

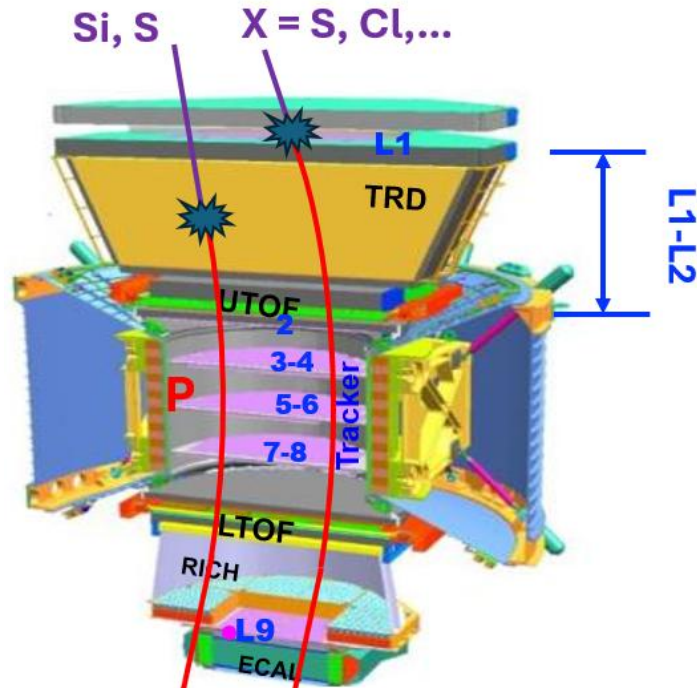
# Updates on MDA (Multimodal Domain-Adversarial) Method for P Signal-Background Identification

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# Machine learning for P background study



**Motivation:**

**Reduce P background after P event selection.**

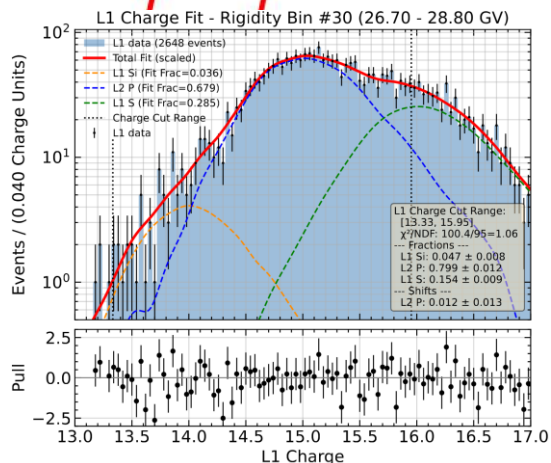
**Method:**

- Using low level Tracker and UTOF reconstructed variables
- **Apply a MDA (multimodal domain adversarial) network to achieve good performance on both MC and Data.** (slides #4)
  - Trained from MC sample
  - Use domain-adversarial training to learn domain-invariant features, to achieve model generalization across MC and Data

**Training samples:**

Si, P, and S event selection

- Signal: MC Si, P, S (MC truth)
- Background: MC Si and S (for Si), Si and S (for P), P and Cl (for S)
- Data



# Input variables for Machine Learning model

- Try to use low-level reconstructed variables whenever possible,
- Use variables that have similar distributions in both MC and Data.

## Tracker:

- **Tracker (main and second track)**
  - **L2** to L8 charge, (Second track Charge to be added in future)
    - Hit Pos for L1 to L8, X- and Y- side
- **Cluster**
  - Number of clusters, for L1-L8, X- and Y- side
- **Rigidity:** Inner+L1 and Inner

## TOF (Standalone)

- Beta;
- UTOF charge;
- TOF charge on L1,L2
- Number of On-Time TOF clusters for L1,L2
- Total number of clusters used for charge estimation

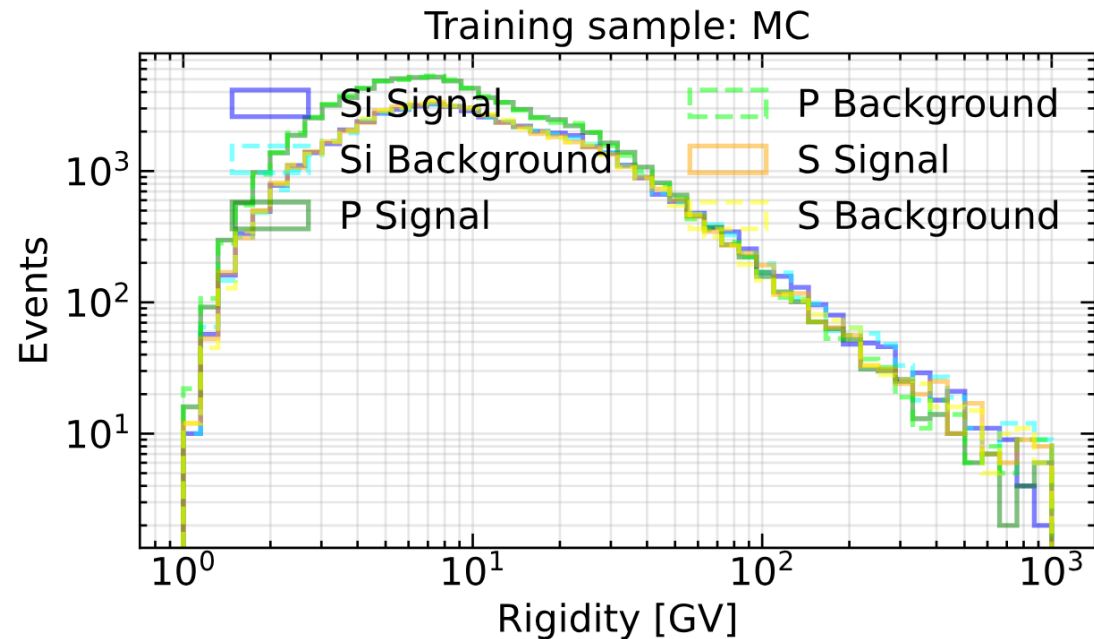
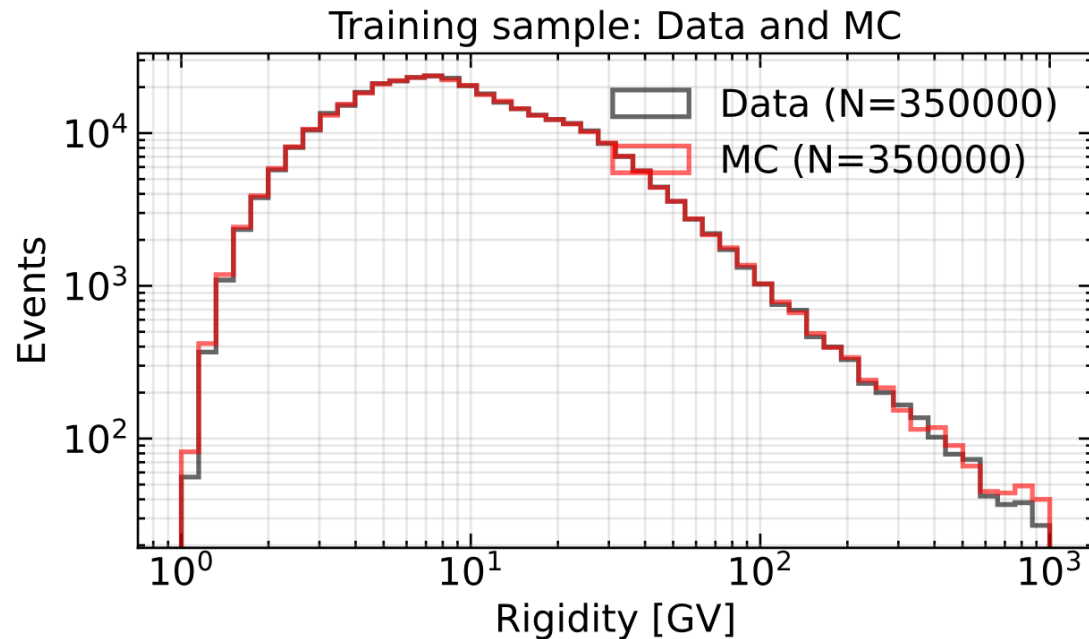
## Note:

- MC and Data samples: similar Rigidity distributions.
- Input variables are normalized according to mean and std.

# Training samples

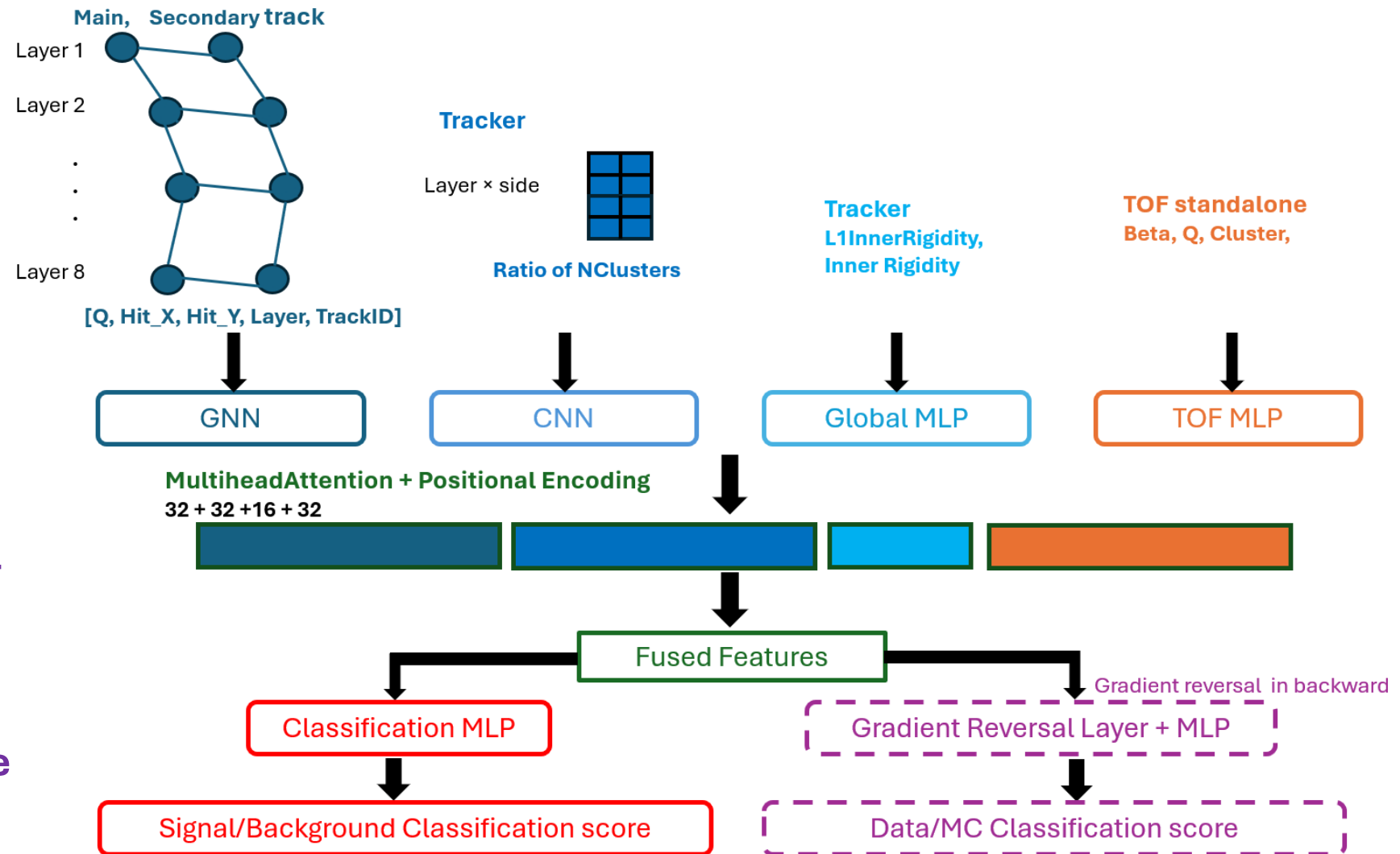
**Data:** 150k events passing Si, P, S event selection

- **Signal:** 75k MC Si, P, S (MC truth) events passing Si, P, S event selection respectively.
- **Background:**
  - 25k Si background events: 81% P and 19% S
  - 25k P background events: 2.2% Si and 97.8% S
  - 25k S background events: 2.7% P and 97.3% Cl



# MDA (multimodal domain-adversarial) Network

1. 4 sub-models to extract input features.
2. Features fused with attention mechanism.
3. Signal/Background classification
4. Domain-Adversarial Neural Network is added to learn features that are similar between MC and Data, ensuring good performance for both MC and Data.



