Machine learning techniques for $\overline{He}$ research in cosmic rays

Francesco Rossi

Introduction

- Large He background
- $\overline{He}$ are rare events, as a rule of thumb $1 : 10^9$ He
- No signal model available, only ^4He Monte Carlo and ISS-data.

Goals:

1) Study He background and find charge confusion sources
2) Develop tools to reduce He contributions.

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1) Study He background and find charge confusion sources
2) Develop tools to reduce He contributions.

Strategy :

G1)

- Use He BC1236 Monte Carlo samples (L1-focused and L1-L9 focused)
- Select “well reconstructed” ^4He events and study the charged confused events

G2)

- Train a classifier (on MC) to recognise different charge confusion sources
- Search for “outliers” in data using an anomaly detection technique.
- Combine the machine learning techniques

Study He background and find charge confusion sources.

Monte carlo selection (He B1236 L1-focused and L1-L9 focused)

IsPhysicsTrigger **TRIGGER**

β clusters ≥ 4 **β**
$\beta > 0$
$\chi^2_{Coo} < 4$

Track number ≥ 1 **TRACK**
track pattern L1&L2&(L3|L4)&(L5|L6)&(L7|L8) (≥ 5)

charge YJ (inner) $\in [1.7, 2.4]$ **TRK**
charge YJ (L1) $\in [1.6, 3.0]$
Inner fiducial volume
L1 fiducial volume
$\chi^2_Y < 10$

TOF charge
charge UTOF $\in [1.5, 3.0]$
charge LTOF ≥ 1.5

Inner rigidities signs **RIGIDITY**

Tracker fiducial volume cut:
- L1: |R|<62cm, |Y|<47cm
- L2: |R|<62cm, |Y|<40cm
- L3: |R|<46cm, |Y|<44cm
- L4: |R|<46cm, |Y|<44cm
- L5: |R|<46cm, |Y|<36cm
- L6: |R|<46cm, |Y|<36cm
- L7: |R|<46cm, |Y|<44cm
- L8: |R|<46cm, |Y|<44cm

UH = Rig. [UH-inner]
LH = Rig. [LH-inner]
Inner = Rig. [inner]

If($R_{inner} < 0) \rightarrow (\mathrm{UH} < 0, \mathrm{LH} < 0)$

Sources of charged confused events

Using He Monte Carlo B1236 L1-focused and L1-L9 focused, and selecting the **reconstructed events with $\mathbf{R} < \mathbf{0}$**, we identified **three sources of charge confusion**

Spillover

Hadronic inelastic

Hadronic elastic *

* Large angle scattering

Sources of charged confused events

Using He Monte Carlo B1236 L1-focused and L1-L9 focused, and selecting the **reconstructed events with $\mathbf{R < 0}$**, we identified **three sources of charge confusion**

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Hadronic inelastic

Hadronic elastic *

Silicon tracker finite resolution

* Large angle scattering

Sources of charged confused events

Using He Monte Carlo B1236 L1-focused and L1-L9 focused, and selecting the **reconstructed events with $\mathbf{R < 0}$**, we identified **three sources of charge confusion**

Spillover

Hadronic inelastic

Hadronic elastic *

Interactions within the detector

* Large angle scattering

Sources of charged confused events

Using He Monte Carlo B1236 L1-focused and L1-L9 focused, and selecting the **reconstructed events with $\mathbf{R} < \mathbf{0}$**, we identified **three sources of charge confusion**

Spillover | Hadronic inelastic | Hadronic elastic *

For each source, we select a sample to be used in the training of a classifier

* Large angle scattering

Sources of charged confused events

Using He Monte Carlo B1236 L1-focused and B1236 L1-L9 focused, and selecting the **reconstructed events with $\mathbf{R < 0}$**, we identified **three sources of charge confusion**

Spillover

Hadronic inelastic

Hadronic elastic *

Search in the secondaries list looking for inelastic interaction products inside the inner tracker

* Large angle scattering

Sources of charged confused events

Using He Monte Carlo B1236 L1-focused and B1236 L1-L9 focused, and selecting the **reconstructed events with $\mathbf{R < 0}$**, we identified **three sources of charge confusion**

Spillover

Hadronic inelastic

Hadronic elastic *

Search in the secondaries list looking for secondaries produced inside the inner tracker (HasSecondary)

Events are not Had. Inel. Interactions and primary nuclei reaches L2

Propagation of two tracks: $R_{true}(L2)$ and $R_{inner}(< 0)$

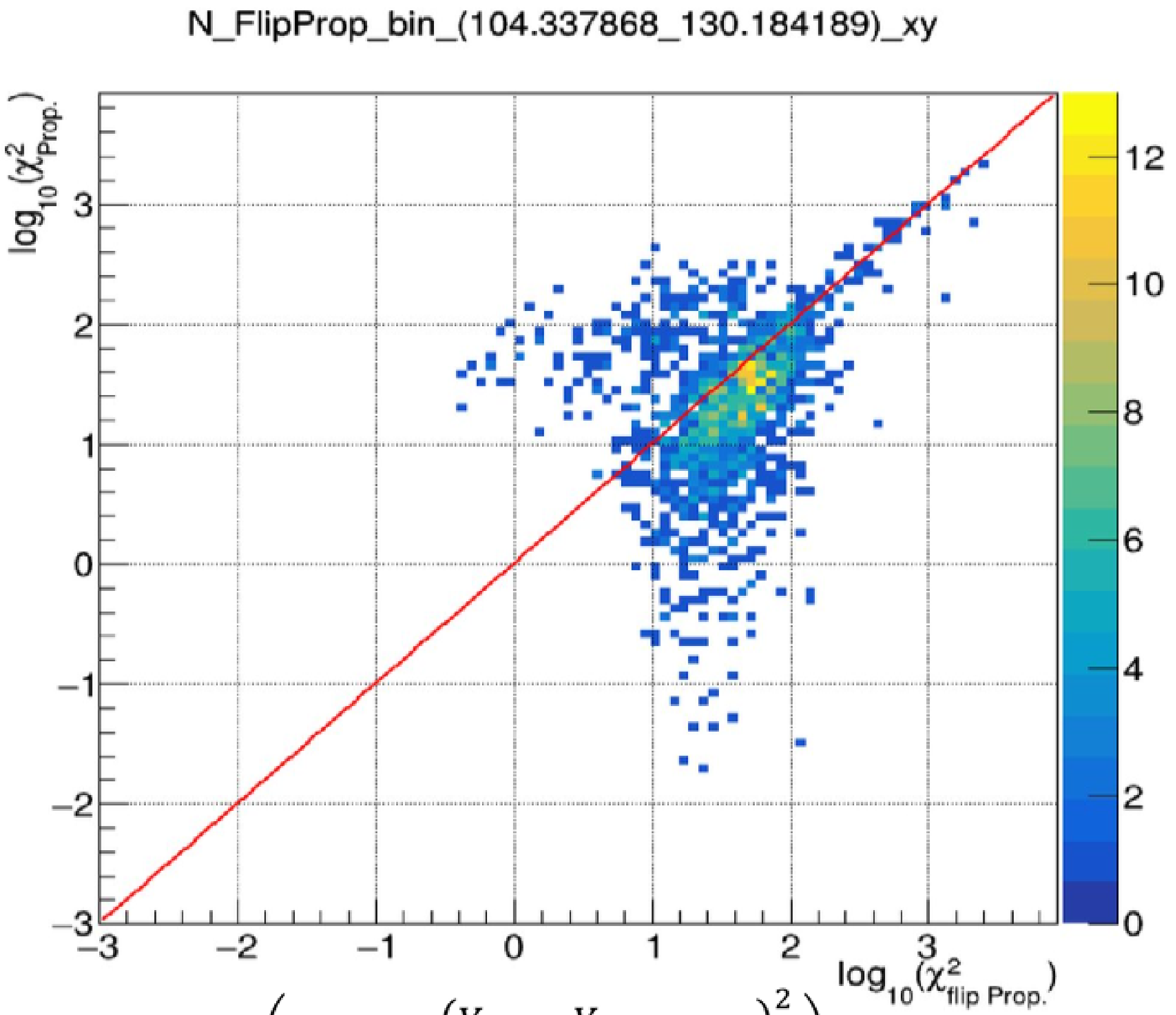
Build two χ^2 comparing y coordinate with MC true info on each layer.

$$\frac{\chi^2_{R_{true}}}{\chi^2_{R_{inner}}} \geq 1.05 \quad \rightarrow \text{El. scat.}$$

$$0.95 \geq \frac{\chi^2_{R_{true}}}{\chi^2_{R_{inner}}} \quad \rightarrow (\text{HasSecondary})\ ?\ \text{Other} : \ \text{Spillover}$$

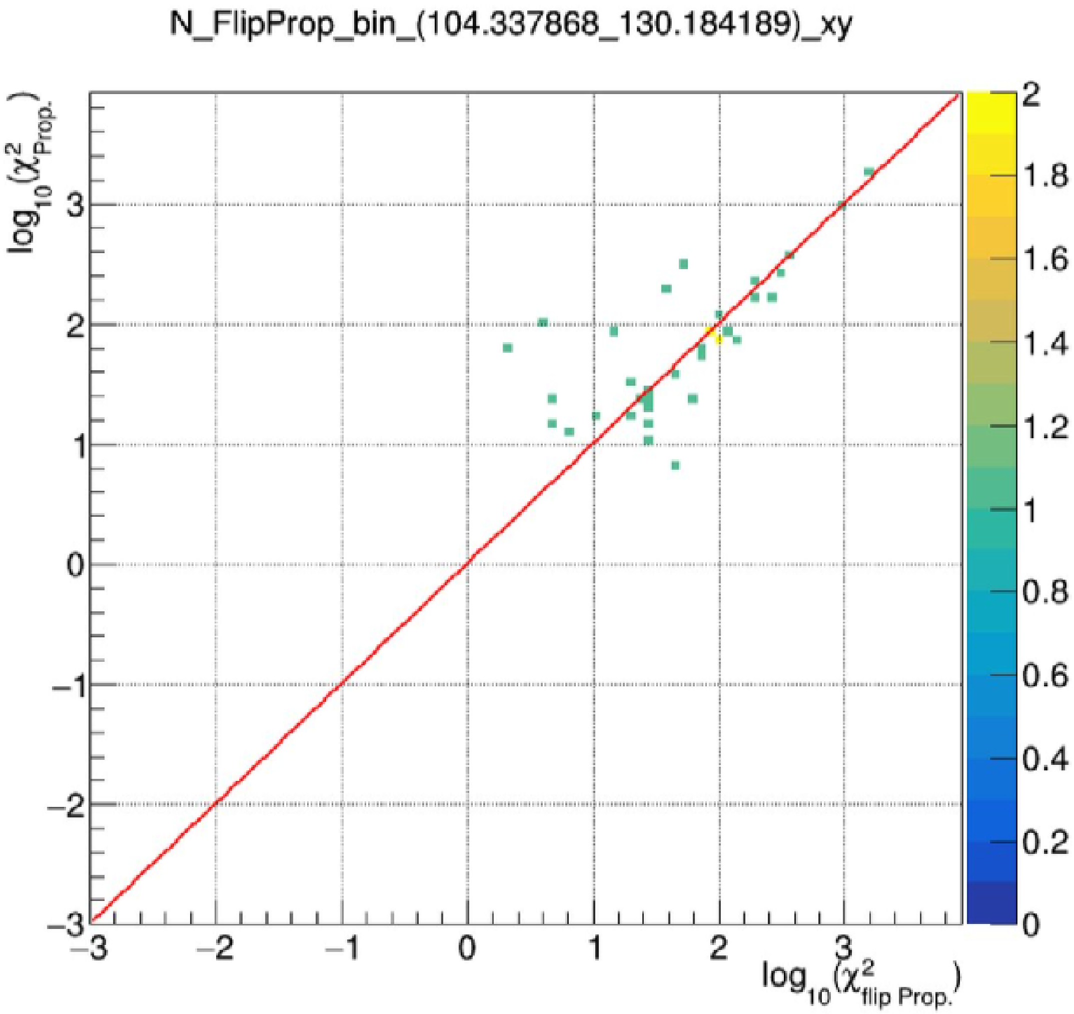
$$0.95 < \frac{\chi^2_{R_{true}}}{\chi^2_{R_{inner}}} < 1.05 \rightarrow (\text{HasSecondary})\ ?\ \text{Other} : \ \text{Spillover}$$

$R_{inner} < 0$ (no secondaries within inner tracker)



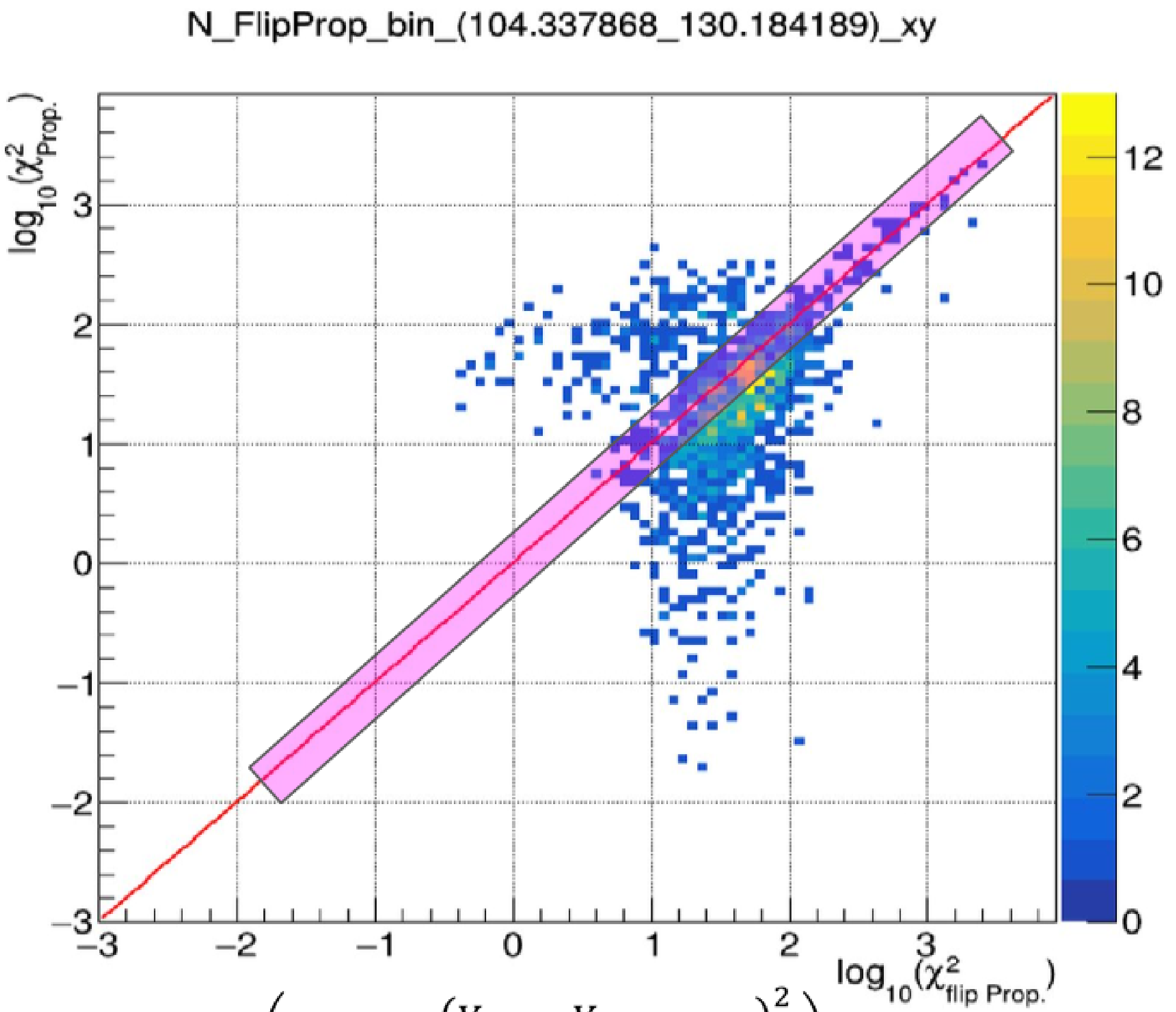
$$\chi^2_{prop} = \frac{\left(\sum_{i-layer} \frac{\left(Y_{MC} - Y_{prop.track}\right)^2}{\sigma^2_{hit}}\right)}{Ndof}$$

$R_{inner} < 0$ (elastic scattering within inner tracker)



$$\sigma^2_{hit} = 15\ \mu\text{m}$$

$R_{inner} < 0$ (no secondaries within inner tracker)



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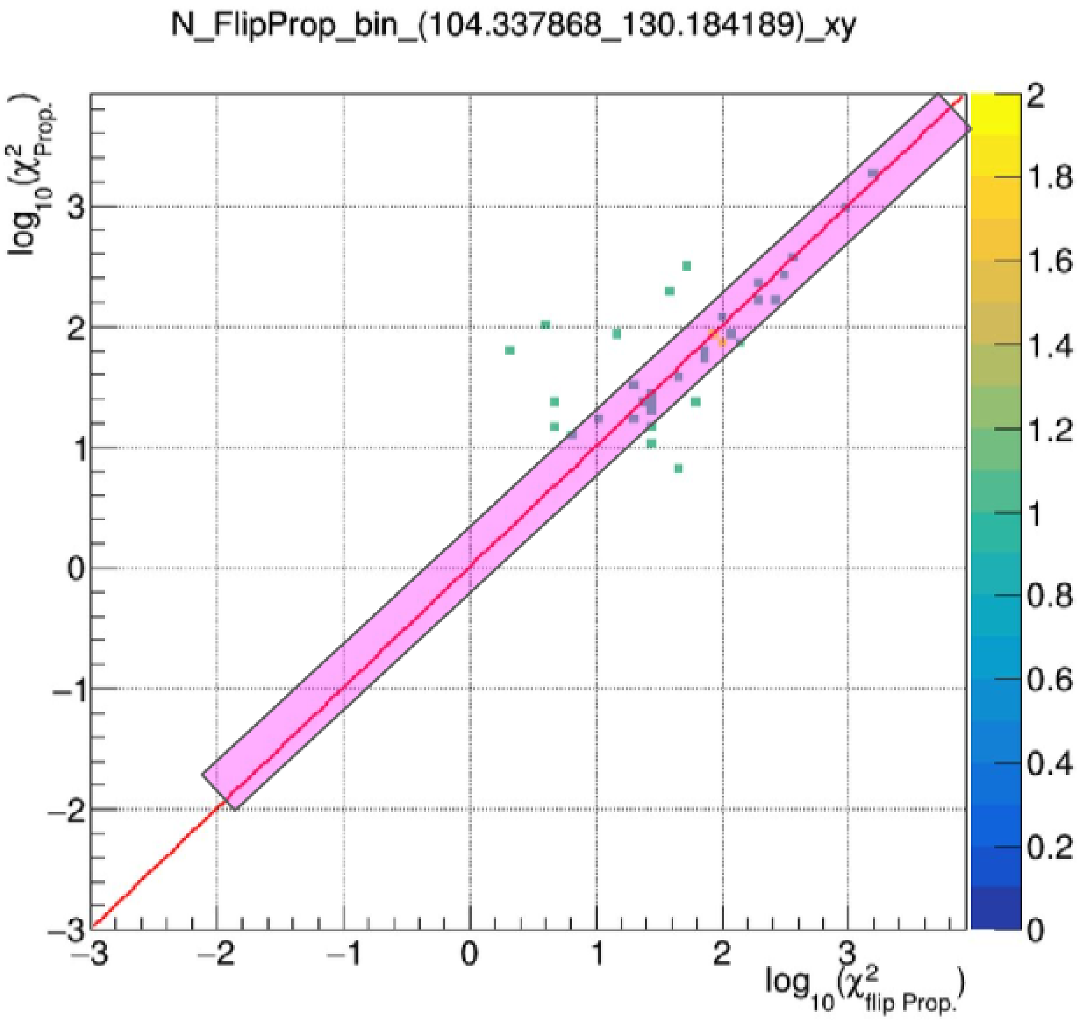

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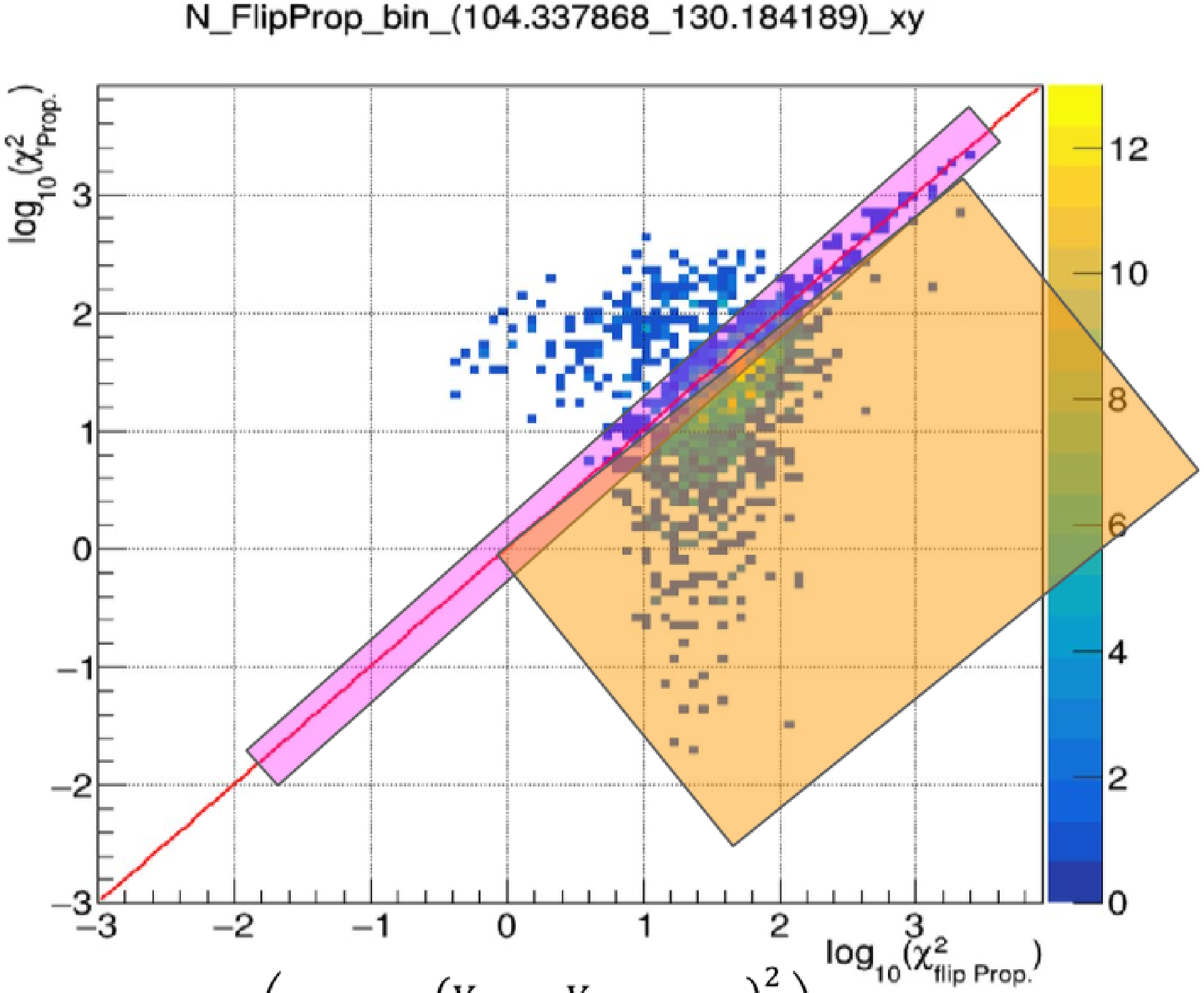

