Deep Learning based Track Segment Reconstruction for Muon Detectors in High Pileup Environments

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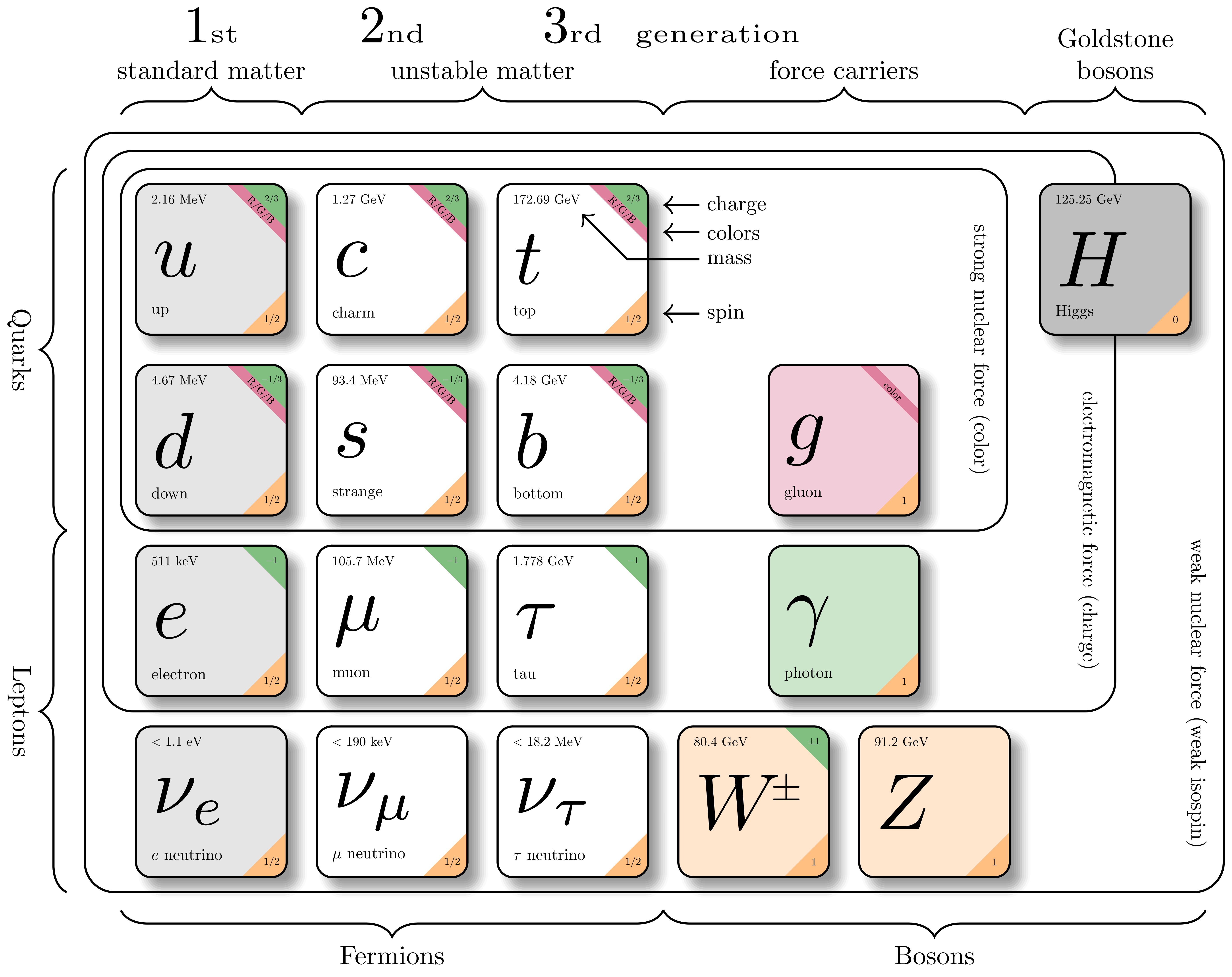
Particle Physics

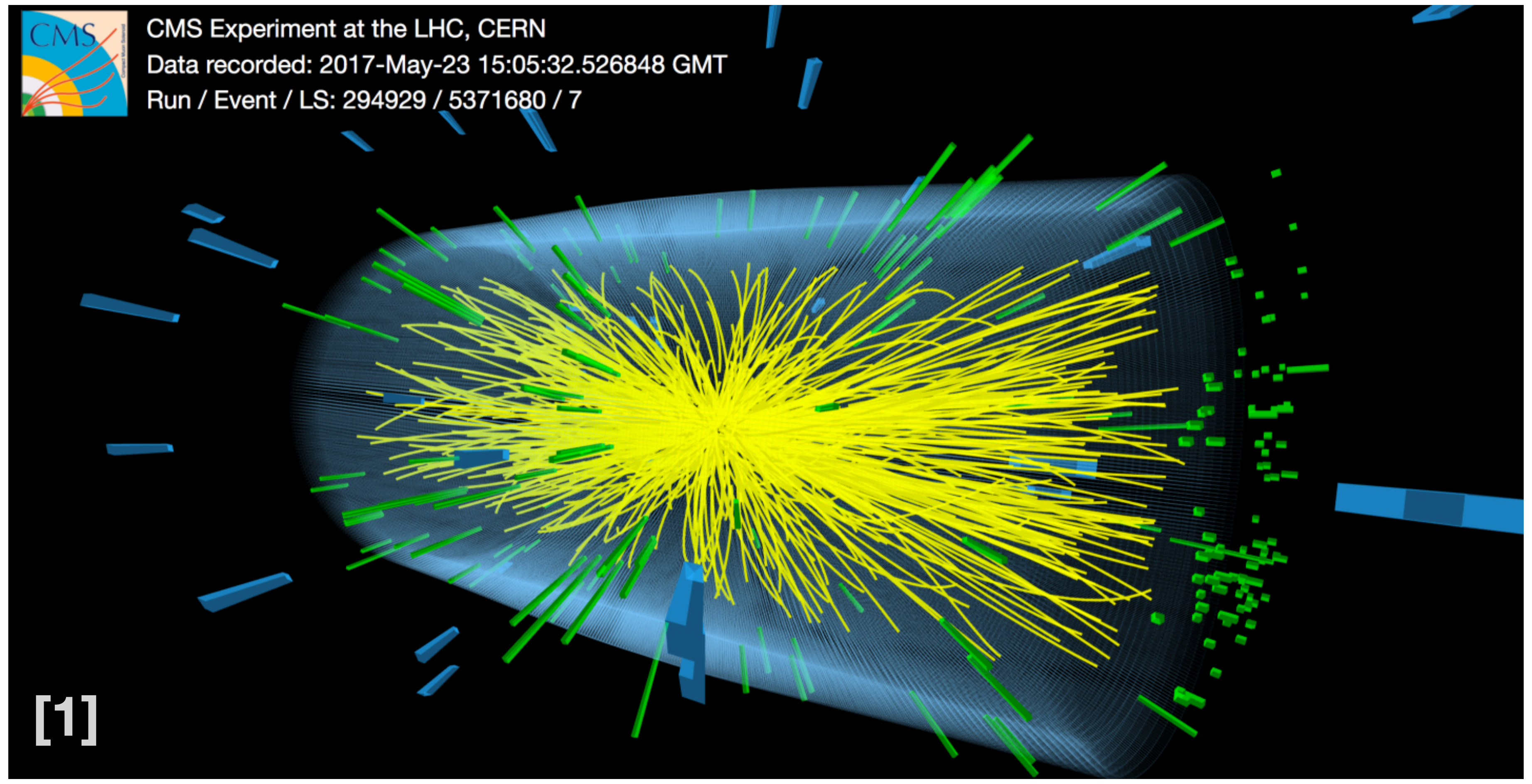
- Seeks to understand fundamental particles and forces
- The Standard Model explains many phenomena, but is incomplete:
  - Dark matter
  - Neutrino mass
  - Matter-antimatter asymmetry
- High-energy colliders like the LHC explore new physics at the smallest scales



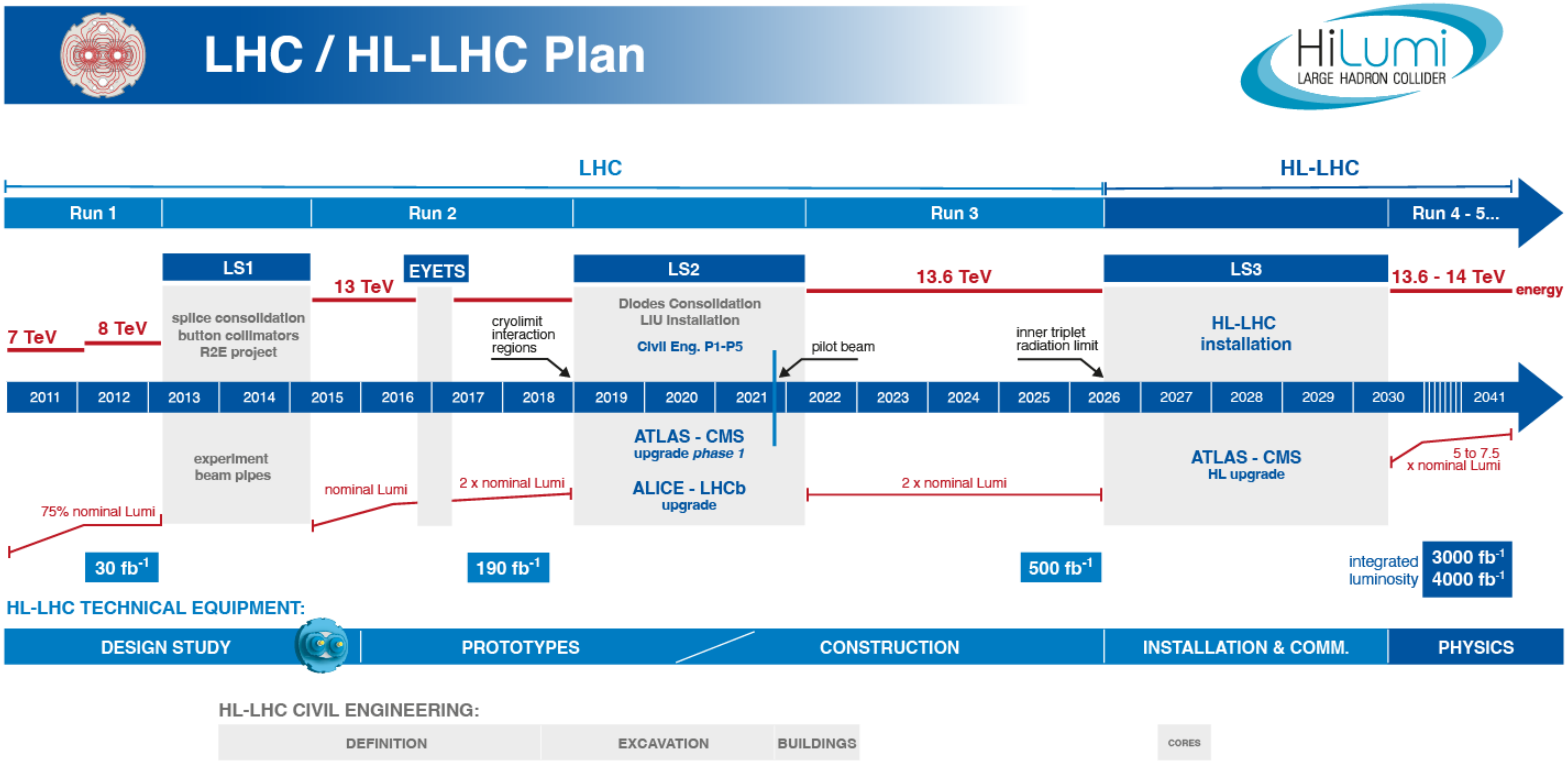
Motivation and Goal

- **Motivation**
  - CERN is planning to increase the luminosity of the Large Hadron Collider (LHC), leading to the High-Luminosity LHC (HL-LHC)
  - The higher the pileup interactions, the more difficult it becomes to reconstruct physics objects like muons
  - There are many efforts to develop and improve reconstruction algorithms like TrackML challenge to address these difficulties
- **Goal**
  - Investigate the use of **deep learning techniques to improve local muon reconstruction** within the ME0 detector
  - Aim to **enhance reconstruction accuracy and efficiency** in the face of **high background particle rates**

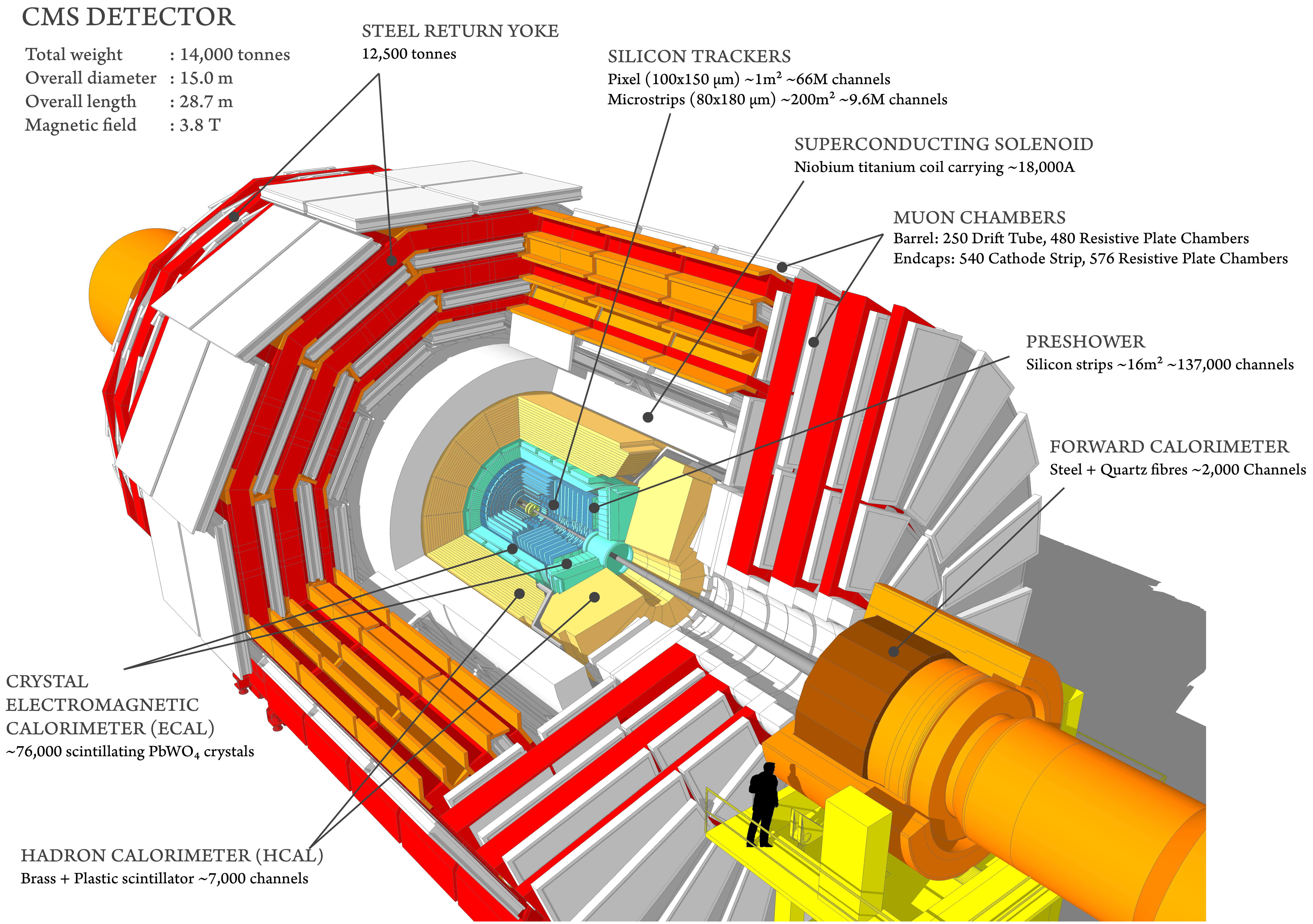
	LHC		HL-LHC	
	Nominal	Run3	Run 4	Run 5
Inst. lumi. [Hz/nb]	10	20	50	75
Average pileup	20	50-60	150	200



