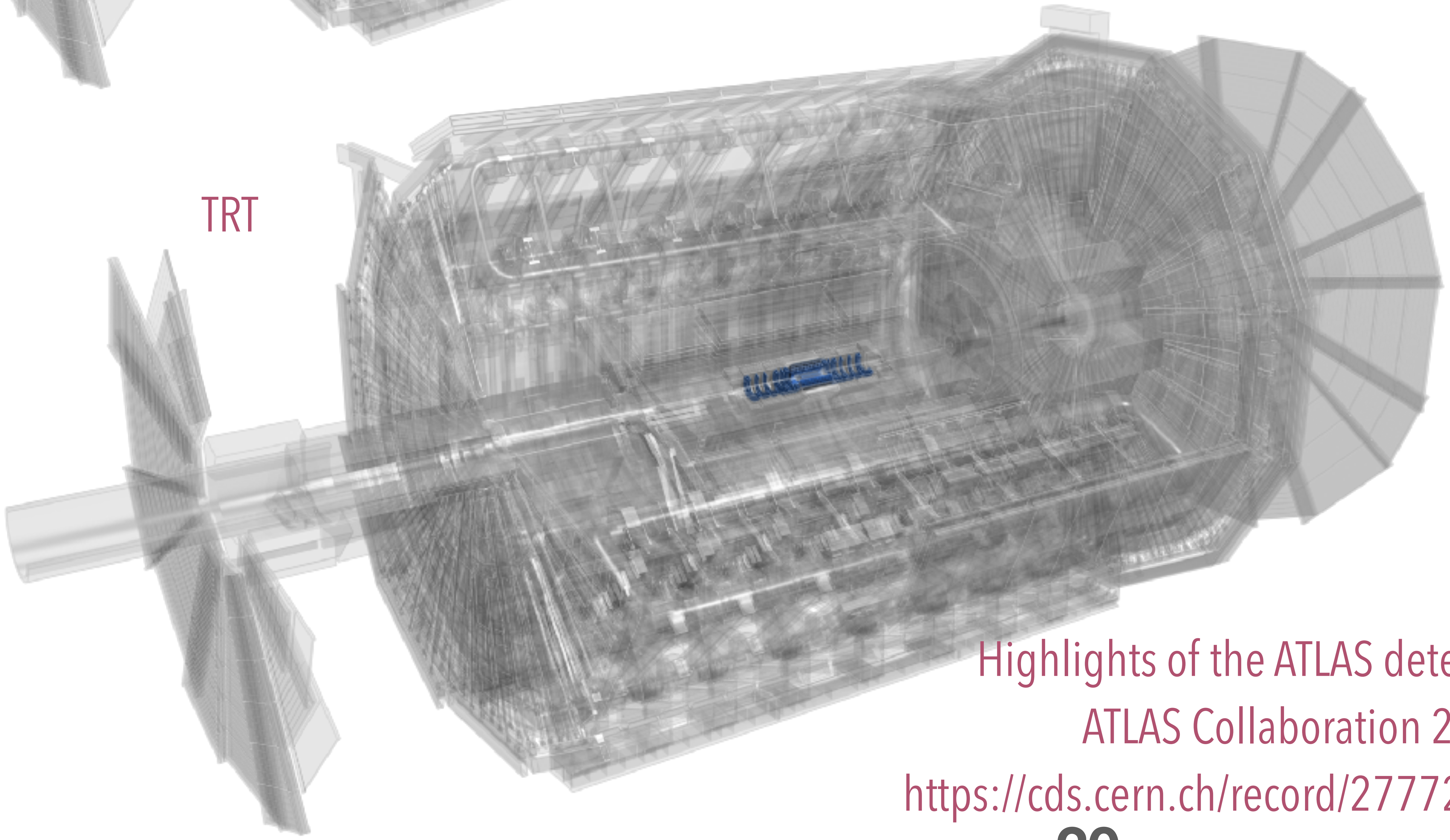

Muon Spectrometer
Muon
Neutrino
Hadronic Calorimeter
Proton
Neutron
The dashed tracks are invisible to the detector
Electromagnetic Calorimeter
Electron
Photon
Solenoid magnet
Transition Radiation Tracker
Tracking
Pixel/SCT detector
ATLAS EXPERIMENT
http://atlas.ch



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







Highlights of the ATLAS detector
ATLAS Collaboration 2008
https://cds.cern.ch/record/2777214/

Results

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  - Same trends
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Signal Efficiency Cut Flow DY spin-1/2 1 gD