# MDA (multimodal domain-adversarial) Network

## (1) 4 sub-models to extract features.

Each sub-model is matched to the structure of its input:

### 1. Tracker GNN

- Input: hit position and Charge on main and second track for each layer and side,
- A graph naturally captures layer-to-layer and cross-track relations.

### 2. Tracker CNN

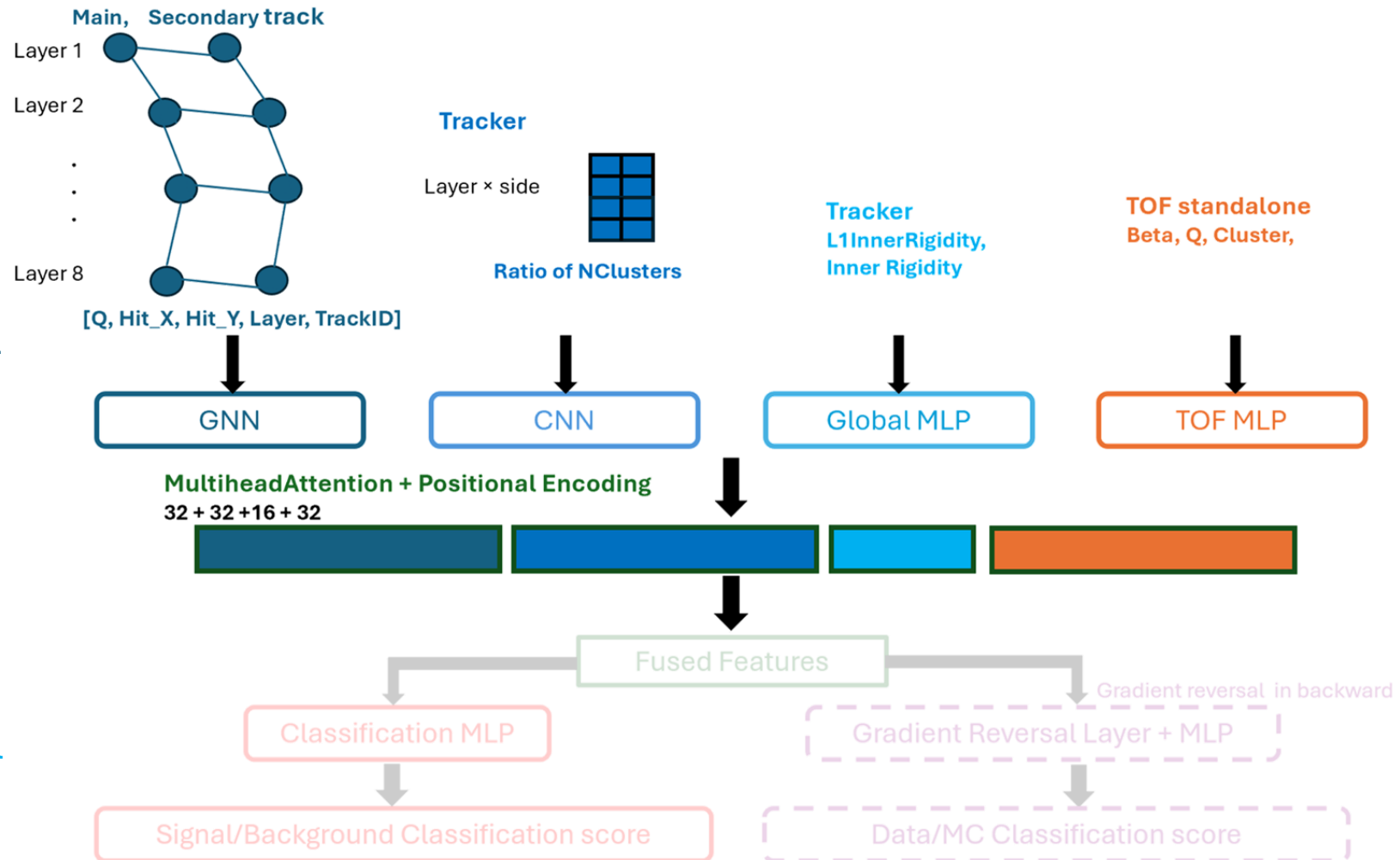
- Input: number of cluster info on each layer and side
- The data looks like an image data

### 3. Global MLP: Rigidity

- event-level Rigidity (global scalar values) are best handled by a small feed-forward network

### 4. TOF MLP

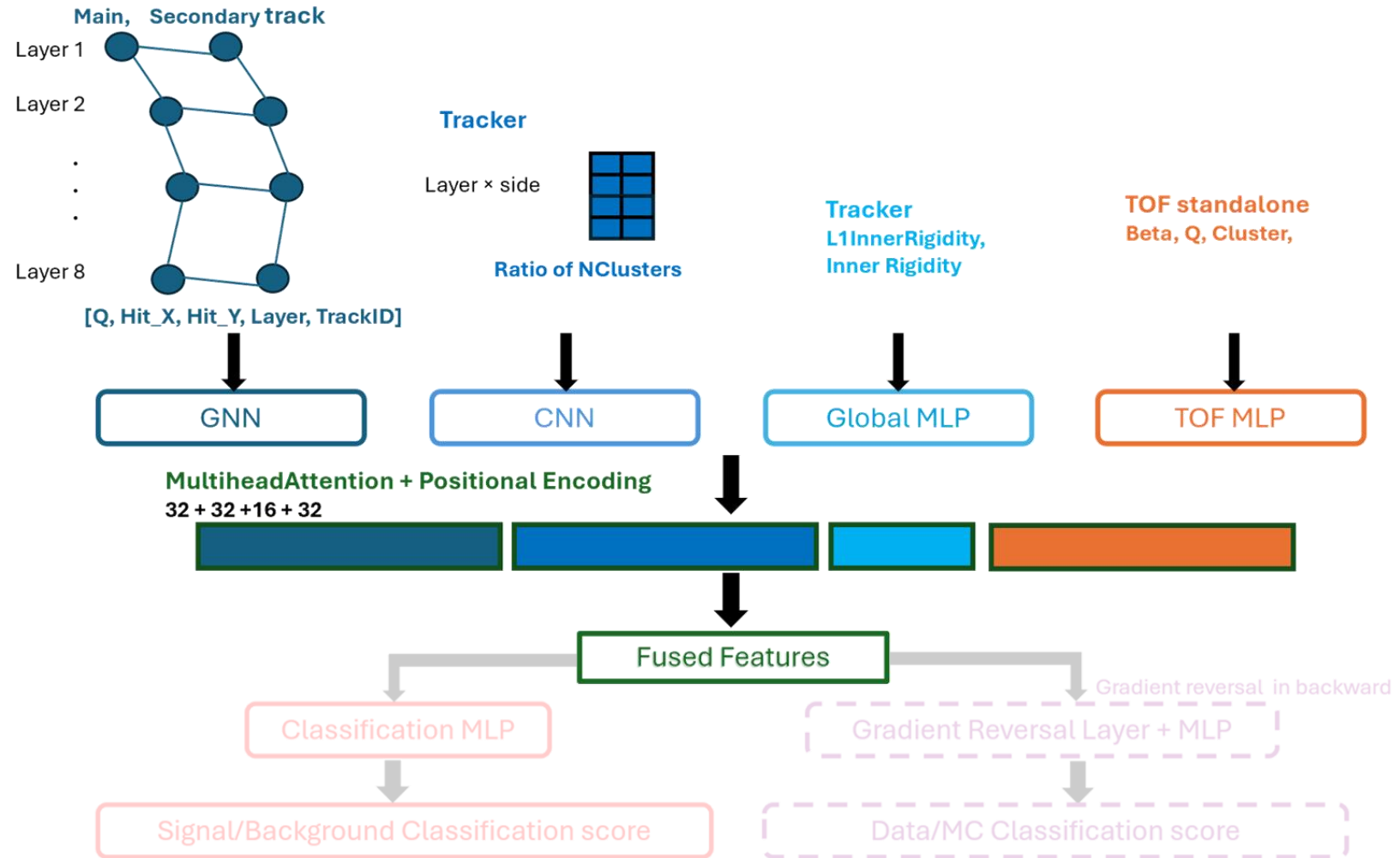
- Tabular numbers (beta, charge, N cluster). MLPs are the standard choice.



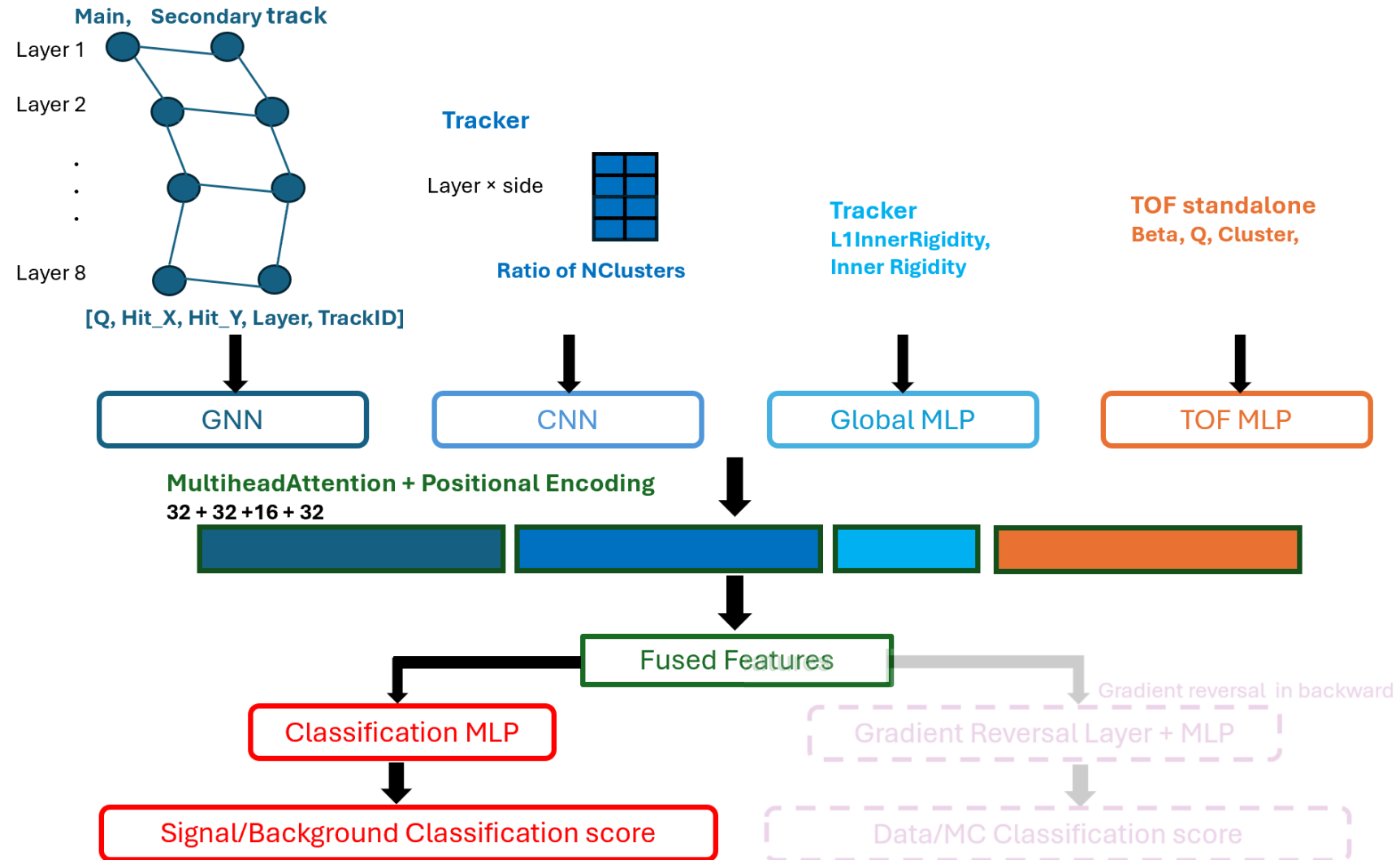
# MDA (multimodal domain-adversarial) Network

## (2) Features from sub-models fused with attention mechanism

- **Mechanism:** multi-head self-attention + positional encoding over the four branch outputs.
- **Effect:** for each event, the model learns how much to rely on each sub-model.
- **Outcome:** the fused feature that uses the most helpful features for each event.