High Luminosity LHC

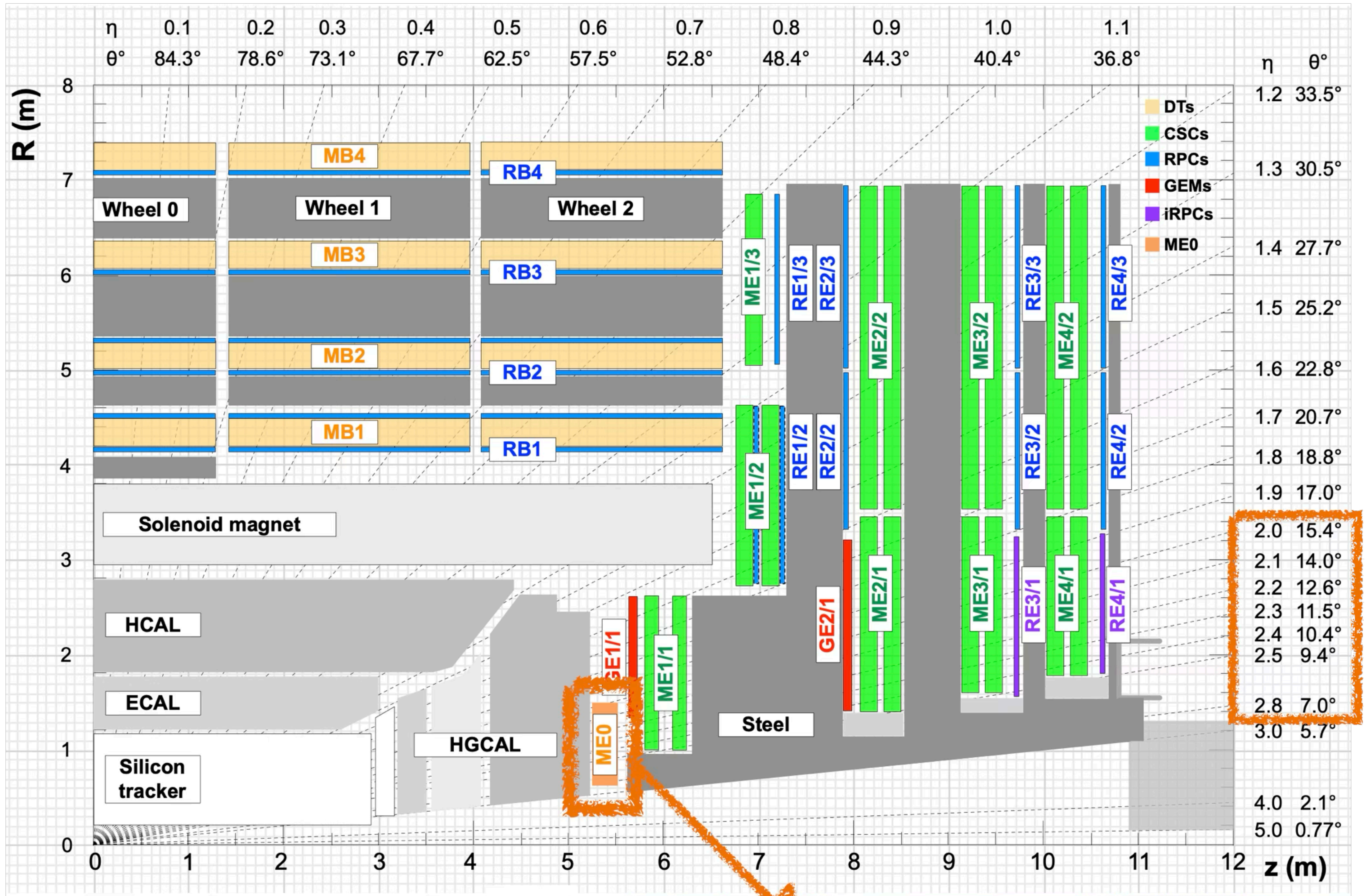


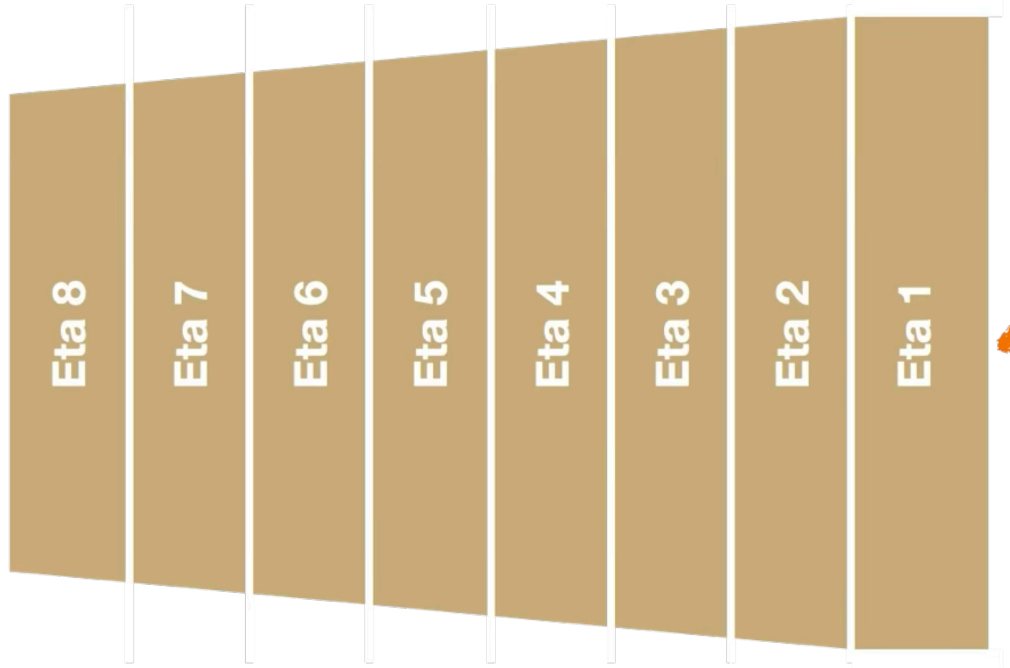
The Compact Muon Solenoid (CMS)

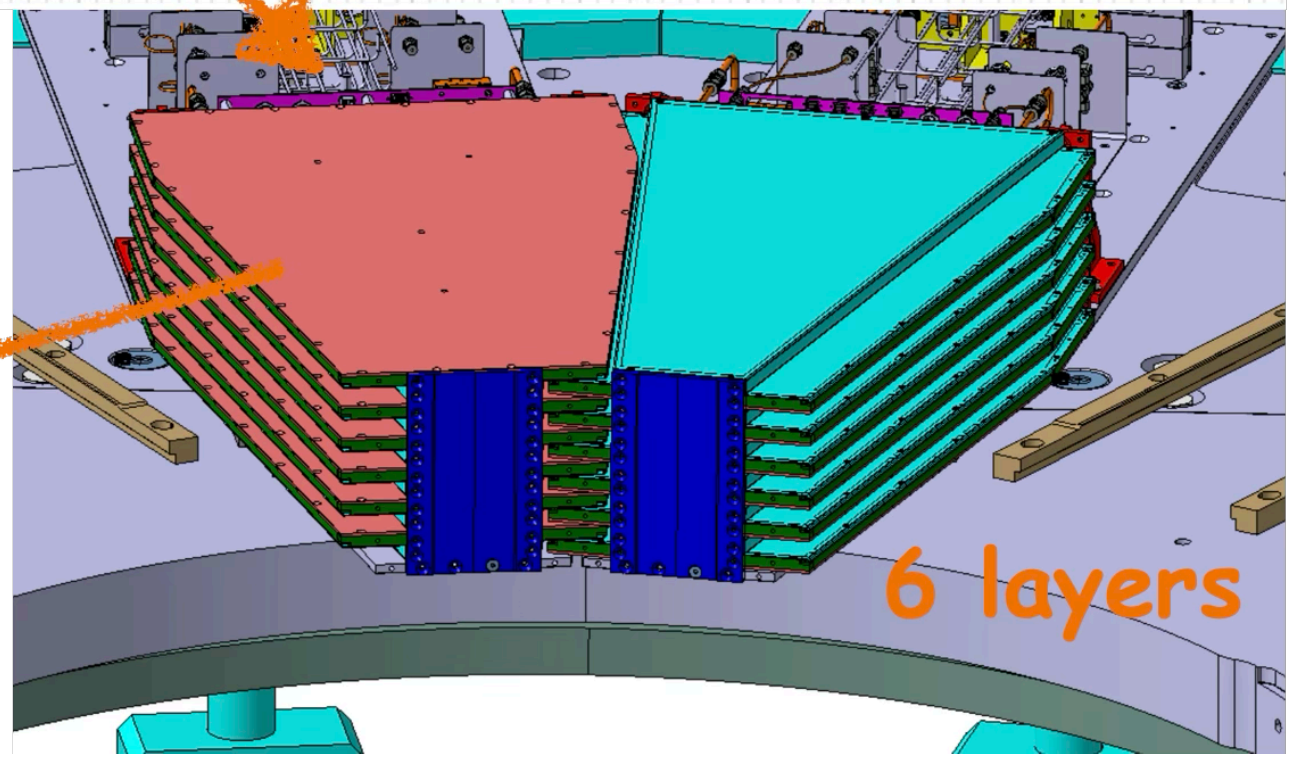


The ME0 Detector

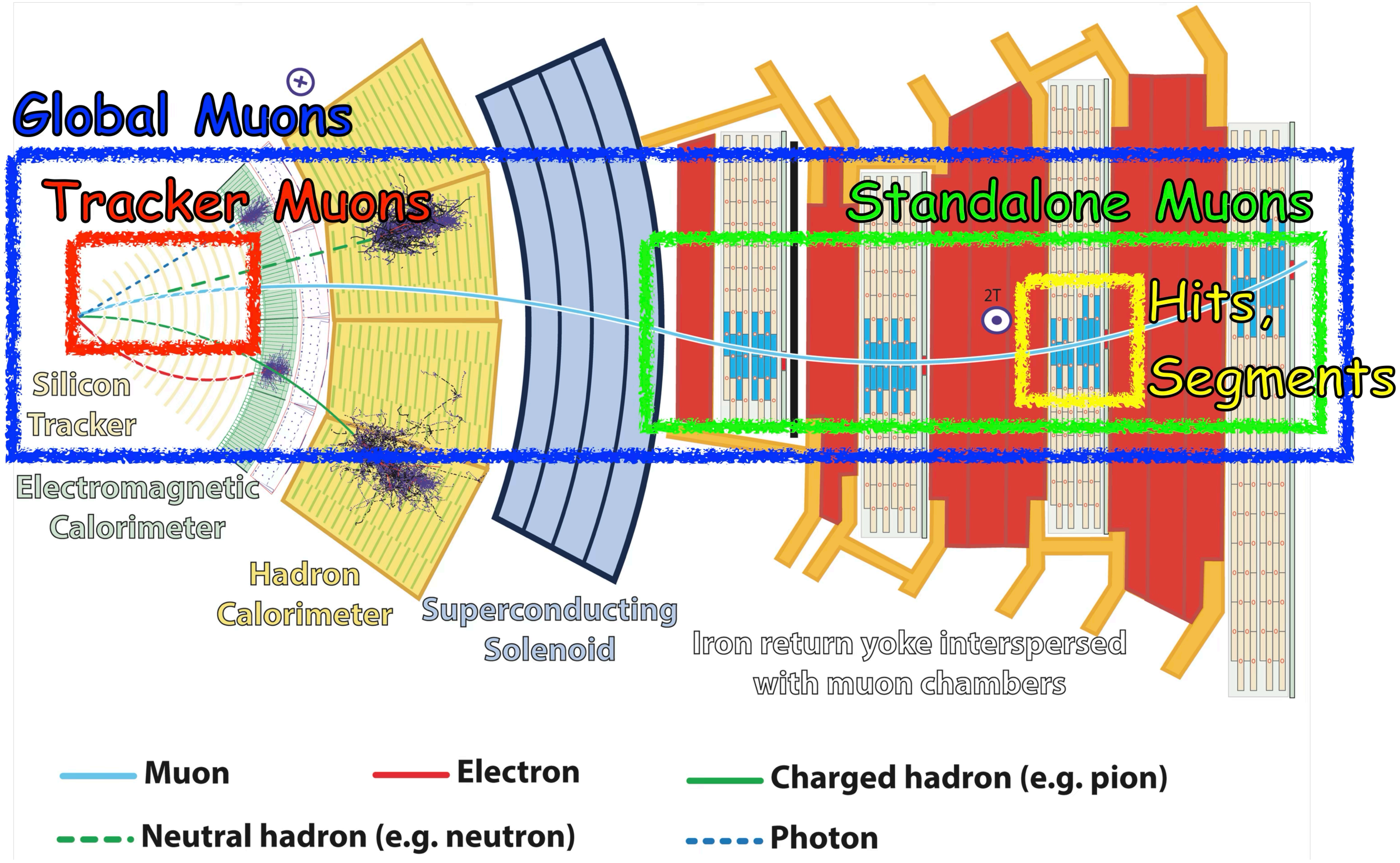
- Based on triple Gas Electron Multiplier (Triple-GEM) technology, a forthcoming component of the CMS experiment muon system
- Cover very forward pseudorapidity region ($2.0 < |\eta| < 2.8$)
- Each endcap region is instrumented with **18 stacks**, and each stack consists of **6 layers of GEM chambers**
- Every layer contains **8 η partitions**, with the largest eta partition having 374 strips and the others having **384 strips**







Muon Reconstruction in CMS

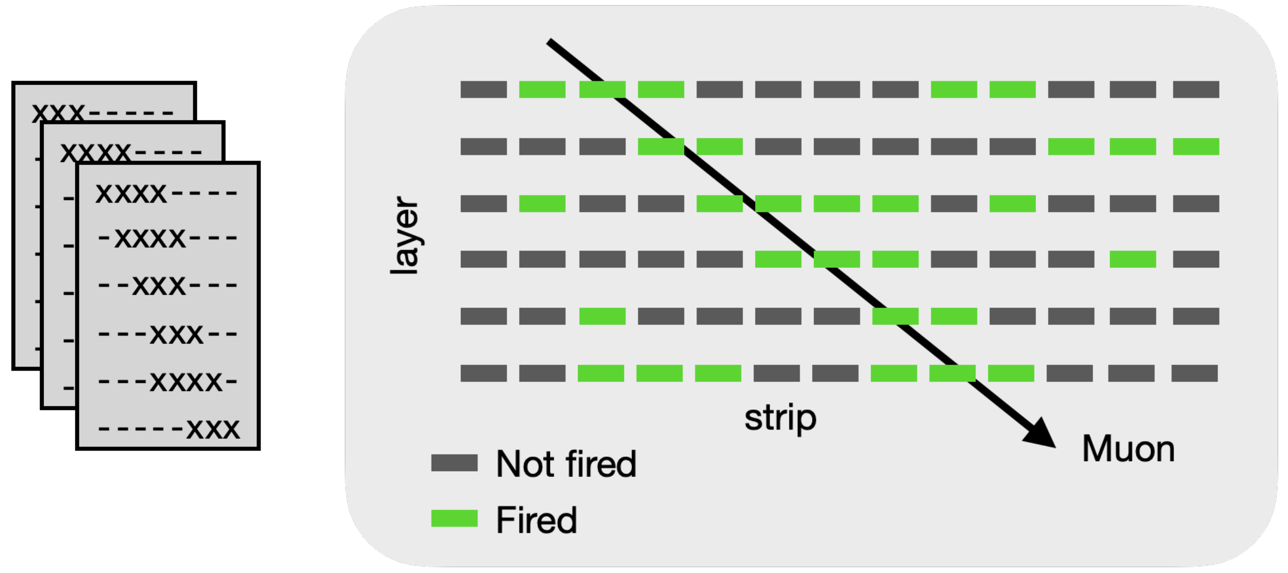


Muon Segment Reconstruction

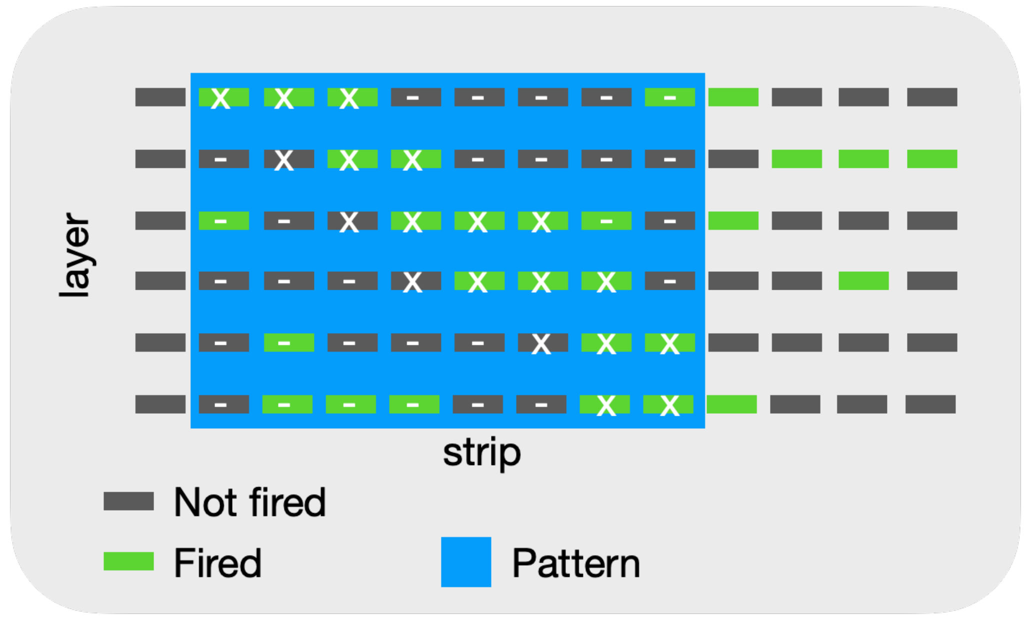
- Muons crossing multi-layer detector, leaves tracks called segments
- Segments are used in seed/track reconstruction
- Two main methods:
  - pattern matching (hardware based L1 trigger)
  - Road Usage algorithm (offline reconstruction)