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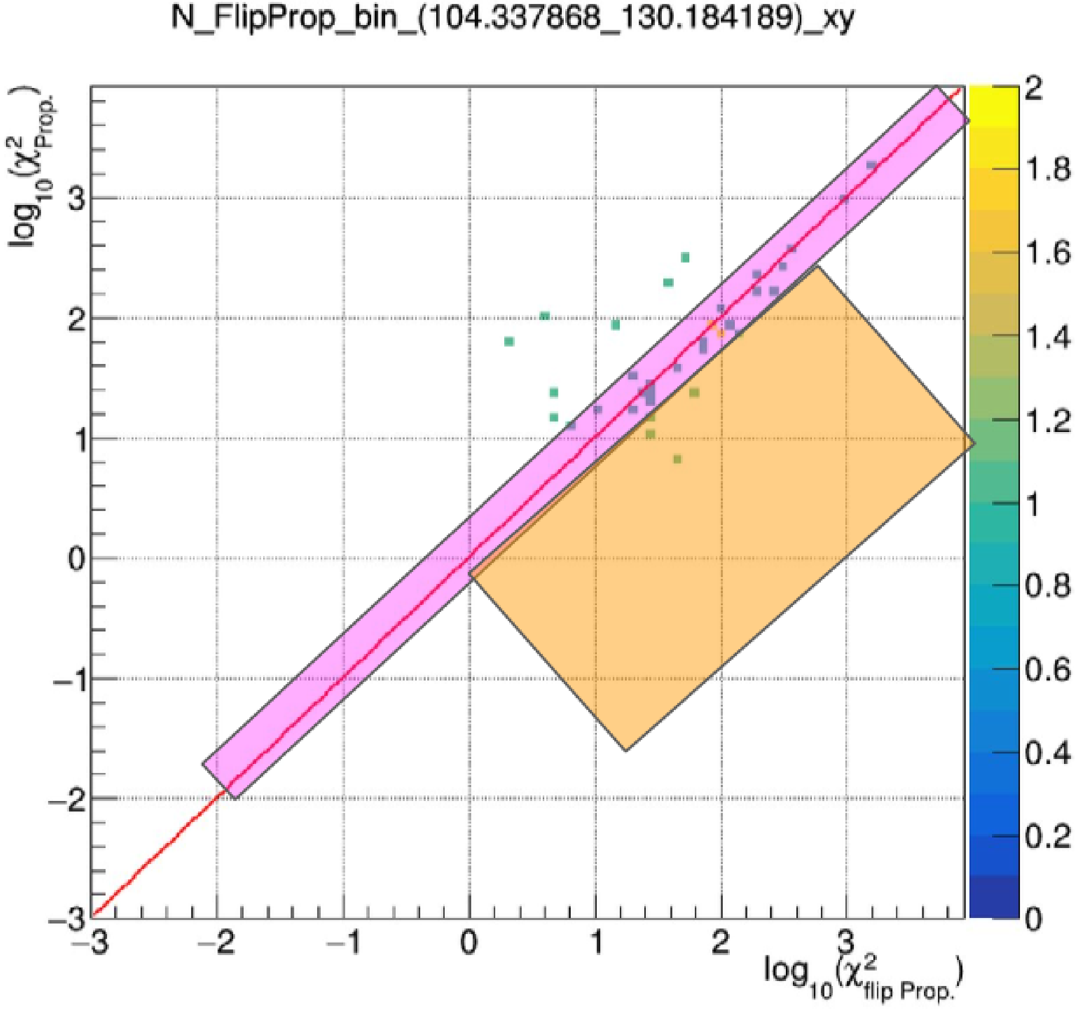

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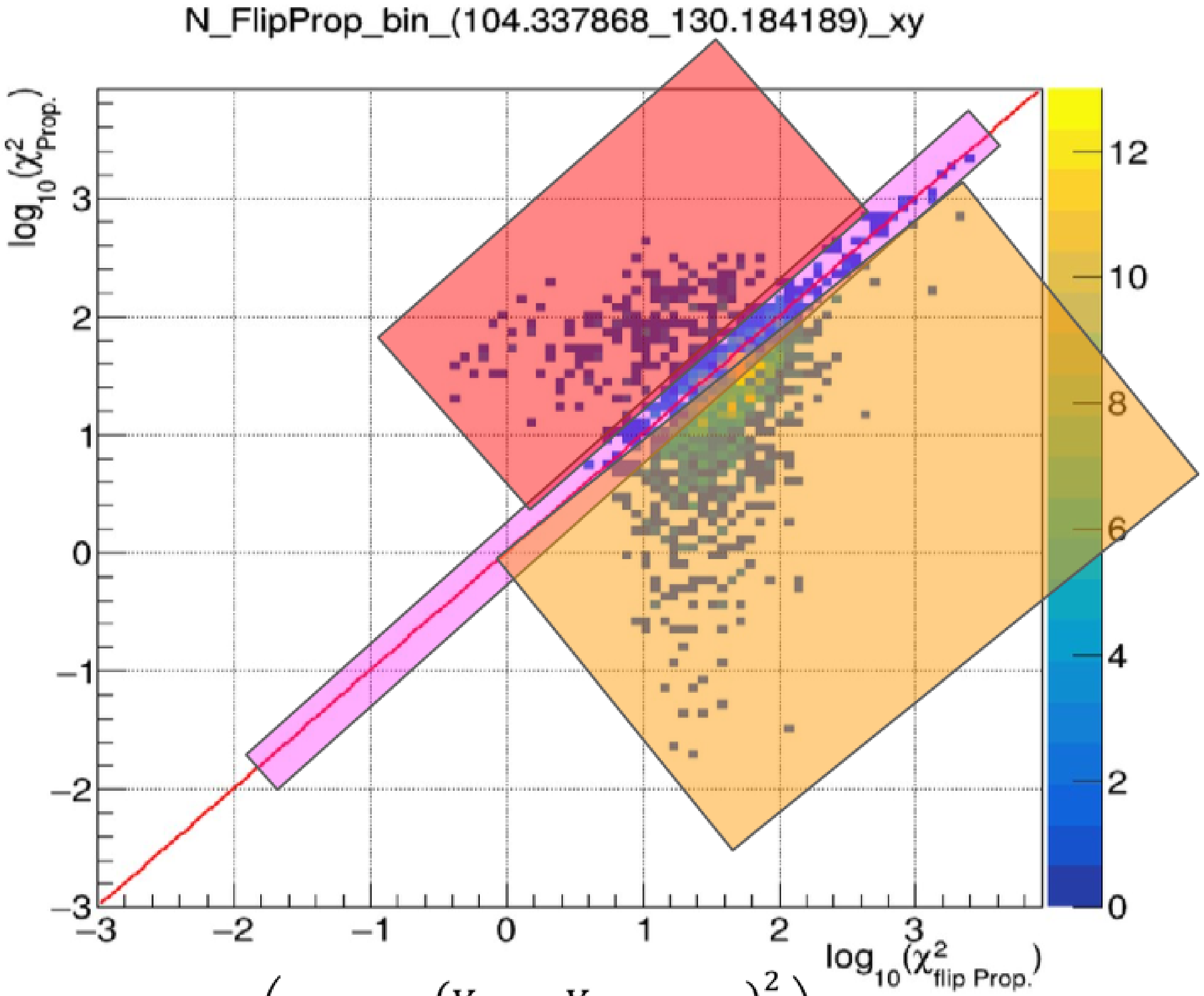

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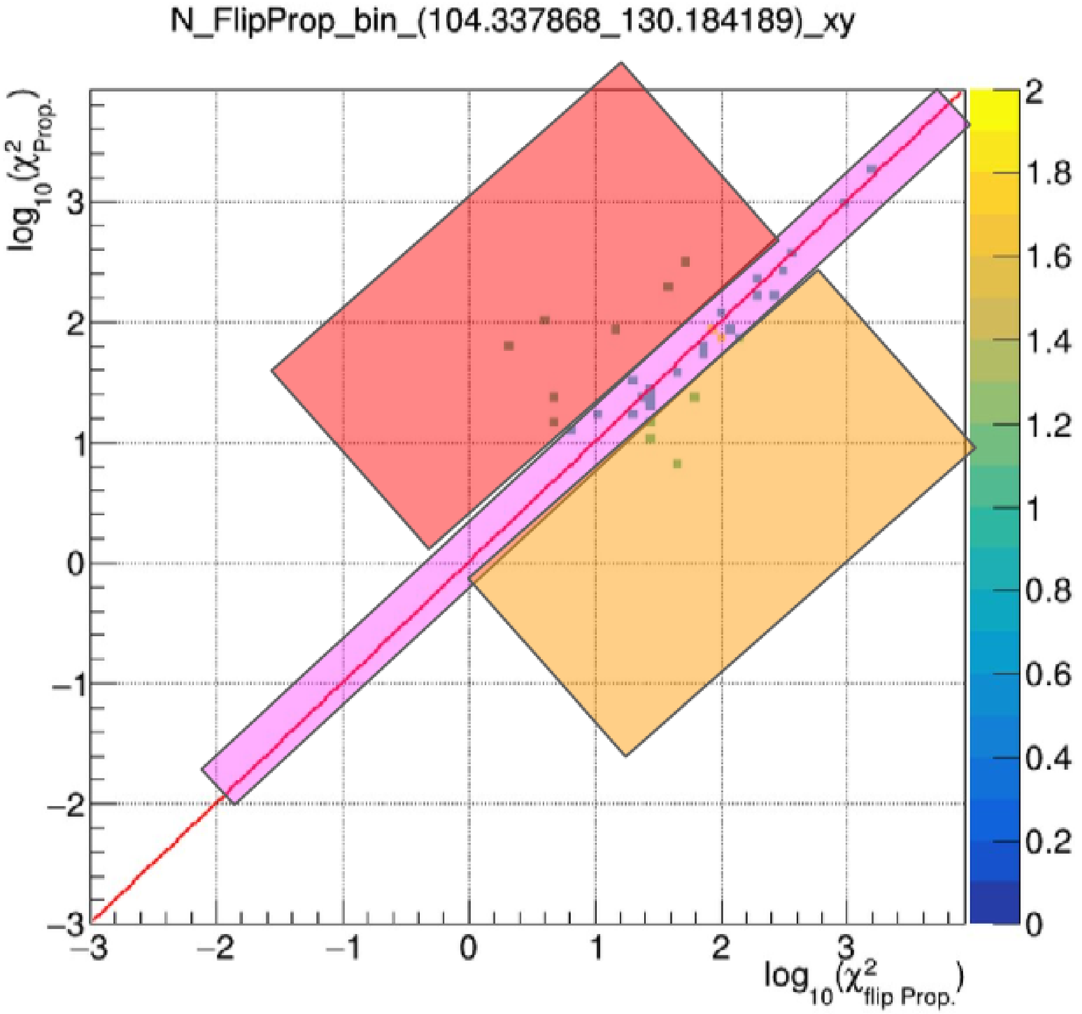


$$\sigma^2_{hit} = 15\ \mu m$$

Tools to reduce He background 1

(supervised learning)

A Fully Connected Neural Network (FCNN) classifier to characterise the He background

- Use the classes previously defined as labels for supervised training
- The Monte Carlo has been weighted using published 7.5 He flux.
- Sample composition (**14 % Spillover, 2.5% El. Scat., 53% Had. Inel., 30% Other)**
- **Training** sample ($\mathbf{1.78 \cdot 10^5}$) and **validation** sample ($\mathbf{0.76 \cdot 10^5}$) events
- Choose variables with good data-MC agreement as input features:

Time Of Flight:

- TOF on-time clusters ($\times$ 4)

Inner Tracker:

- TRK min feet-distance ($\times$ 4)
- TRK Y cluster ($\times$ 7)
- TRK Max cluster distance ($\times$ 7)
- TRK track hit |Y| ($\times$ 7)
- TRK NormEdep2Y* ($\times$ 7)

Anti-Coincidence system:

- ACC counters

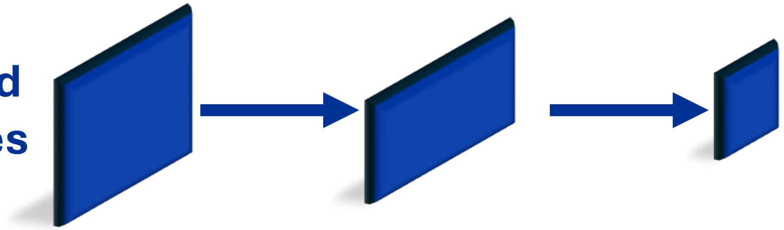
$$^{*}\mathrm{NormEdep2Y} = \frac{Track\ E_{dep}\ Y}{Cluster\ E_{dep}\ Y(2\ cm\ from\ Track\ hit) +\ Track\ E_{dep} Y}$$

Total number of input features = 37

Fully Connected Neural Network (FCNN) structure

- FCNN **structure**:
  - PyTorch
  - Four linear layers: [37, 15, 10, 4]
  - Activation functions: ReLu, Softmax (last layer)

37 optimized input **features**

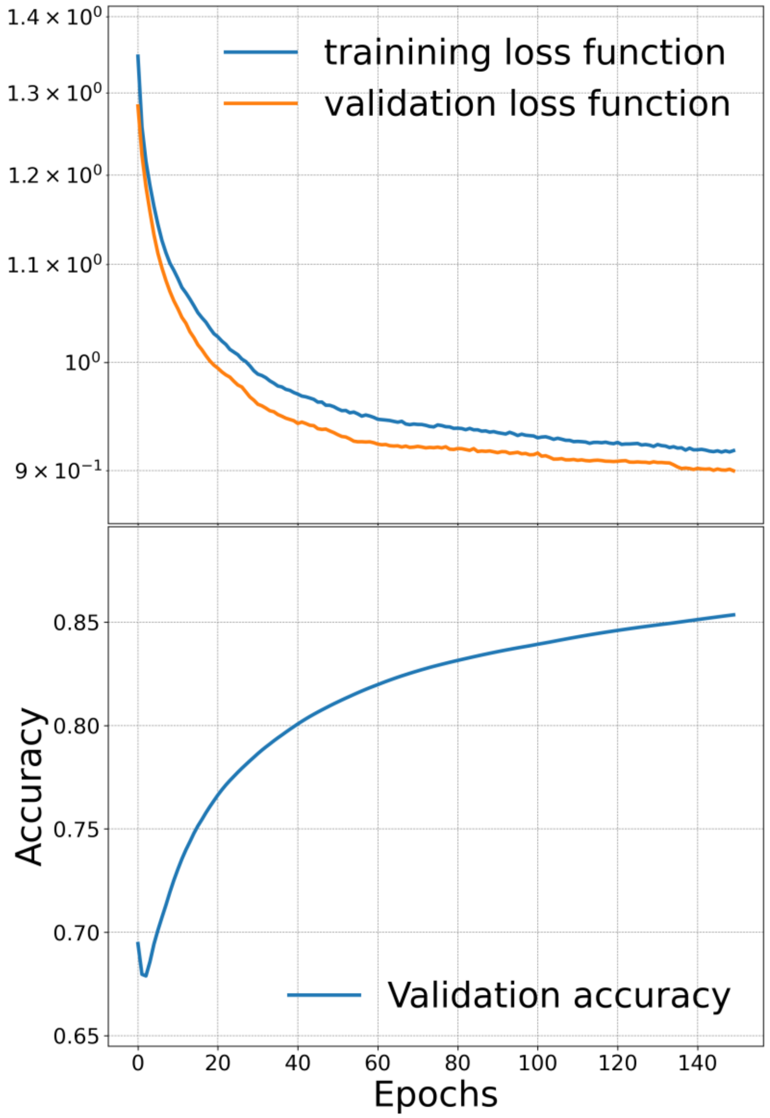


FCNN output

3 hidden layer with 15 nodes

- FCNN **hyperparameters**:
  - Optimizer: Adam
  - Learning rate: $5.0 \cdot 10^{-4}$
  - Batch size: $7.0 \cdot 10^{2}$
  - Drop-out: $1.0 \cdot 10^{-1}$
  - Loss function: Cross Entropy

Training sample ($\mathbf{1.78 \cdot 10^5}$) and **validation** sample ($\mathbf{0.76 \cdot 10^5}$) are **unbalanced**



Discriminants

- The network returns a vector of four elements.
- Each element corresponds to the probability that the current event is belongs to one of the four classes:

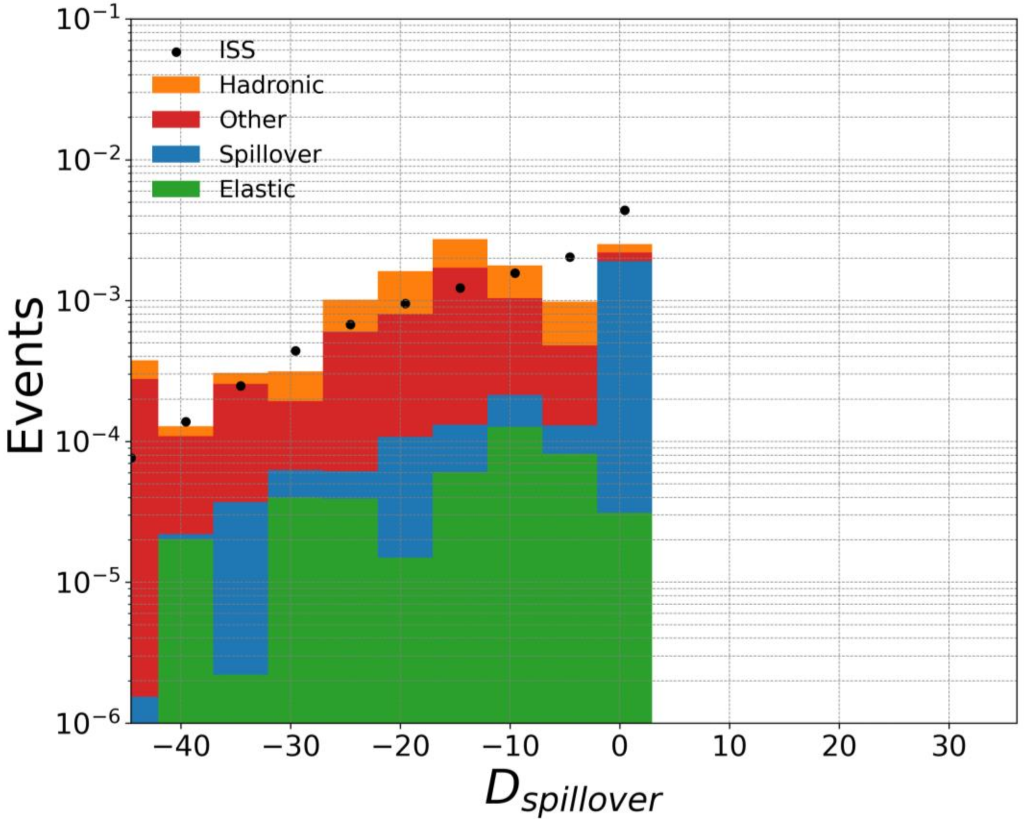
$$\text{FCNN output} = \left(p_{spillover},\ p_{Had.Inel},\ p_{El.Scat.},\ p_{Other}\right)$$

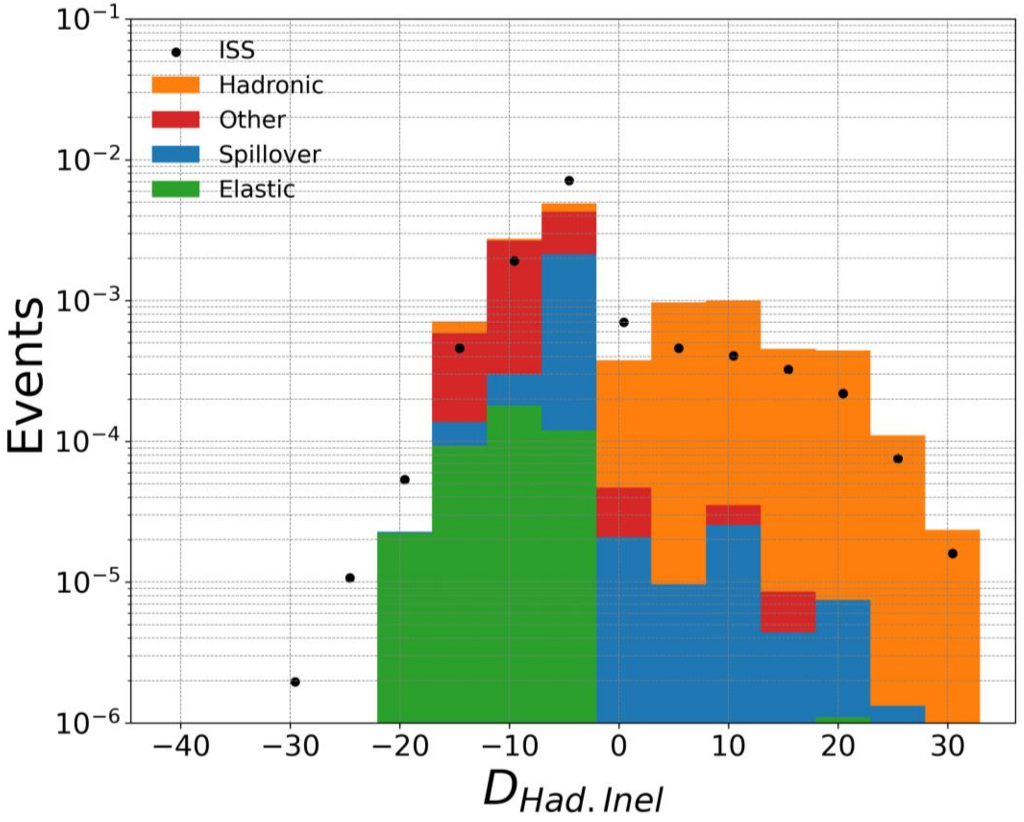
- The fraction of each class is defined as: $f_{Had.inel.} = \frac{\#Had.inel.}{\#Spillover + \#Had.Inel + \#El.scat. + \#Other}$
- The discriminant is defined as

$$D_{Had.\,inel} = \log_{10}\left(\frac{p_{Had.inel}}{f_{Spillover} \cdot p_{Spillover} + f_{El.scat.} \cdot p_{El.scat.} + f_{Other} \cdot p_{Other}}\right)$$

- **Applying the Monte Carlo selection (+ RTI cuts and NO cutoff) to data: $\mathbf{1.25 \cdot 10^5}$ events with $\boldsymbol{R_{inner} < 0}$**

Discriminants for spillover and Had. inel.

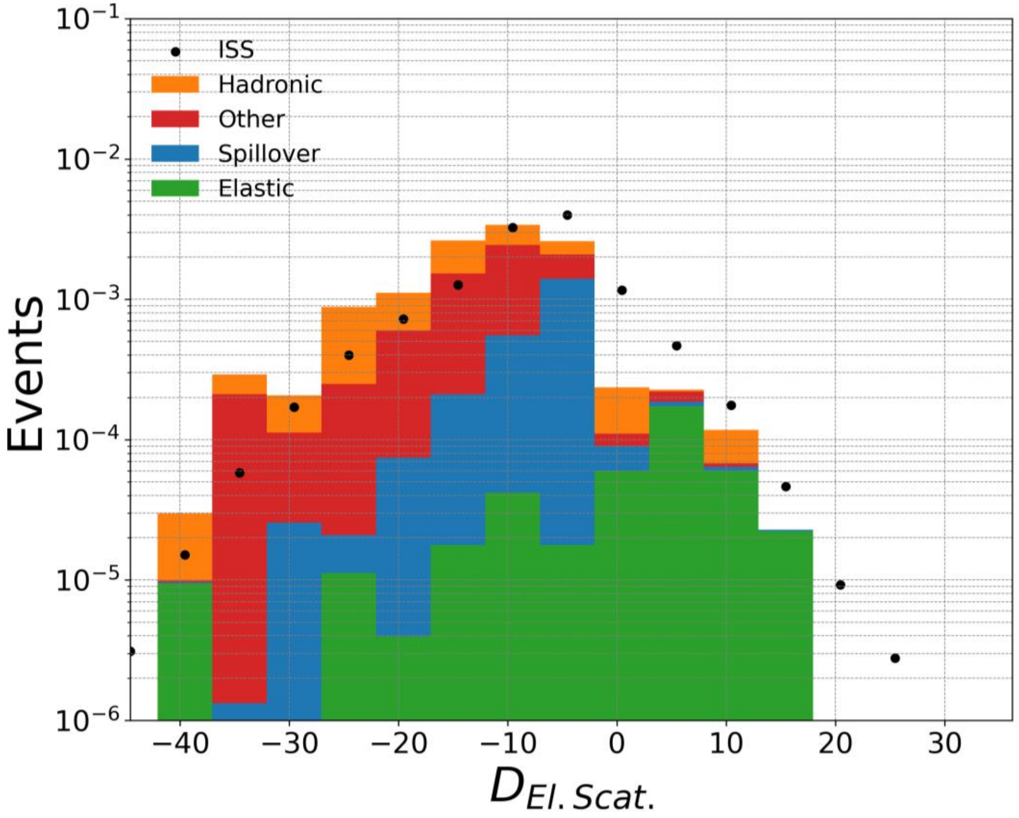




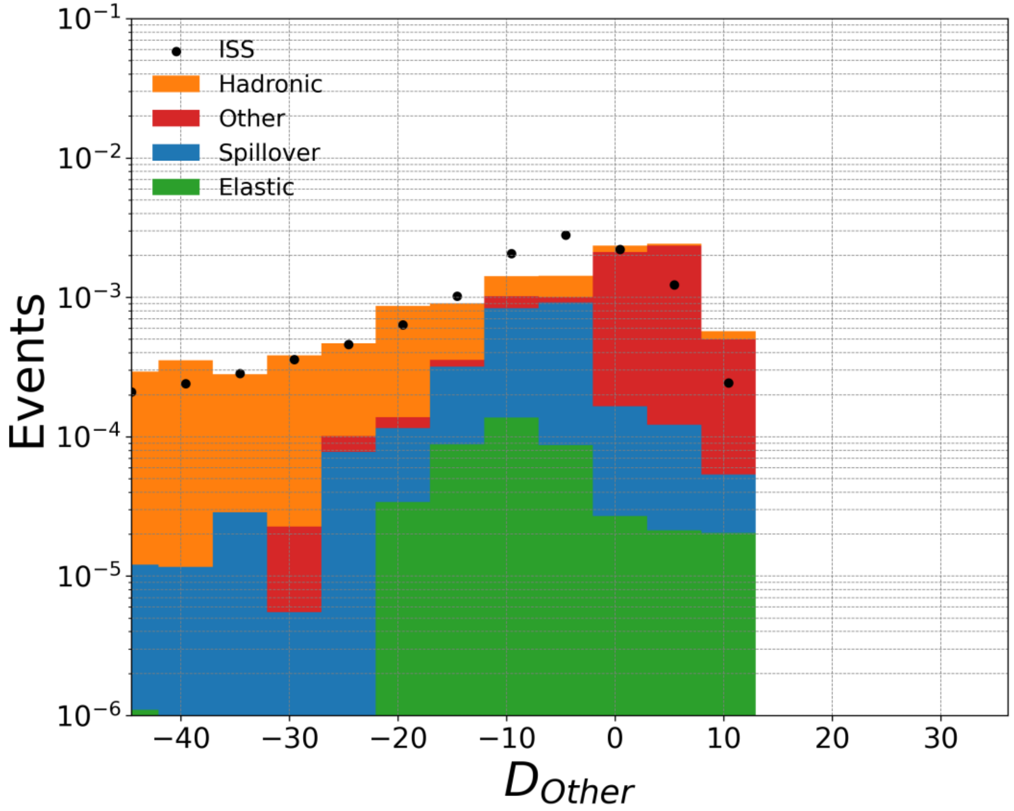
$$D_{Spill} = \log_{10}\left(\frac{p_{Spill}}{f_{Inel} \cdot p_{Inel.} + f_{El.} \cdot p_{El} + f_{Ot} \cdot p_{Ot}}\right)$$

$$D_{El.} = \log_{10}\left(\frac{p_{Inel.}}{f_{Spill} \cdot p_{Spill} + f_{El} \cdot p_{El} + f_{Ot} \cdot p_{Ot}}\right)$$