# MDA (multimodal domain-adversarial) Network



## (3) Signal/Background Classifier:

The fused information is fed to a Signal/Background Classifier to distinguish between signal and background events for **MC sample**.



# MDA (multimodal domain-adversarial) Network

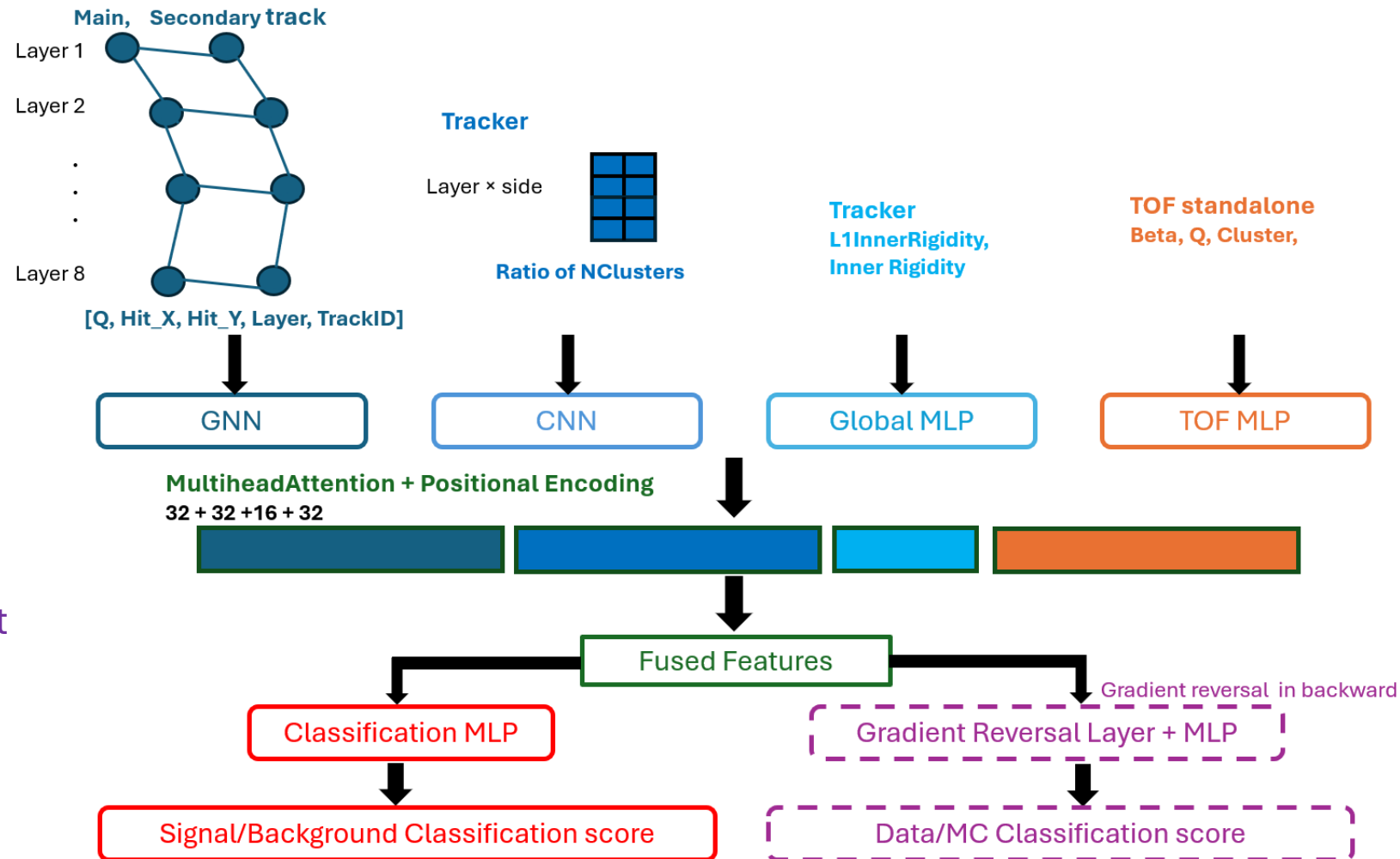
## (4) Adversarial training to extract features that minimize the ability for Data / MC classification

### 1. Method\*:

- Data / MC Classifier: to distinguish MC from Data.
- Adversarial Feedback: The model gets **penalized when data/MC classifier succeeds**.

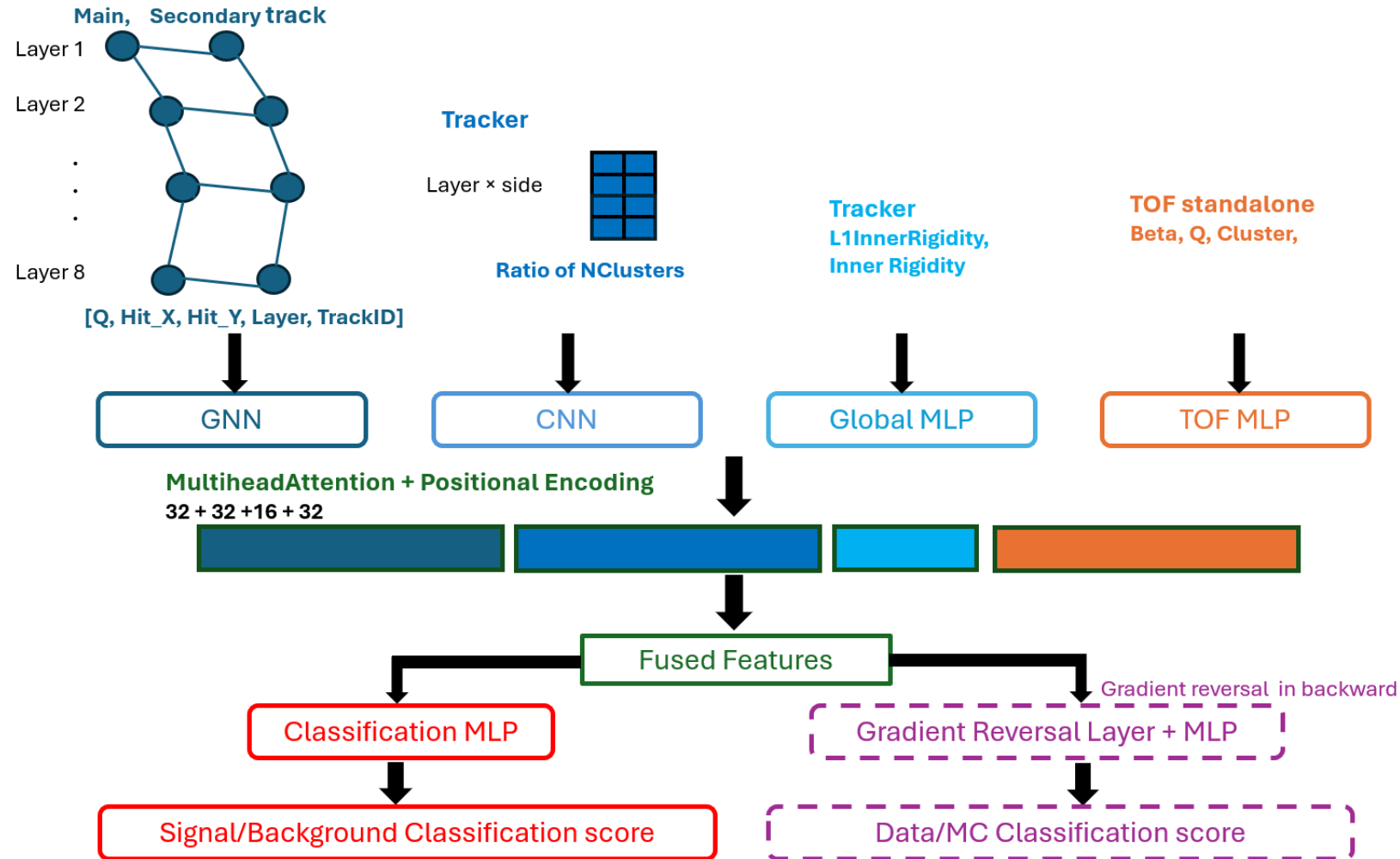
### 2. Outcome:

- The model is forced to focus on physics-relevant features that exist in both MC and Data.
- As a result, the model extracts features that are as similar as possible between MC and data.



\* Domain-Adversarial Training of Neural Networks, [arXiv:1505.07818](https://arxiv.org/abs/1505.07818)

# MDA (multimodal domain-adversarial) Network



## Final Objective:

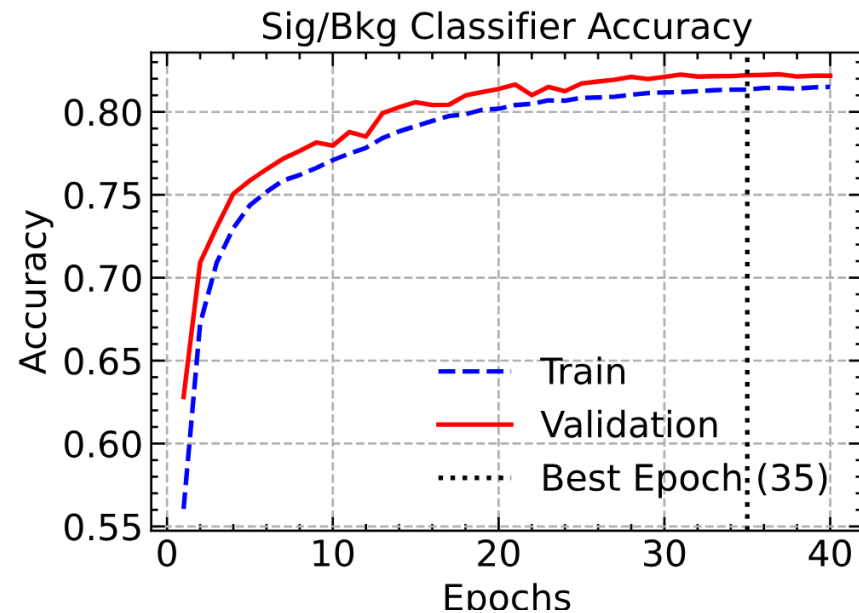
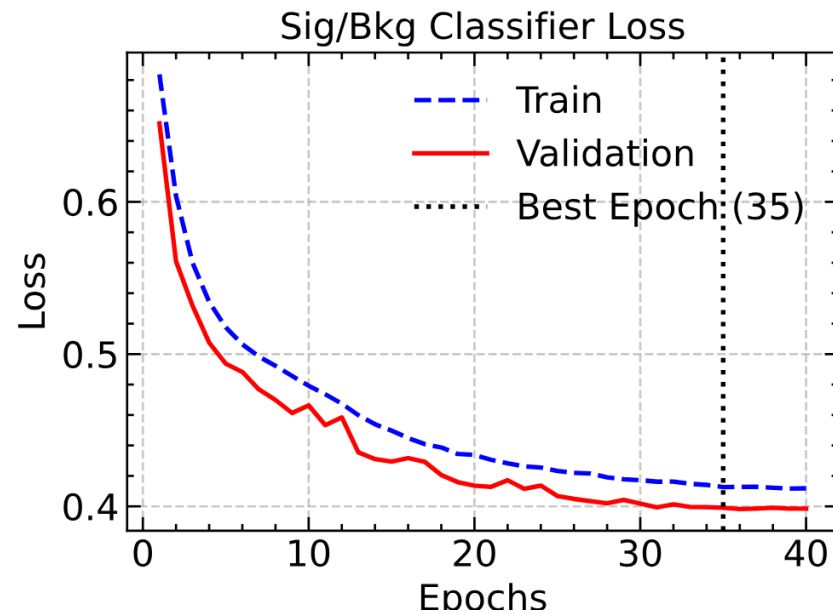
1. **Data / MC Classifier** performs at chance level (overall classification score  $\sim 50\%$ ), indicating the extracted features make MC and Data look indistinguishable.
2. **Signal/Background Classifier** bases its decision on physics-relevant features, not on differences between MC and data.