Pattern Matching

1. Scan with predefined patterns

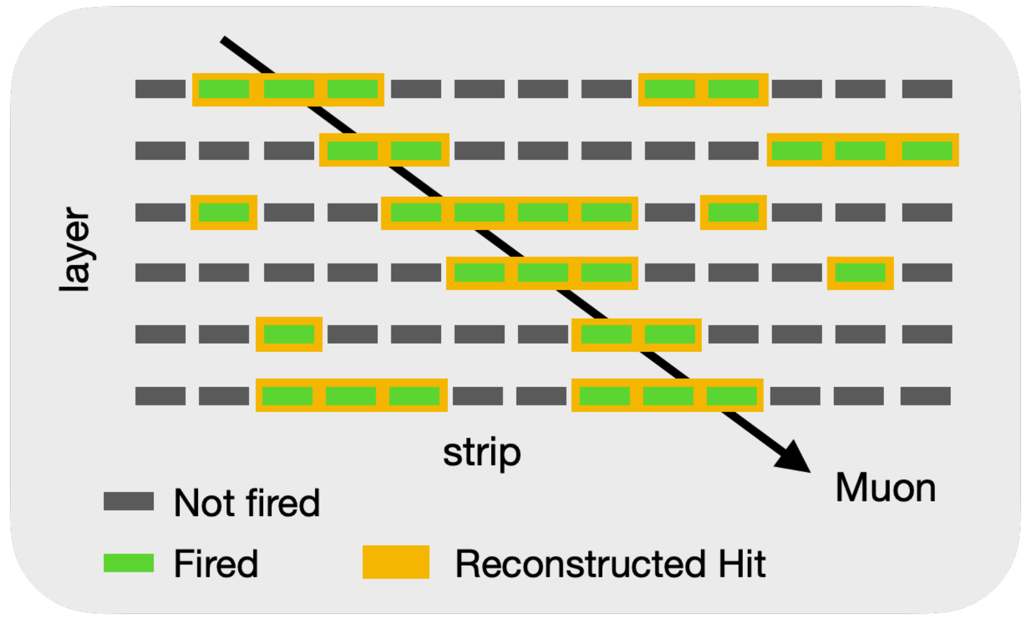


2. Select segments that match the pattern

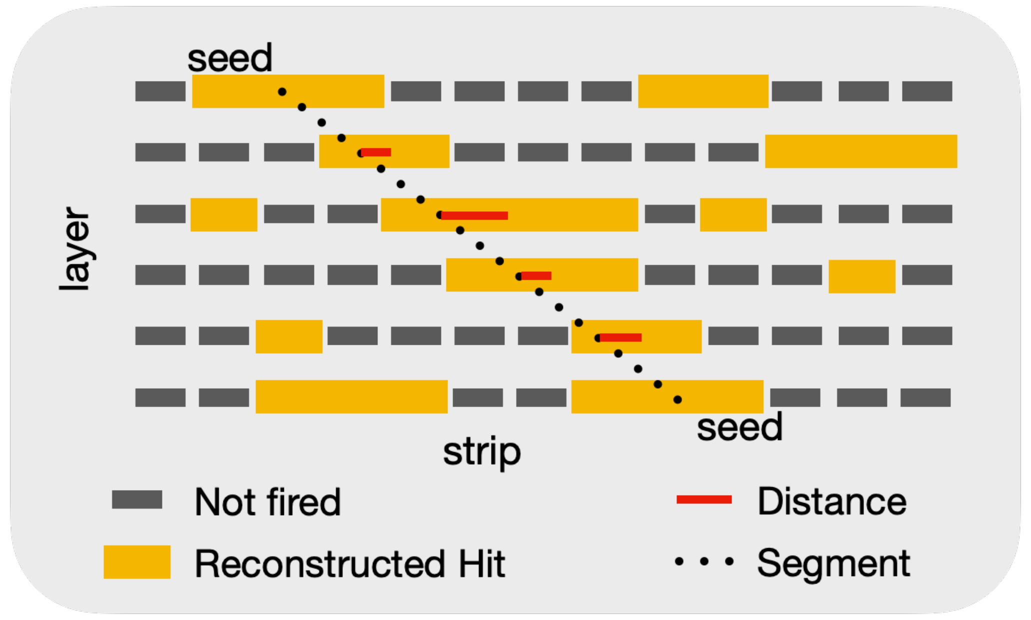


Road Usage Algorithm

1. Hit reconstruction



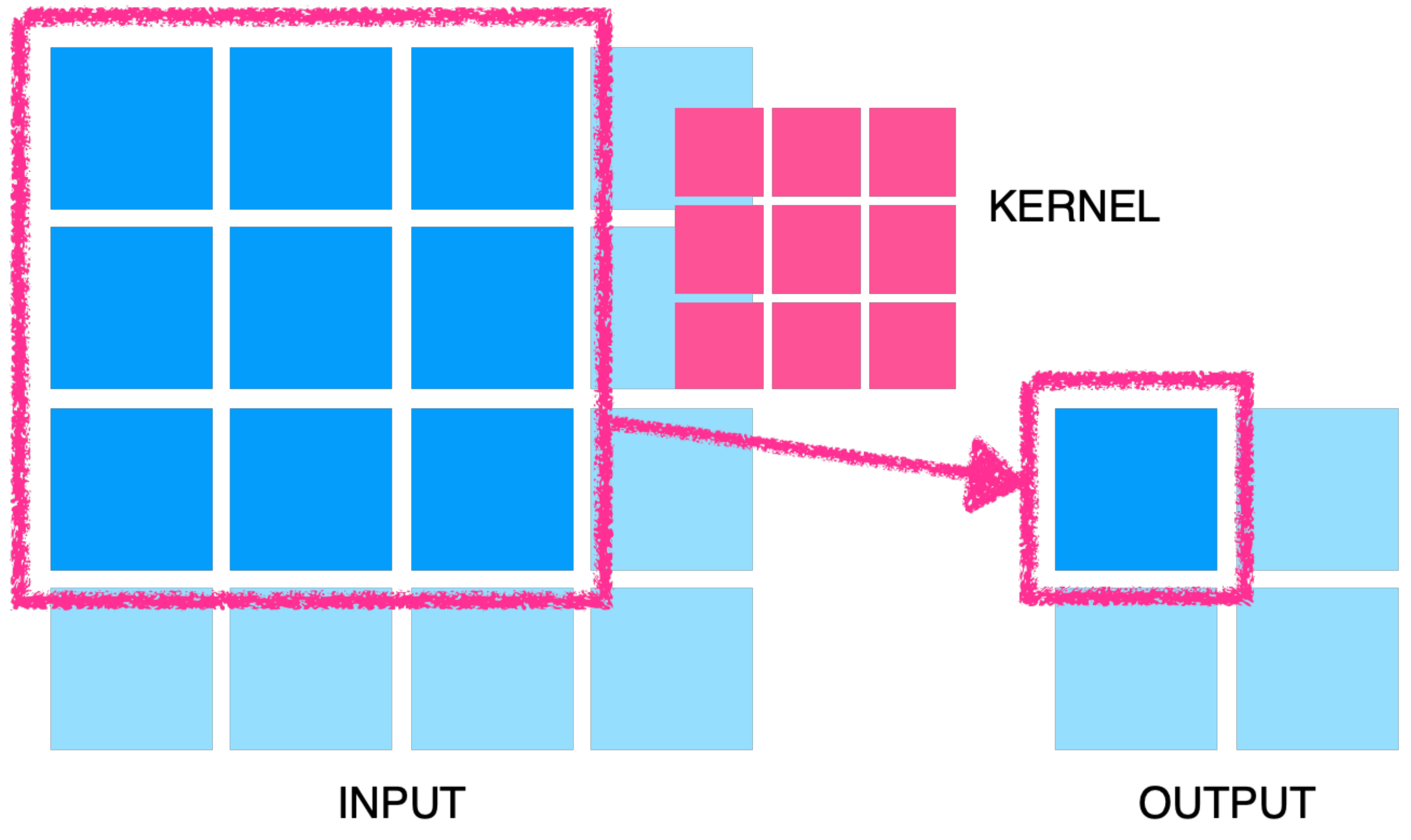
2. Linear fitting after seed pair selection



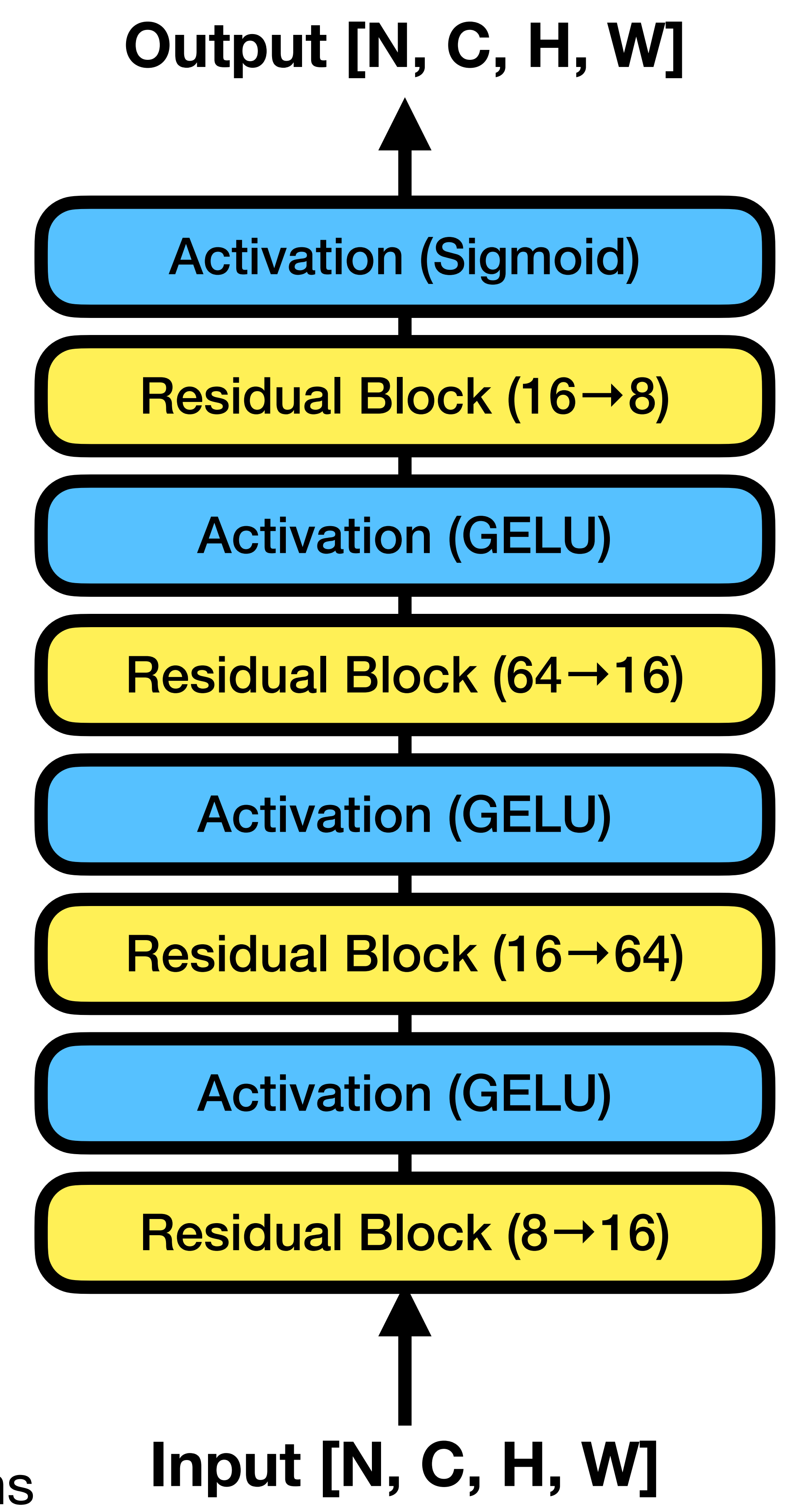
3. Select segment with lowest χ^2 error

Model Architecture: ME0SegCNN2d

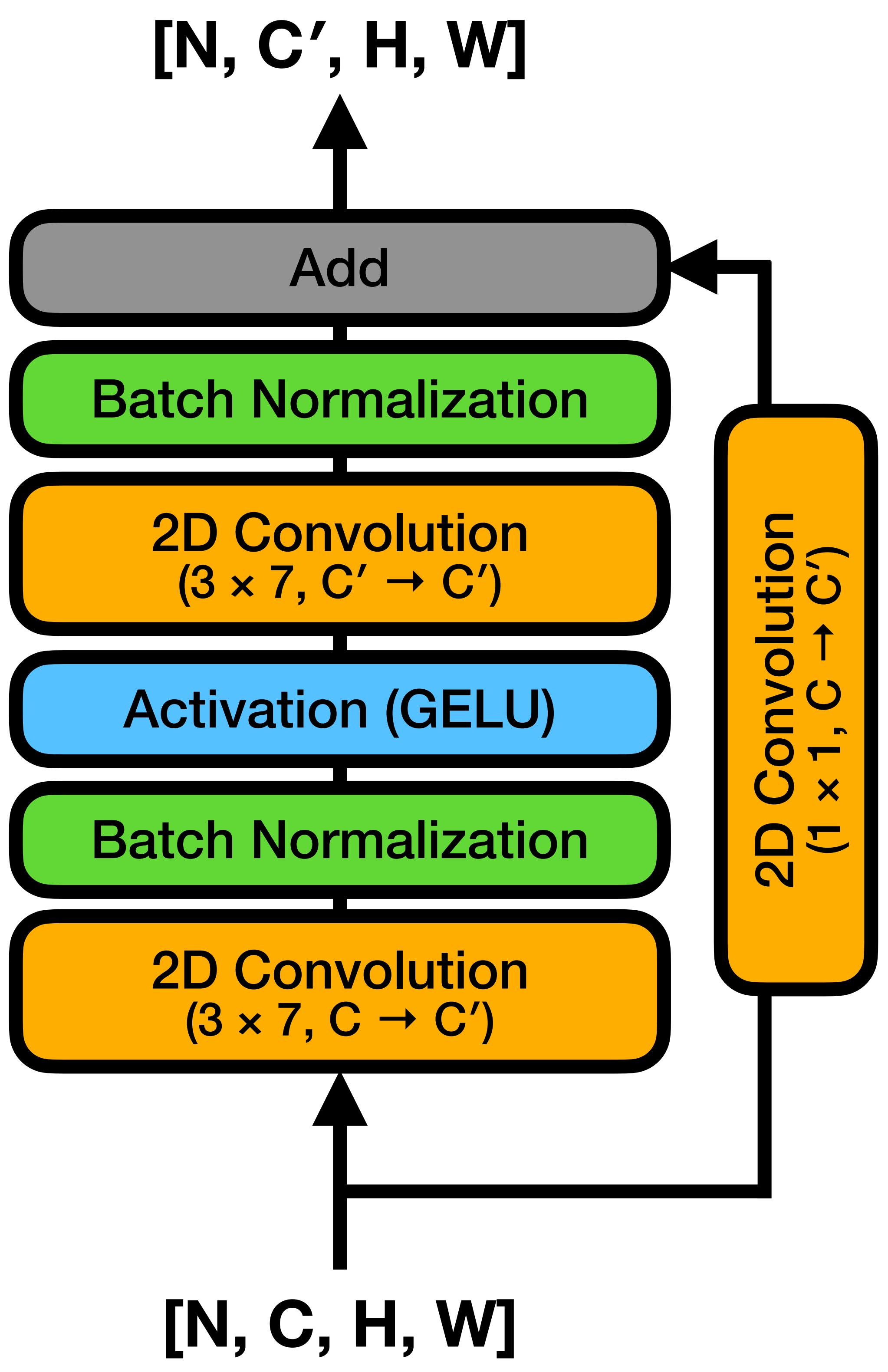
- Input size: **8 channels 2D image**, matching the geometry of the ME0 stack ([8, 6, 384])
  - The channels represent the each η partition's **hit map**
- Output size: same with input
  - Each pixel represents a strip, and the value indicates **score of whether that strip has a hit caused by a muon**



N: Batch size
C: Number of η partitions
H: Number of layers
W: Number of strips



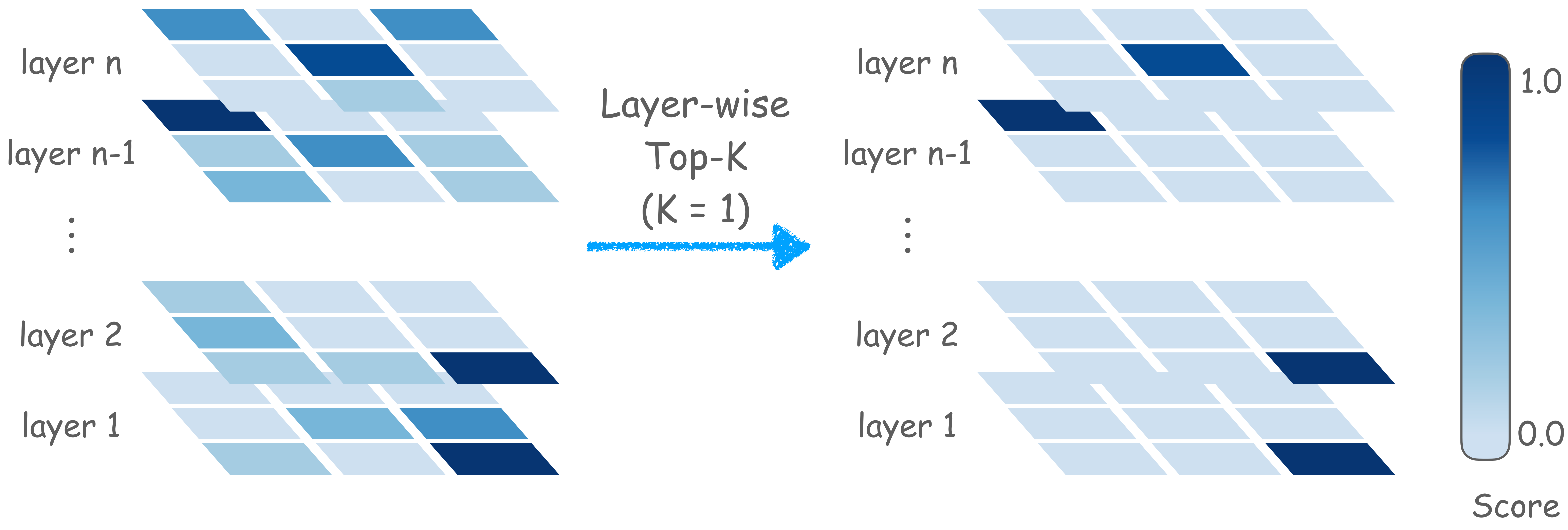
ME0SegCNN2d



Residual Block (C → C′)