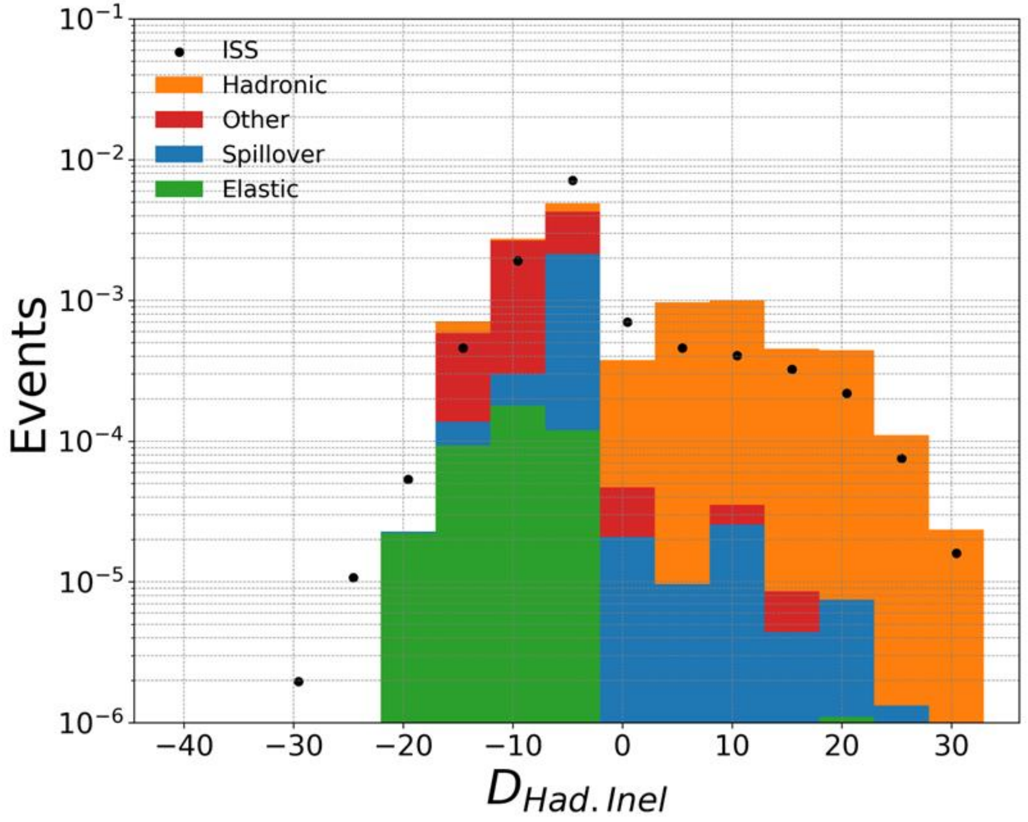
Discriminant for el. scat. and the fourth class



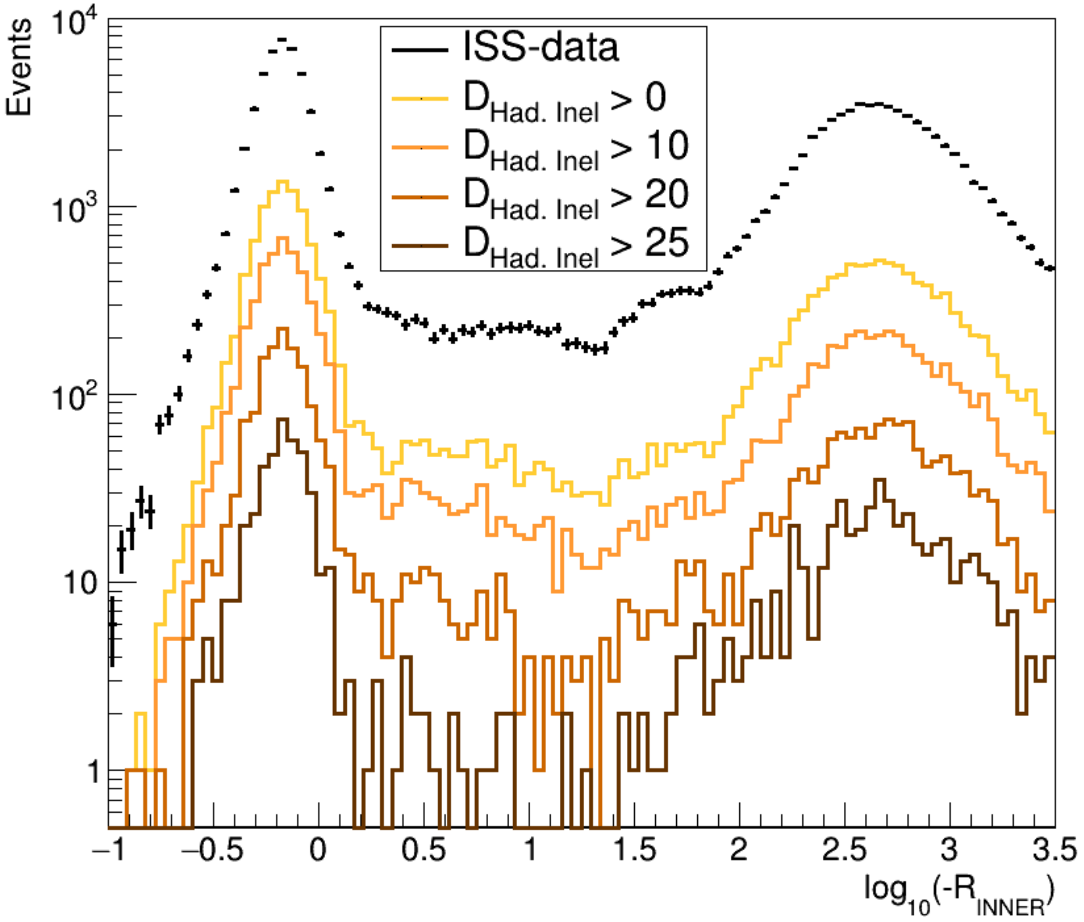
$$D_{El} = \log_{10}\left(\frac{p_{El.}}{f_{Inel} \cdot p_{Inel} + f_{Spill} \cdot p_{Spill} + f_{Ot} \cdot p_{Ot}}\right)$$



$$D_{Ot} = \log_{10}\left(\frac{p_{Ot}}{f_{Inel} \cdot p_{Inel} + f_{Spill} \cdot p_{Spill} + f_{El} \cdot p_{El}}\right)$$



$$D_{El.} = \log_{10}\left(\frac{p_{Inel.}}{f_{Spill}\cdot p_{Spill} + f_{El}\cdot p_{El} + f_{Ot}\cdot p_{Ot}}\right)$$



Tools to reduce He background 2

("unsupervised" learning)

Unsupervised learning and autoencoders (AEs)

Why do we need unsupervised learning?

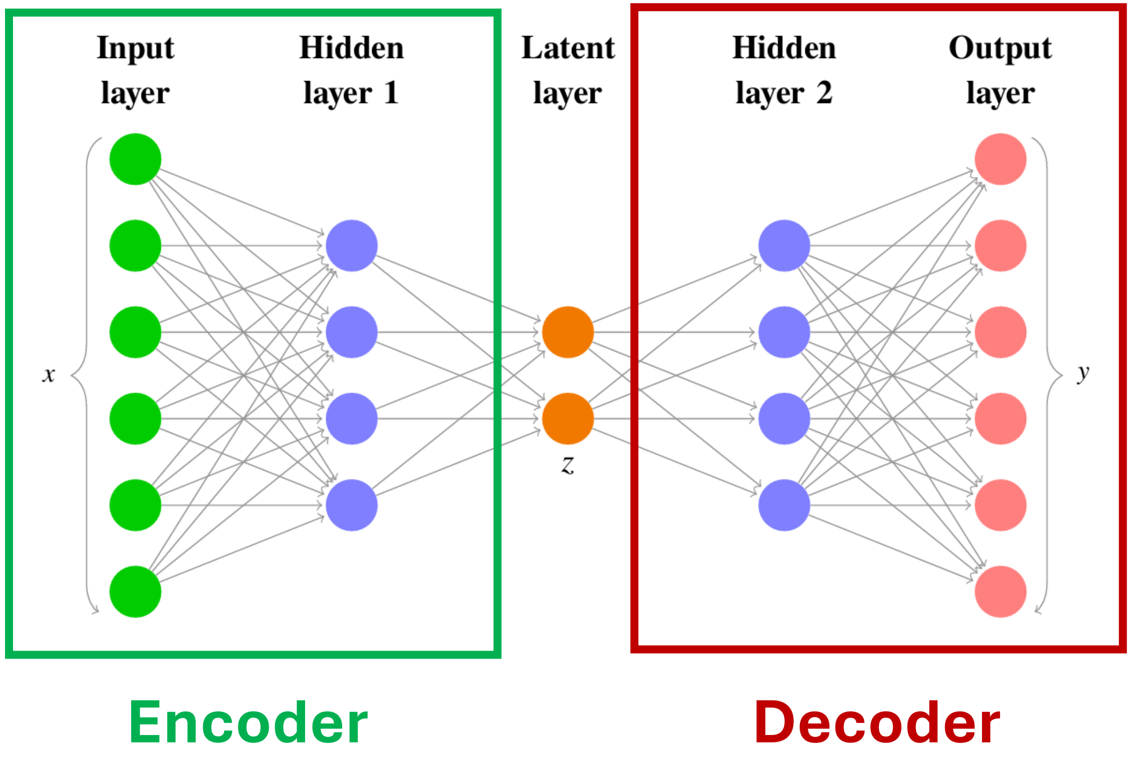
- Unsupervised learning does not need a signal model, it is **model-independent**.

Why autoencoders?

- The network's goal is to reproduce the input, the loss function is the Mean Square Error between the input ($\boldsymbol{X}$) and output ($\boldsymbol{Y}$) of the AE:

$$L = \frac{(\boldsymbol{X} - \boldsymbol{Y})^2}{N_{Features}}$$

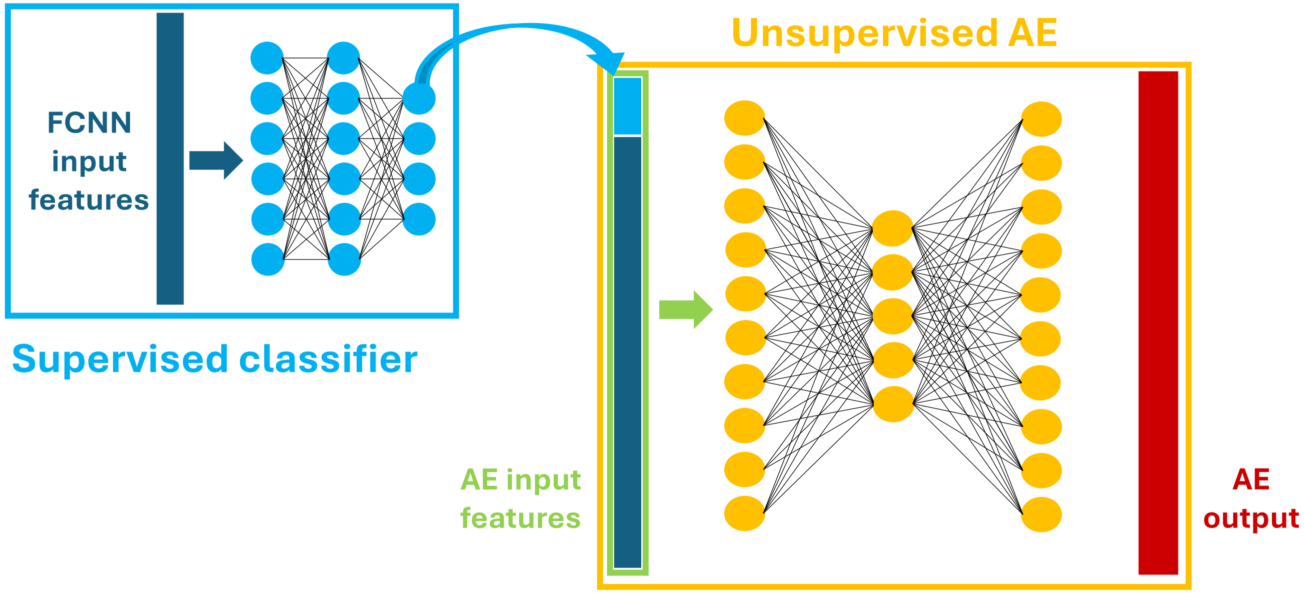
- Since signal events are rare, the network should reconstruct them poorly.



AEs structure and training

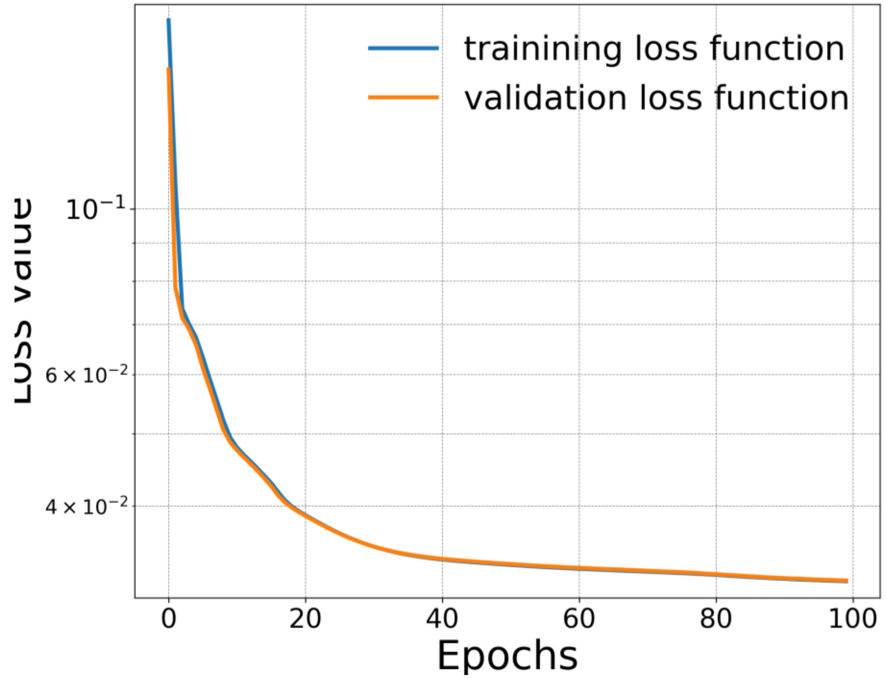
Structure:

- [41, 10, 5, 10, 41] (PyTorch)
- Activation functions: ReLu, sigmoid (last layer)
- Optimizer: Adam
- Learning rate: $1.0 \cdot 10^{-4}$
- Batch size: $1.0 \cdot 10^{2}$
- Loss function: MSE



Training:

- **Training** sample $(\mathbf{0.62 \cdot 10^5})$ and **validation** sample $(\mathbf{0.62 \cdot 10^5})$ events
- The AE receives as input the 37 features previously described + the 4 FCNN discriminants



Anomaly detection

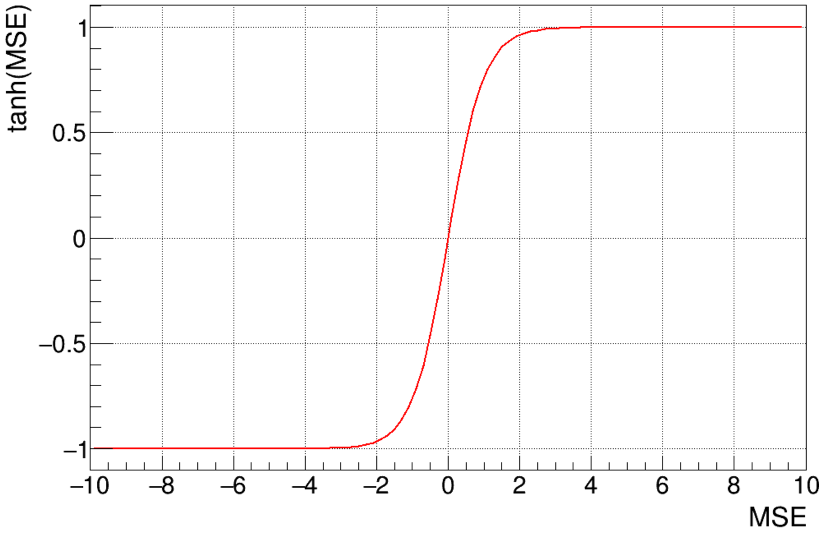
- An anomaly is an event with a high reconstruction error
- The reconstruction error is evaluated using:

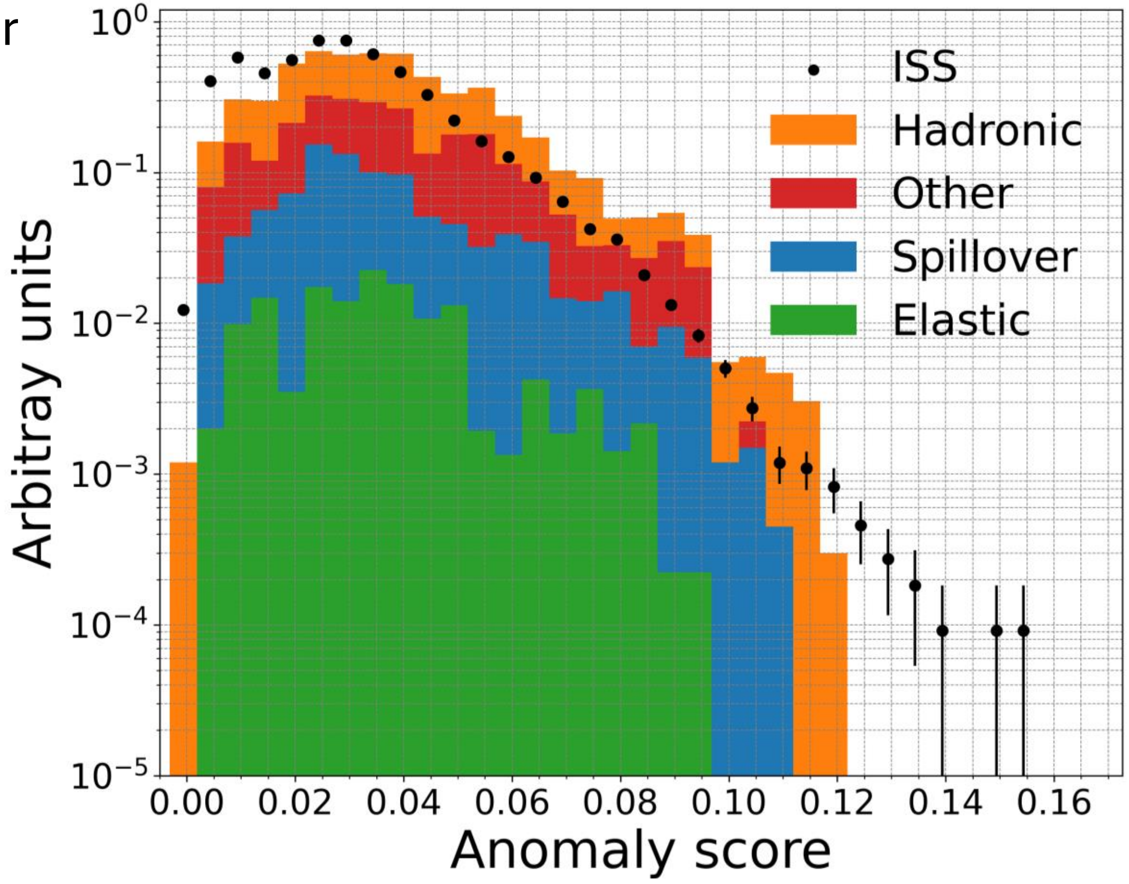
$$\mathrm{MSE} = \frac{(\boldsymbol{X} - \boldsymbol{Y})^2}{N_{features}}$$

$\boldsymbol{X}$ = input
$\boldsymbol{Y}$ = AE's output

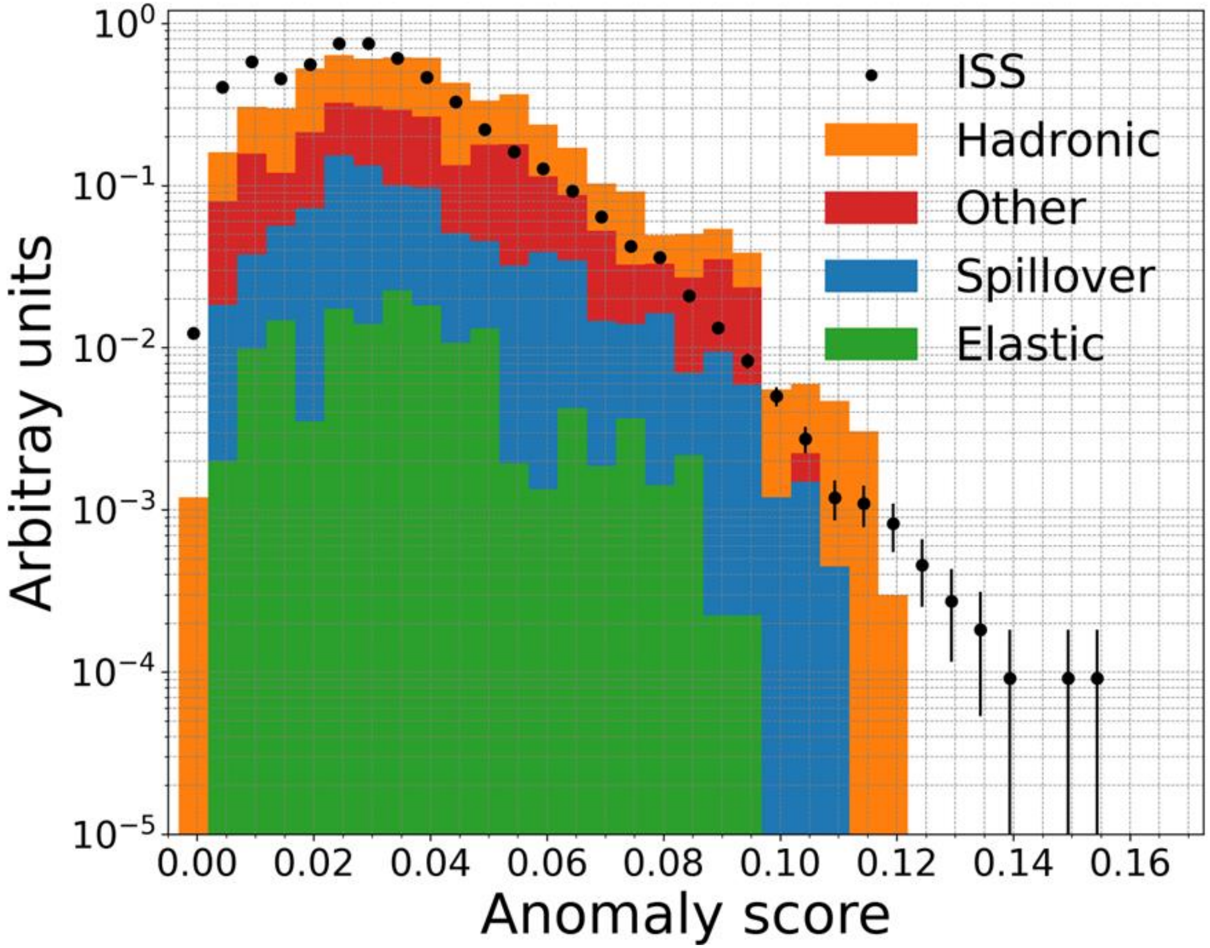
- To have an anomaly score defined between $[0,1]$, the tanh function is used:

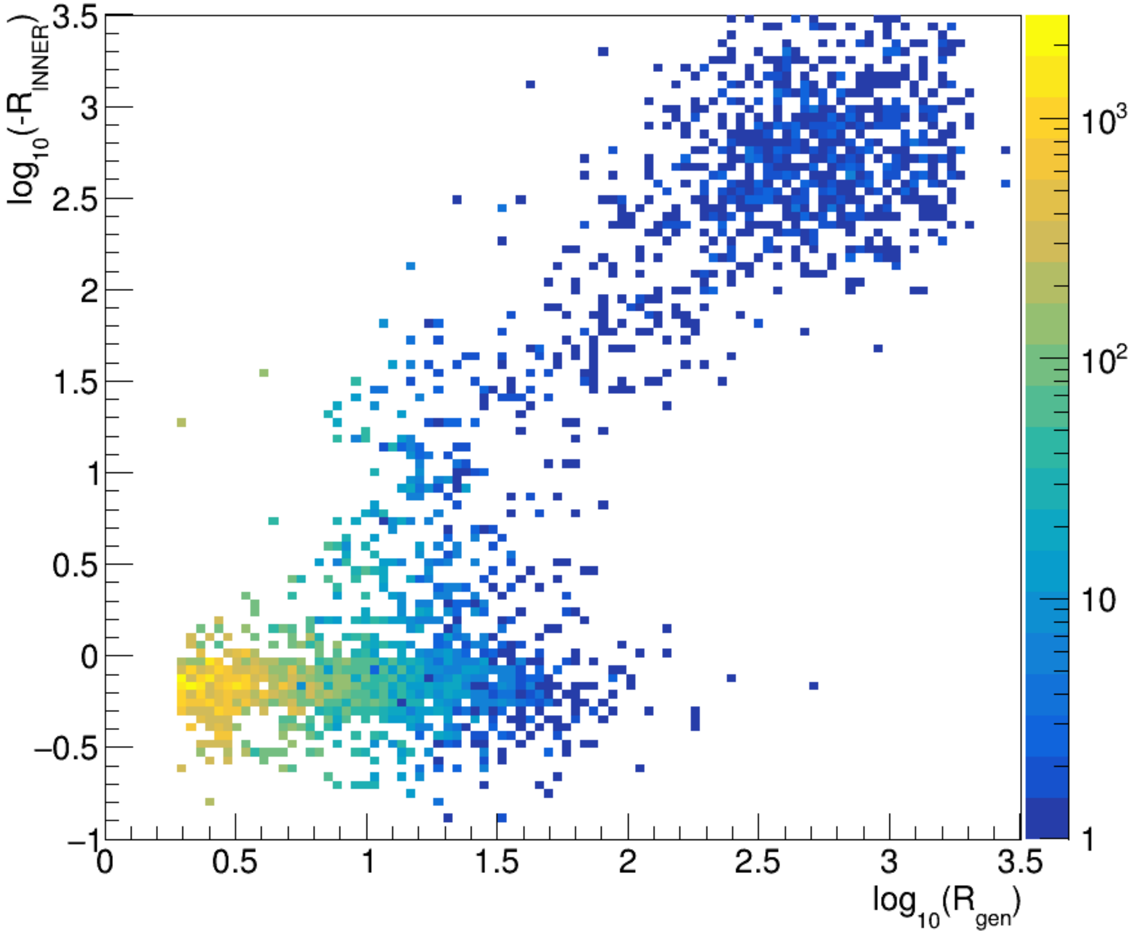
$$\text{Anomaly score} = \tanh(\mathrm{MSE})$$



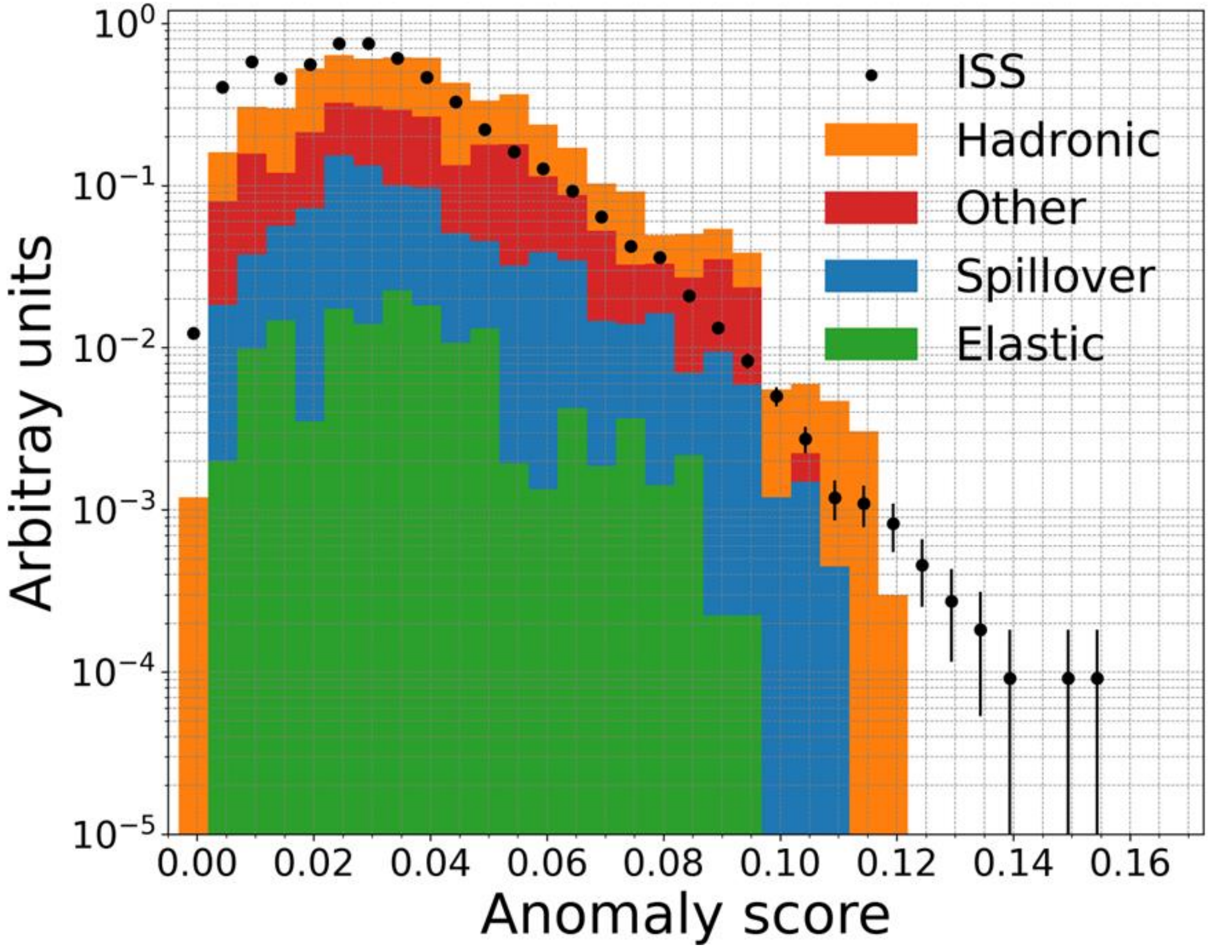


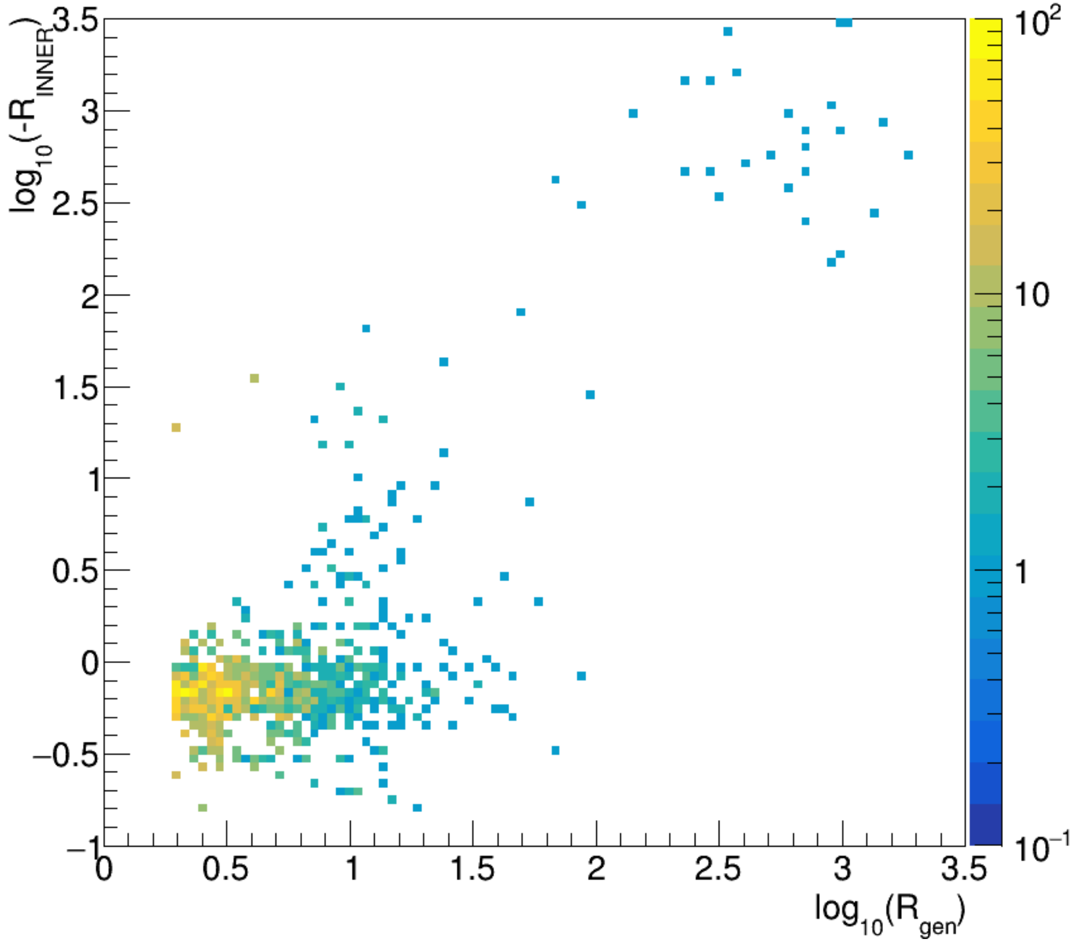
Anomaly score and MC migration matrix



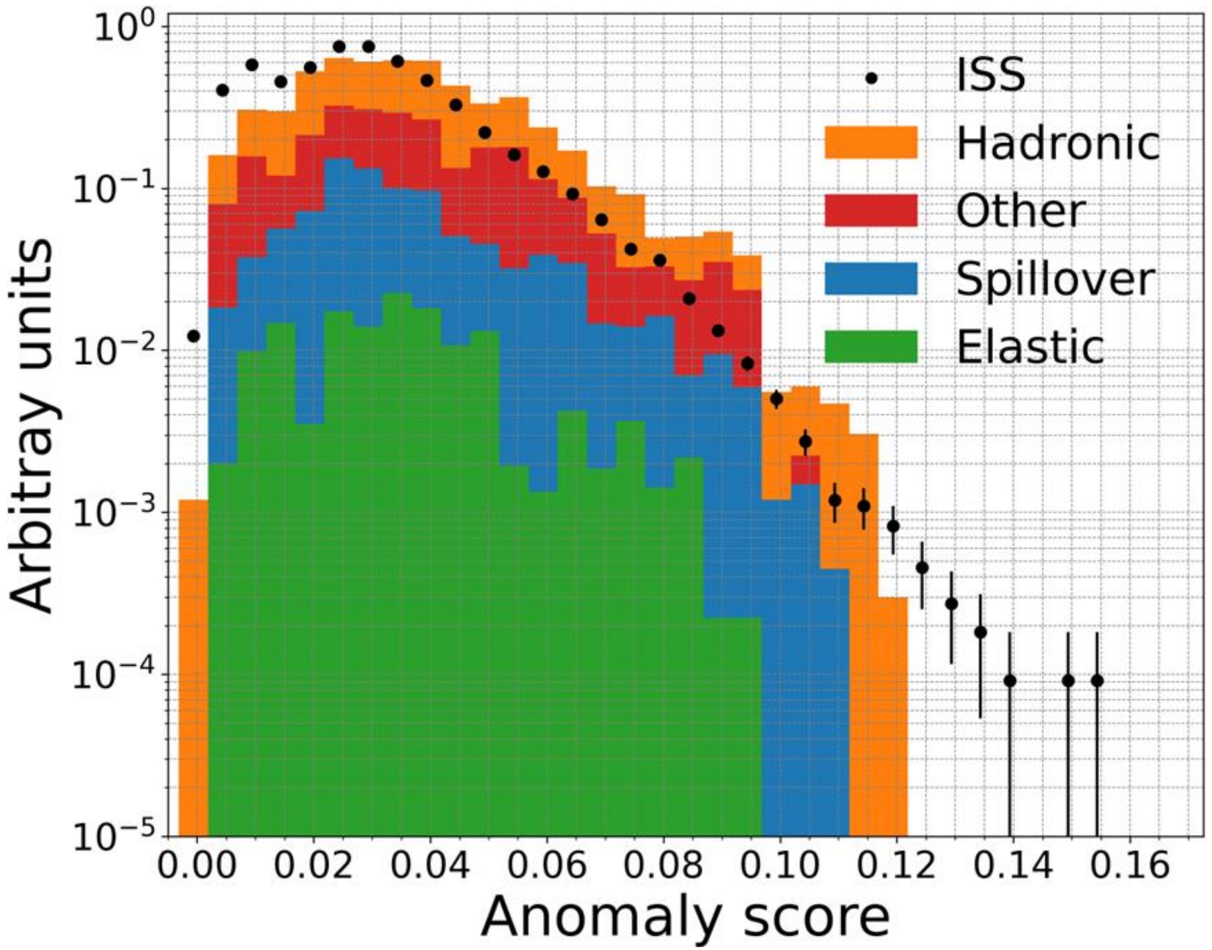


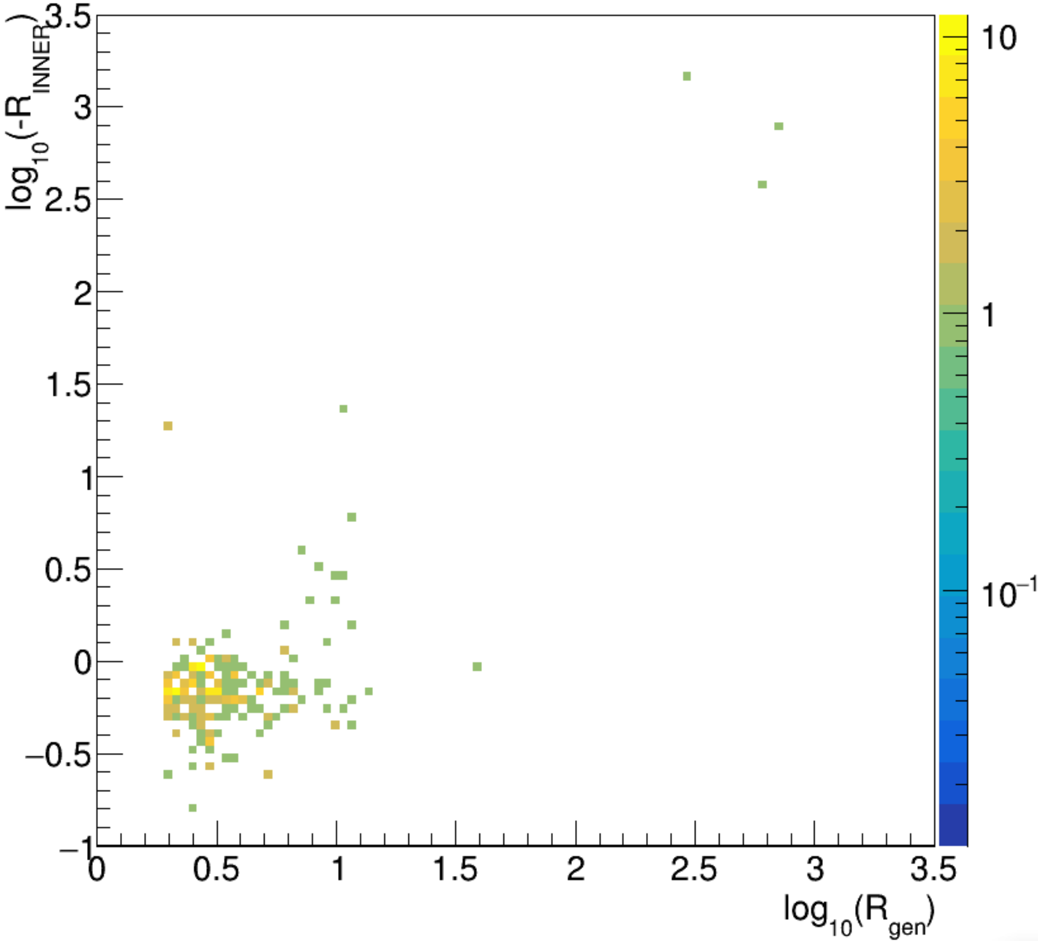
Anomaly score > 0.08 and MC migration matrix



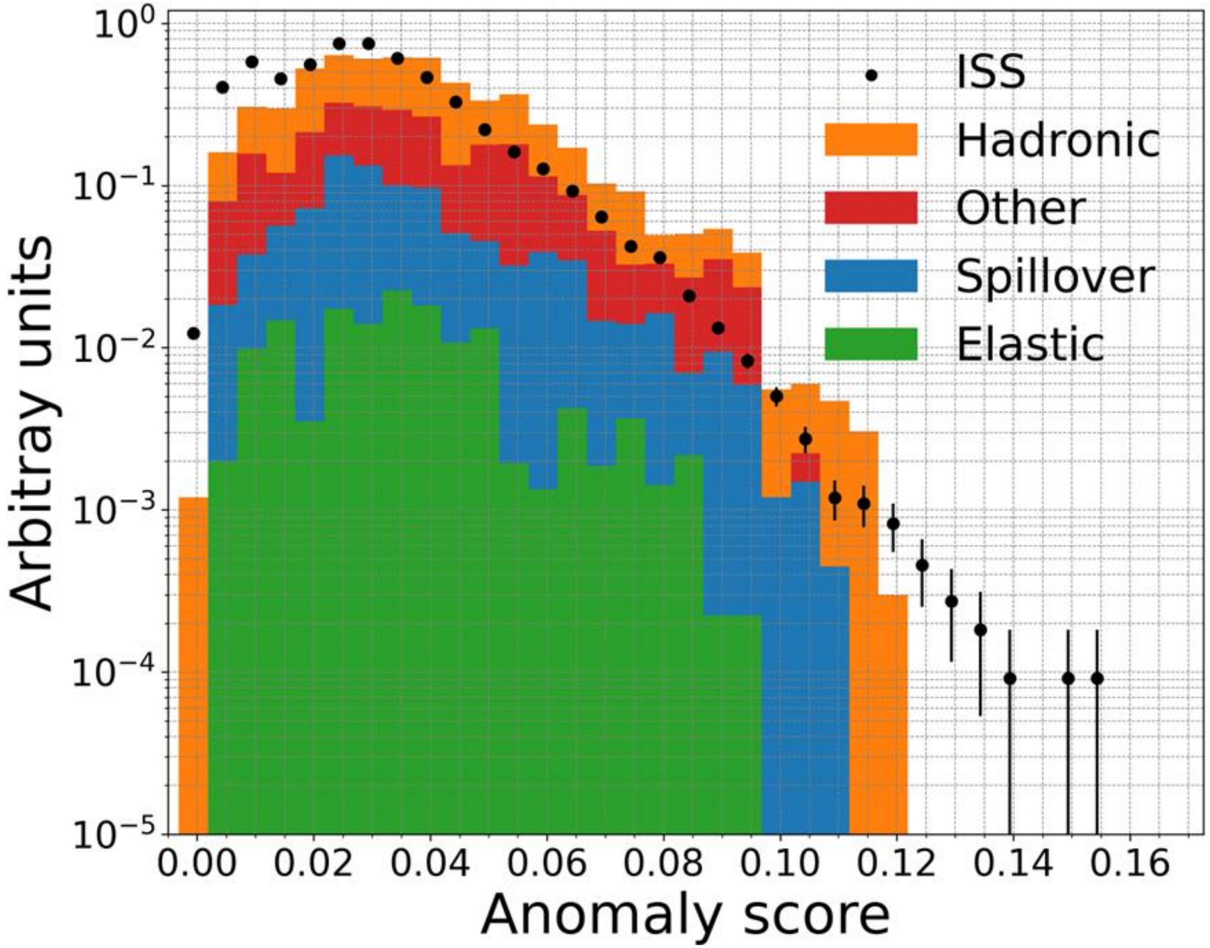


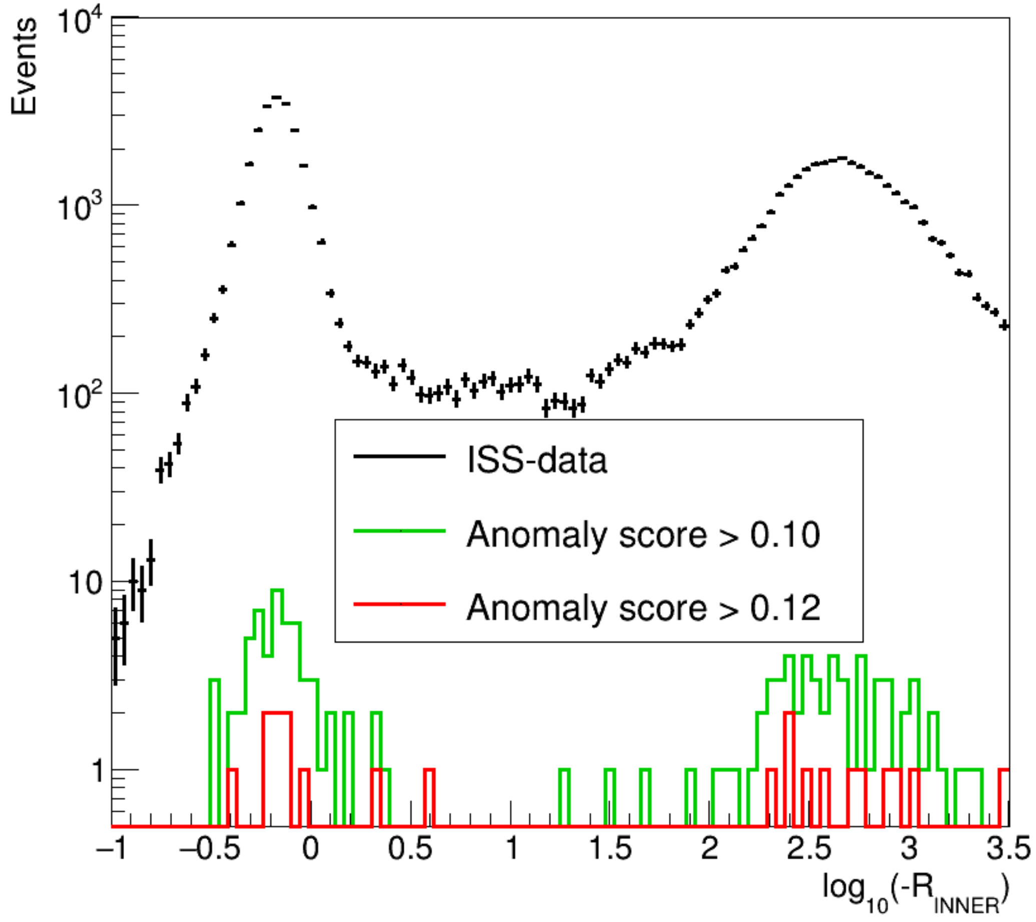
Anomaly score > 0.10 and MC migration matrix





ISS-data from 06.11.2011 to 11.11.2023





Conclusions

- Labelling charge confusion sources from the Monte Carlo simulation is possible.
- Irreducible background as spillover induces arbitrary choices.
- Unsupervised learning can compensate for the absence of a signal model.
- The combination of a classifier and anomaly detection technique seems promising.

Prospects

- Modify the propagator to take into account energy losses and multiple scattering.
- Investigate new input features to discriminate between spillover and elastic scattering.
- More studies on the rigidity dependence of the input variables.

- Optimize the FCNN classifier and the AE
- Checks on data outliers

Conclusions

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Thank you for your attention!