# Model training and validation

Training sample (Si, P, S event selection):

- **MC-Signal: 175k Si, P, S MC**
- **MC-Background: 175k Si, P, S, Cl MC** (to be tuned for optimization)
- **Data: 100K Si, 150K P, 100K S events**

**87.5k MC events with the same species combination for validation**

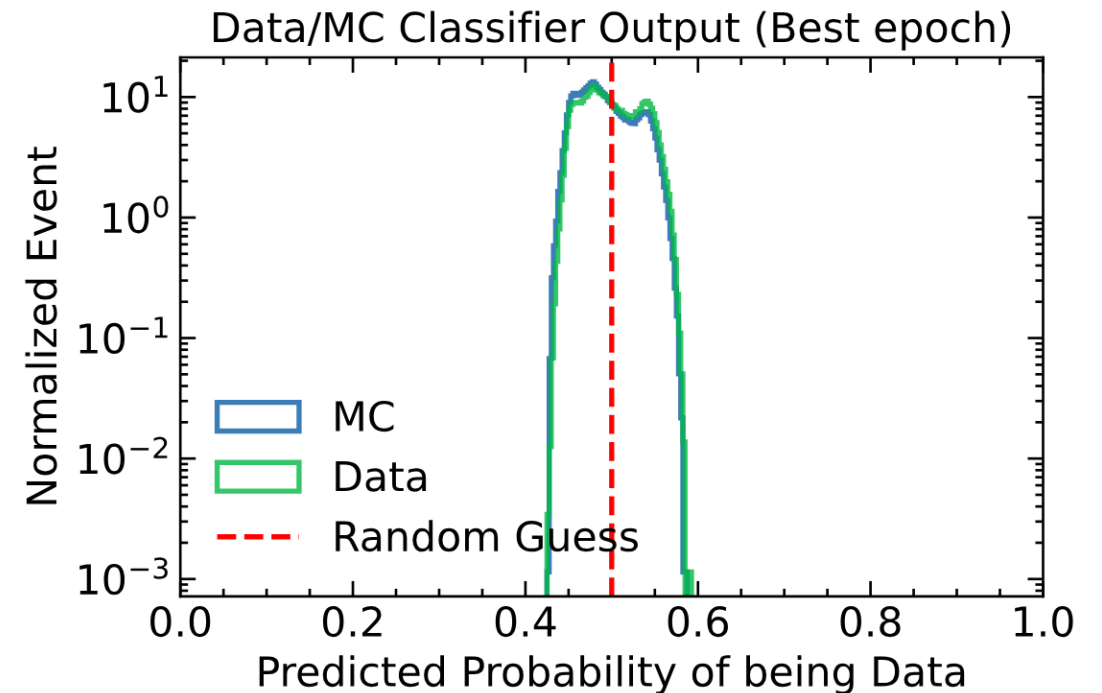
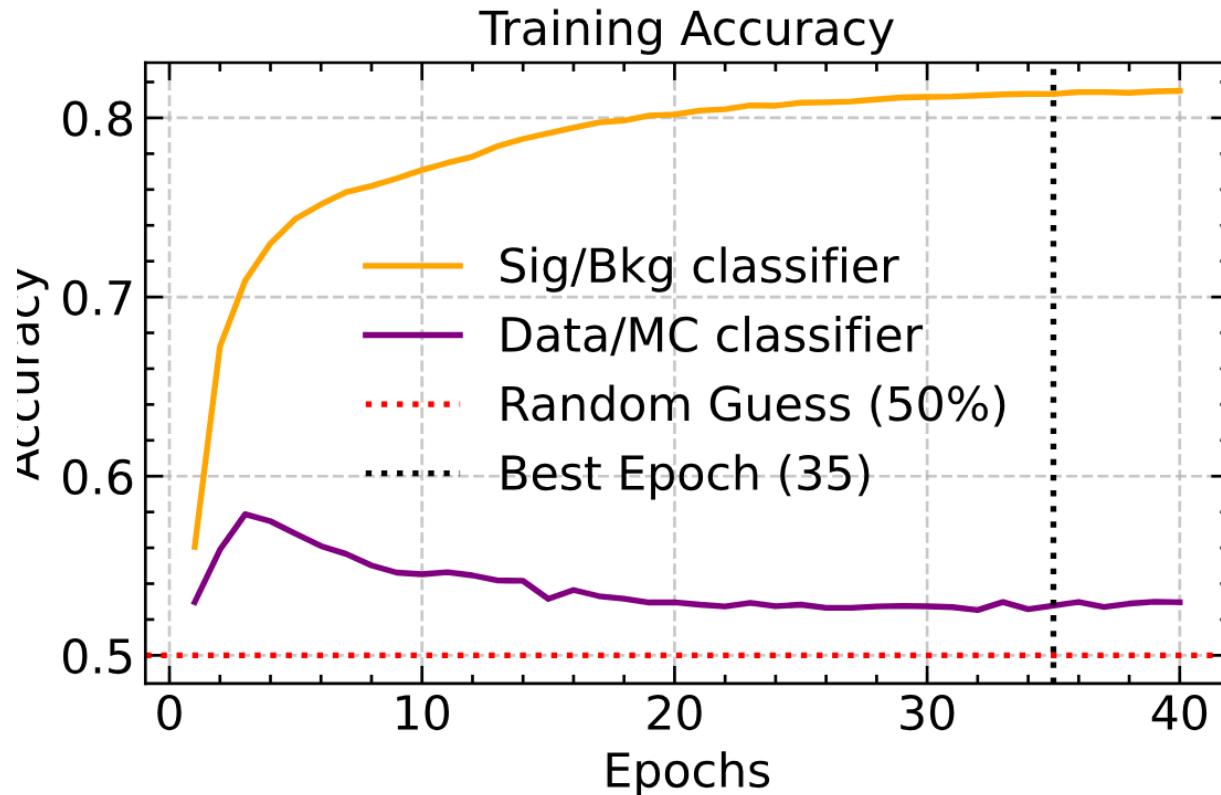


**To do: Model tuning for optimization**

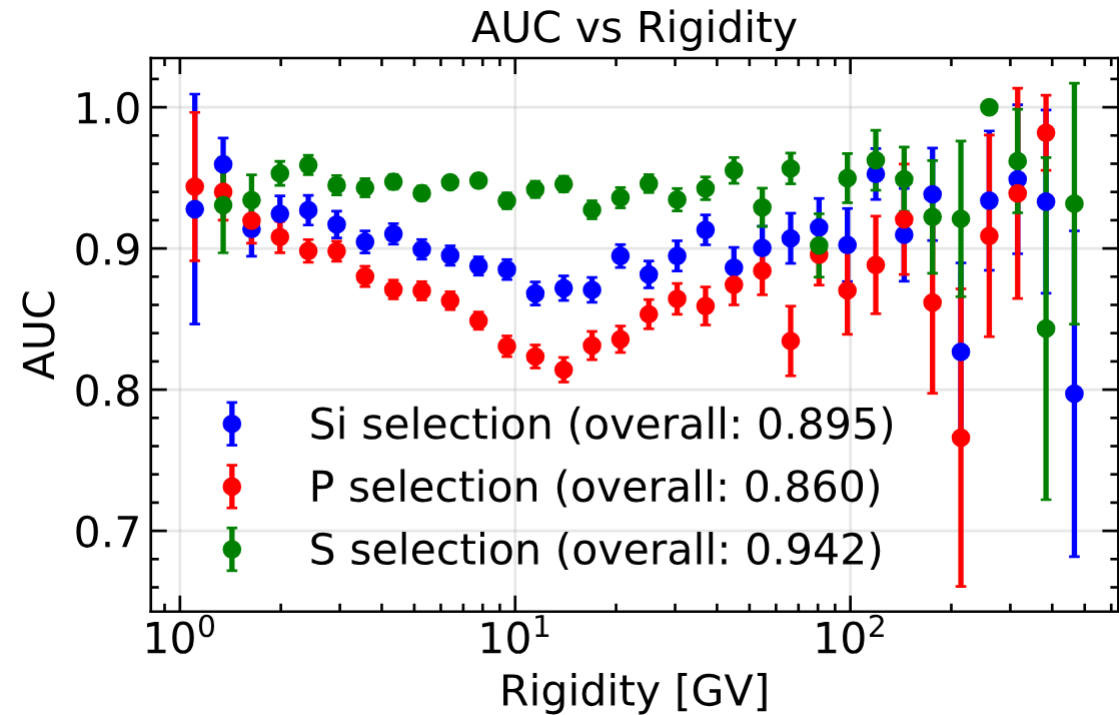
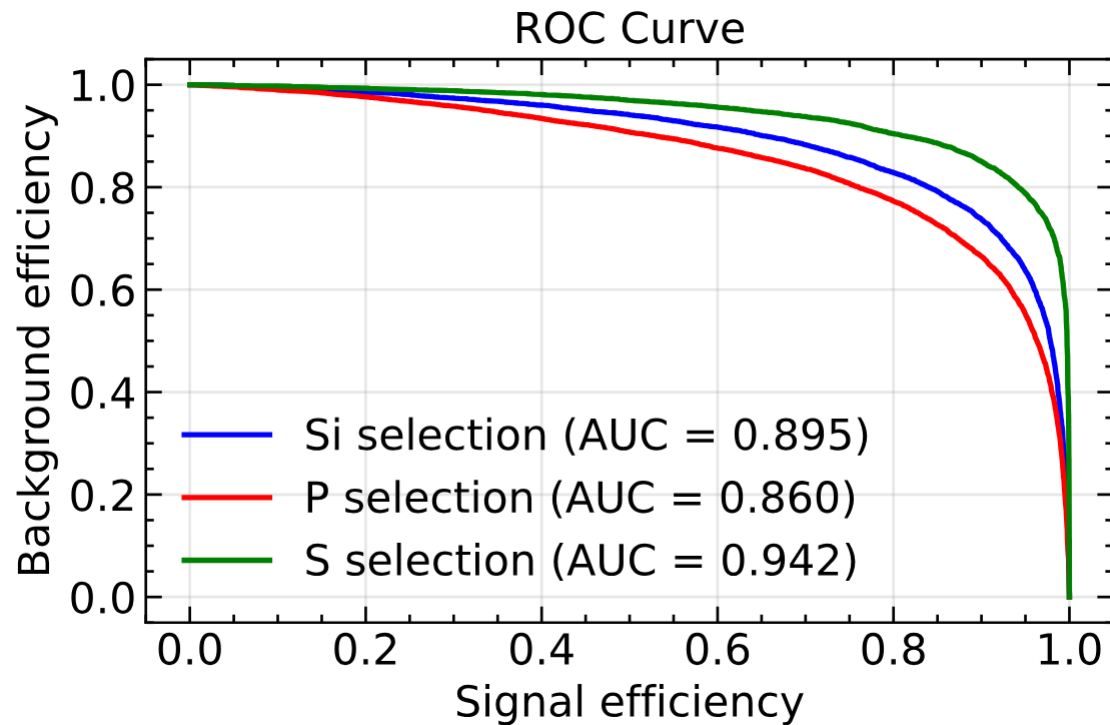
# Model training and validation: MC/Data classifier