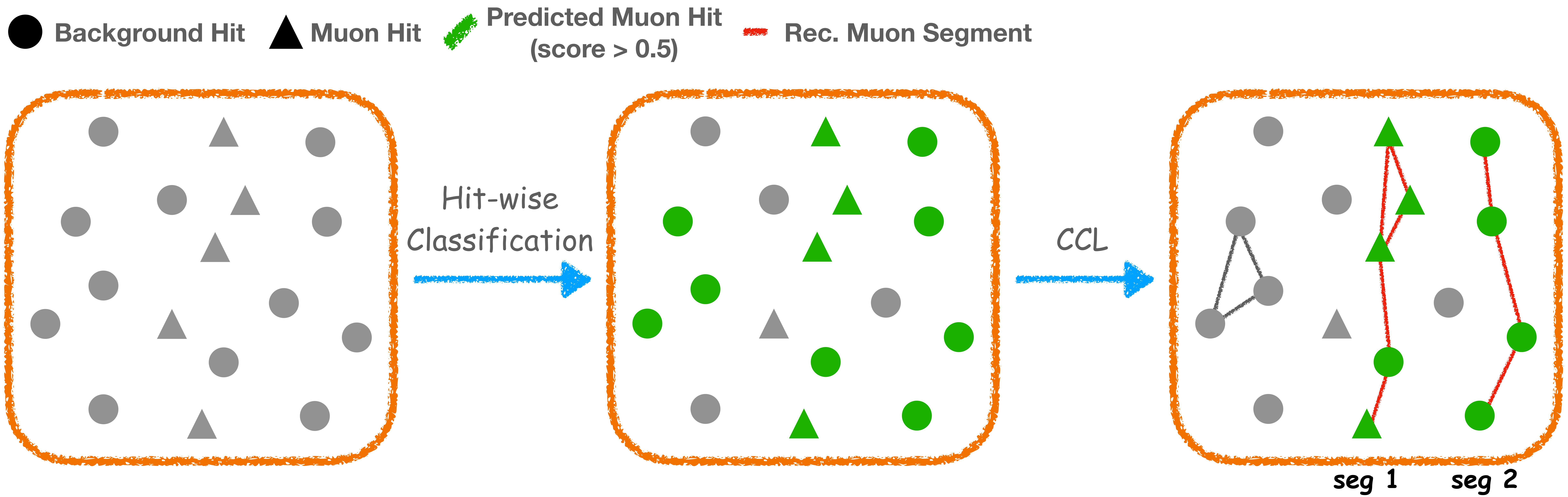
Postprocessing: Layer-wise Top-K

- Layer-wise Top-K **retains only the top-k scoring strips** within each layer across all iη, masking all other values to zero (in this study k = 1)
- **Downside: not guaranteed to be spatially adjacent**



Postprocessing: CCL

- Connected Component Labeling (CCL) groups predicted muon hits into unified segments by clustering hits that satisfy the spatial proximity criteria: $|\Delta i\eta| \leq 1$, $|\Delta \text{strip}| \leq 4$, and $1 \leq |\Delta \text{layer}| \leq 3$



Criteria and Metrics

- **Rec. Segment definition (a)**

(a) Consisting of hits on at least 4 layers

- **Muon-segment matching (b)**

(b1) At least 4 layers have muon hits

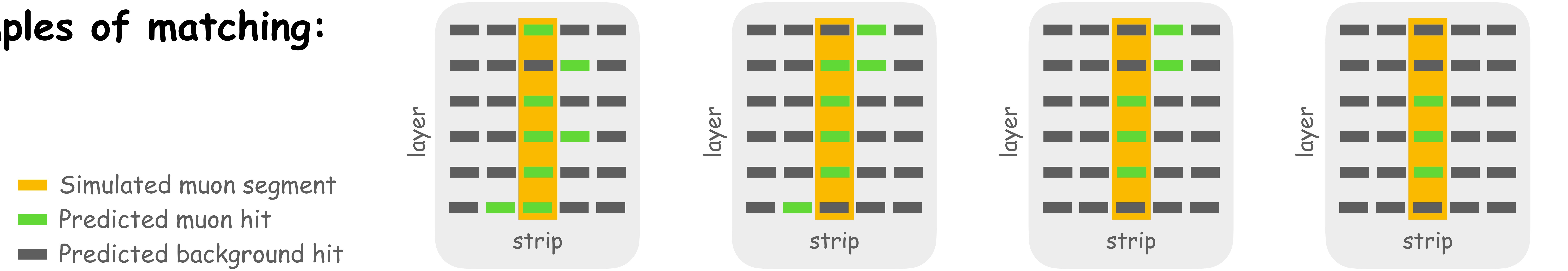
(b2) $\frac{\text{Numbe of muon hits in a segment}}{\text{Number of hits in a segment}} \geq 0.6$

- **Segment-level Metrics**

$$\text{Segment Rec. Efficiency} = \frac{N_{\text{correct}}}{N_{\text{muon}}}$$

$$\text{Segment Rec. Fake Fraction} = \frac{N_{\text{fake}}}{N_{\text{rec. seg}}}$$

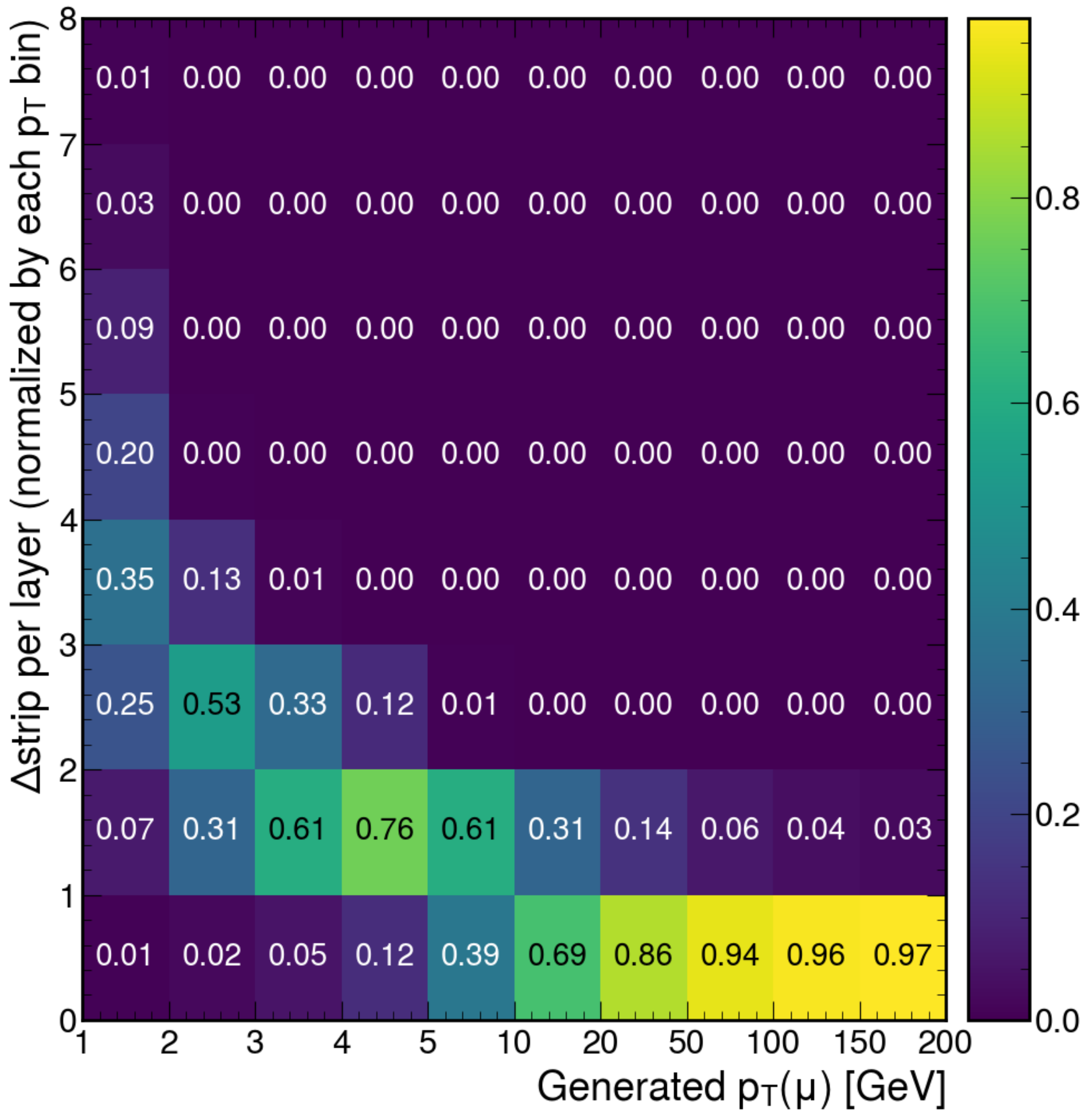
Examples of matching:

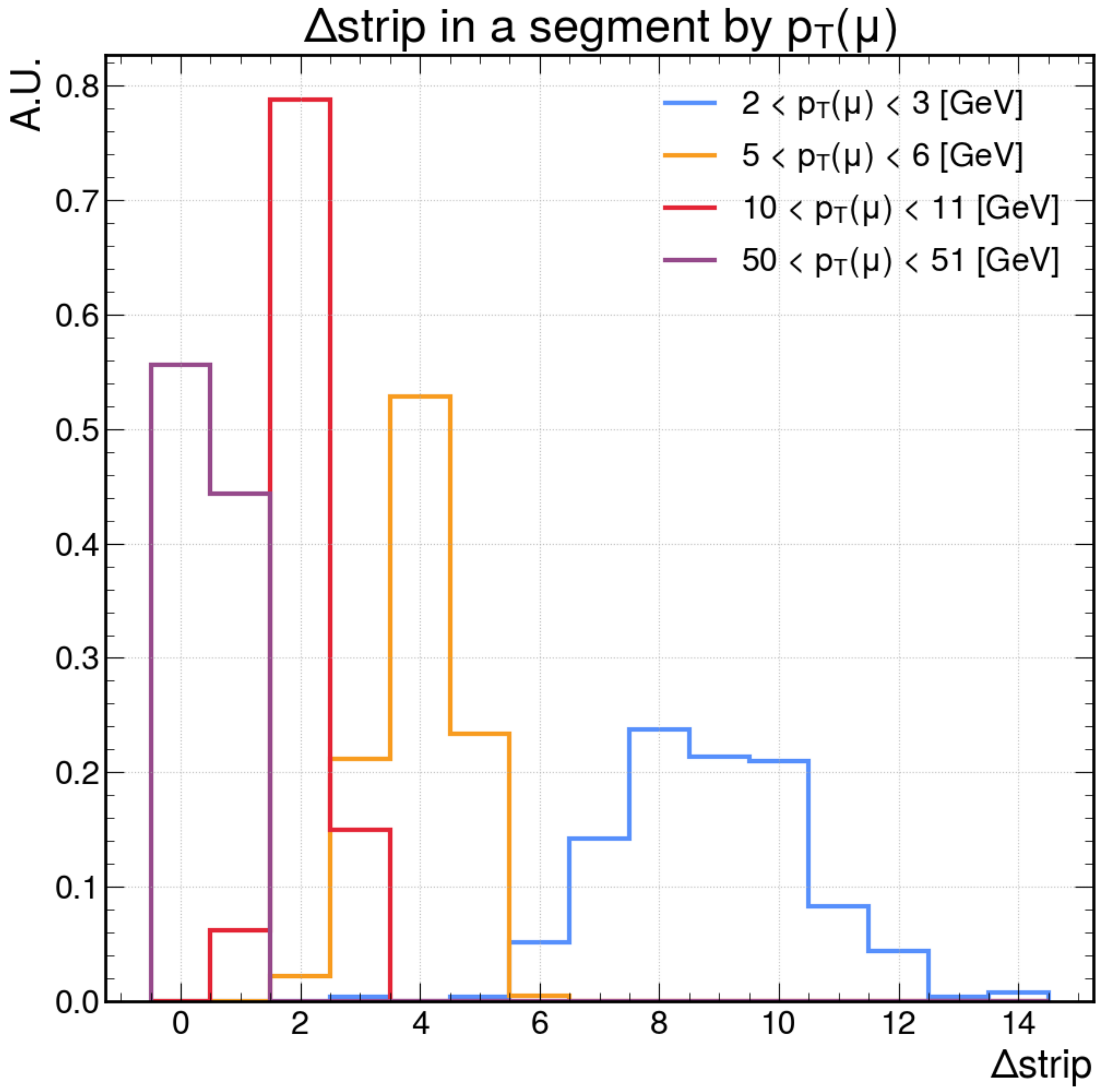


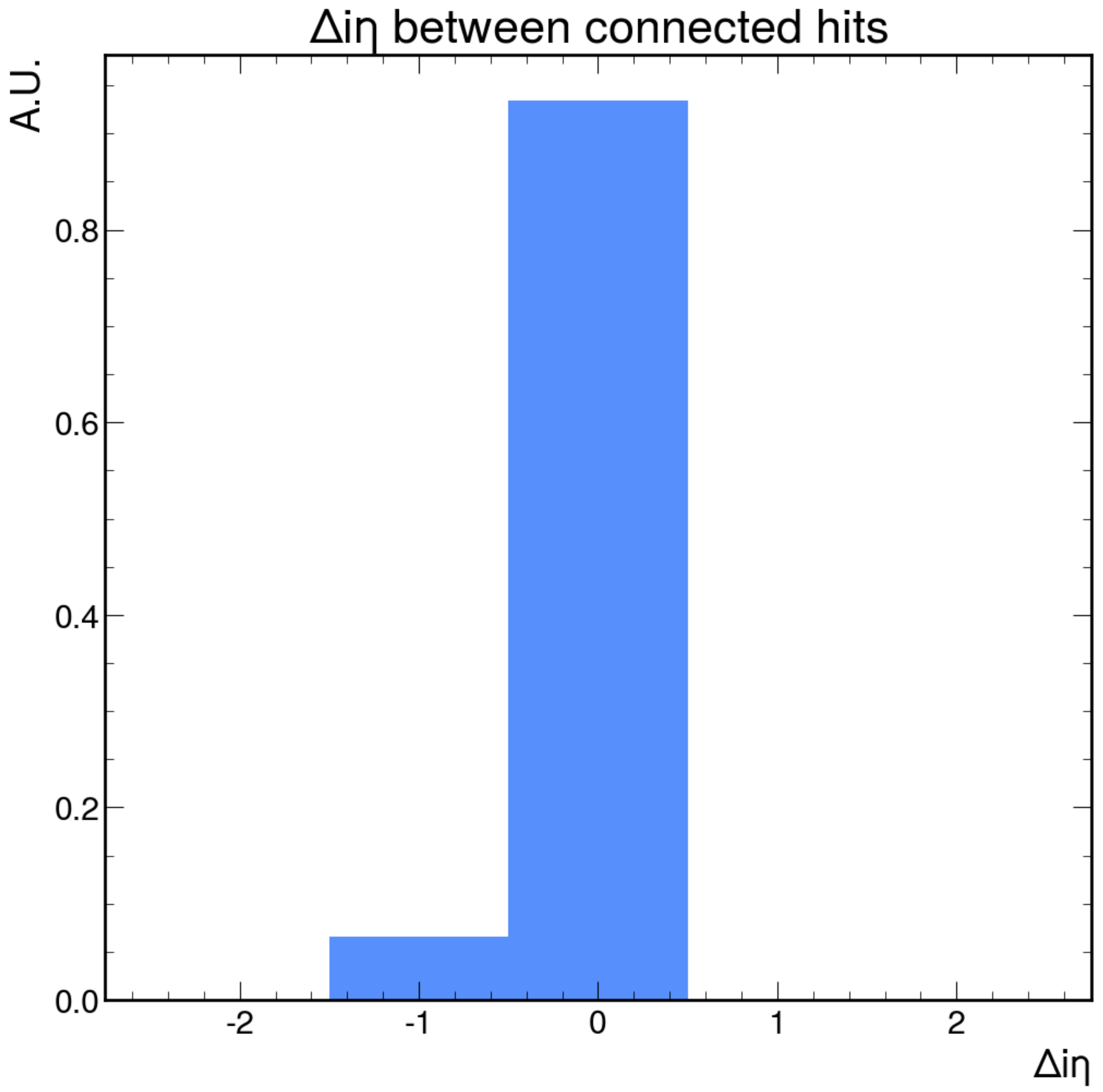
	Correct	Fake	Fake	Not reconstructed
a	O (6)	O (6)	O (5)	X (3)
b1	O (5)	O (4)	X (3)	X (3)
b2	O (0.63)	X (0.57)	O (0.6)	O (1.0)

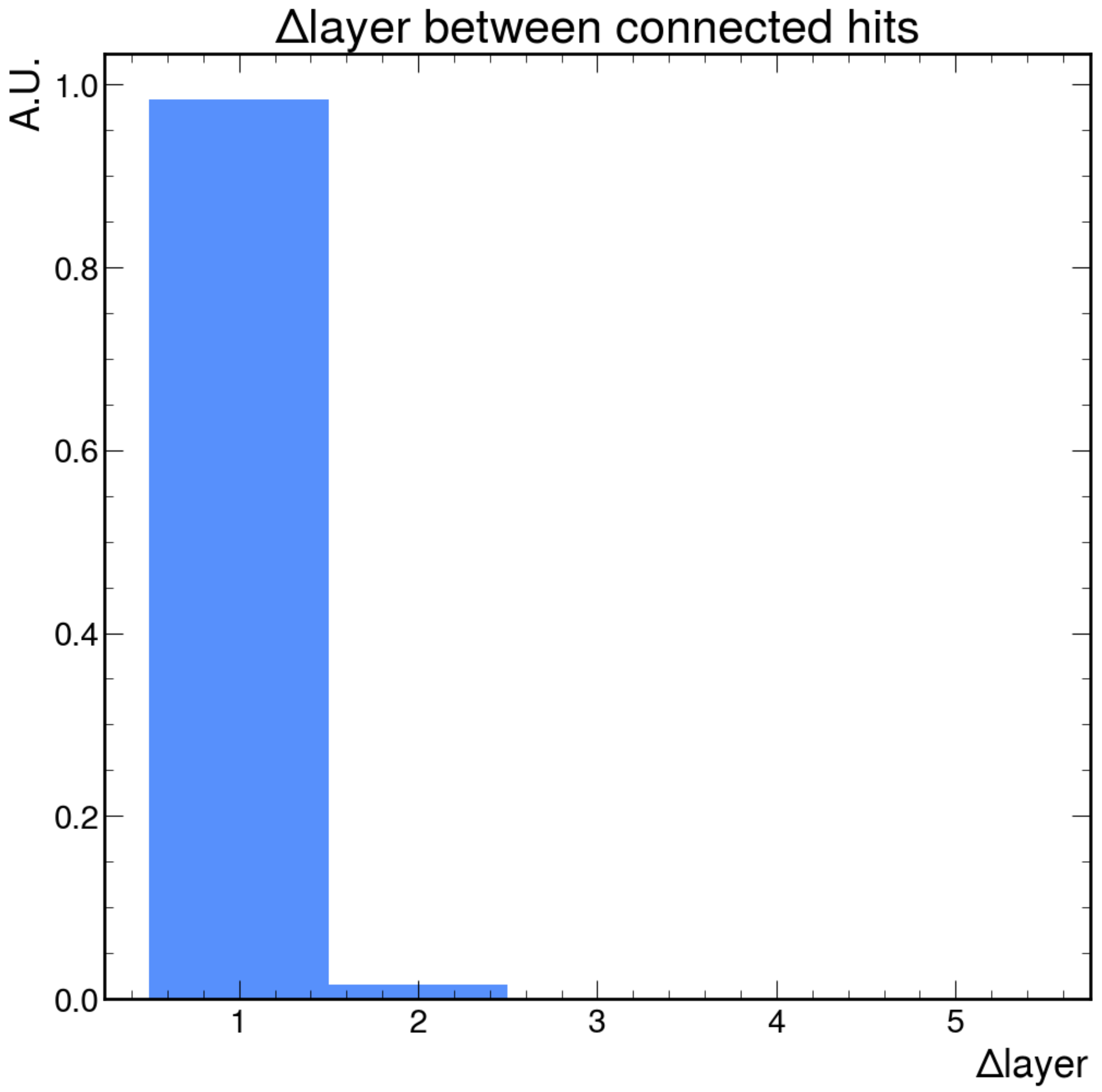
Sample Generation

- Fast simulation of a six-layered GEM detector response to muons in a magnetic field within an HL-LHC-like environment
- Signal: A muon with pT ranging from 1 to 200 GeV in each stack per event
- Backgrounds: average 75 particles in each stack per event (PU200)
- Detector efficiency: 98%