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Backup

Elastic scattering Monte Carlo

Selection

Selezione comune attualmente usata

IsPhysicsTrigger

β > 0
TOF hits = 4
Chi2Coo < 4

Track number >= 1
charge YJ (inner) ϵ [1.7, 2.4]
inner fiducial volume
charge YJ (L1) ϵ [1.6, 3.0]
track pattern 5/8 (L1-inner)
χ_Y^2 < 10

charge (UTOF) ϵ [1.5, 3.0]
charge (LTOF) > 1.5

(R_{UH} , R_{LH} < 0) oppure (R_{UH} , R_{LH} > 0)

NoCut	15376772	1
RTIGood	15376772	1
RTIIsInSAA(0)	15376772	1
RTILiveTimeFraction(0.5)	15376772	1
IsPhysicsTrigger	7526862	0.4892
BetaPos(0.2)	6383353	0.4148
NTOFBetaClusters(4)	5849648	0.3801
BetaChi2Coo(4)	4476765	0.2907
NTrTracks(1)	4476765	0.2907
HasGBLFitInner	4472418	0.2904
ChargeInnerTrackerYJ(1.7,2.4)	3905926	0.2535
CheckFiducialInner	3311273	0.2149
ChargeLayer1(1.6,3)	2997280	0.1946
IsInsideL1Fiducial	2997274	0.1946
CheckTrackPattern(5)	2680073	0.1740
Chi2Y_GBL_InnerOnly(10)	2573763	0.1672
ChargeUpperTof(1.5,3)	2550871	0.1657
ChargeLowerTof(1.5,30)	2529516	0.1642
HasGBLFitUHInner	2434282	0.1581
HasGBLFitLHInner	2433791	0.1580
SignUHandLH	2379294	0.1545

0 1 2

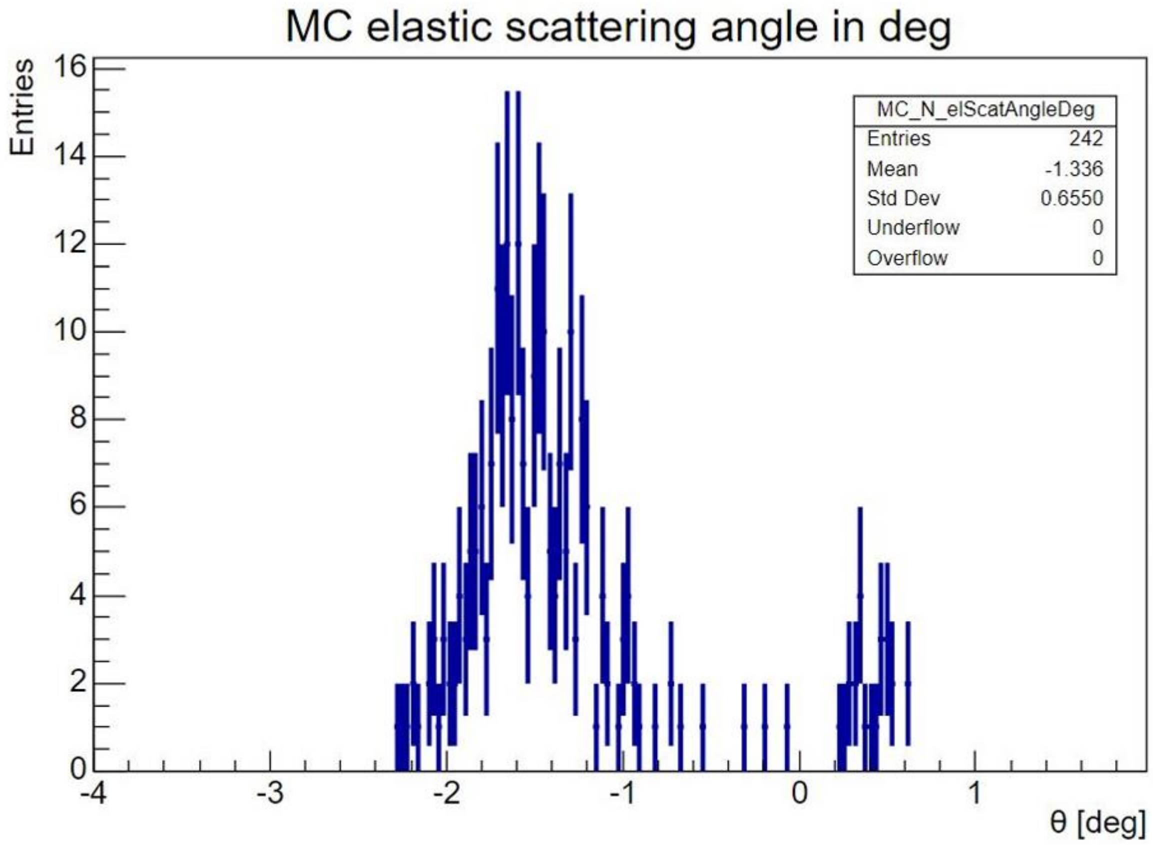
R_{inner} < 0 → 696 eventi

Distribution of the scattering angle ($R < 0$)

$R_{inner} < 0$ ⟶ 696 eventi

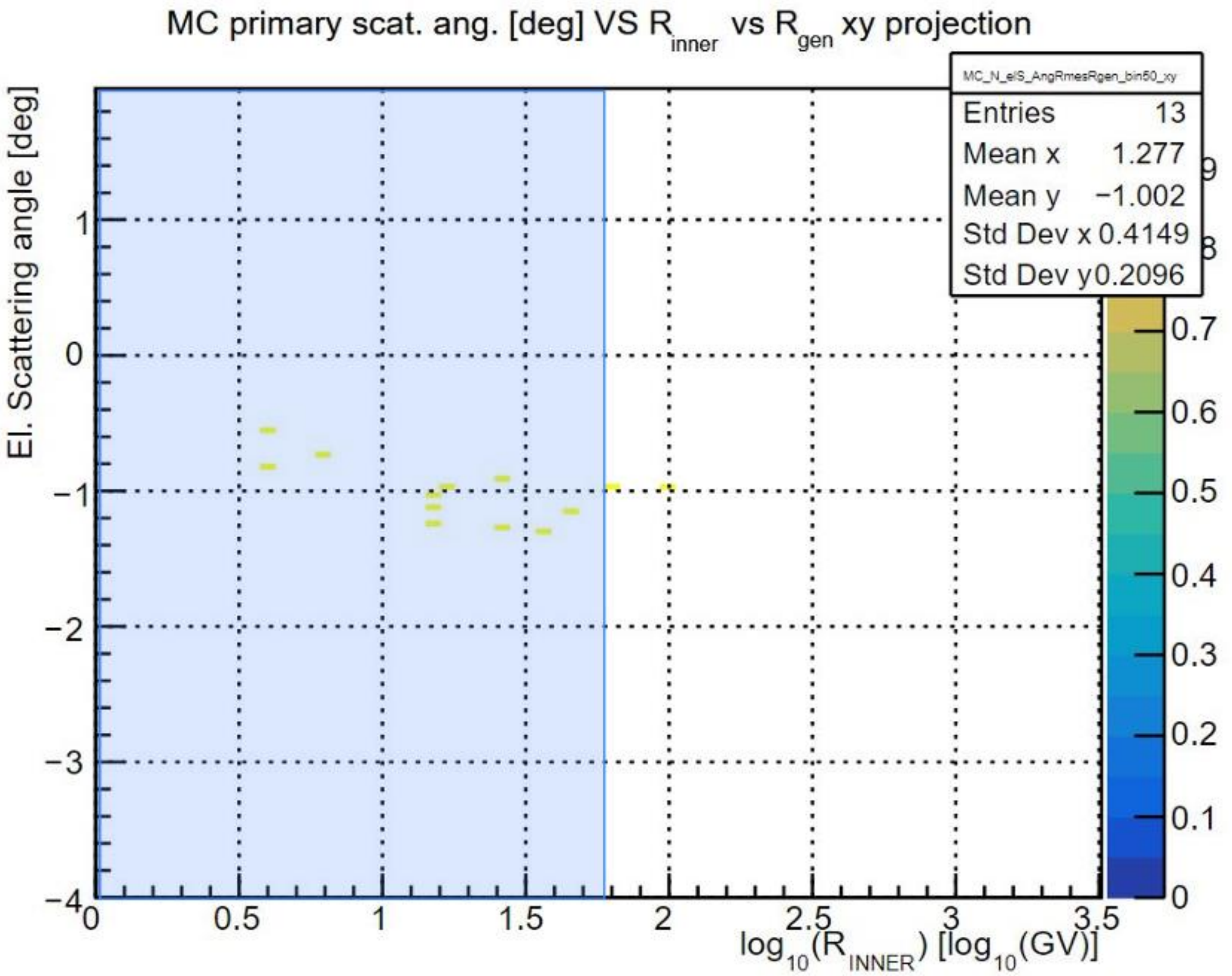
Verità MC per scattering elastic

242 eventi con scattering elastico nell'inner tracker



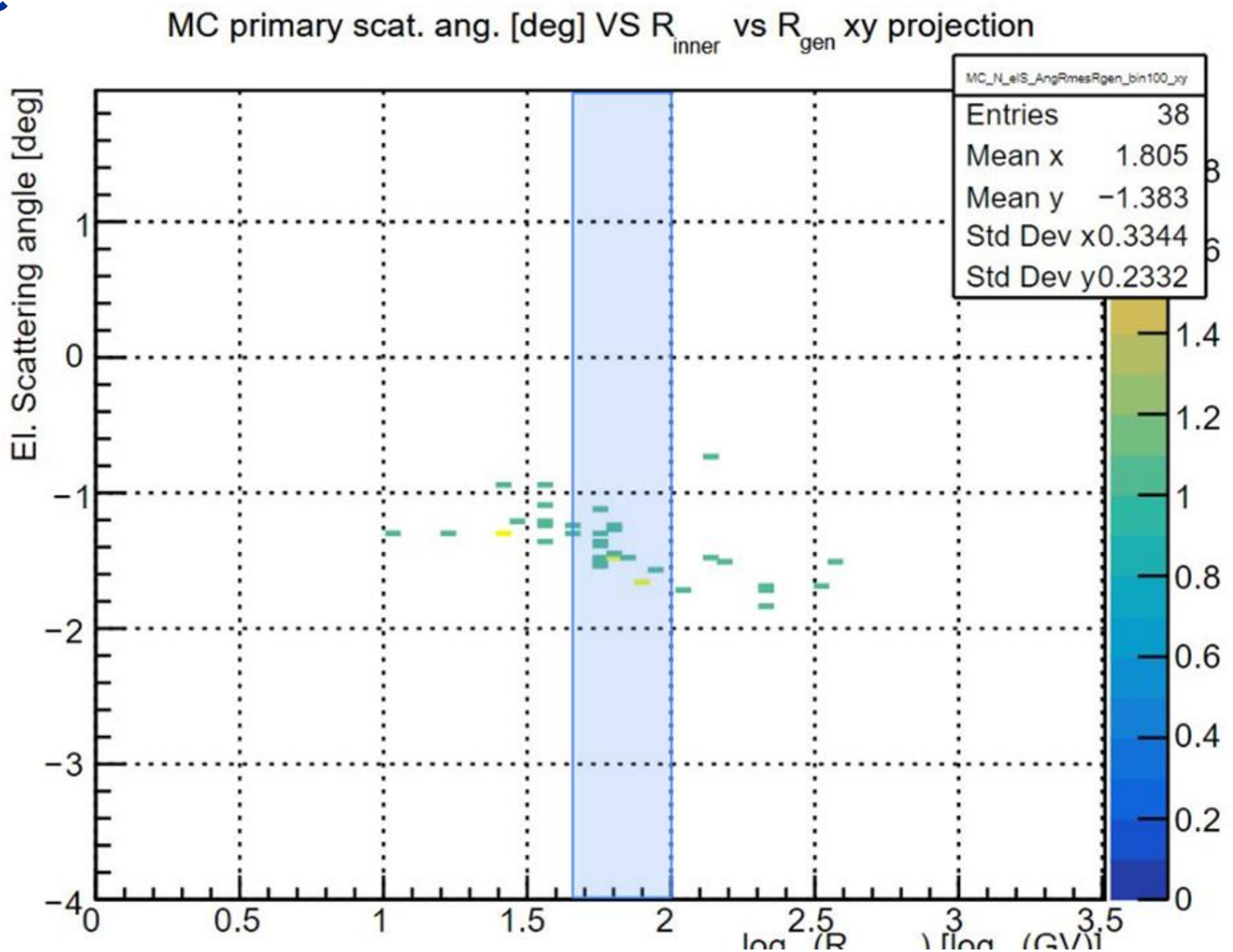
$(\boldsymbol{R_{inner}} < \boldsymbol{0})$ and elasti scattering inside the inner tracker

$$R_{gen} \in [0, 50[$$
$$\log_{10}(R_{gen}) < 1.67$$



$(R_{inner} < 0)$ and elastic scattering inside the inner tracker

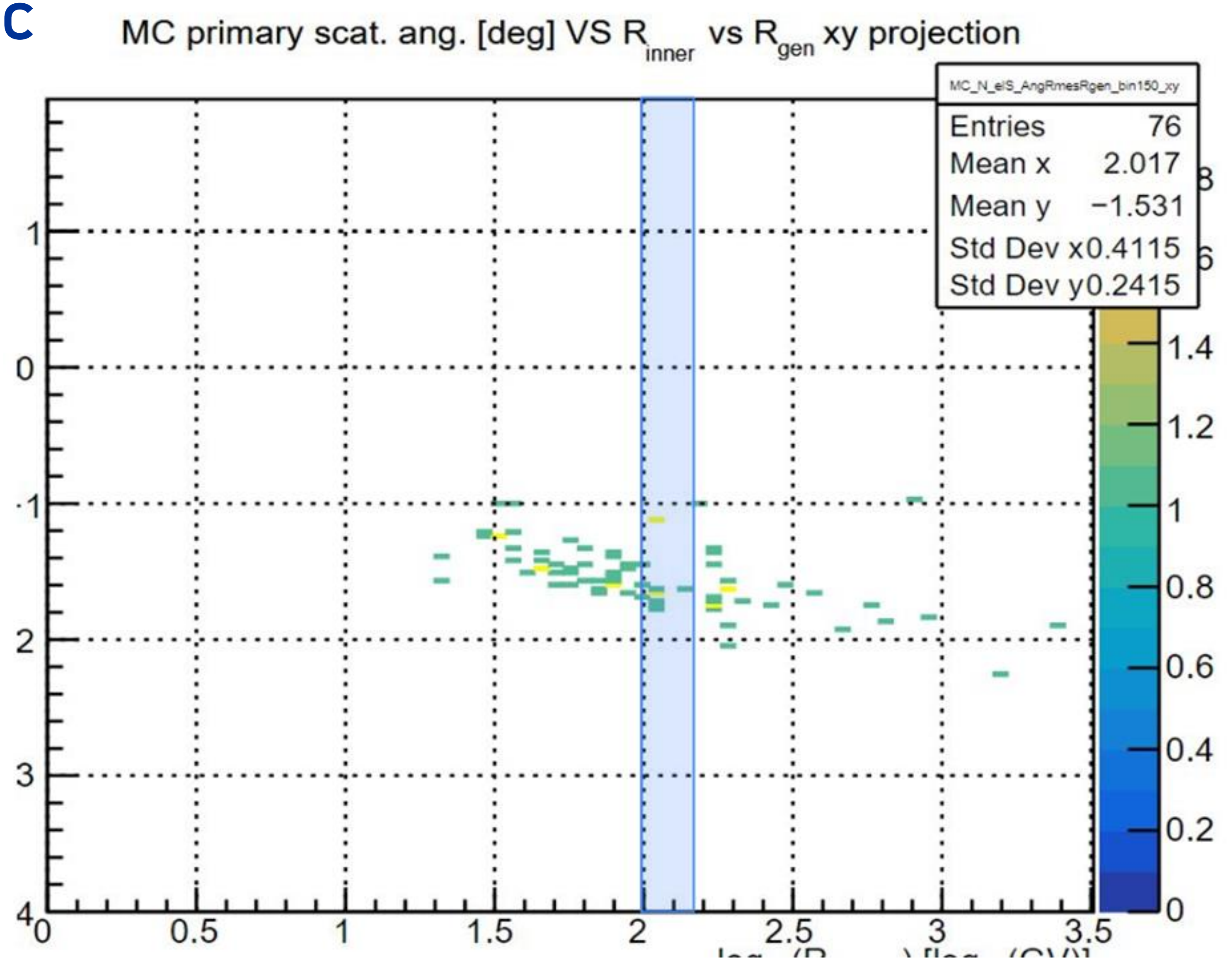
$$R_{gen} \in [50, 100[$$
$$\log_{10}(R_{gen}) < 2.0$$



$(R_{inner} < 0)$ and elastic scattering inside the inner tracker

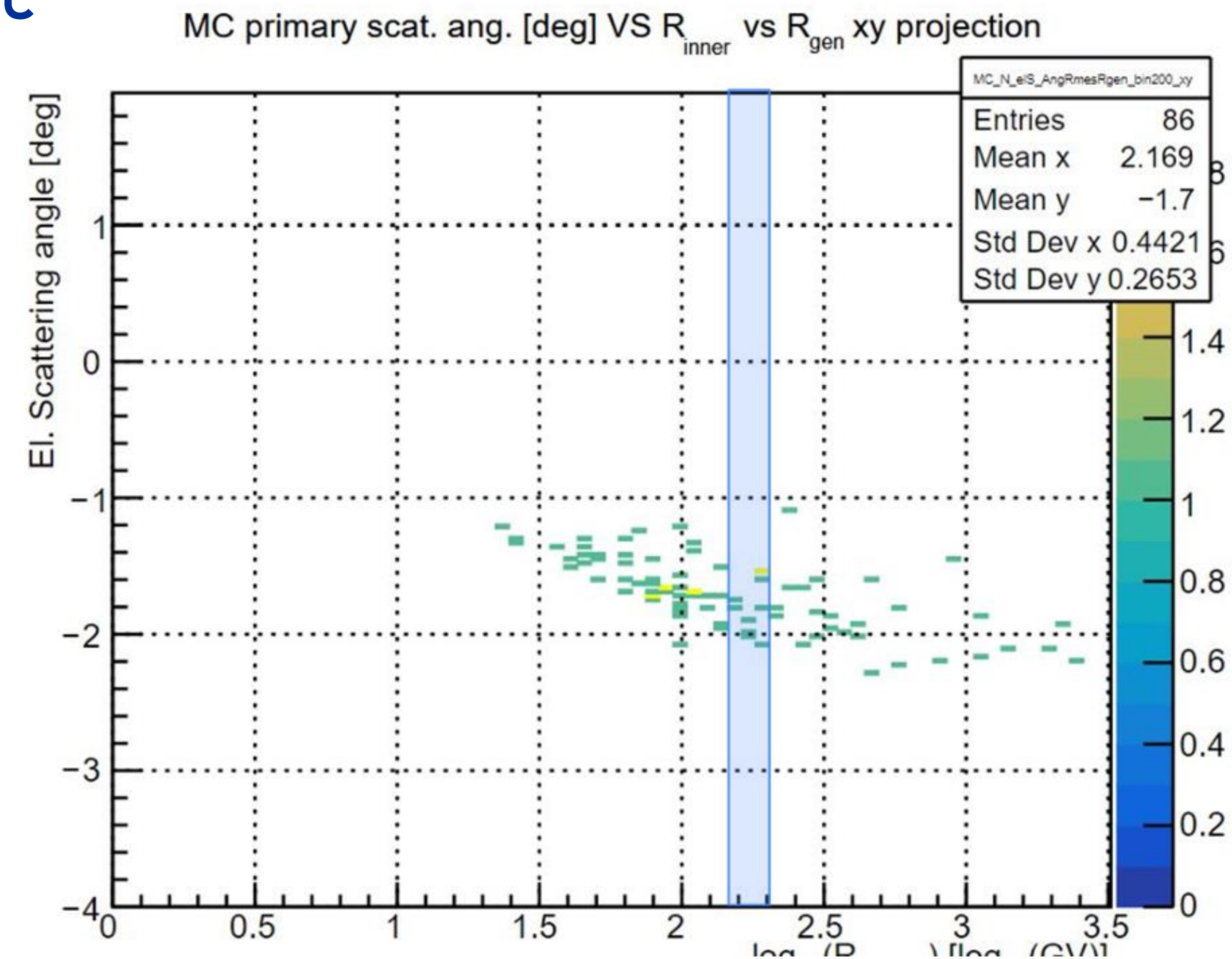
$$R_{gen} \in [100, 150[$$

$$\log_{10}(R_{gen}) < 2.18$$

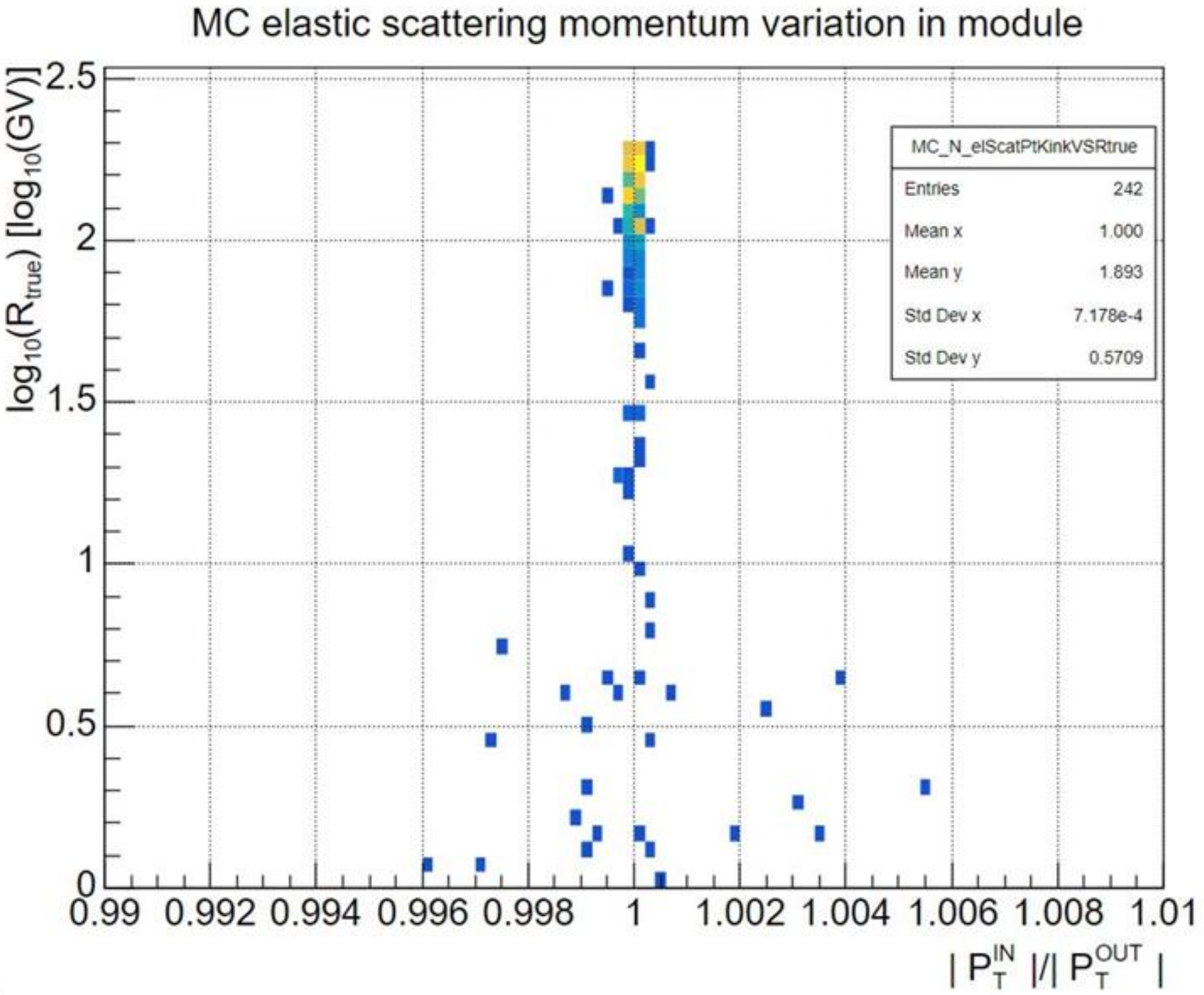


$(R_{inner} < 0)$ and elastic scattering inside the inner tracker

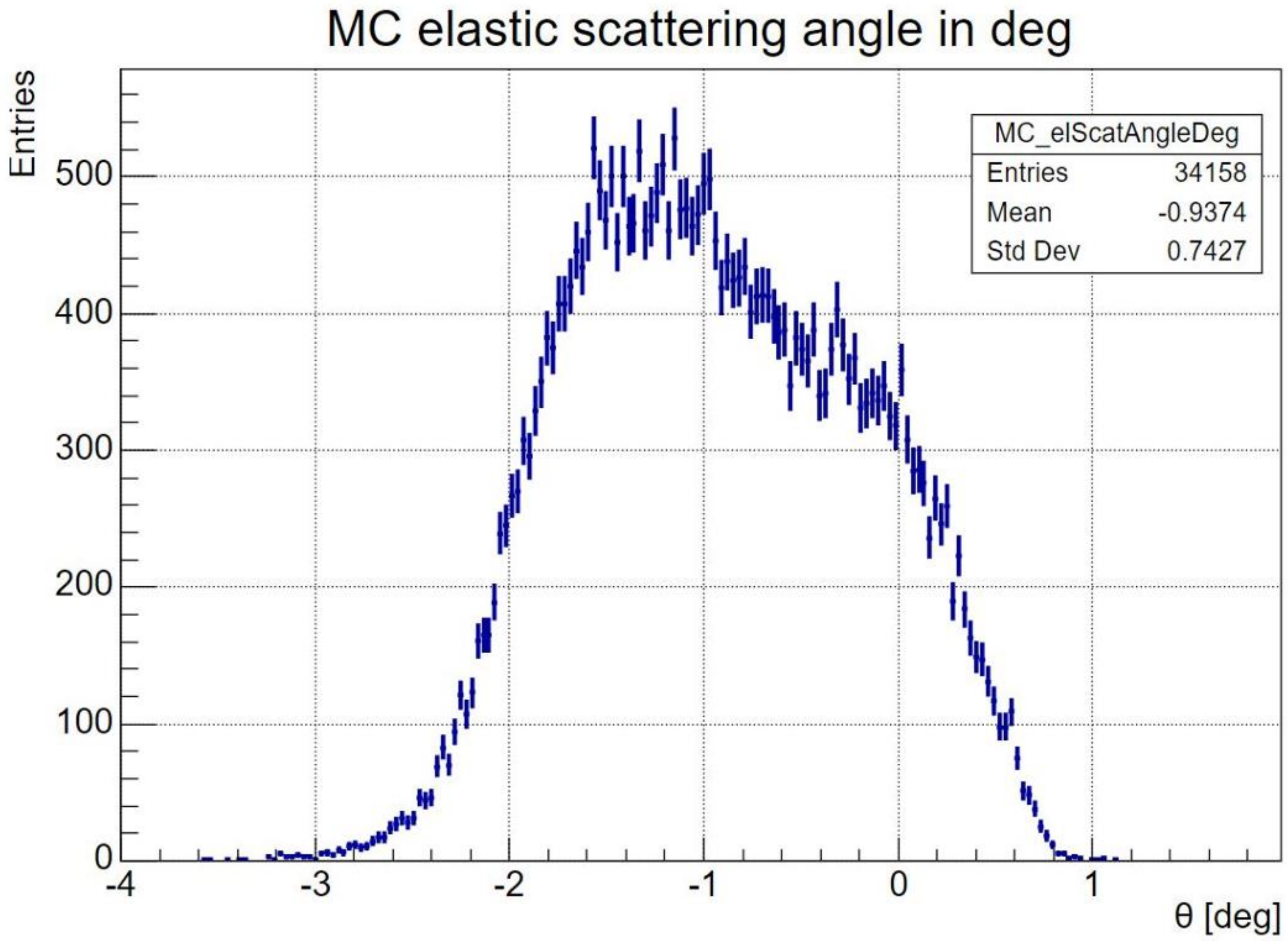
$$R_{gen} \in [150, 200[$$
$$\log_{10}(R_{gen}) < 2.30$$