## MC and Data used in Training:

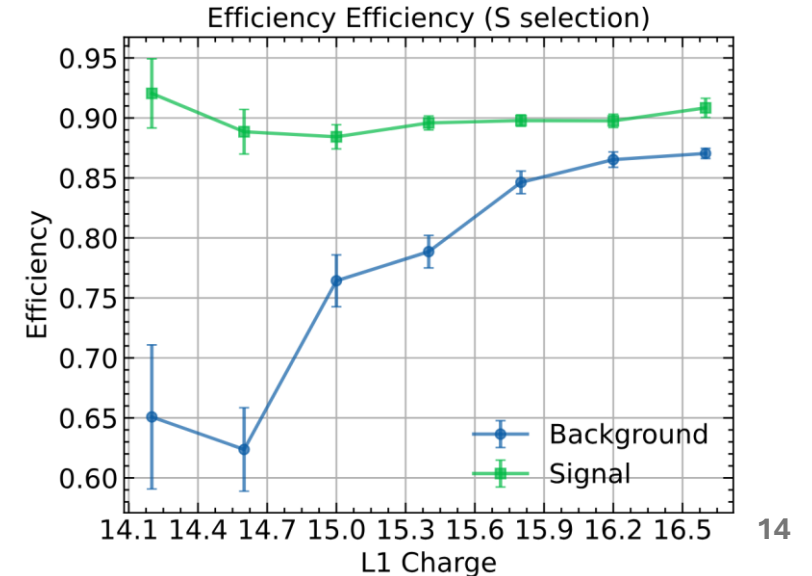
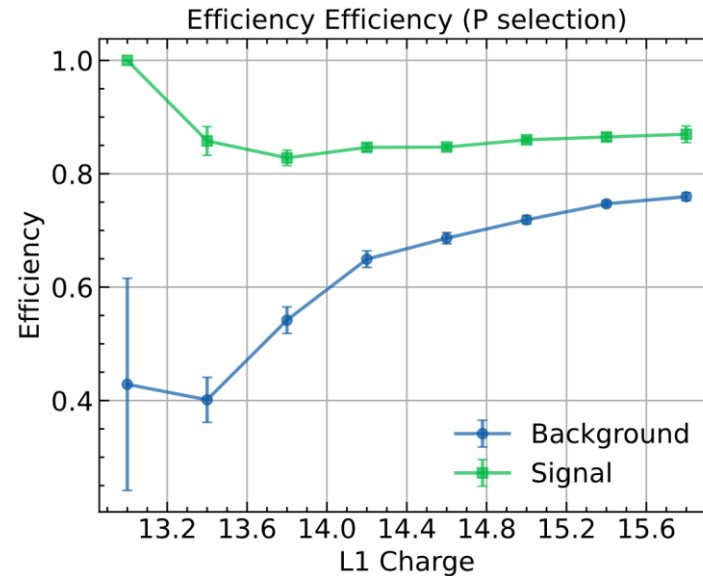
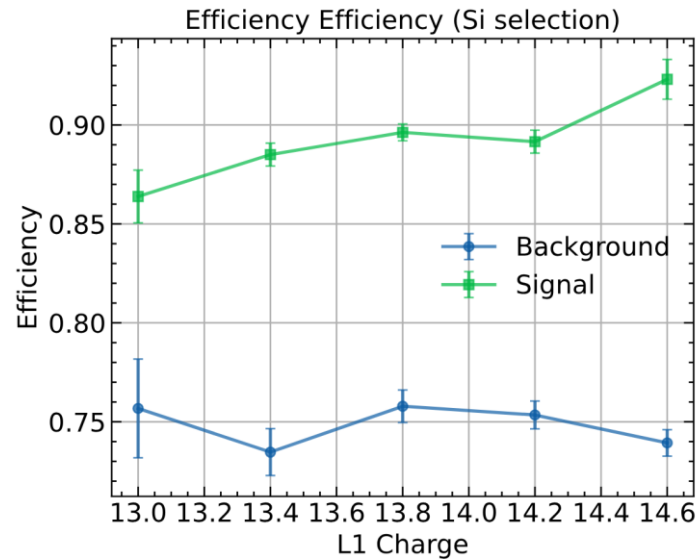
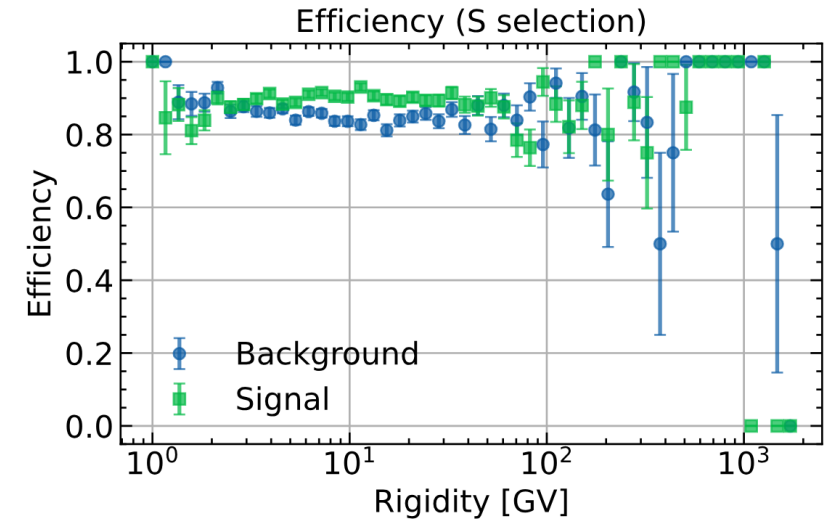
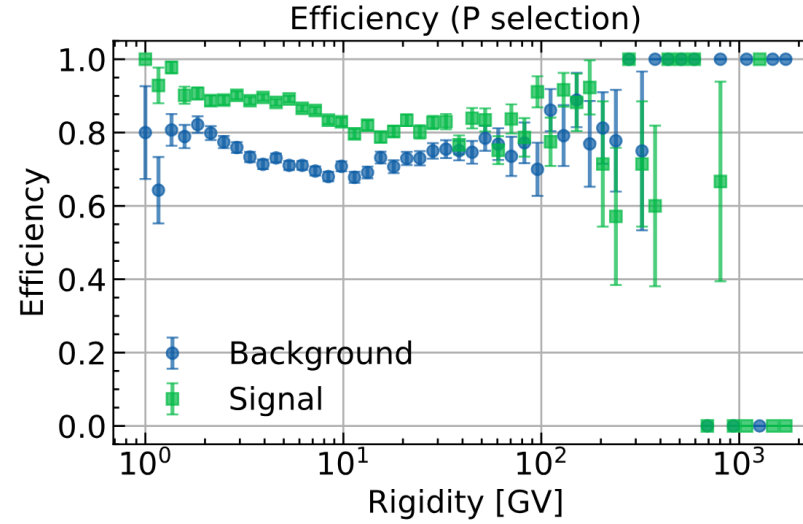
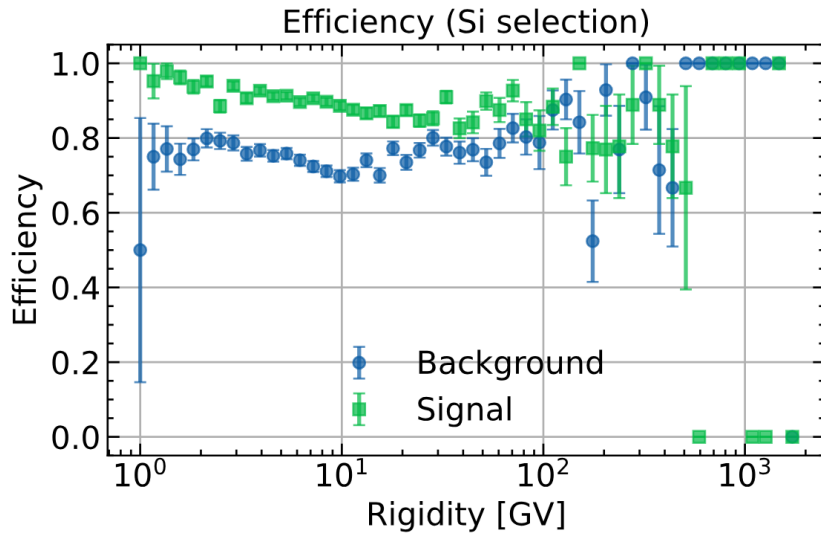
- **MC/Data classifier** to learn features that are similar between MC and Data, ensuring model to perform well on both MC and data.
- **Signal/background classifier** to optimize classification performance.