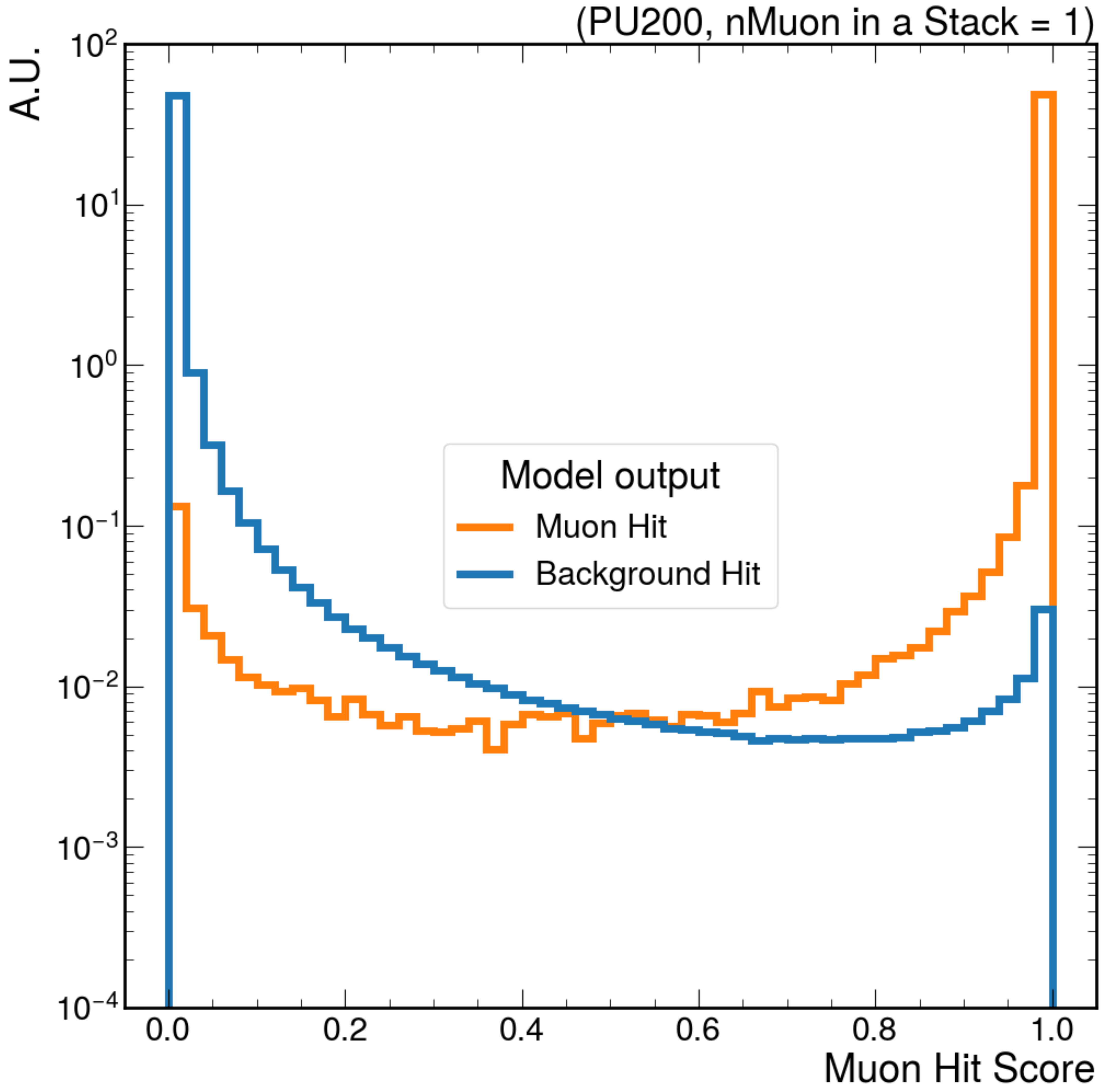


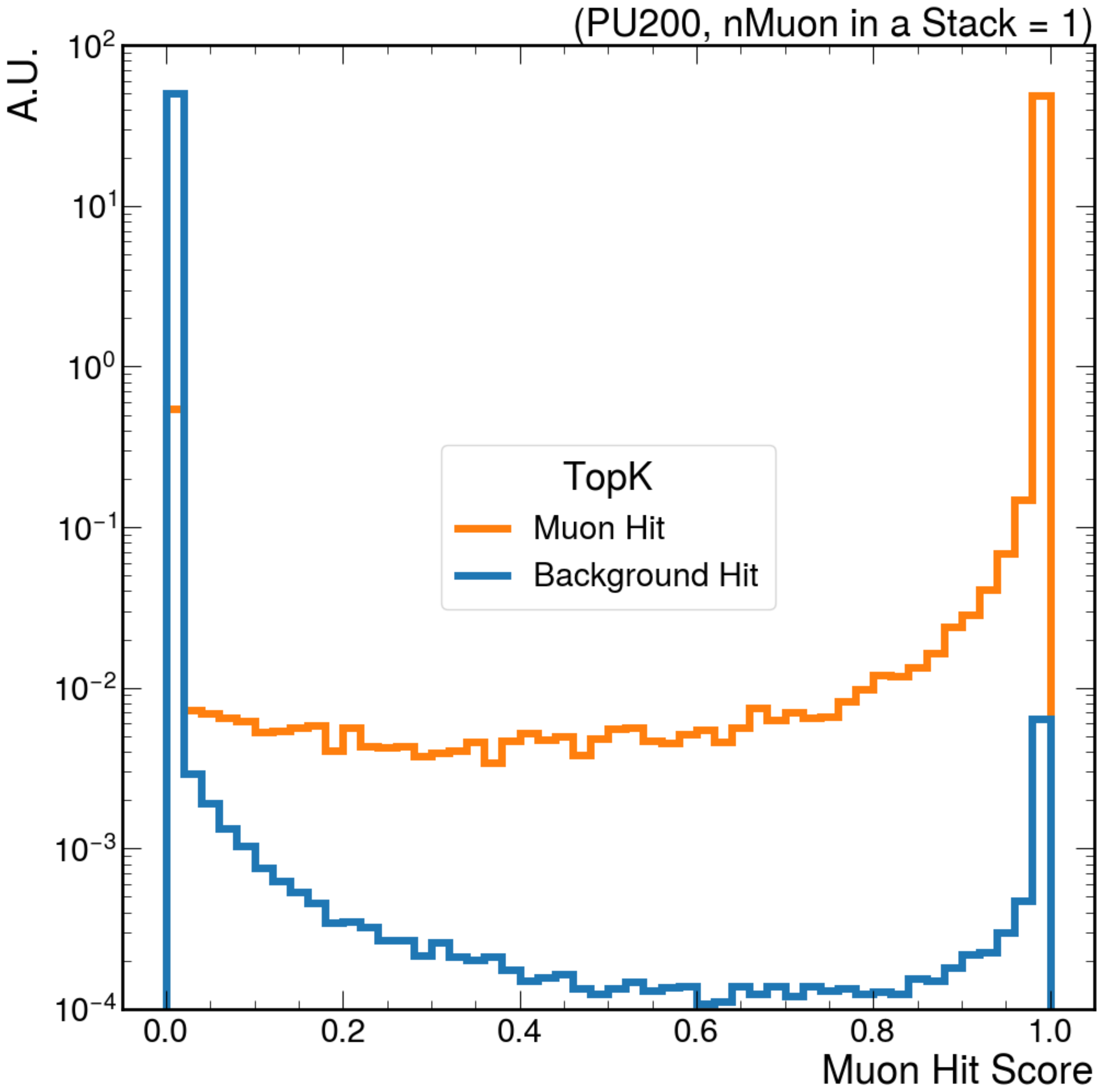




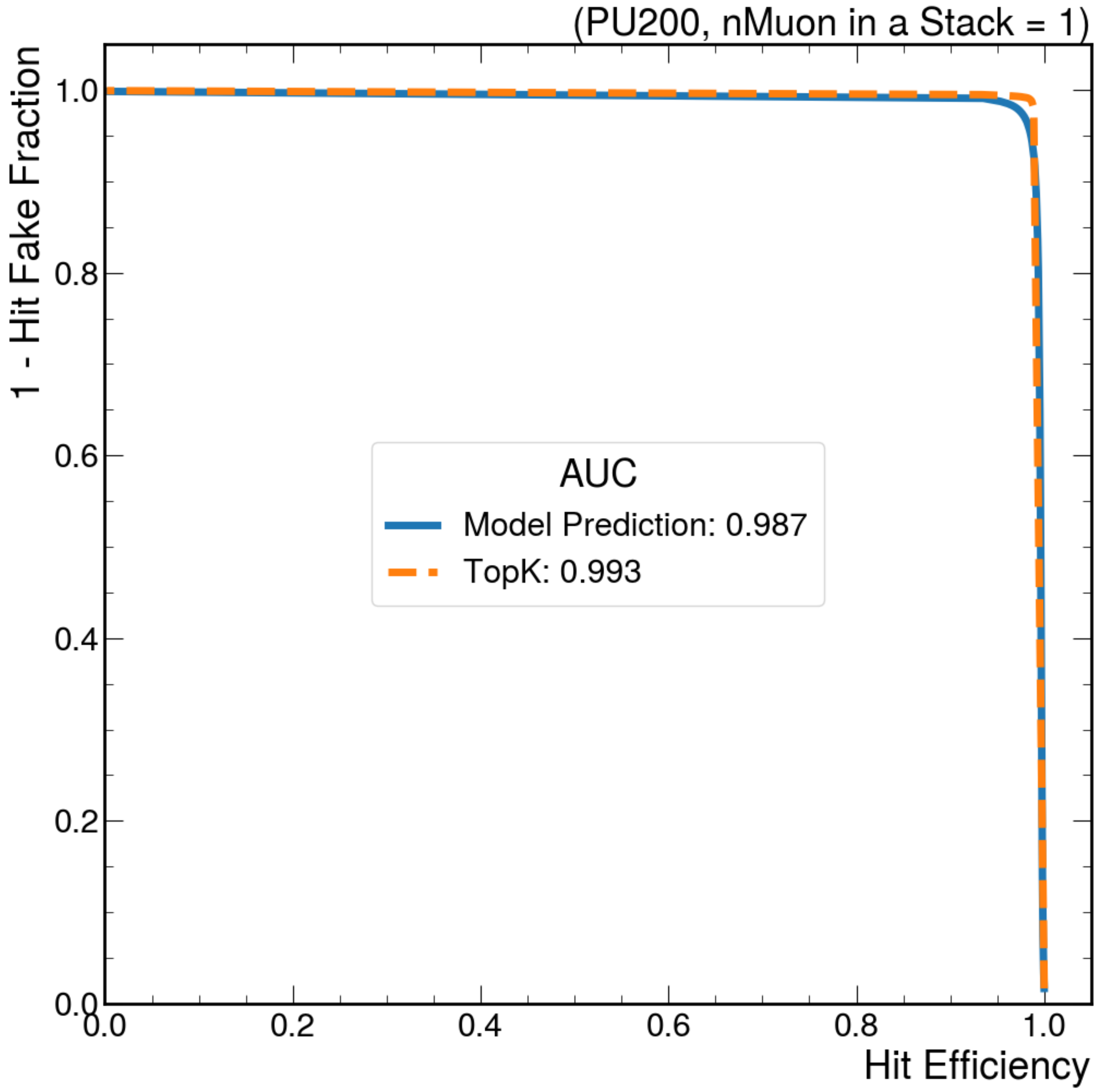


Model Response

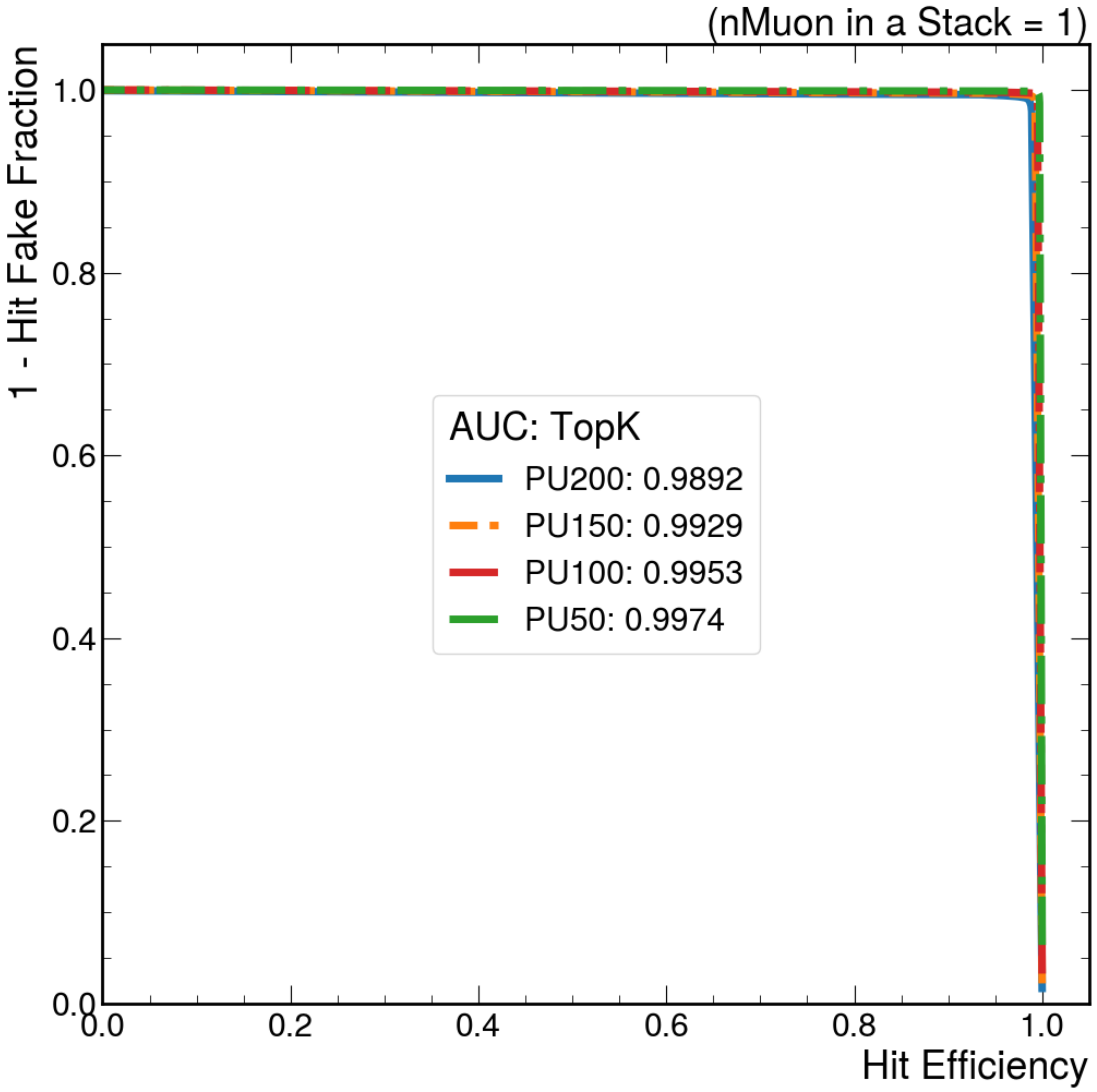




ROC Curve



(PU200, nMuon in a Stack = 1)
1 - Hit Fake Fraction
Hit Efficiency
AUC
Model Prediction: 0.987
TopK: 0.993

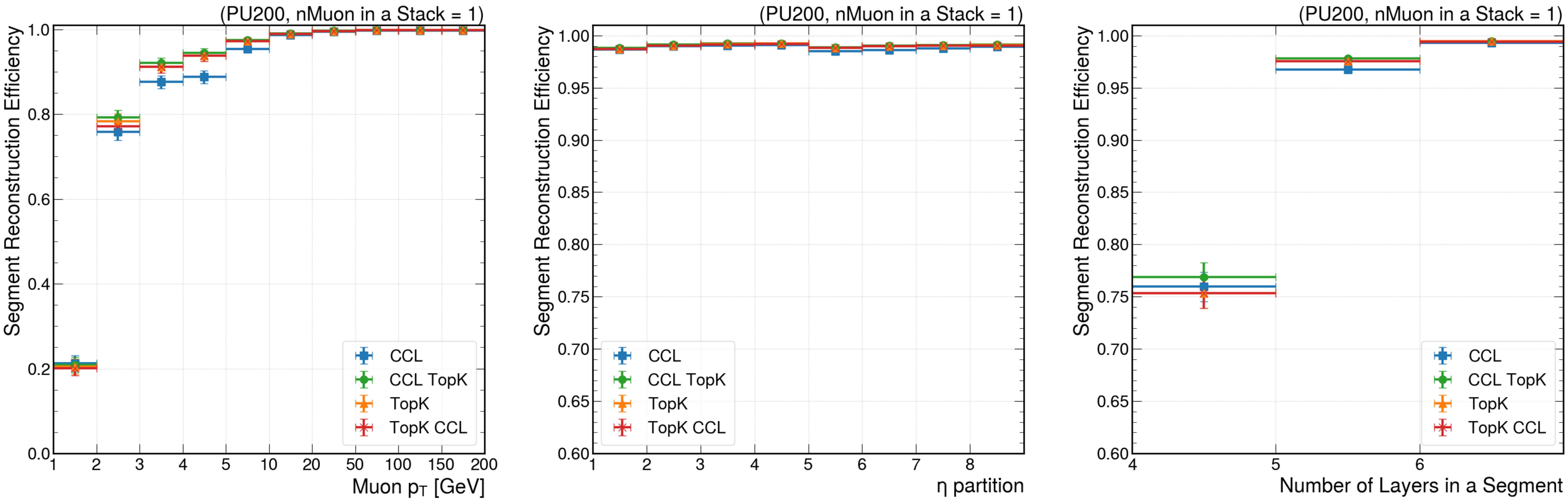


(nMuon in a Stack = 1)
1 - Hit Fake Fraction
Hit Efficiency
AUC: TopK
PU200: 0.9892
PU150: 0.9929
PU100: 0.9953
PU50: 0.9974