$(R_{inner} < 0)$ and elastic scattering inside the inner tracker

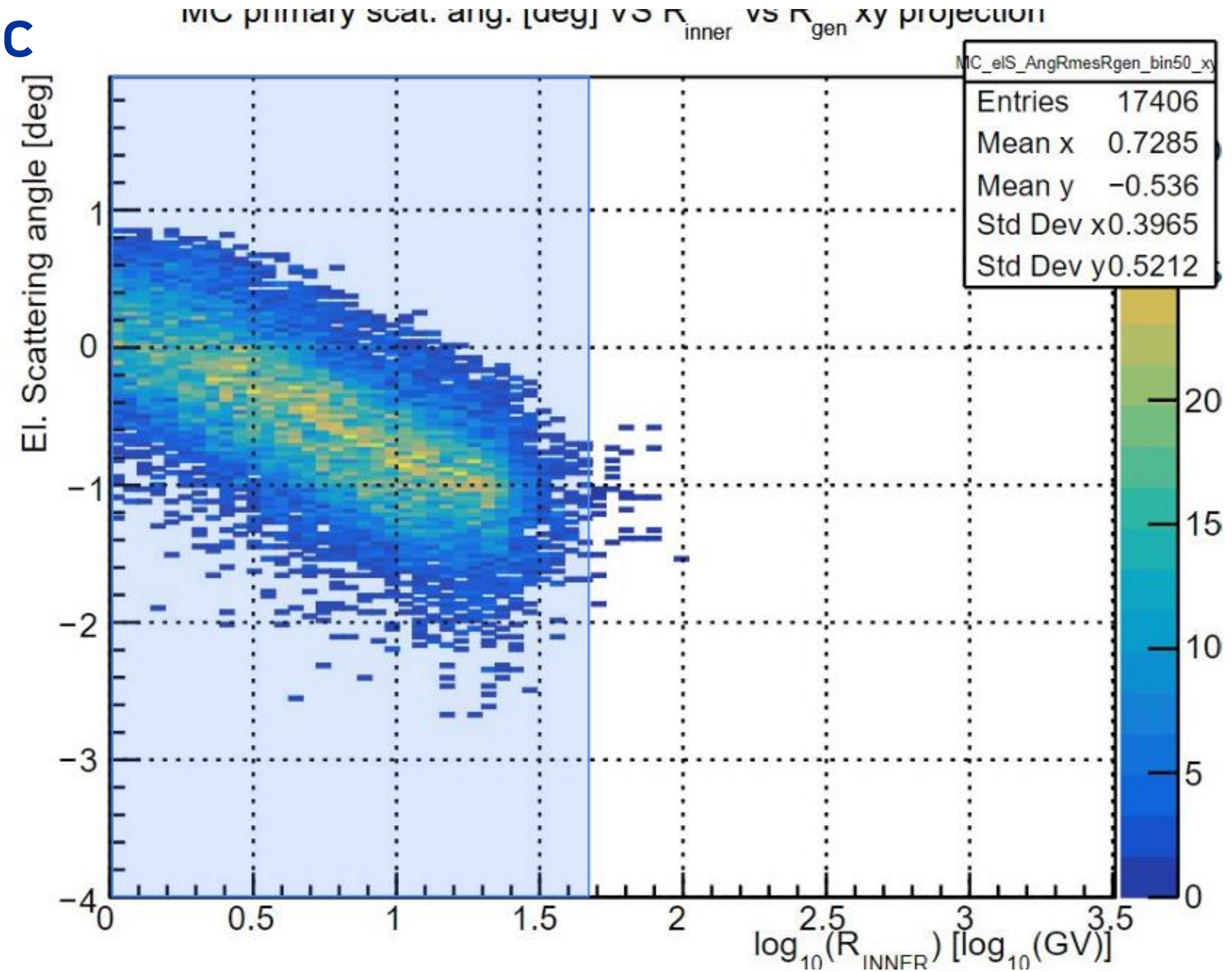


Distribution of the scattering angle ($R > 0$)



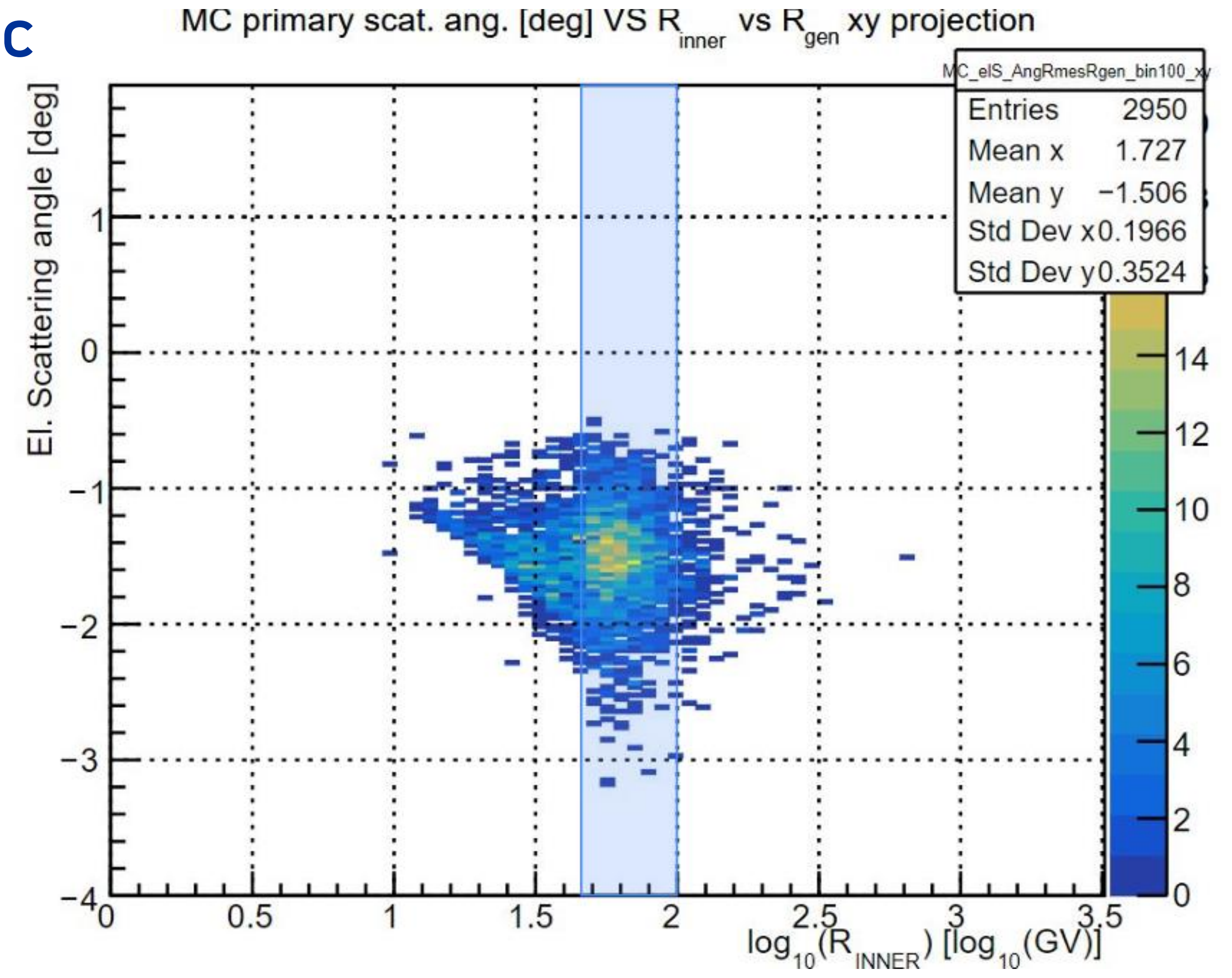
$(\boldsymbol{R_{inner}} > \mathbf{0})$ and elastic scattering inside the inner tracker

$$R_{gen} \in [50, 100[$$
$$\log_{10}(R_{gen}) < 2.0$$



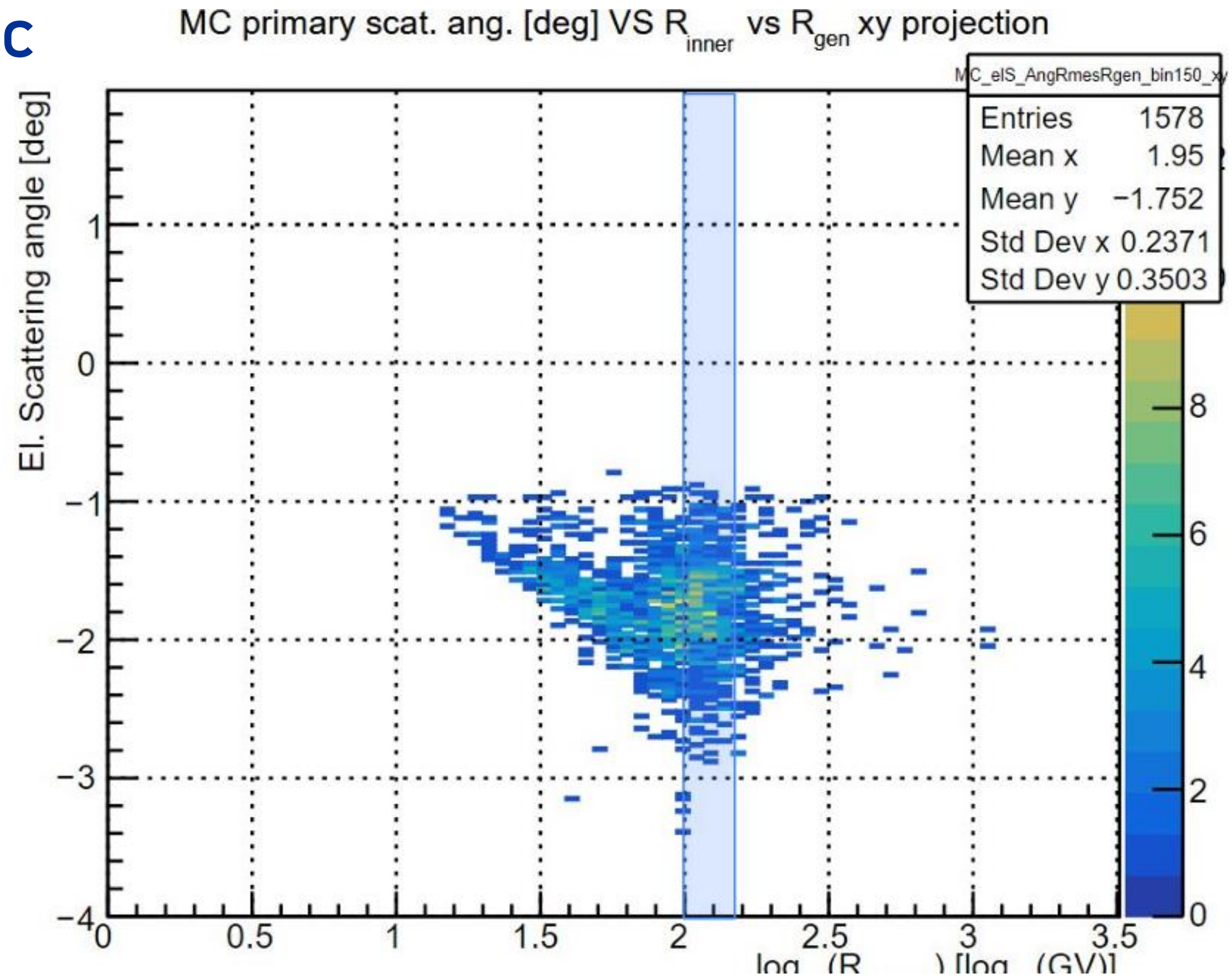
$(R_{inner} > 0)$ and elastic scattering inside the inner tracker

$$R_{gen} \in [50, 100[$$
$$\log_{10}(R_{gen}) < 2.0$$



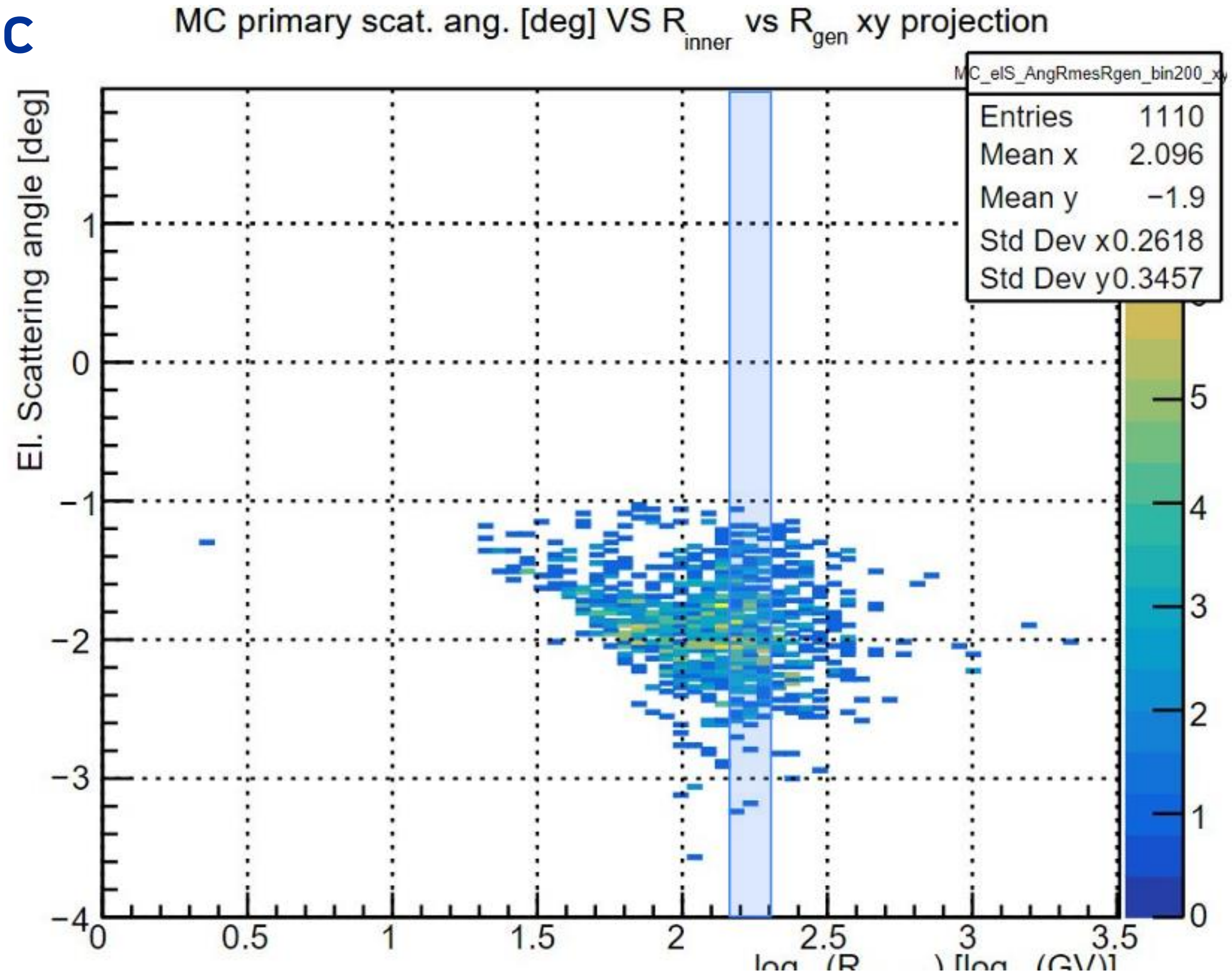
$(R_{inner} < 0)$ and elastic scattering inside the inner tracker

$$R_{gen} \in [100, 150[$$
$$\log_{10}(R_{gen}) < 2.18$$

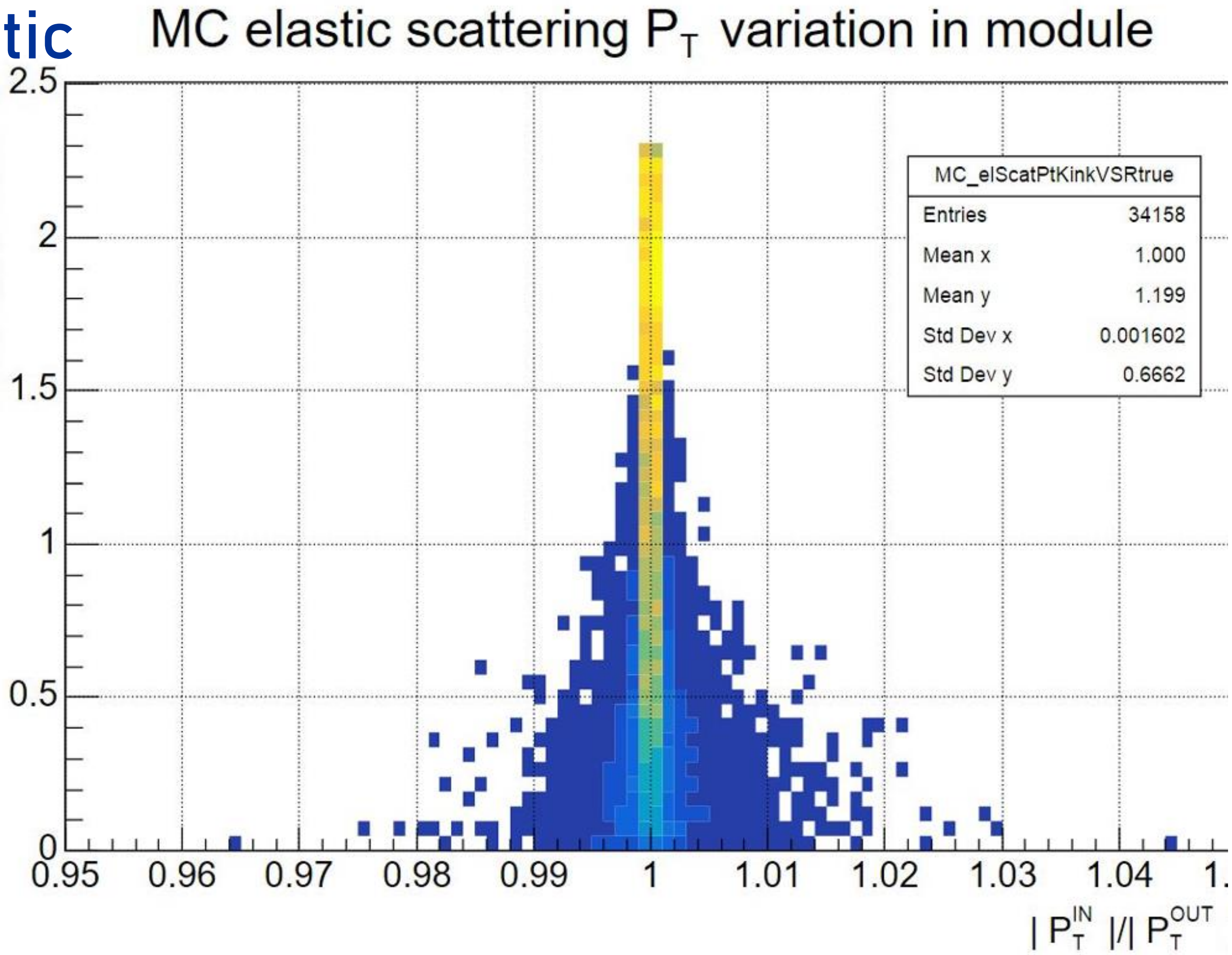


$(R_{inner} < 0)$ and elastic scattering inside the inner tracker

$$R_{gen} \in [150, 200[$$
$$\log_{10}(R_{gen}) < 2.30$$



$(R_{inner} < 0)$ and elastic scattering inside the inner tracker



Data-Monte Carlo

A Fully Connected Neural Network (FCNN) classifier to characterise the He background

- Use the classes previously defined as labels for supervised training
- The Monte Carlo has been weighted using published 7.5 He flux.
- Sample composition (**14 % Spillover, 2.5% El. Scat., 53% Had. Inel., 30% Other)**
- **Training** sample ($\mathbf{1.78 \cdot 10^5}$) and **validation** sample ($\mathbf{0.76 \cdot 10^5}$) events
- Choose variables with good data-MC agreement as input features:

Time Of Flight:

- TOF on-time clusters ($\times$ 4)

Inner Tracker:

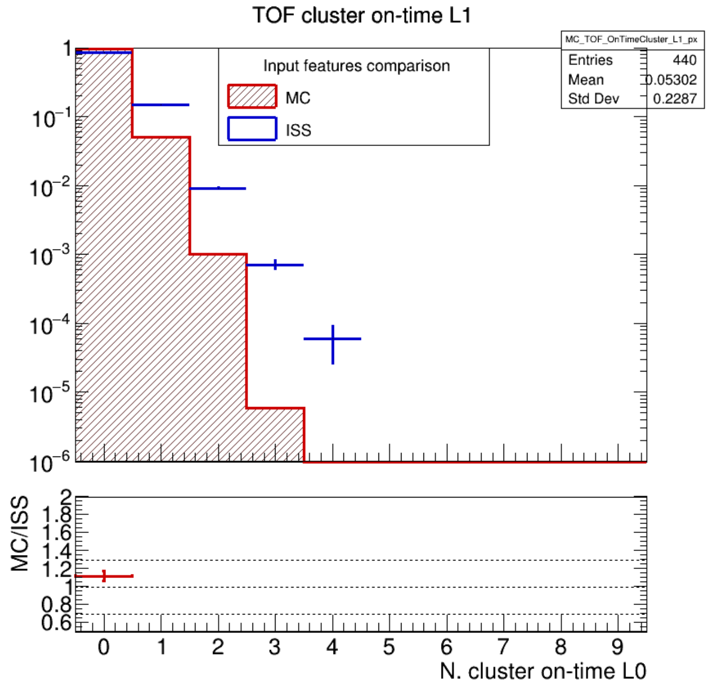
- TRK min feet-distance ($\times$ 4)
- TRK Y cluster ($\times$ 7)
- TRK Max cluster distance ($\times$ 7)
- TRK track hit |Y| ($\times$ 7)
- TRK NormEdep2Y* ($\times$ 7)