# Validation



# Validation results: efficiency (threshold =0.5)

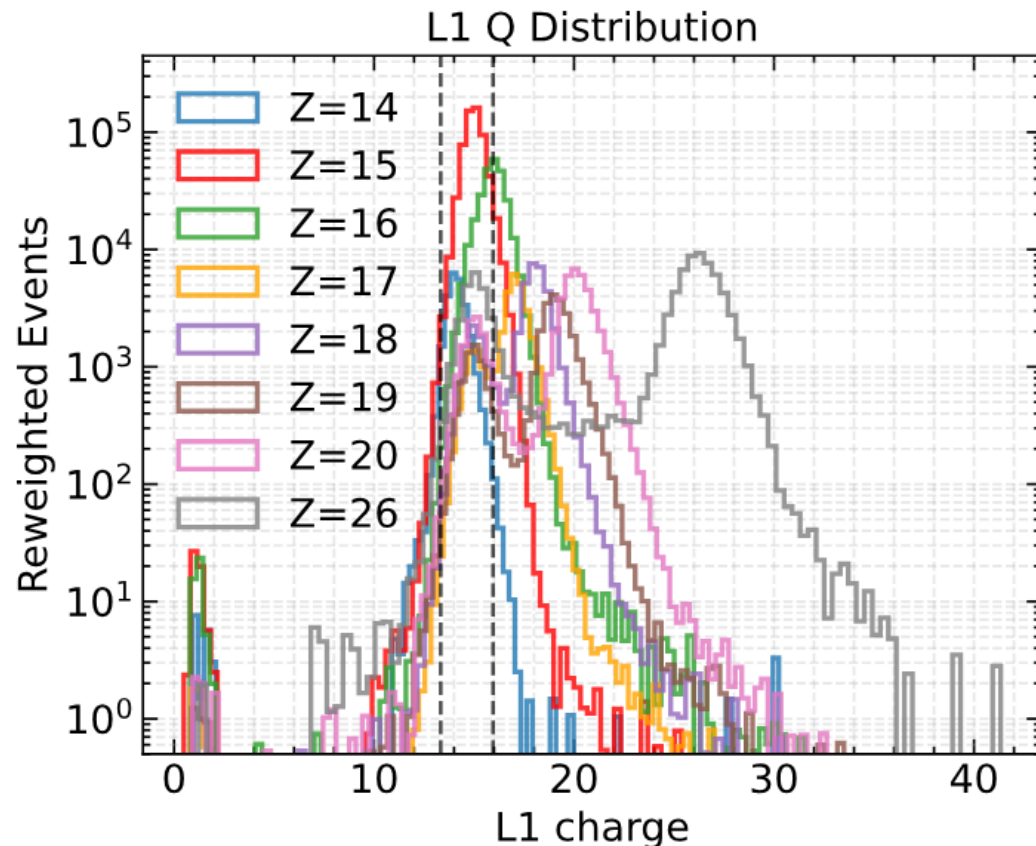


# Model generalization: validation with global MC

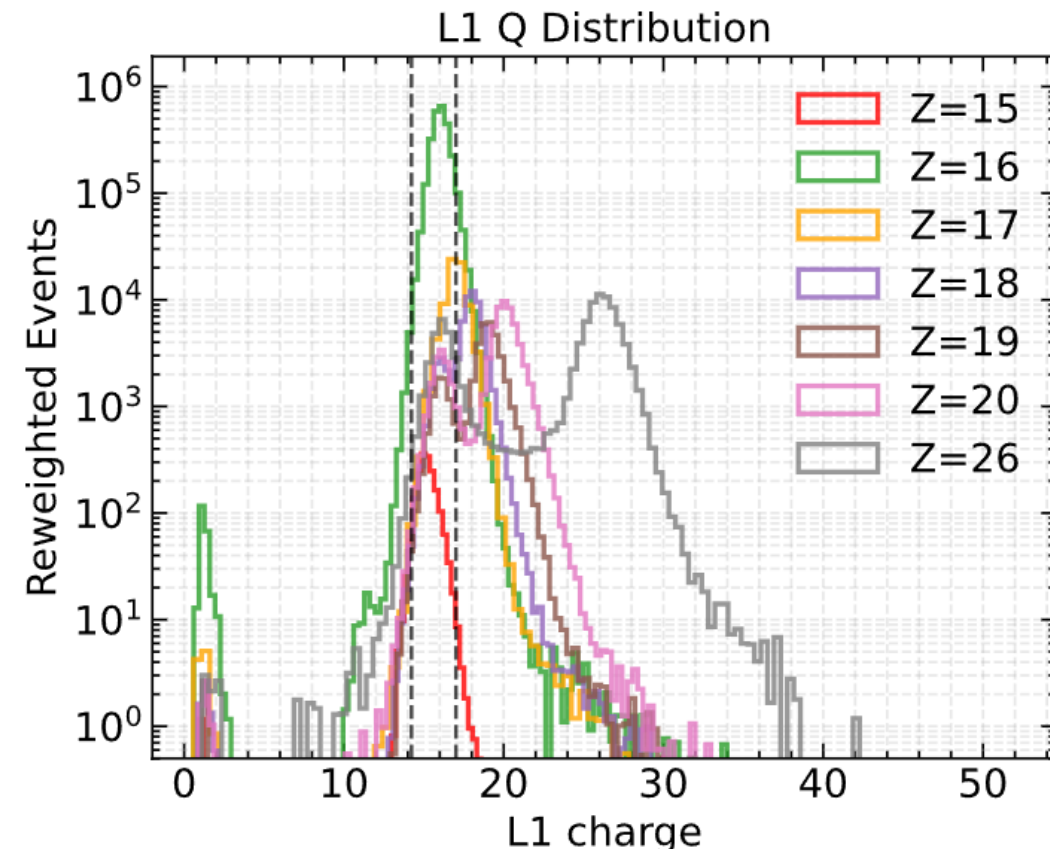
Sample for performance validation:

**reweighted Si, P, S, Cl, Ar, K, Ca and Fe MC samples**

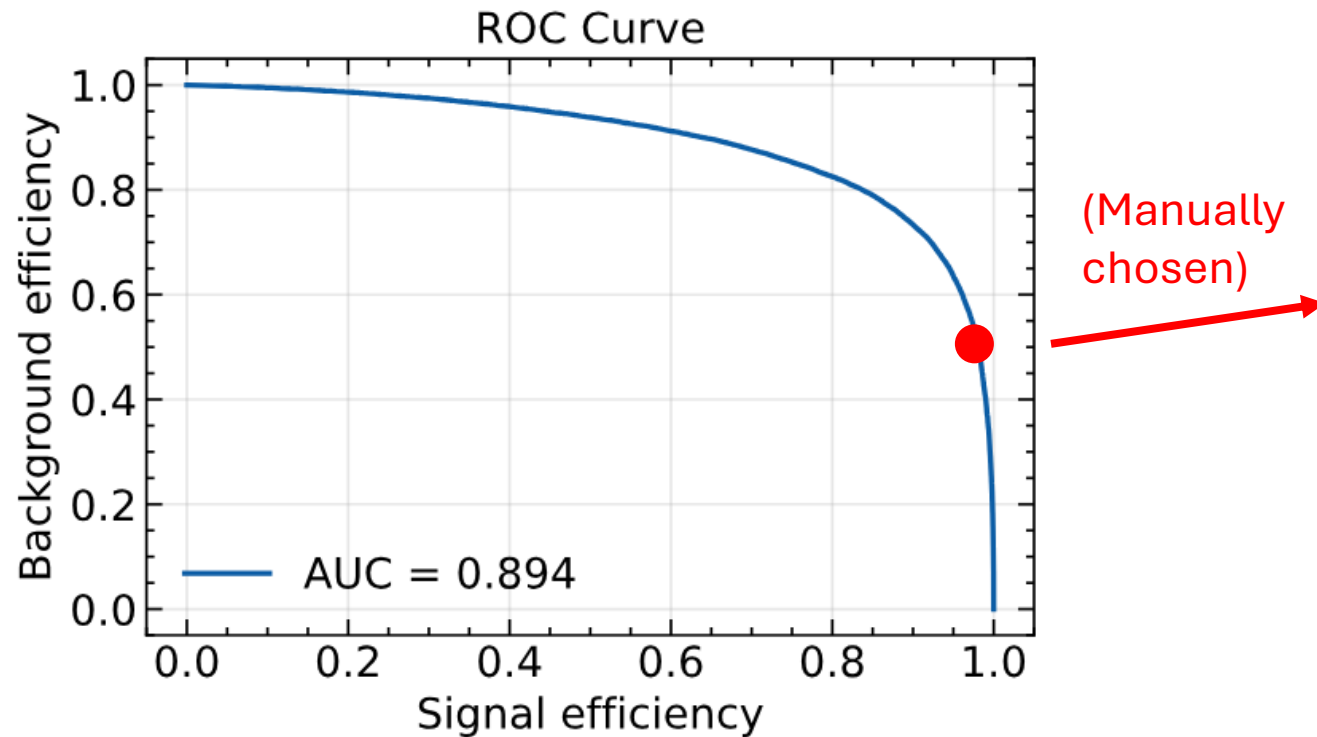
Global MC : P event selection  
without L1 Charge cut



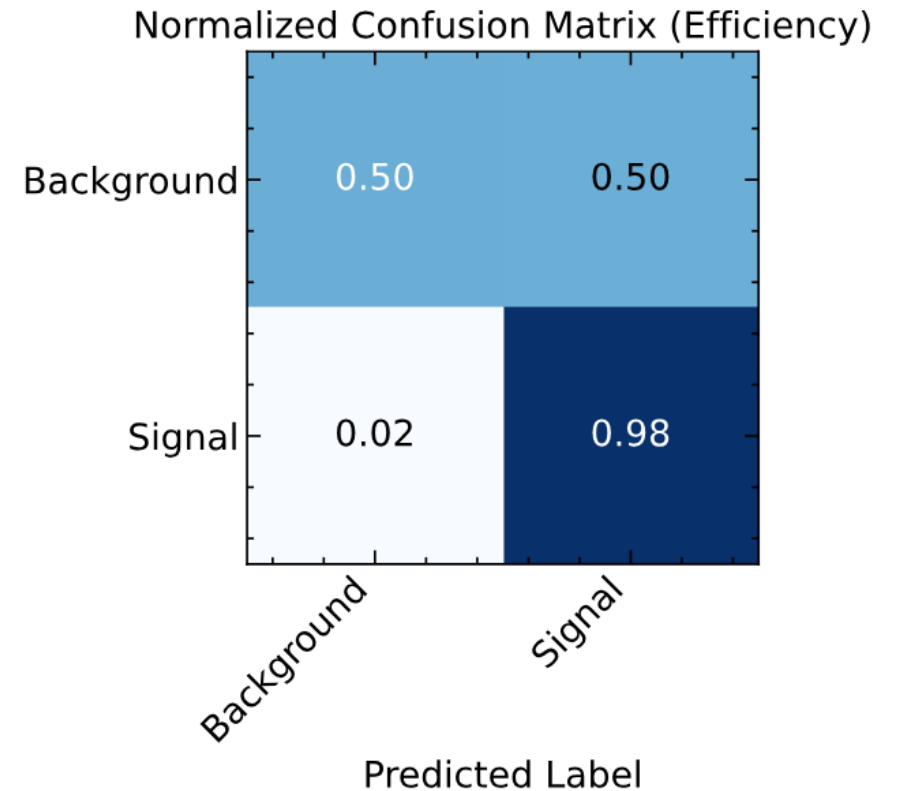
Global MC : S event selection  
without L1 Charge cut



# Model generalization: test with global MC



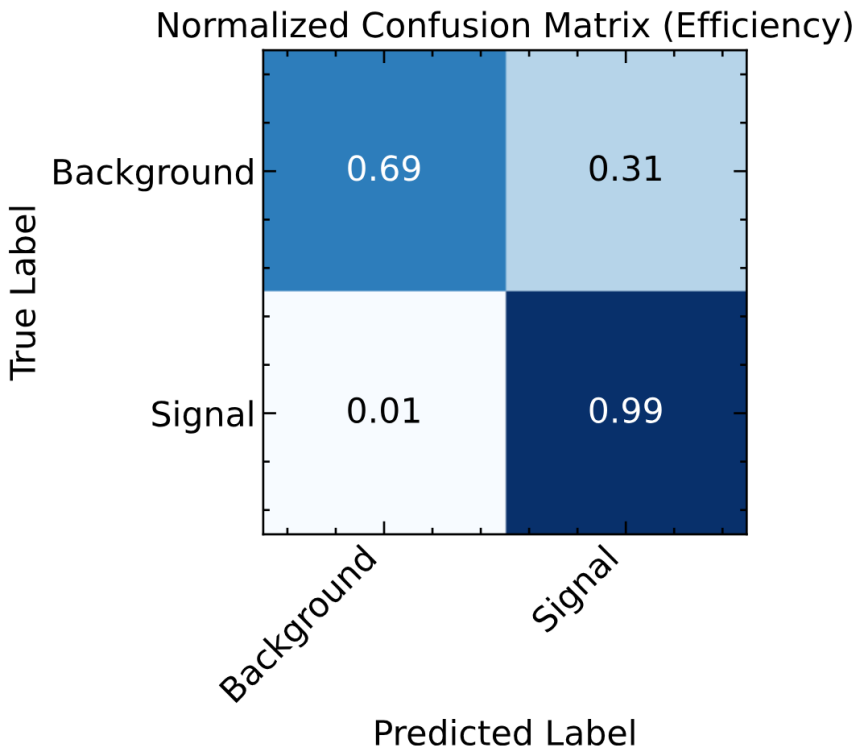
Efficiency for events in **P** Global MC