Segment Reconstruction Efficiency

	CCL	CCL TopK	TopK	TopK CCL
overall	0.9881	0.9909	0.9902	0.9902
pT > 5	0.9947	0.9968	0.9964	0.9964

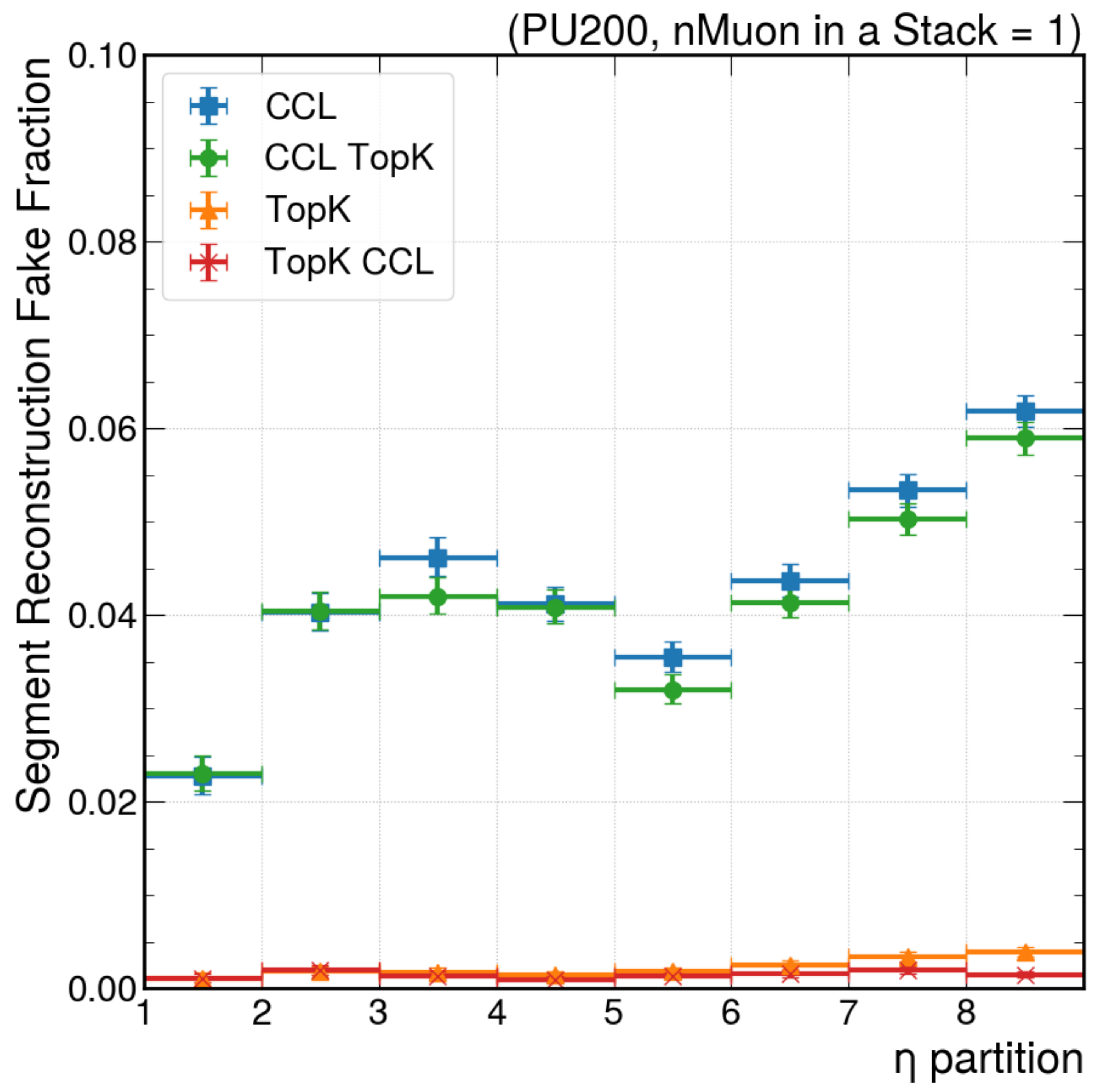
Definition : $\dfrac{N_{\text{correct}}}{N_{\text{muon}}}$

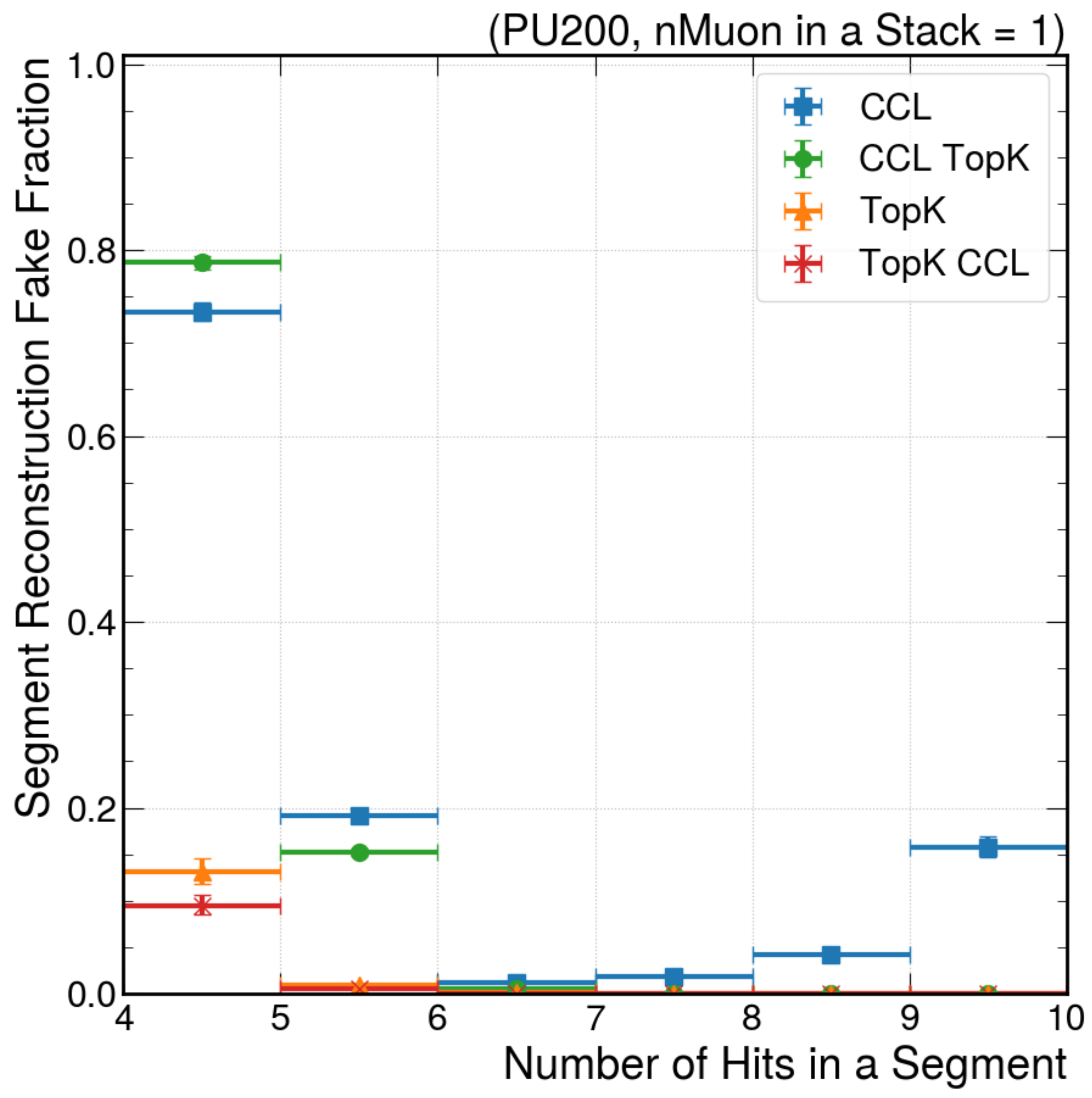


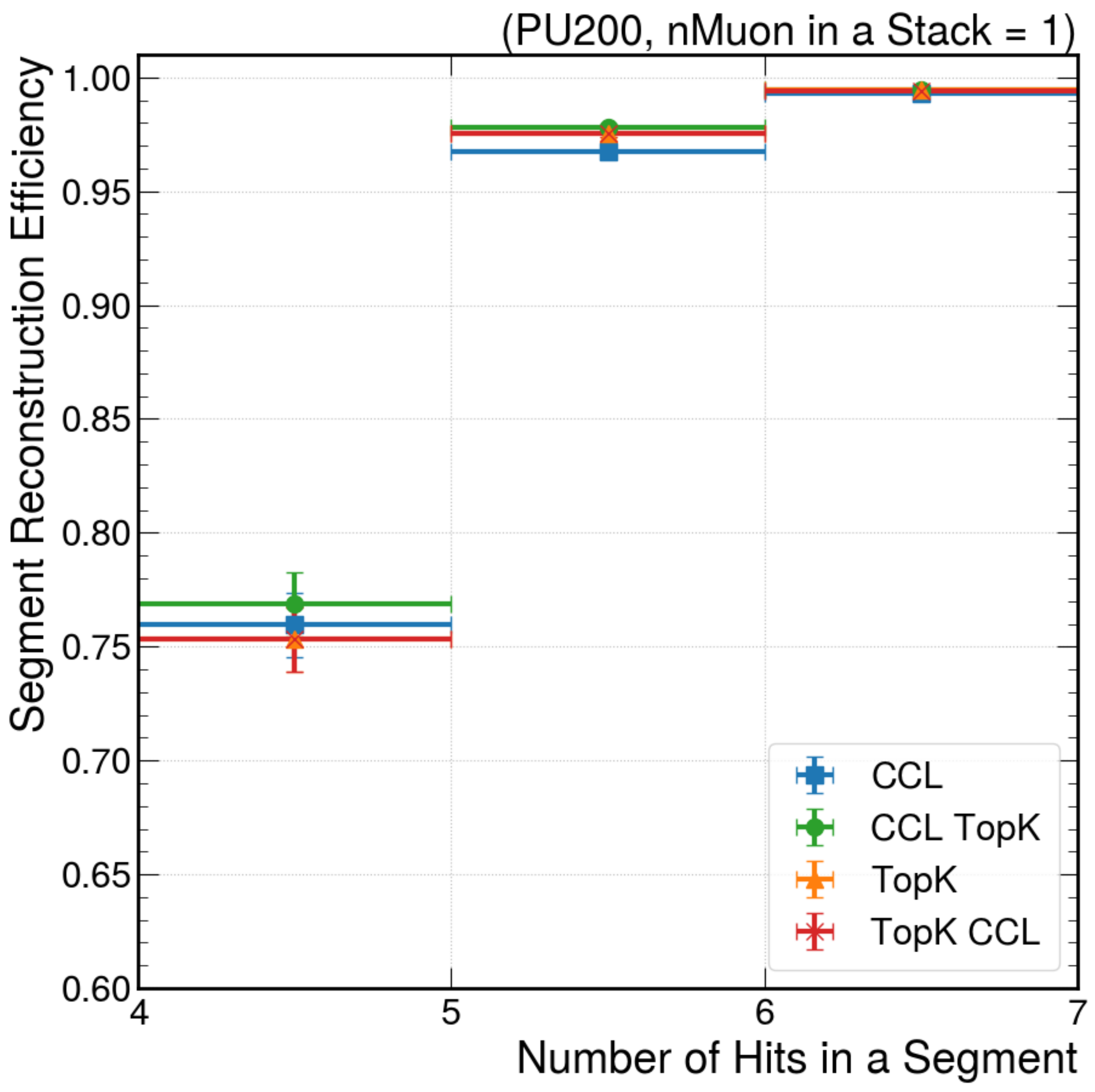
Segment Reconstruction Fake Fraction

	CCL	CCL TopK	TopK	TopK CCL
Fake Fraction (1 Muon stack)	0.0462	0.0435	0.0024	0.0015
# of rec. Segments (0 Muon stack / total: 100,000)	4668	4668	5587	4265