<table>
<tr><td></td><td></td><td colspan="2">200 GeV</td><td colspan="2">1500 GeV</td><td colspan="2">4000 GeV</td></tr>
<tr><td></td><td>Preselection</td><td colspan="2">1</td><td colspan="2">1</td><td colspan="2">1</td></tr>
<tr><td>Training</td><td>w</td><td colspan="2">0.99</td><td colspan="2">0.98</td><td colspan="2">0.98</td></tr>
<tr><td rowspan="2">2gD 200 GeV</td><td rowspan="2">TRT information</td><td>f_{HT}</td><td>RF</td><td>f_{HT}</td><td>RF</td><td>f_{HT}</td><td>RF</td></tr>
<tr><td>0.92</td><td>0.86</td><td>0.89</td><td>0.83</td><td>0.65</td><td>0.75</td></tr>
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</table>

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

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

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

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

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

SUPERVISED MACHINE LEARNING

Training Set

x *features*

y *labels*

Learning algorithm

Cost function

$min[J(\theta)]$

θ *parameters*

Training Score

hypothesis function

$$h_\theta(x) = P(y = 1 \mid x; \theta)$$

Test Set

x *features*

y *labels*

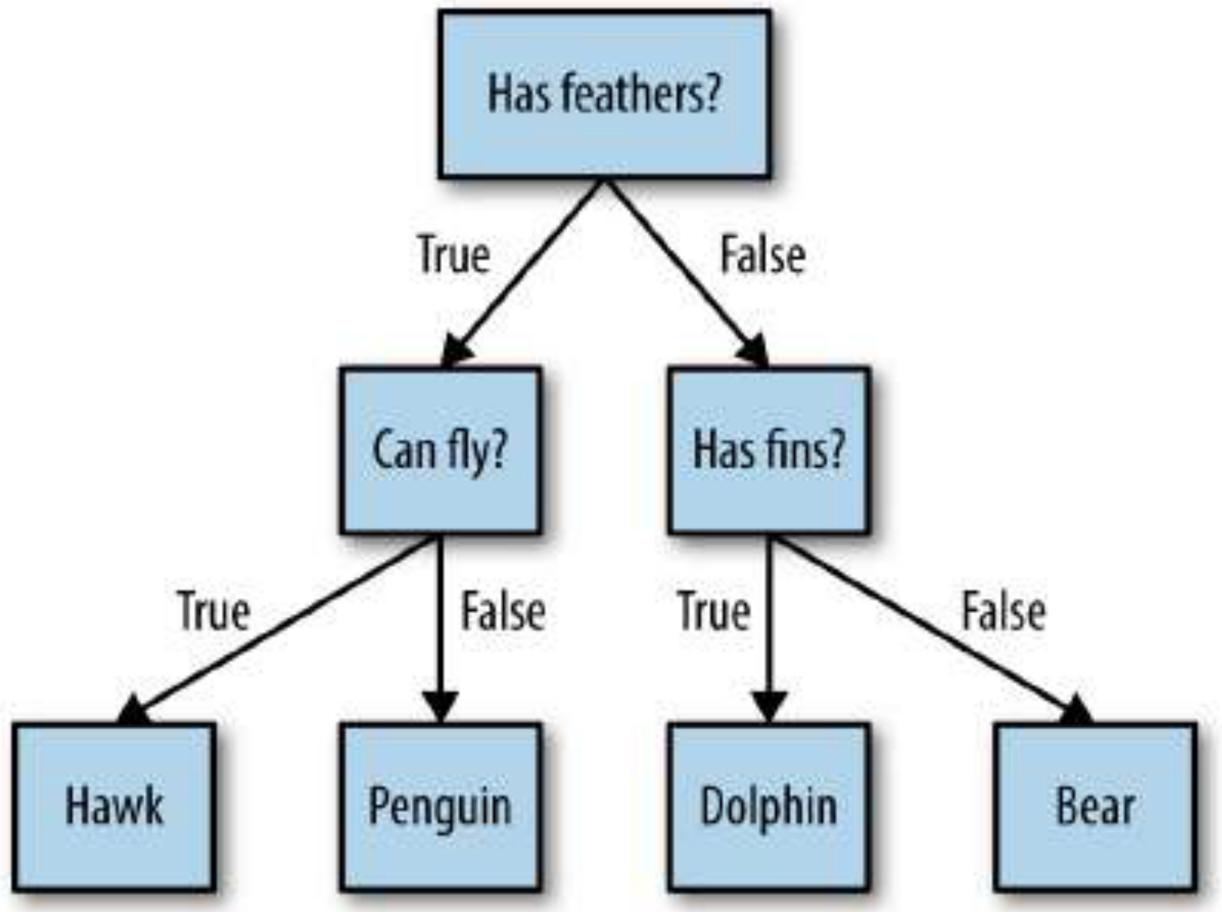
hypothesis function

$P(y = 1 \mid x; \theta)$

Test Score

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.*