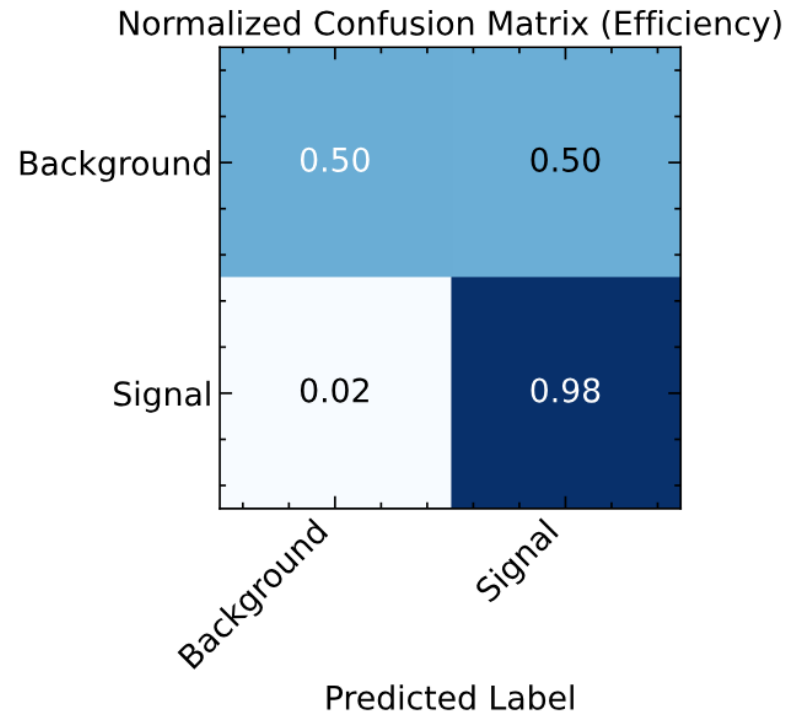


# Model generalization: test with global MC

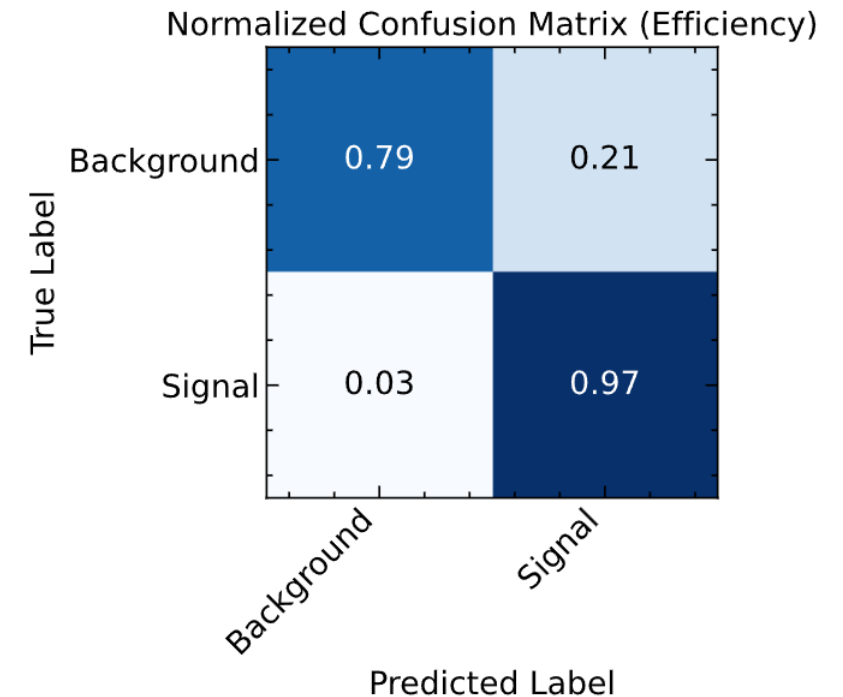
**Si** Global MC



**P** Global MC

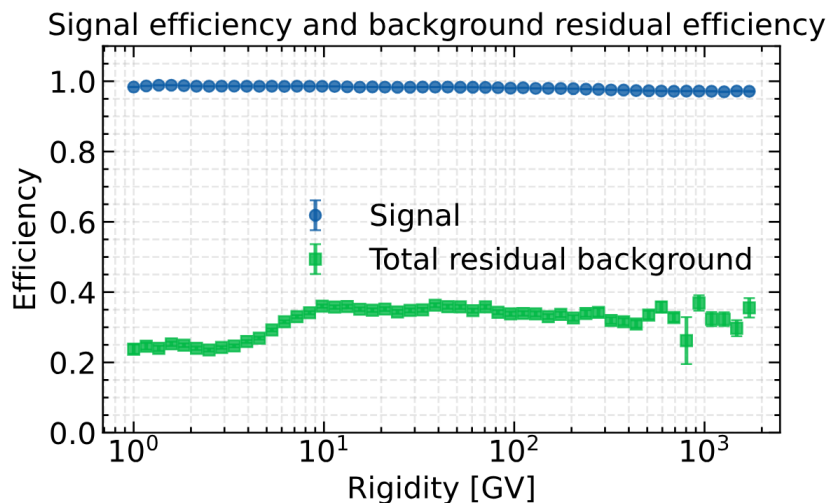


**S** Global MC

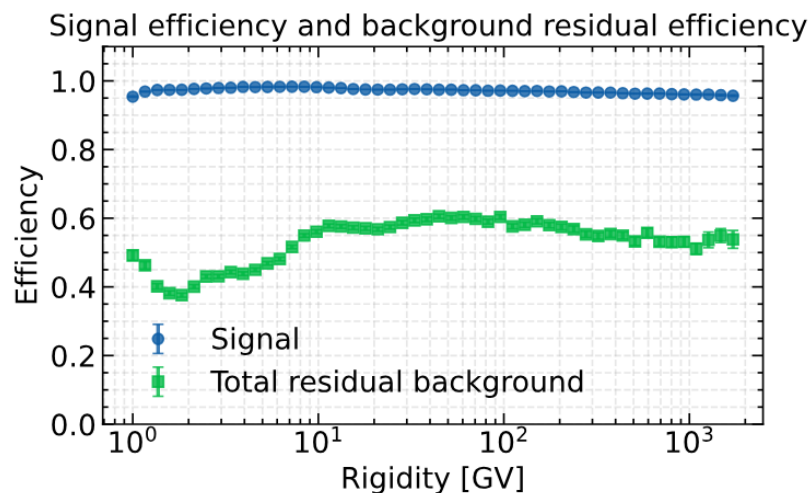


# Test with **global MC**: Efficiency (for events passed event selection in L1 cut range)

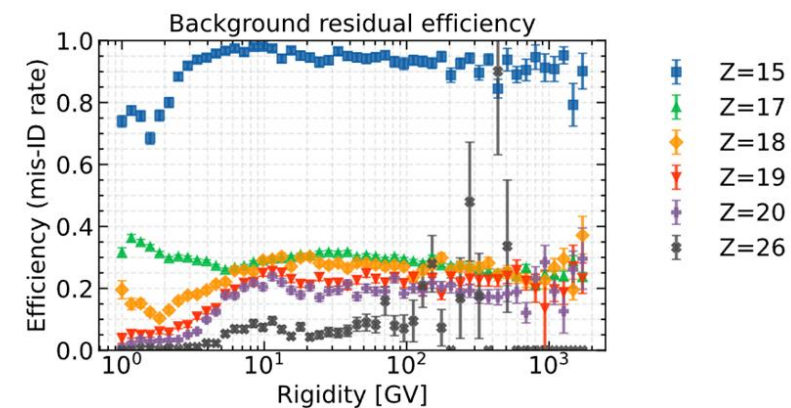
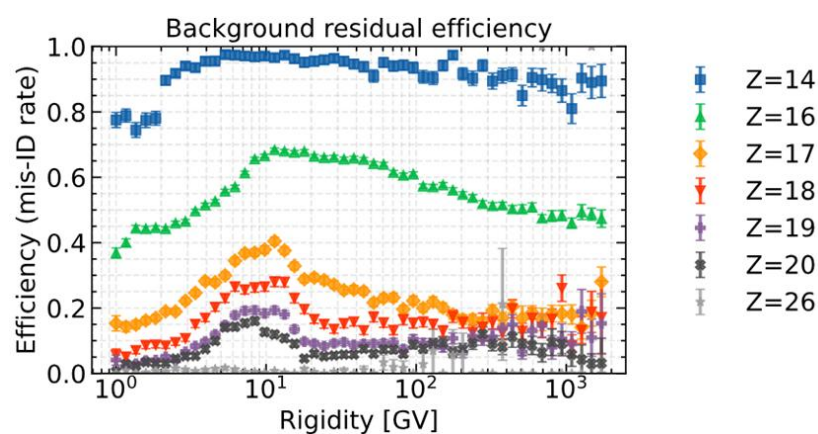
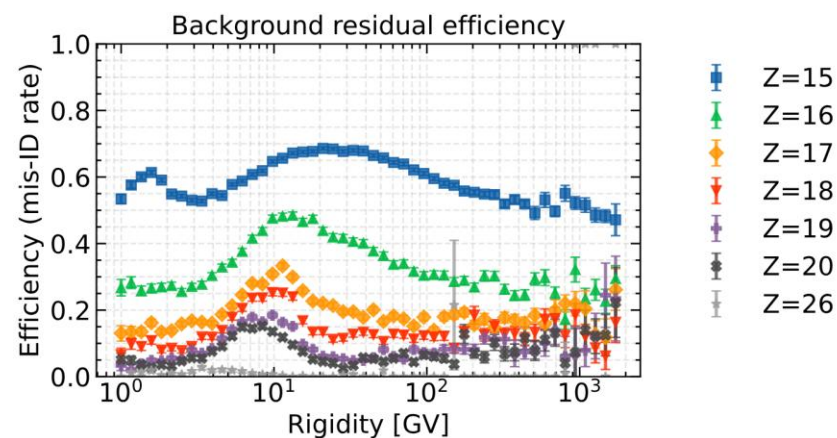
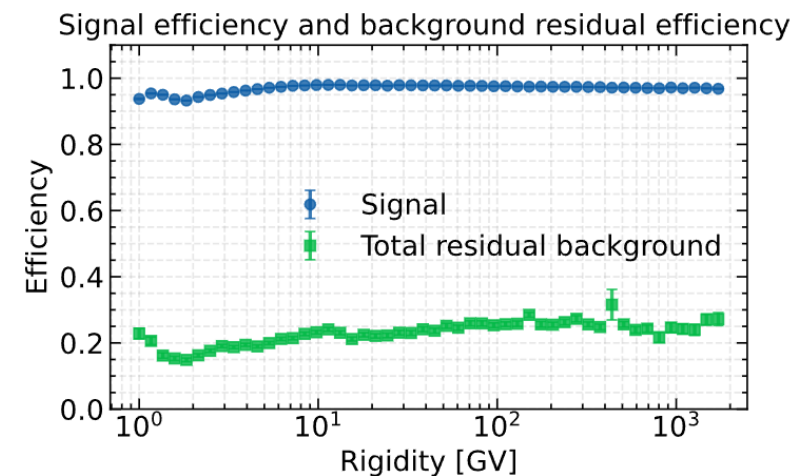
**Si** global MC