Definition : $\frac{N_{\text{fake}}}{N_{\text{rec. seg}}}$





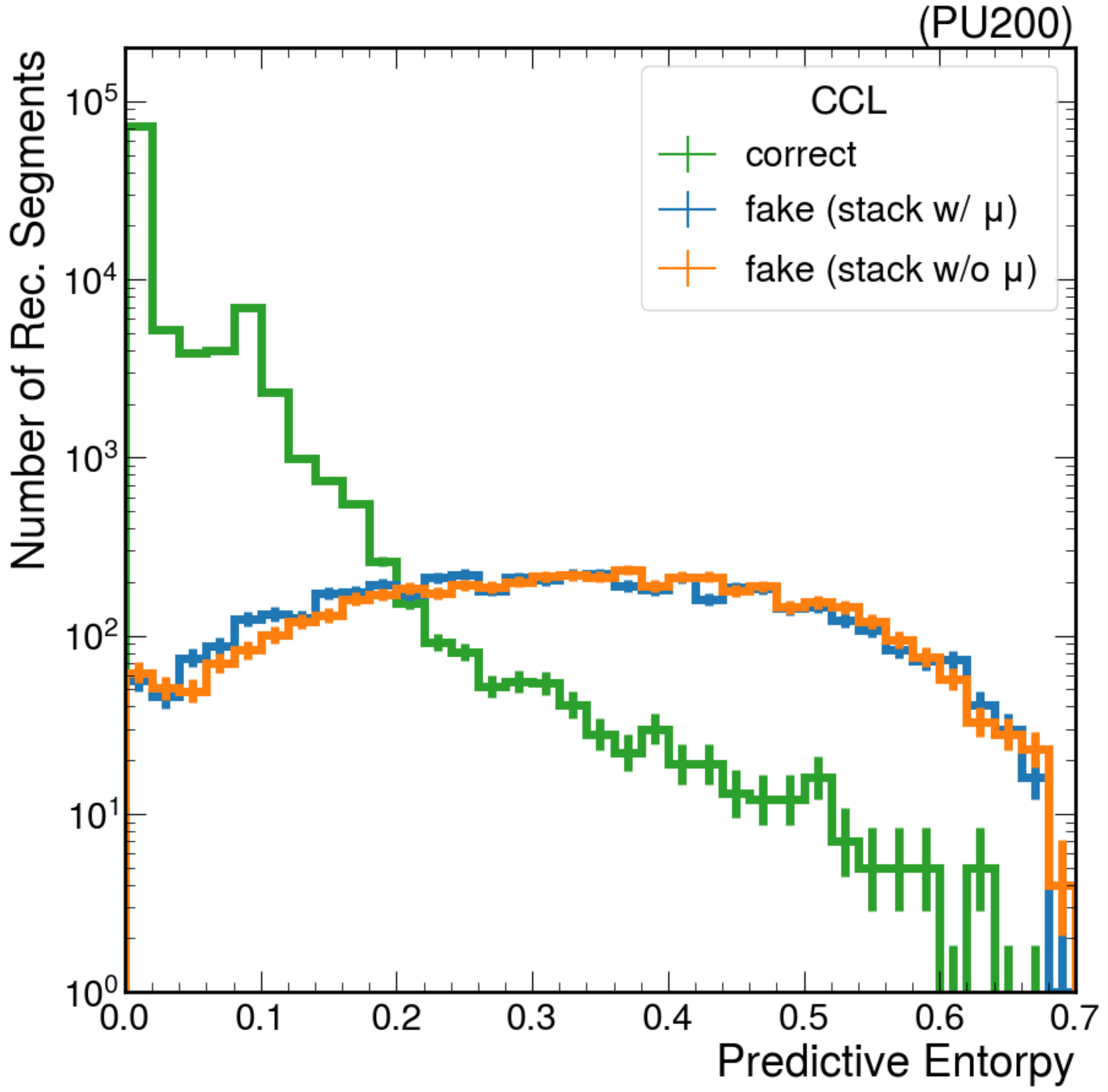


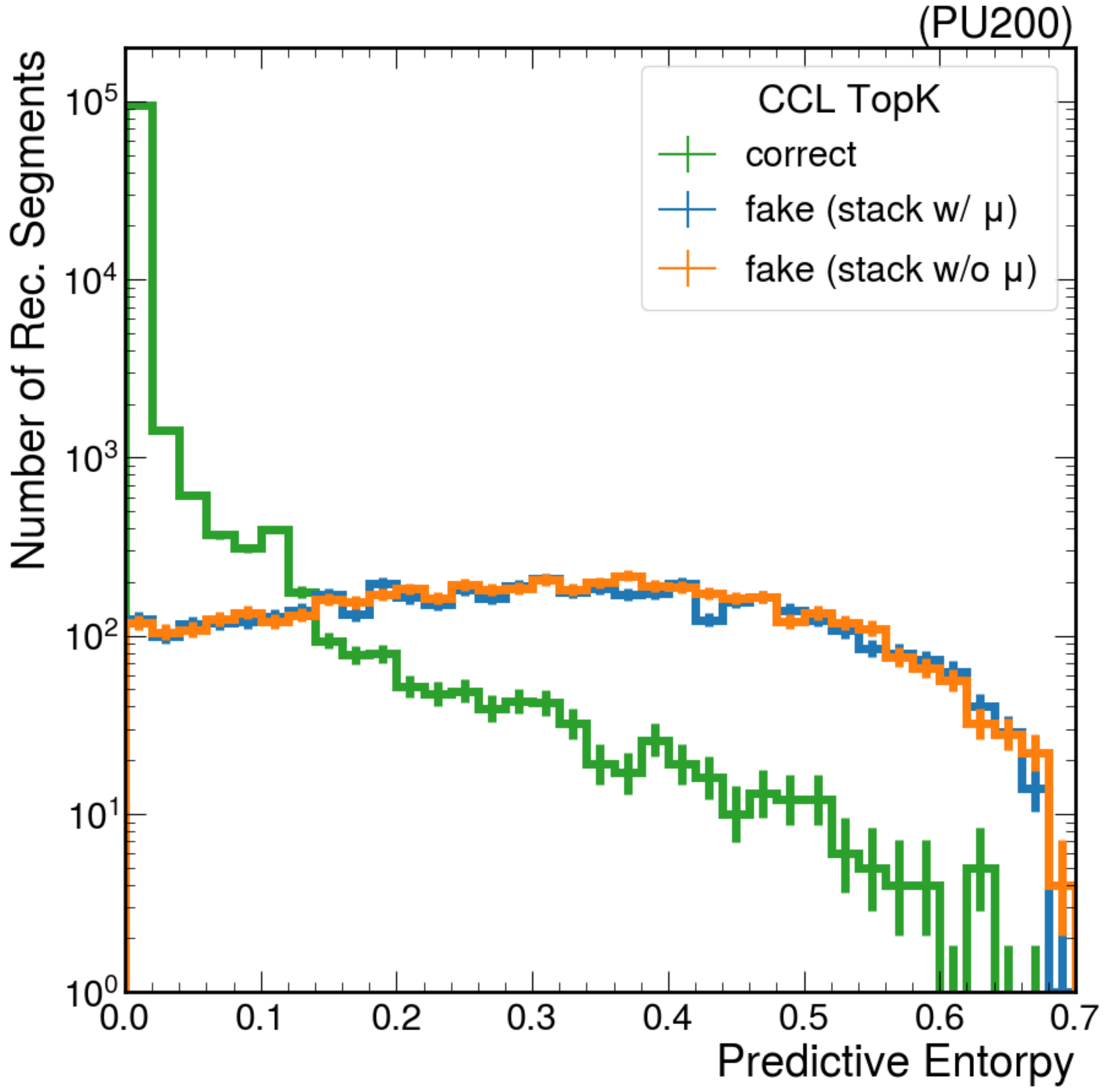
Predictive Entropy

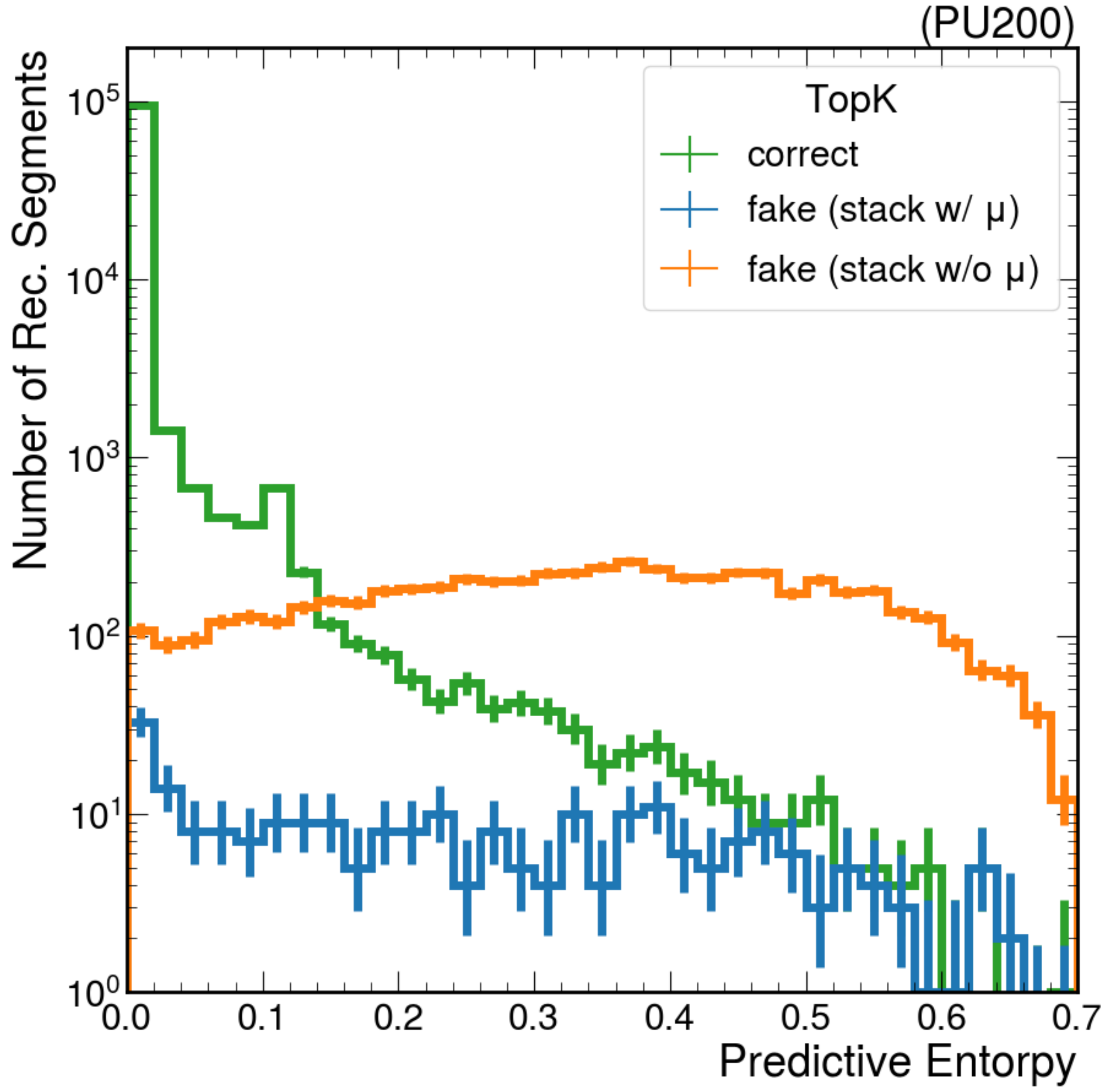
$$H[\hat{y}] = -\frac{1}{N} \sum_{i:\hat{y}_i > 0.5} [\hat{y}_i \log \hat{y}_i + (1 - \hat{y}_i) \log(1 - \hat{y}_i)]$$

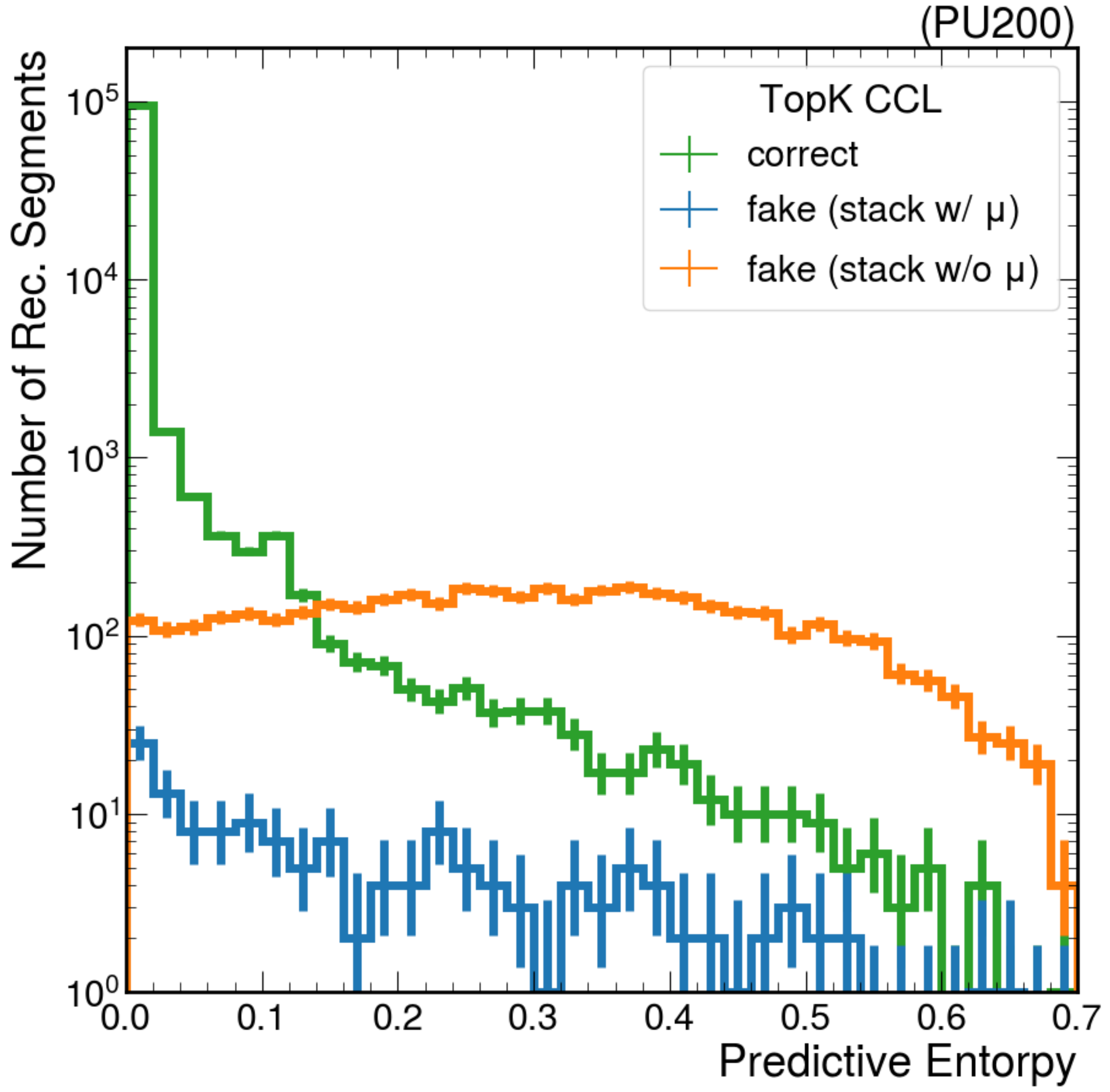
$\hat{y}_i$: Muon hit score of the i-th positive hit, constrained to $\hat{y}_i > 0.5$

N : Number of predictive positive hits (where $\hat{y}_i > 0.5$) in a stack









Conclusion

- **Reconstructed segments** in high-pileup ME0-like environments using a CNN based **hit-wise classification model**
- **Developed a post-processing pipeline** (layer-wise Top-K and CCL) to convert model predictions into physical segments
- **Achieved high performance**, characterized by **high efficiency** and a **low fake fraction**
- **Future Work:** Extend the framework to multi-muon environments by implementing layer-wise Top-2 filtering followed by CCL

	CCL	CCL TopK	TopK	TopK CCL
Efficiency (overall)	0.9881	0.9909	0.9902	0.9902
Efficiency (pT > 5)	0.9947	0.9968	0.9964	0.9964
Fake Fraction (1 Muon stack)	0.0462	0.0435	0.0024	0.0015
# of rec. Segments (0 Muon stack / total: 100,000)	4668	4668	5587	4265

BACKUP

Predictive Entropy: correct only

$$H[\hat{y}] = -\frac{1}{N} \sum_{i:\hat{y}_i > 0.5} [\hat{y}_i \log \hat{y}_i + (1 - \hat{y}_i)\log(1 - \hat{y}_i)]$$