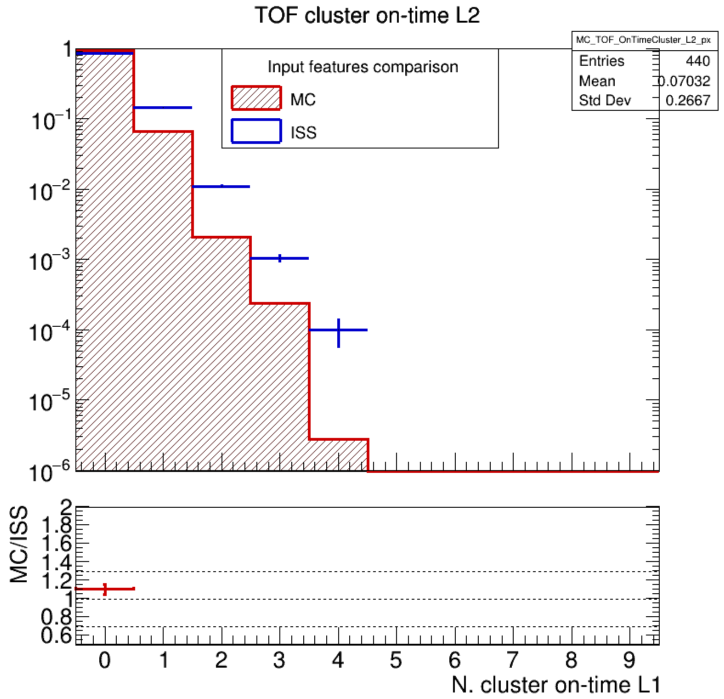
Anti-Coincidence system:

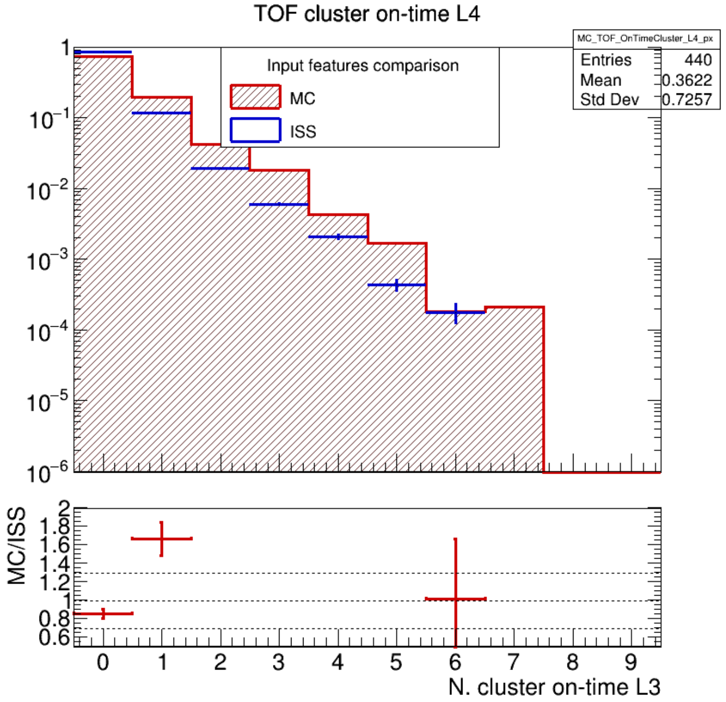
- ACC counters

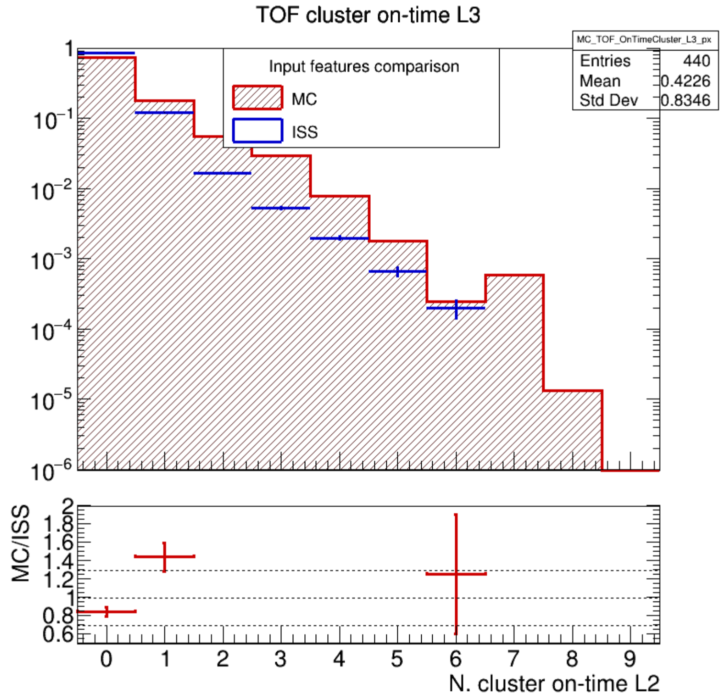
$$^{*}\mathrm{NormEdep2Y} = \frac{Track\ E_{dep}\ Y}{Cluster\ E_{dep}\ Y(2\ cm\ from\ Track\ hit) +\ Track\ E_{dep} Y}$$

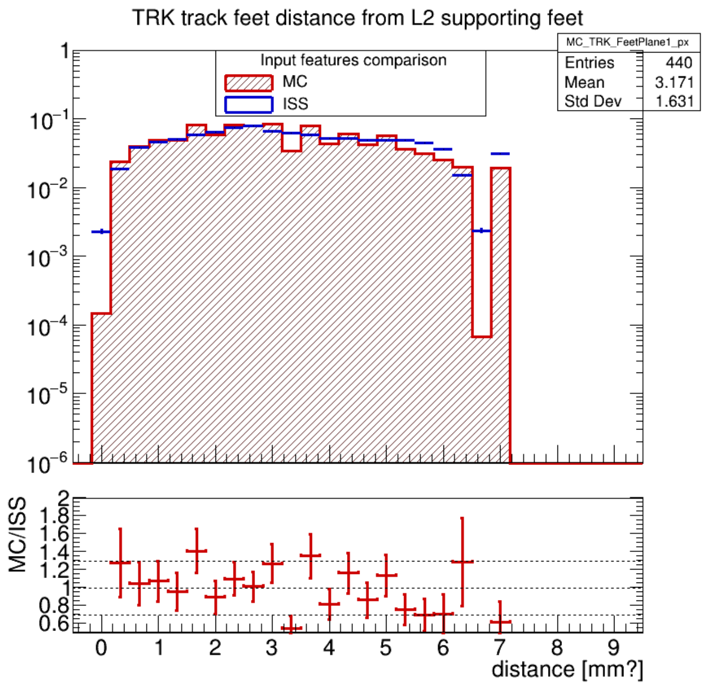
Total number of input features = 37

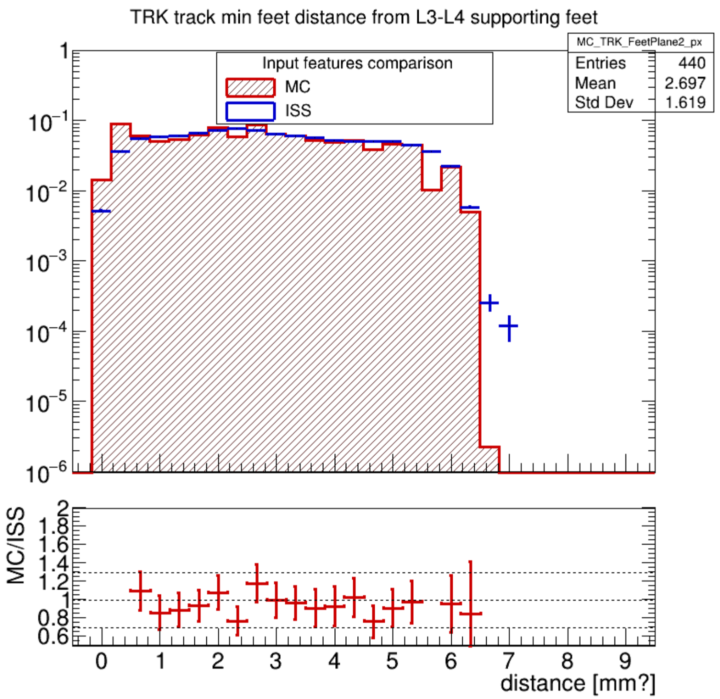

TOF cluster on-time L1
Input features comparison
MC
ISS
MC_TOF_OnTimeCluster_L1_px
Entries 440
Mean 0.05302
Std Dev 0.2287
MC/ISS
N. cluster on-time L0

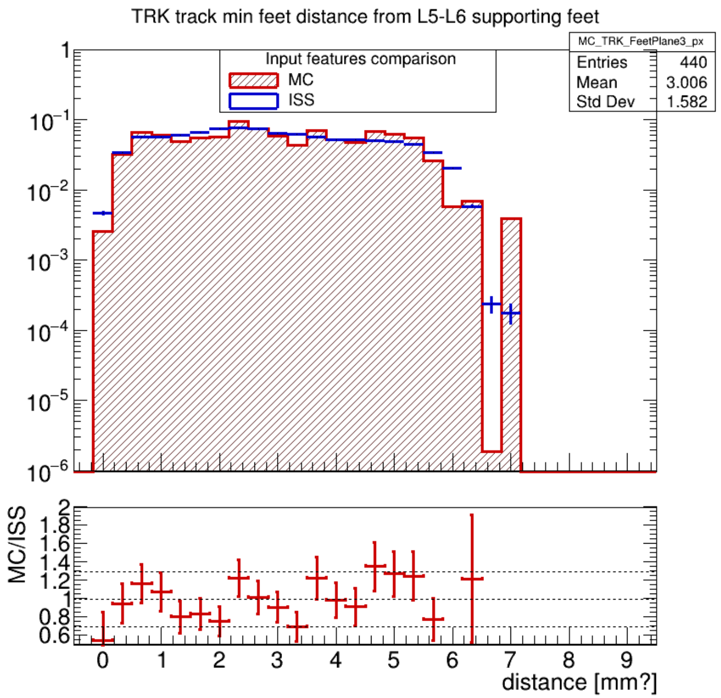

TOF cluster on-time L2
Input features comparison
MC
ISS
MC_TOF_OnTimeCluster_L2_px
Entries 440
Mean 0.07032
Std Dev 0.2667
MC/ISS
N. cluster on-time L1

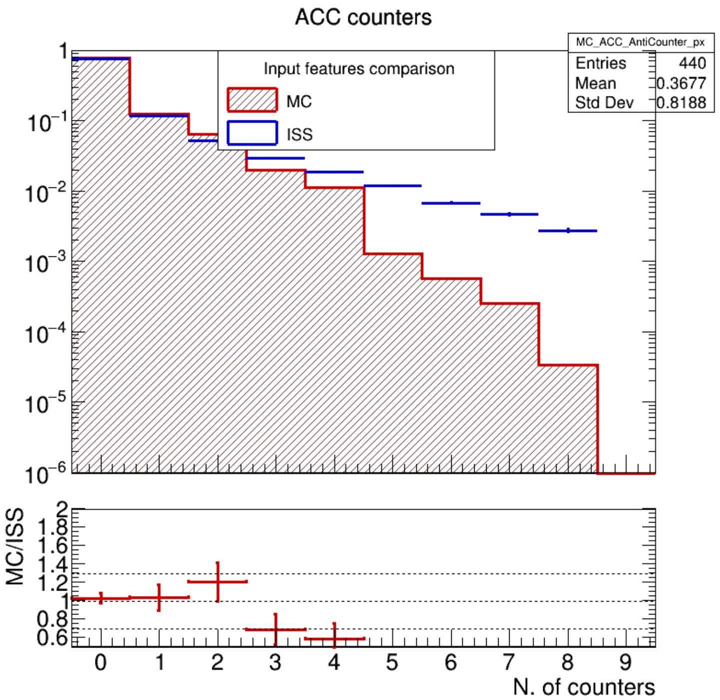

TOF cluster on-time L4
Input features comparison
MC
ISS
MC_TOF_OnTimeCluster_L4_px
Entries 440
Mean 0.3622
Std Dev 0.7257
MC/ISS
N. cluster on-time L3

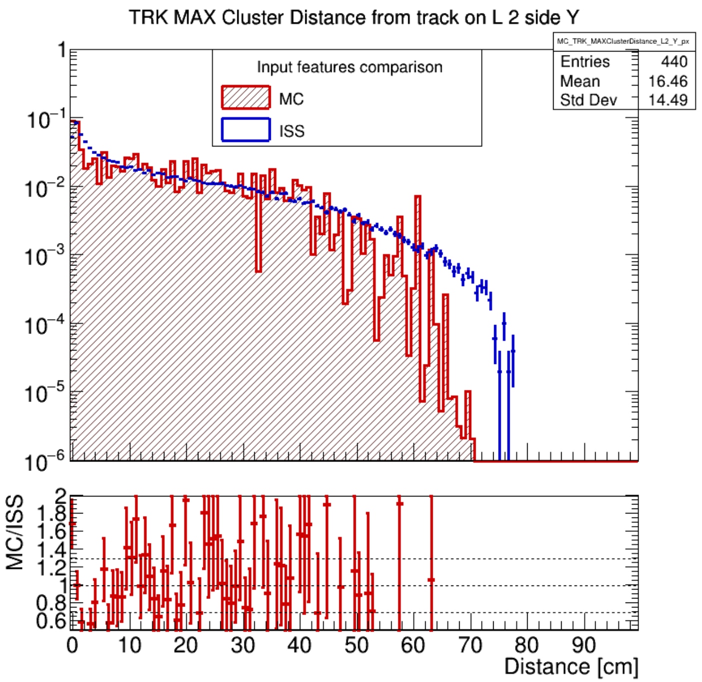

TOF cluster on-time L3
Input features comparison
MC
ISS
MC_TOF_OnTimeCluster_L3_px
Entries 440
Mean 0.4226
Std Dev 0.8346
MC/ISS
N. cluster on-time L2

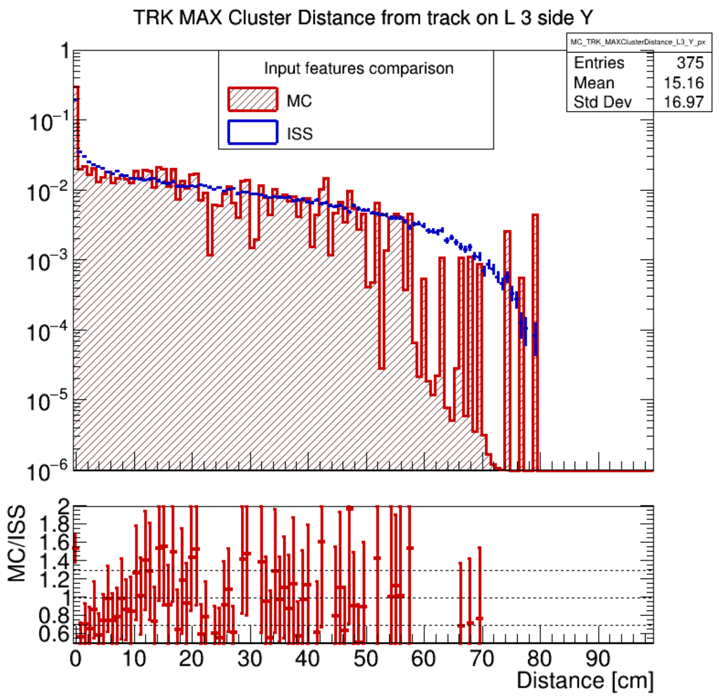

TRK track feet distance from L2 supporting feet
MC_TRK_FeetPlane1_px
Entries 440
Mean 3.171
Std Dev 1.631
Input features comparison
MC
ISS
MC/ISS
distance [mm?]

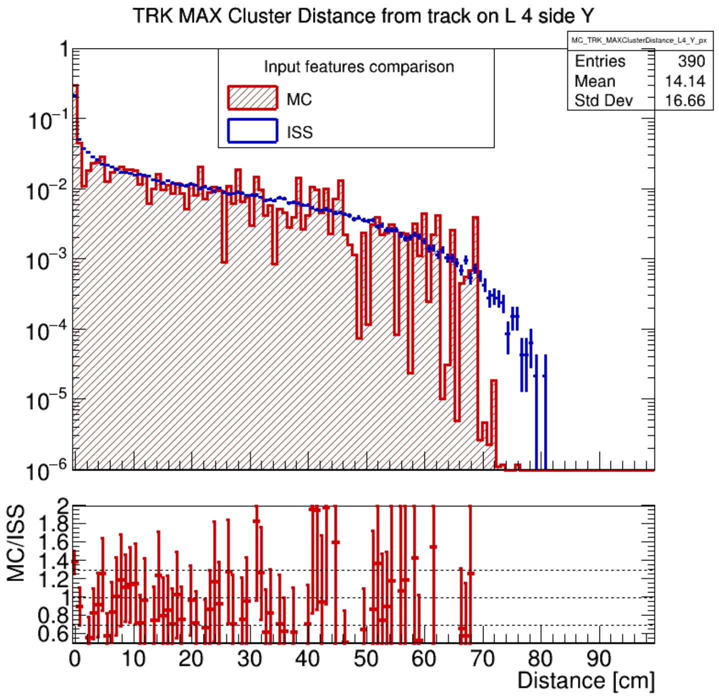

TRK track min feet distance from L3-L4 supporting feet
MC_TRK_FeetPlane2_px
Entries 440
Mean 2.697
Std Dev 1.619
Input features comparison
MC
ISS
MC/ISS
distance [mm?]

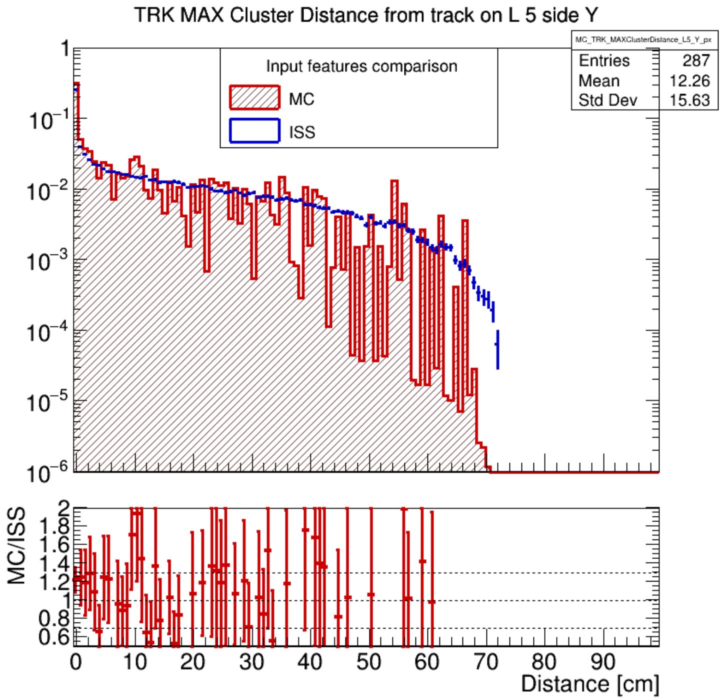

TRK track min feet distance from L5-L6 supporting feet
MC_TRK_FeetPlane3_px
Entries 440
Mean 3.006
Std Dev 1.582
Input features comparison
MC
ISS
MC/ISS
distance [mm?]

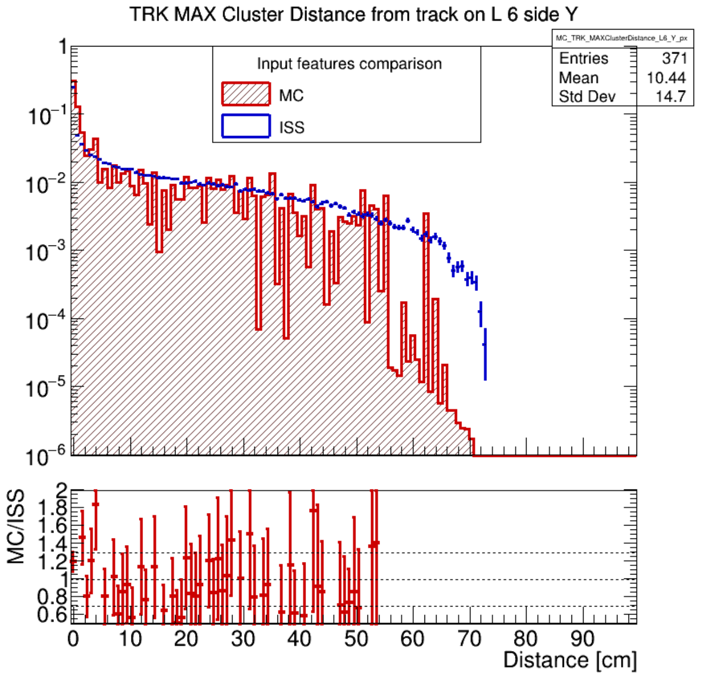

ACC counters
MC_ACC_AntiCounter_px
Entries 440
Mean 0.3677
Std Dev 0.8188
Input features comparison
MC
ISS
MC/ISS
N. of counters

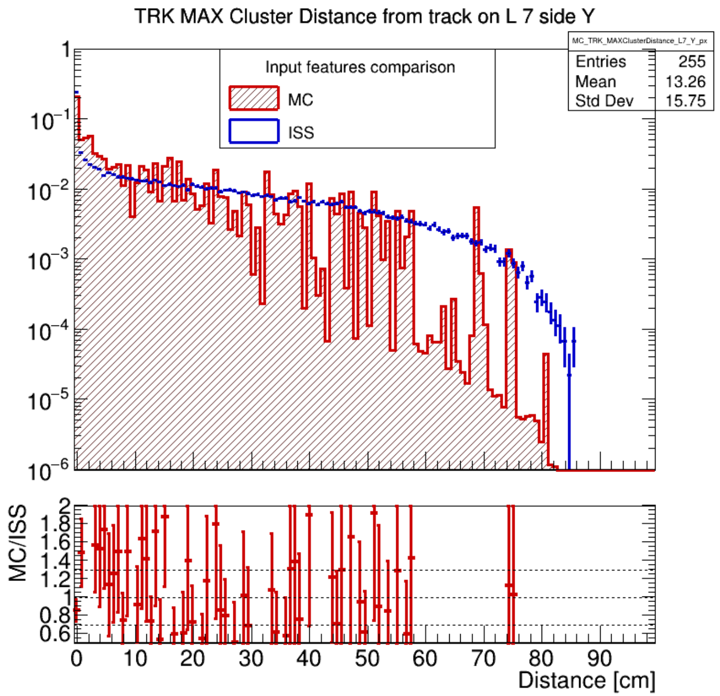

TRK MAX Cluster Distance from track on L 2 side Y
Input features comparison
MC
ISS
Entries 440
Mean 16.46
Std Dev 14.49
MC/ISS
Distance [cm]

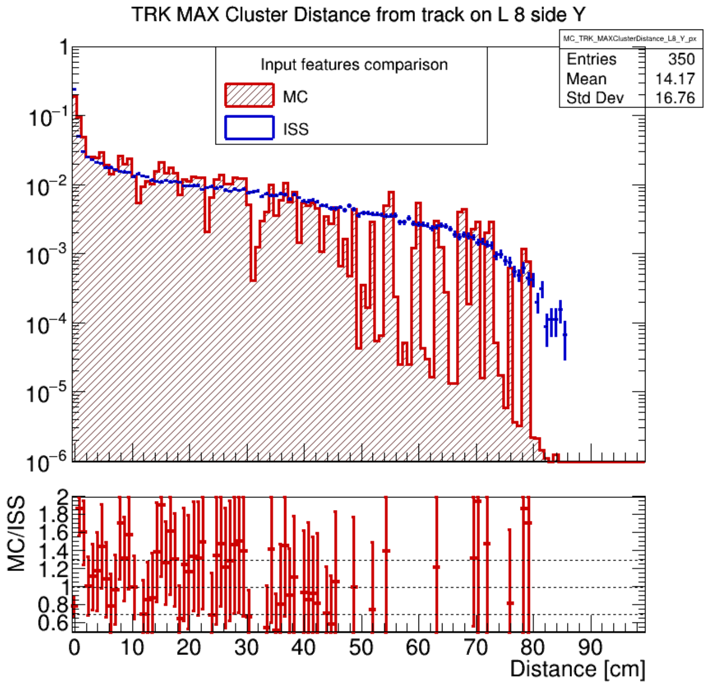

TRK MAX Cluster Distance from track on L 3 side Y
Input features comparison
MC
ISS
Entries 375
Mean 15.16
Std Dev 16.97
MC/ISS
Distance [cm]

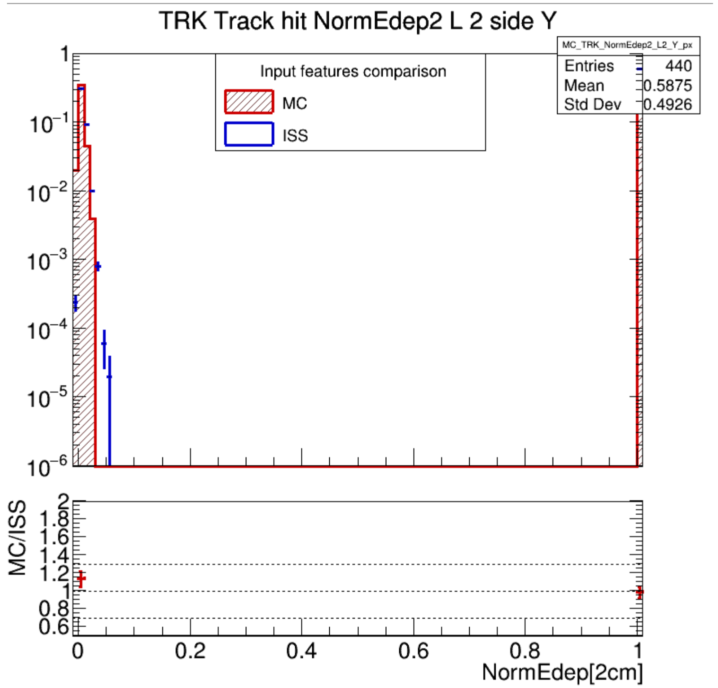

TRK MAX Cluster Distance from track on L 4 side Y
Input features comparison
MC
ISS
Entries 390
Mean 14.14
Std Dev 16.66
MC/ISS
Distance [cm]