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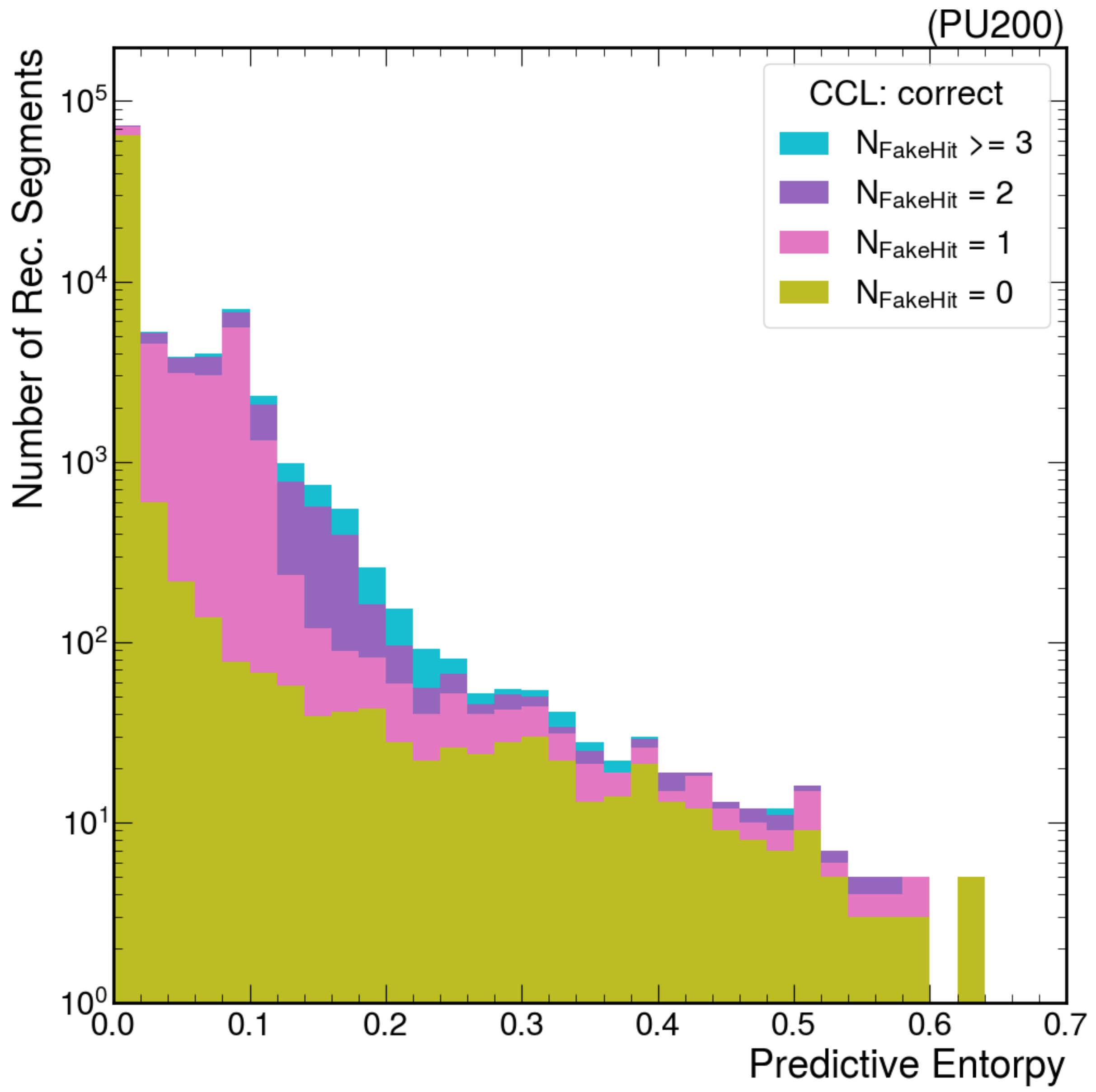
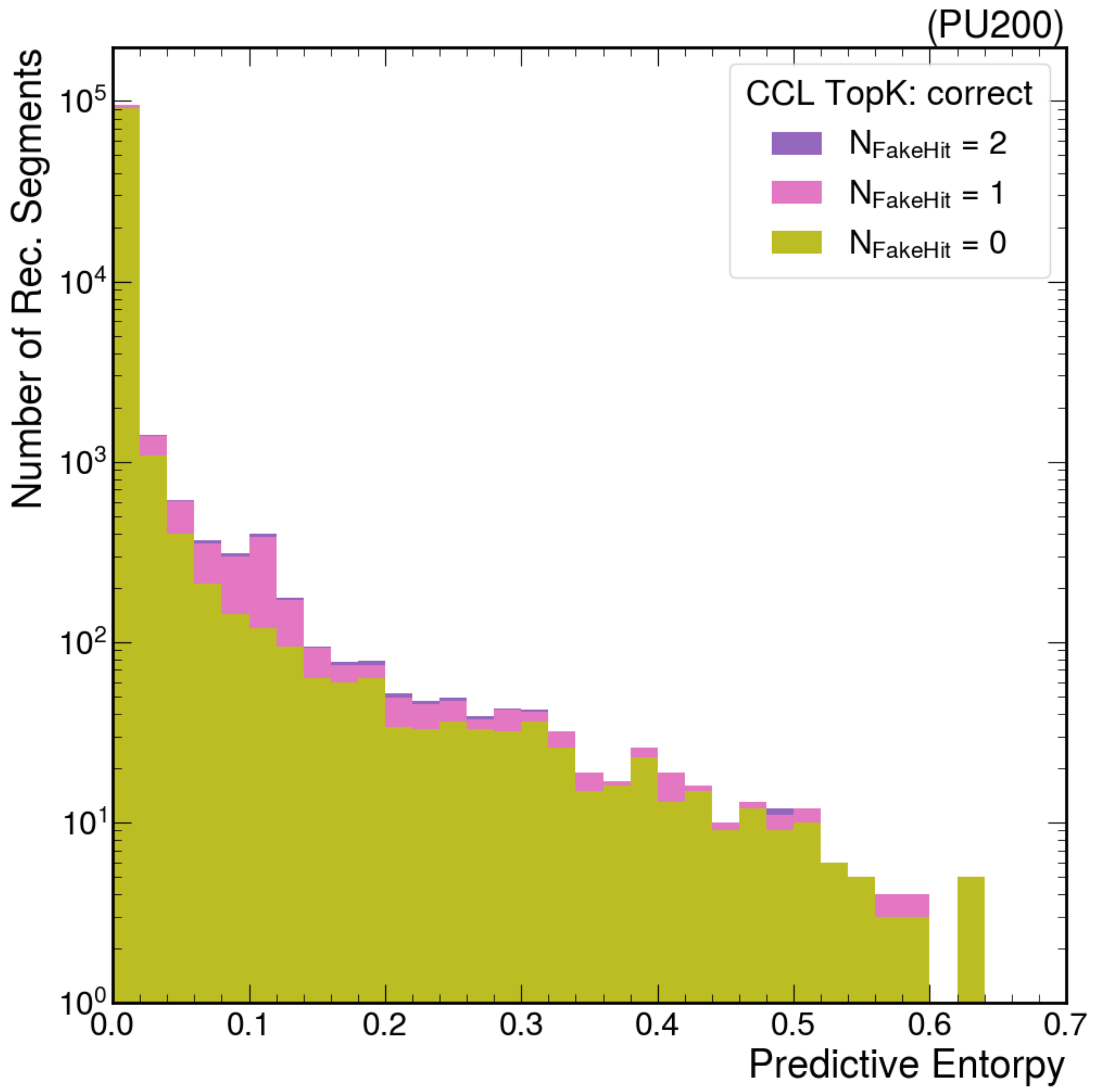
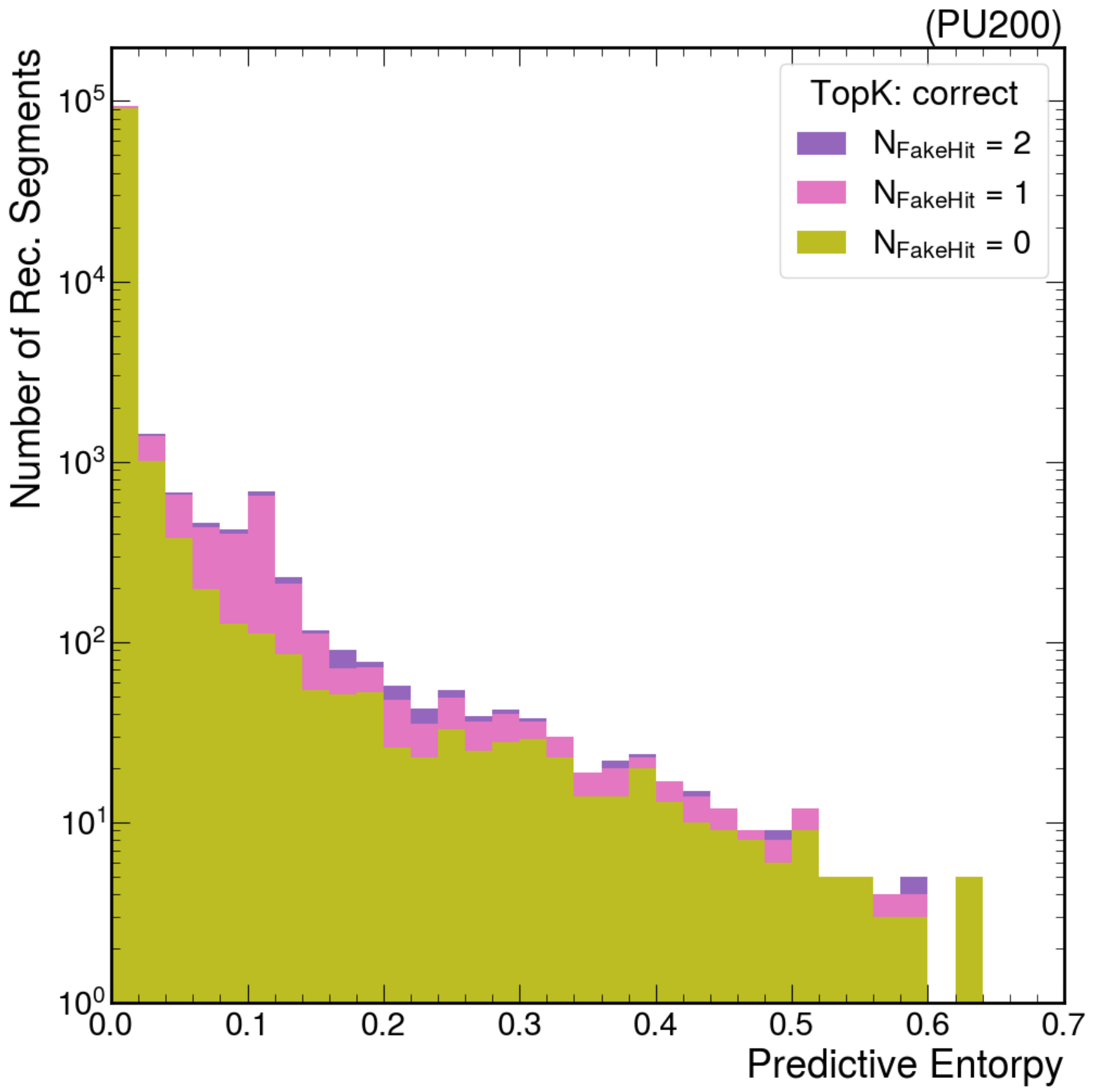
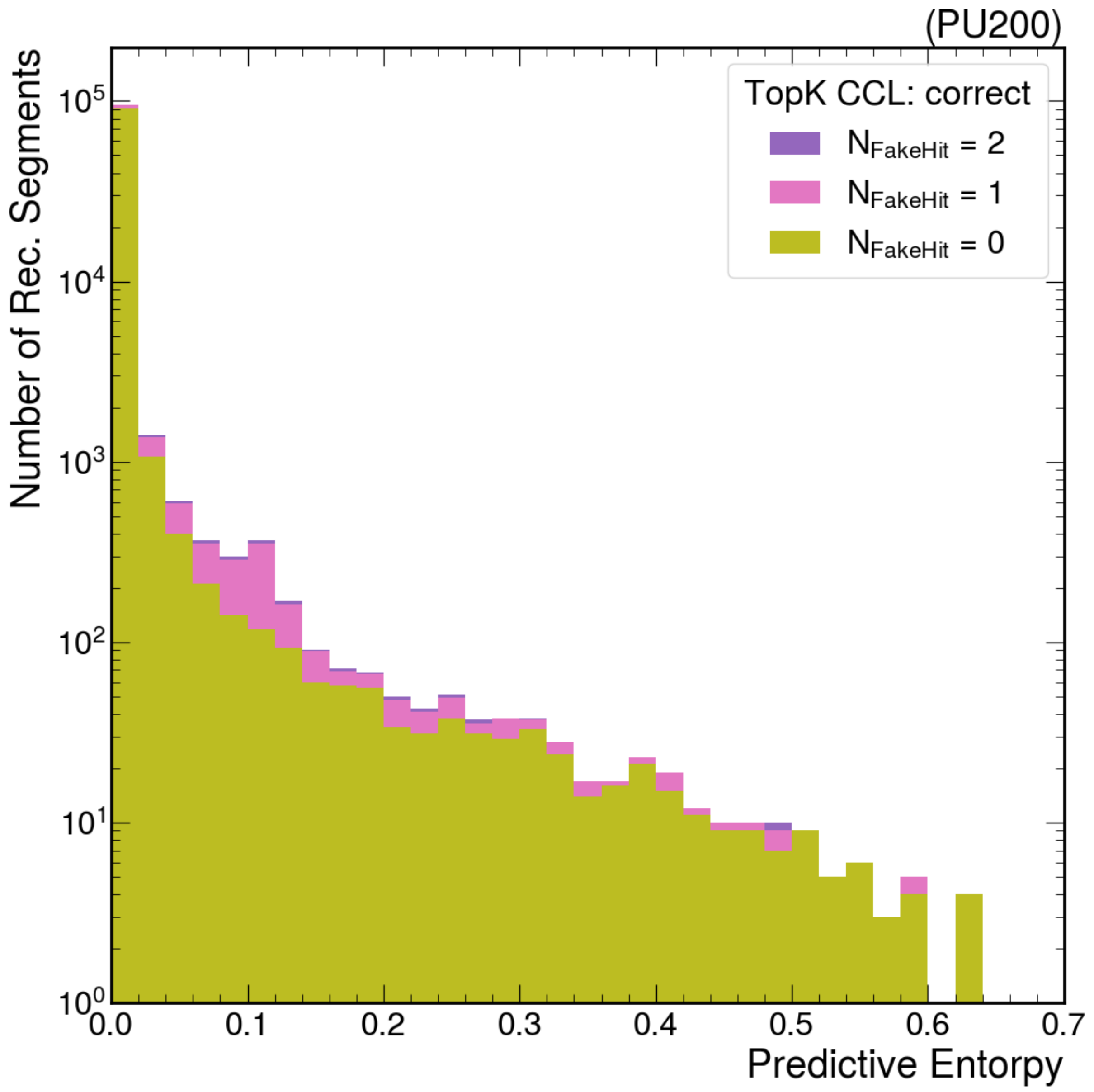






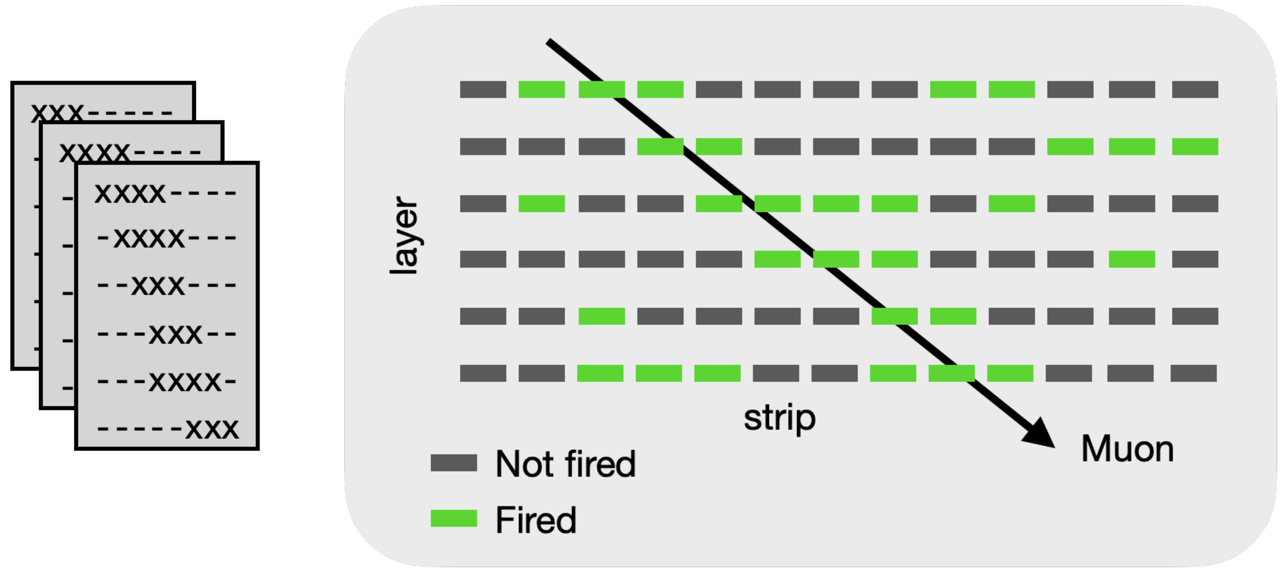


Muon Segment Reconstruction

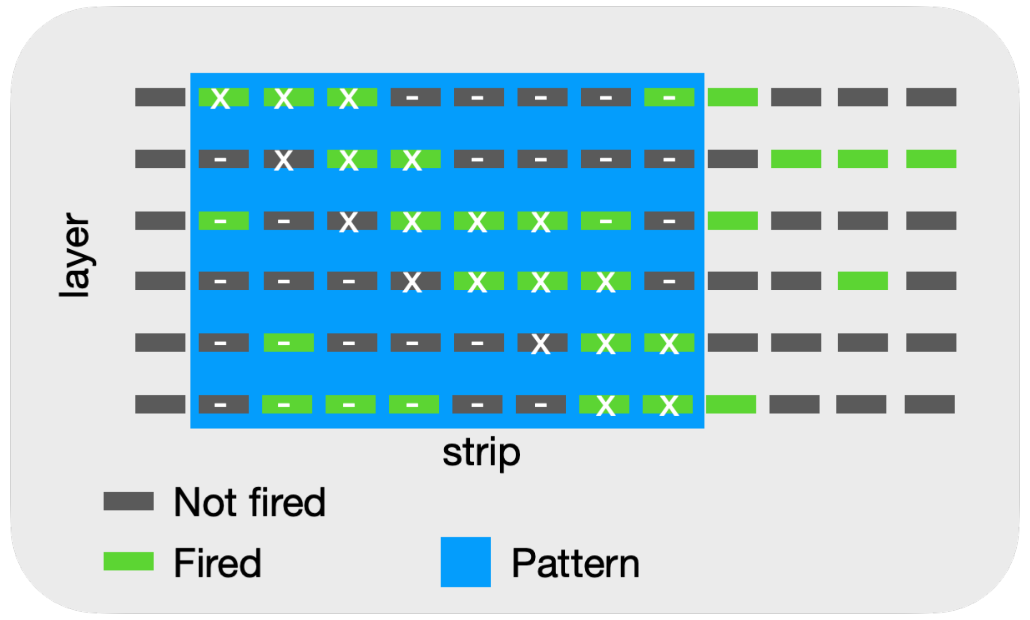
- Muons crossing multi-layer detector, leaves tracks called segments
- Segments are used in seed/track reconstruction
- Two main methods:
  - pattern matching (hardware based L1 trigger)
  - Road Usage algorithm (offline reconstruction)
- Road Usage Algorithm (RU)
  - Translated CSC RU segment builder algorithm for ME0
  - Selects a seed pair and performs linear fitting to choose the segment with the lowest χ^2 error

Pattern Matching

1. Scan with predefined patterns

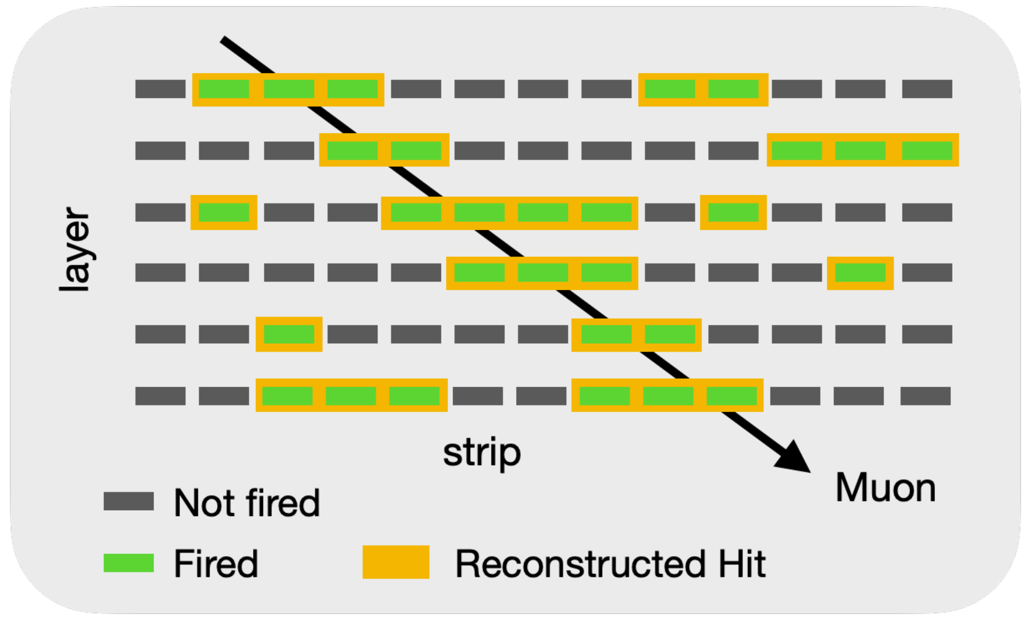


2. Select segments that match the pattern

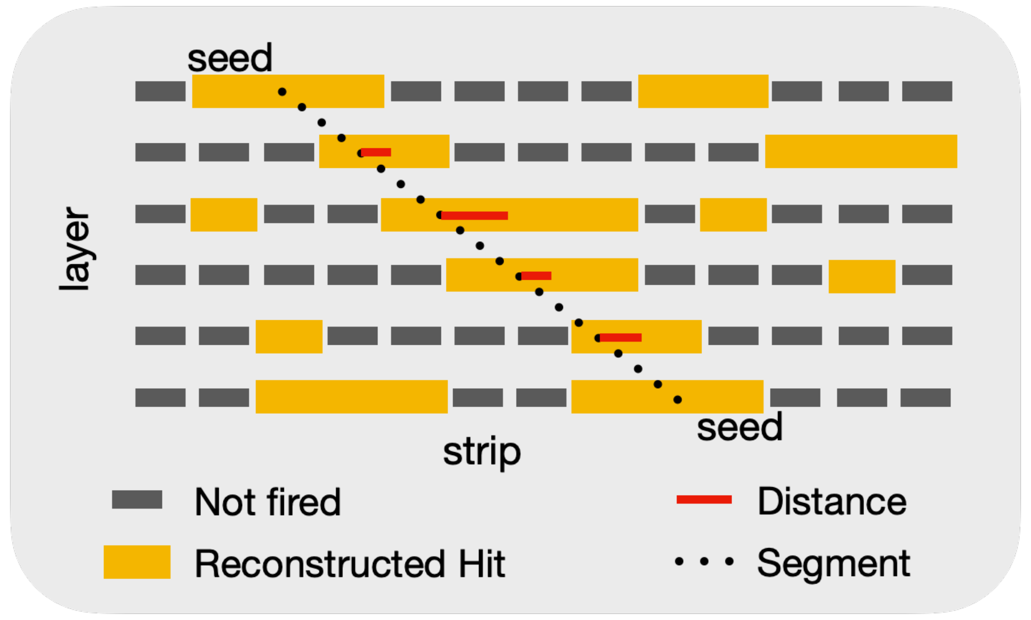


Road Usage Algorithm

1. Hit reconstruction



2. Linear fitting after seed pair selection



3. Select segment with lowest χ^2 error

Number of Hits in a Reconstructed Segment