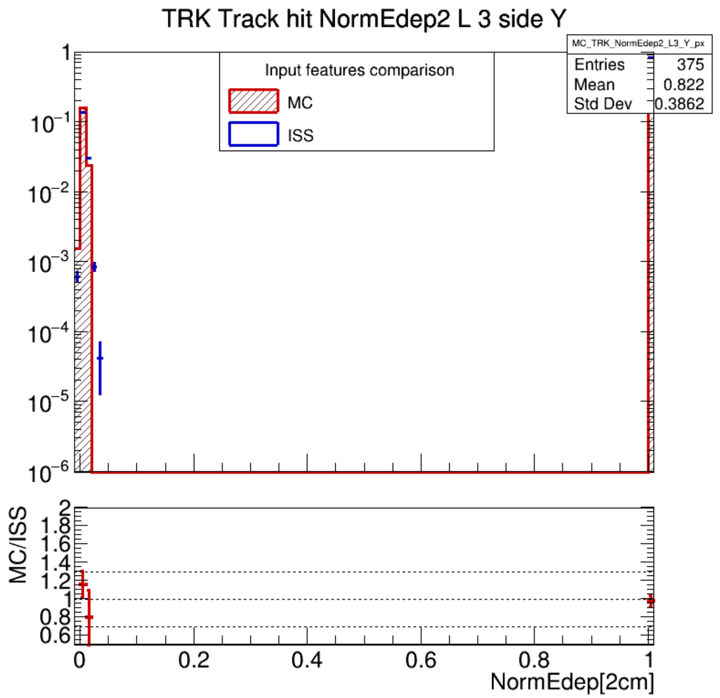

TRK MAX Cluster Distance from track on L 5 side Y
Input features comparison
MC
ISS
Entries 287
Mean 12.26
Std Dev 15.63
MC/ISS
Distance [cm]

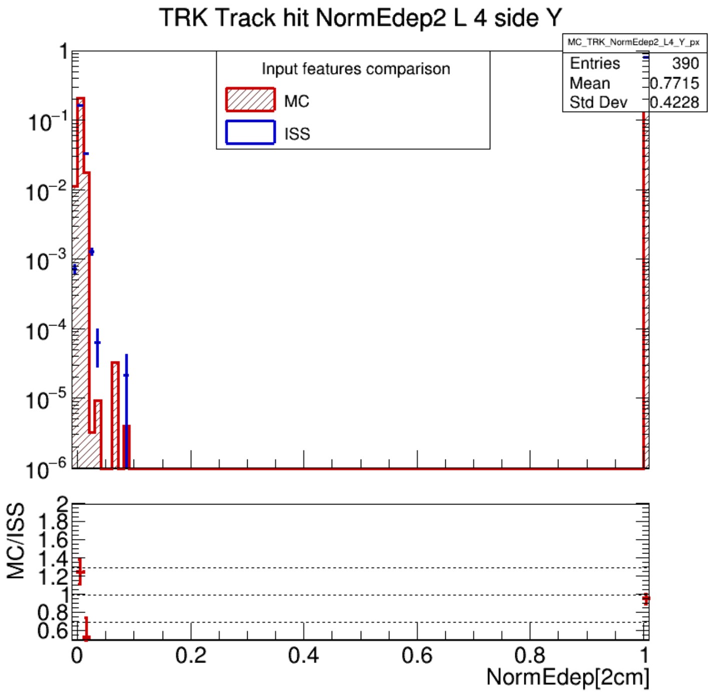

TRK MAX Cluster Distance from track on L 6 side Y
Input features comparison
MC
ISS
Entries 371
Mean 10.44
Std Dev 14.7
MC/ISS
Distance [cm]

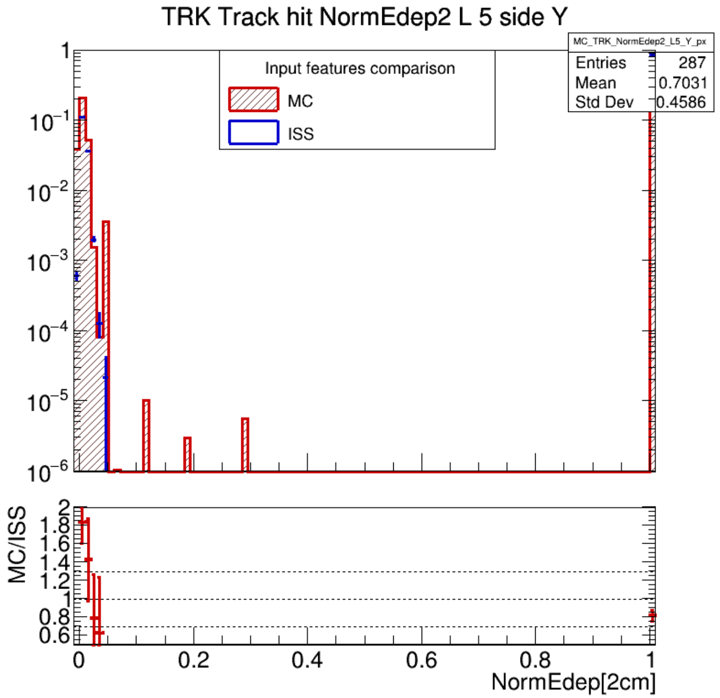

TRK MAX Cluster Distance from track on L 7 side Y
Input features comparison
MC
ISS
Entries 255
Mean 13.26
Std Dev 15.75
MC/ISS
Distance [cm]

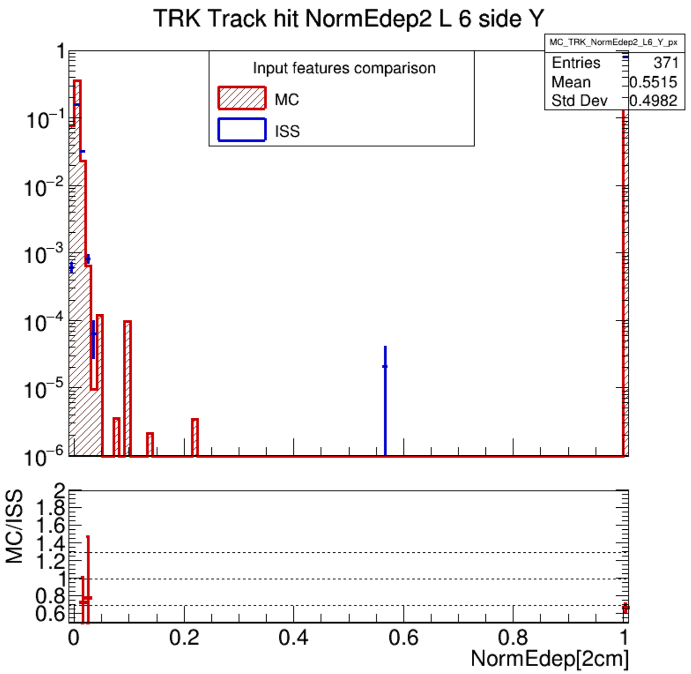

TRK MAX Cluster Distance from track on L 8 side Y
Input features comparison
MC
ISS
Entries 350
Mean 14.17
Std Dev 16.76
MC/ISS
Distance [cm]

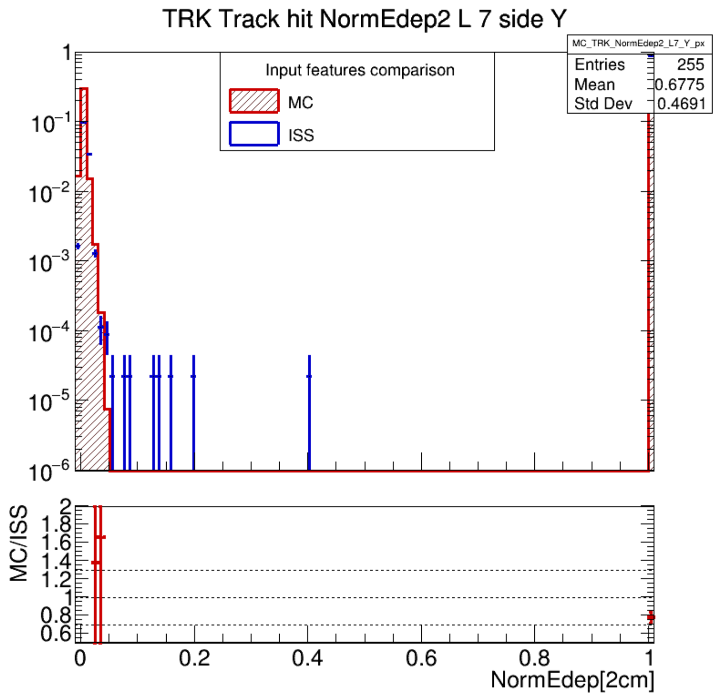

TRK Track hit NormEdep2 L 2 side Y
MC_TRK_NormEdep2_L2_Y_px
Entries 440
Mean 0.5875
Std Dev 0.4926
Input features comparison
MC
ISS
MC/ISS
NormEdep[2cm]

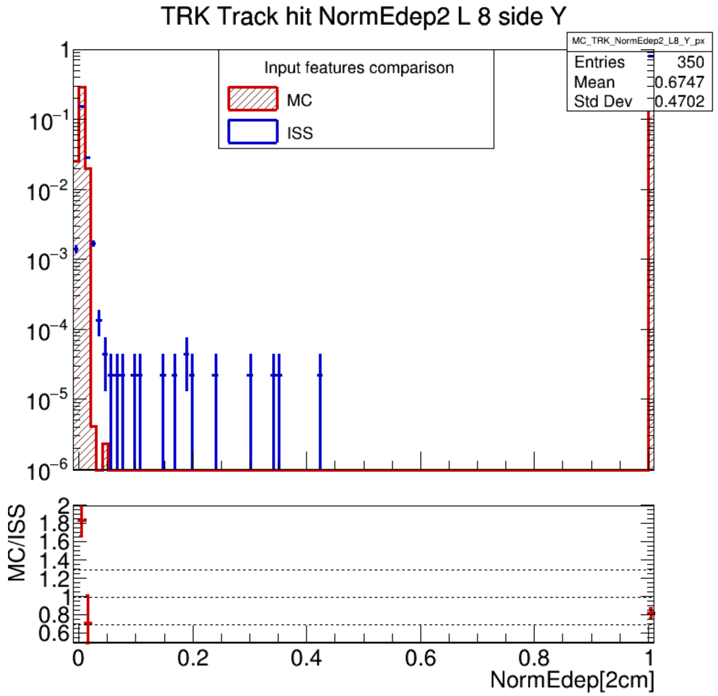

TRK Track hit NormEdep2 L 3 side Y
MC_TRK_NormEdep2_L3_Y_px
Entries 375
Mean 0.822
Std Dev 0.3862
Input features comparison
MC
ISS
MC/ISS
NormEdep[2cm]

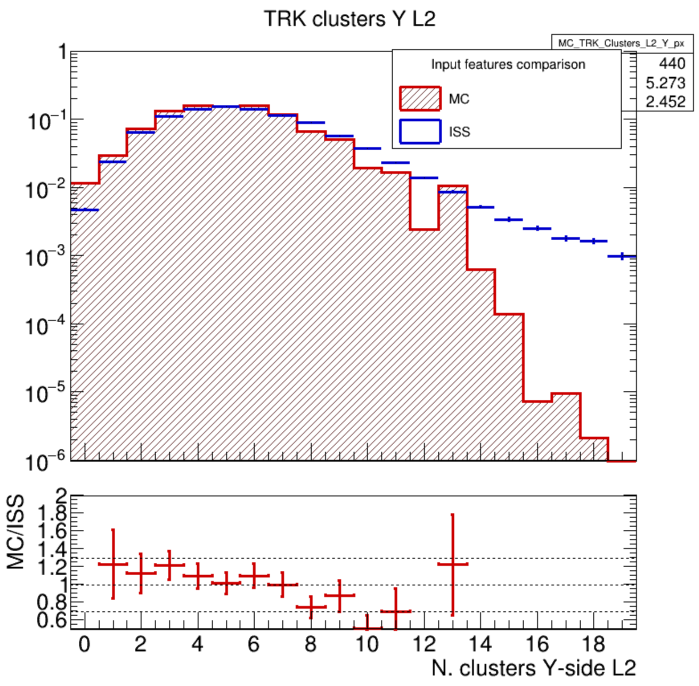

TRK Track hit NormEdep2 L 4 side Y
MC_TRK_NormEdep2_L4_Y_px
Entries 390
Mean 0.7715
Std Dev 0.4228
Input features comparison
MC
ISS
MC/ISS
NormEdep[2cm]

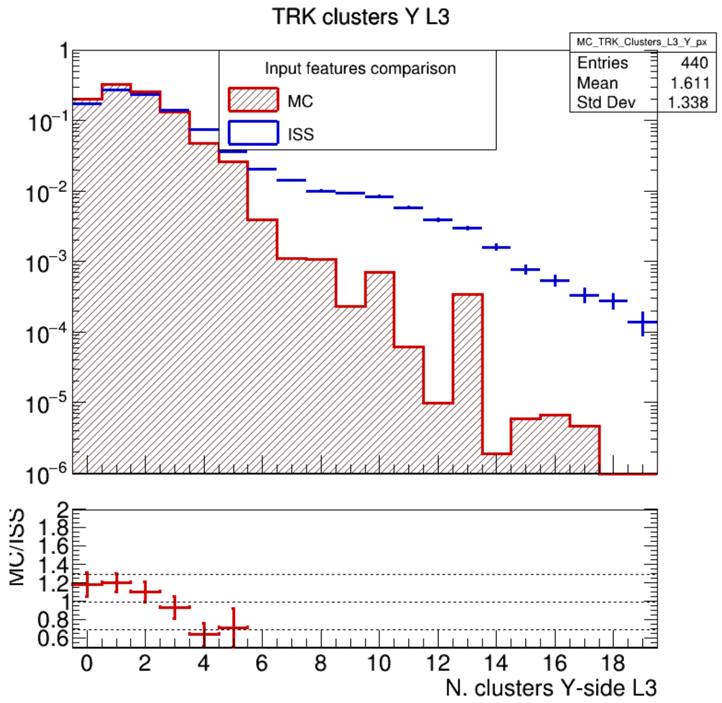

TRK Track hit NormEdep2 L 5 side Y
MC_TRK_NormEdep2_L5_Y_px
Entries 287
Mean 0.7031
Std Dev 0.4586
Input features comparison
MC
ISS
MC/ISS
NormEdep[2cm]

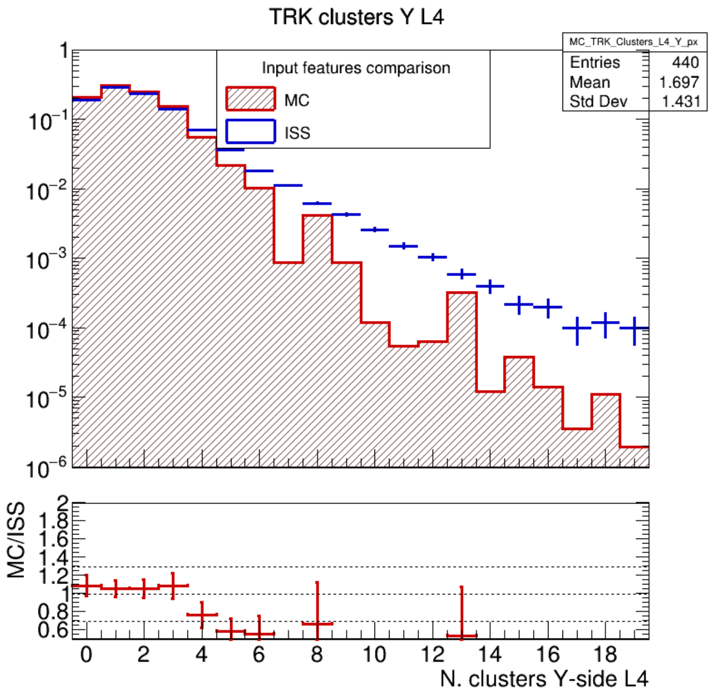

TRK Track hit NormEdep2 L 6 side Y
MC_TRK_NormEdep2_L6_Y_px
Entries 371
Mean 0.5515
Std Dev 0.4982
Input features comparison
MC
ISS
MC/ISS
NormEdep[2cm]

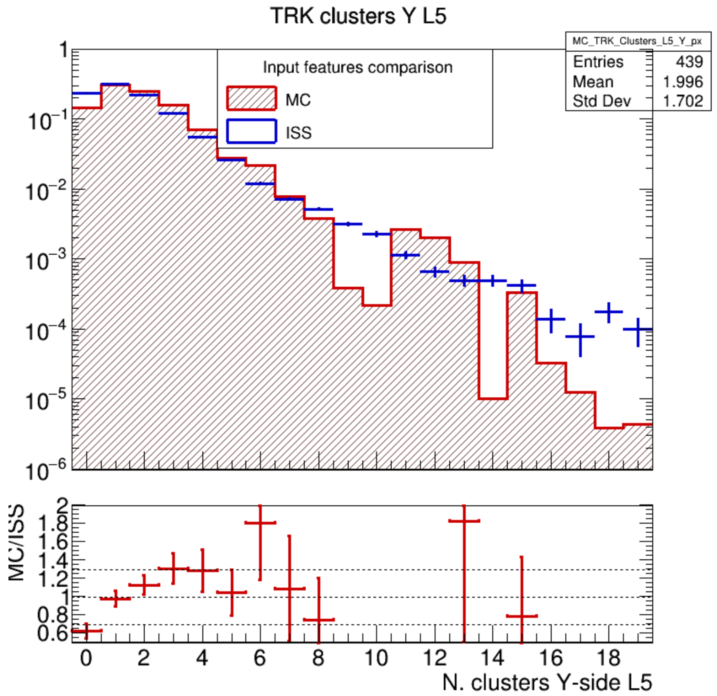

TRK Track hit NormEdep2 L 7 side Y
MC_TRK_NormEdep2_L7_Y_px
Entries 255
Mean 0.6775
Std Dev 0.4691
Input features comparison
MC
ISS
MC/ISS
NormEdep[2cm]

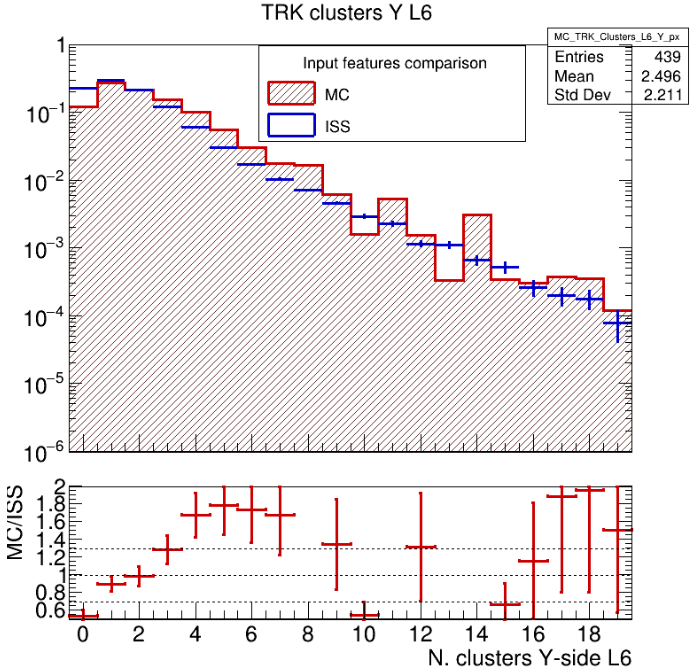

TRK Track hit NormEdep2 L 8 side Y
MC_TRK_NormEdep2_L8_Y_px
Entries 350
Mean 0.6747
Std Dev 0.4702
Input features comparison
MC
ISS
MC/ISS
NormEdep[2cm]

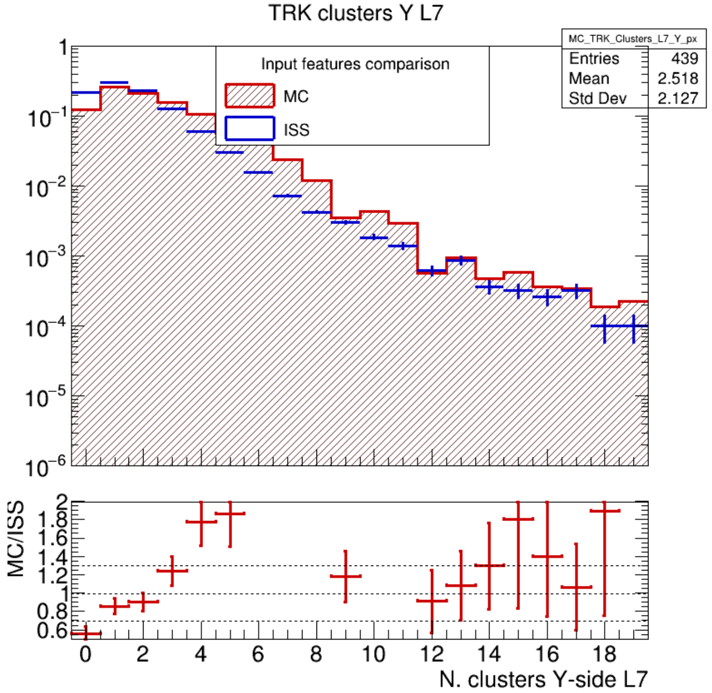

TRK clusters Y L2
MC_TRK_Clusters_L2_Y_px
440
5.273
2.452
Input features comparison
MC
ISS
MC/ISS
N. clusters Y-side L2

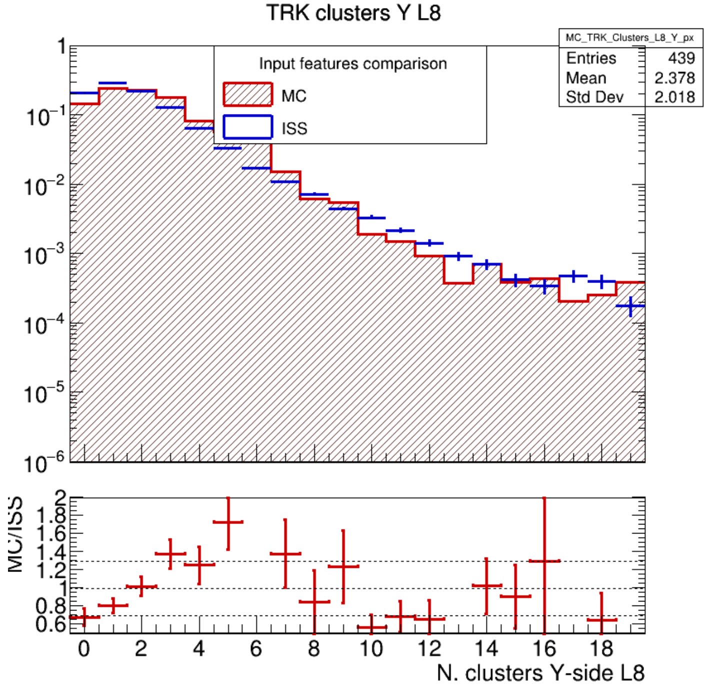

TRK clusters Y L3
MC_TRK_Clusters_L3_Y_px
Entries 440
Mean 1.611
Std Dev 1.338
Input features comparison
MC
ISS
MC/ISS
N. clusters Y-side L3


TRK clusters Y L4
MC_TRK_Clusters_L4_Y_px
Entries 440
Mean 1.697
Std Dev 1.431
Input features comparison
MC
ISS
MC/ISS
N. clusters Y-side L4


TRK clusters Y L5
MC_TRK_Clusters_L5_Y_px
Entries 439
Mean 1.996
Std Dev 1.702
Input features comparison
MC
ISS
MC/ISS
N. clusters Y-side L5


TRK clusters Y L6
MC_TRK_Clusters_L6_Y_px
Entries 439
Mean 2.496
Std Dev 2.211
Input features comparison
MC
ISS
MC/ISS
N. clusters Y-side L6


TRK clusters Y L7
MC_TRK_Clusters_L7_Y_px
Entries 439
Mean 2.518
Std Dev 2.127
Input features comparison
MC
ISS
MC/ISS
N. clusters Y-side L7


TRK clusters Y L8
MC_TRK_Clusters_L8_Y_px
Entries 439
Mean 2.378
Std Dev 2.018
Input features comparison
MC
ISS
MC/ISS
N. clusters Y-side L8

Input features