**P** global MC

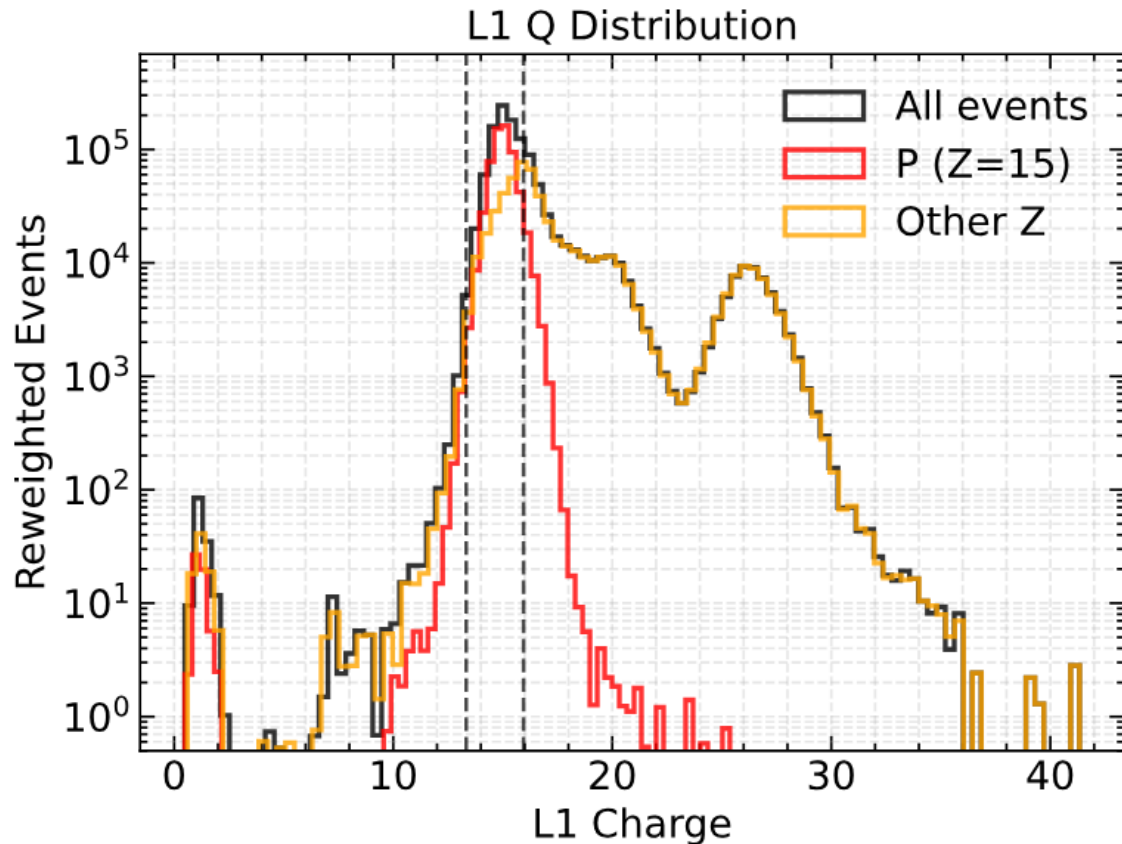


**S** global MC



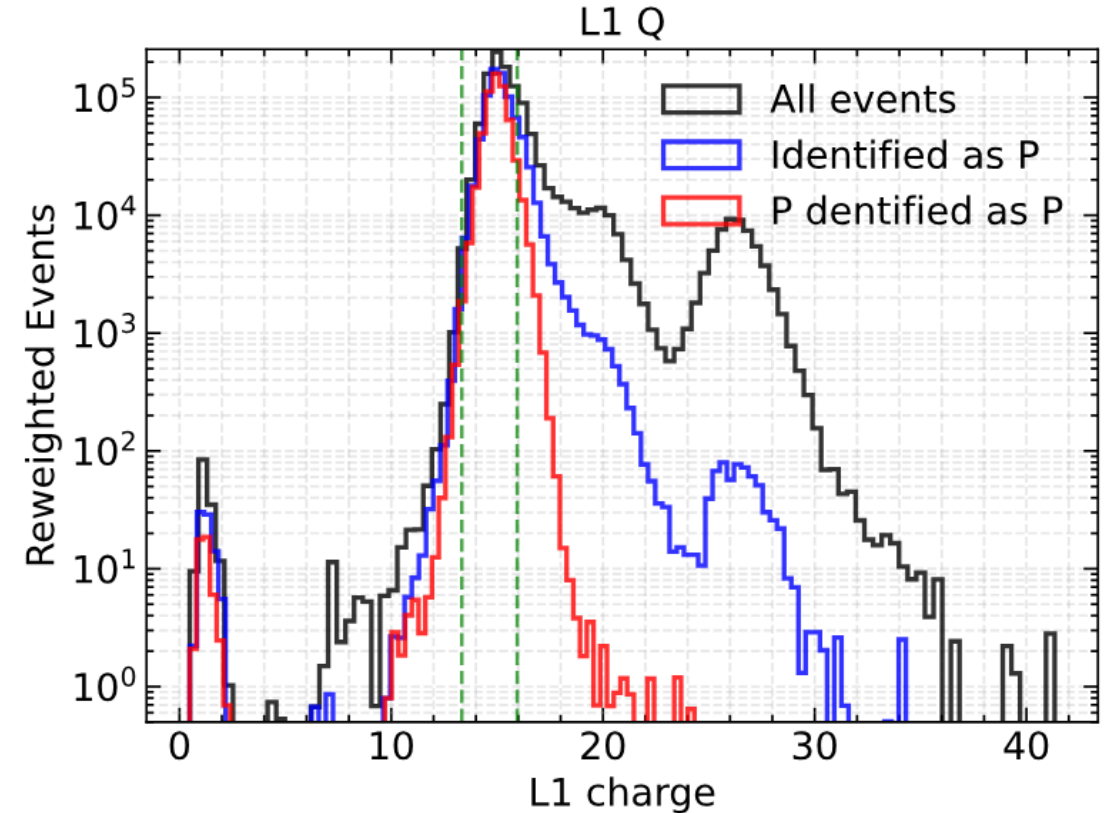
# Motivation of adding ML cut in addition to event selection:

P global MC L1 Q distribution (MC truth)



- With 'standard' P event selection, the events shown in **black curve** are selected in flux analysis.
- Significant **background** (orange curve) existed.

P global MC L1 Q distribution: Before and after ML identification

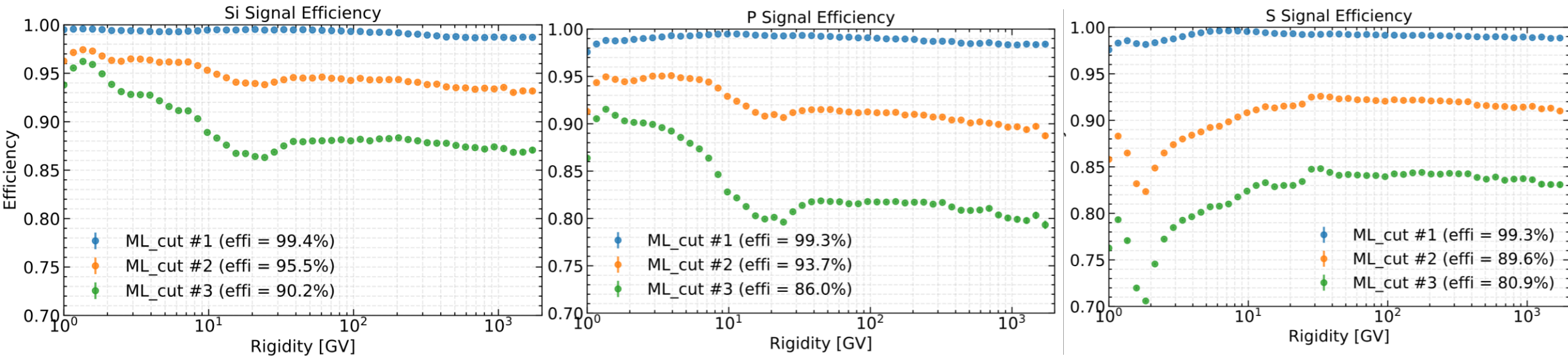


**Add an additional cut from ML predication:**

- the sample to used in the flux analysis are the events shown in **red+blue curve**.
- **Background** events reduced.

# Efficiency of ML cut based on Si, P, S global MC ( $Z=14,15,16-20, 26$ )

Efficiency based on 3 different choice of ML signal/background identification output threshold value:

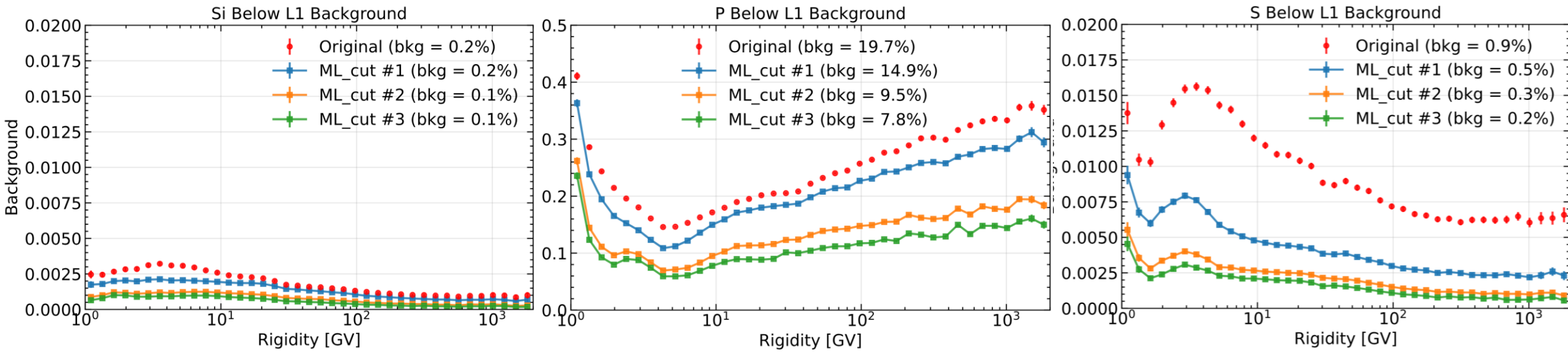


(N.B. efficiency for data will be lower with the same threshold value)



# Below L1 background before/after ML cut based on Si, P, S global MC (Z=14,15,16-20, 26)

- Based on 3 different choice of ML signal/background identification output threshold value:
- Event selection for global MC samples:
  - Si, S, P (Z=14,15,16) event selection
  - **For element>Z: Select events survived on L1.**
- Background calculated from MC truth.



**On-going: test with Data**

# Summary

A MDA Network has been developed for Si, P, S Signal-Background identification:

- The identification power is achieved with Multimodal network using Tracker and TOF reconstructed information
- The generalization power is achieved by adding Domain-Adversarial network to learn features that are similar between MC and Data, ensuring consistent performance across both MC and data.

On-going and to-do

- Apply to Data
- P efficiency estimation

# Backups

# Samples

## Si, P, and S event selection

- Signal: MC Si, P, S (MC truth)
- Background: MC Si and S (for Si), Si and S (for P), P and Cl (for S)
- Data

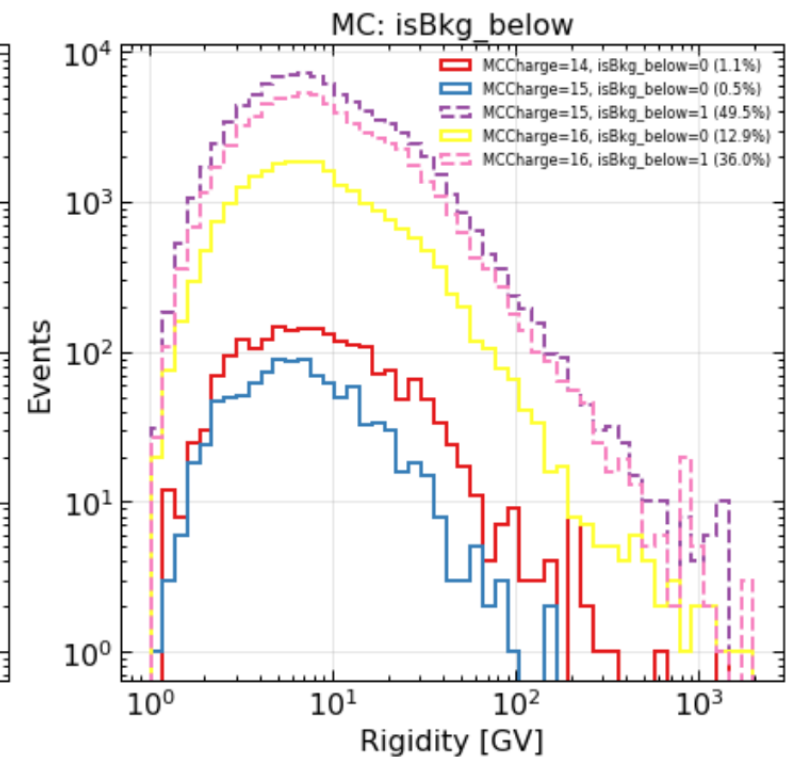
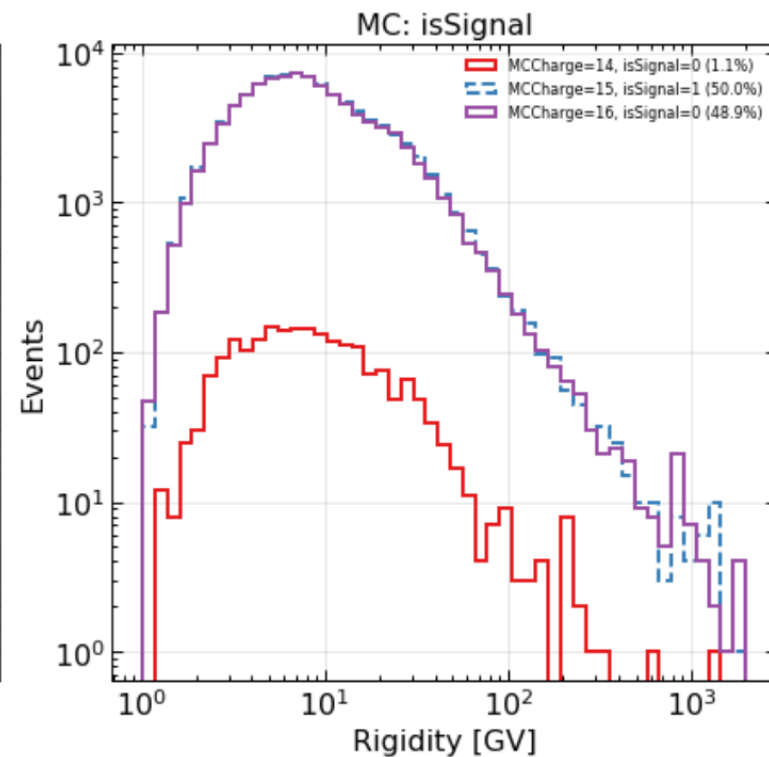
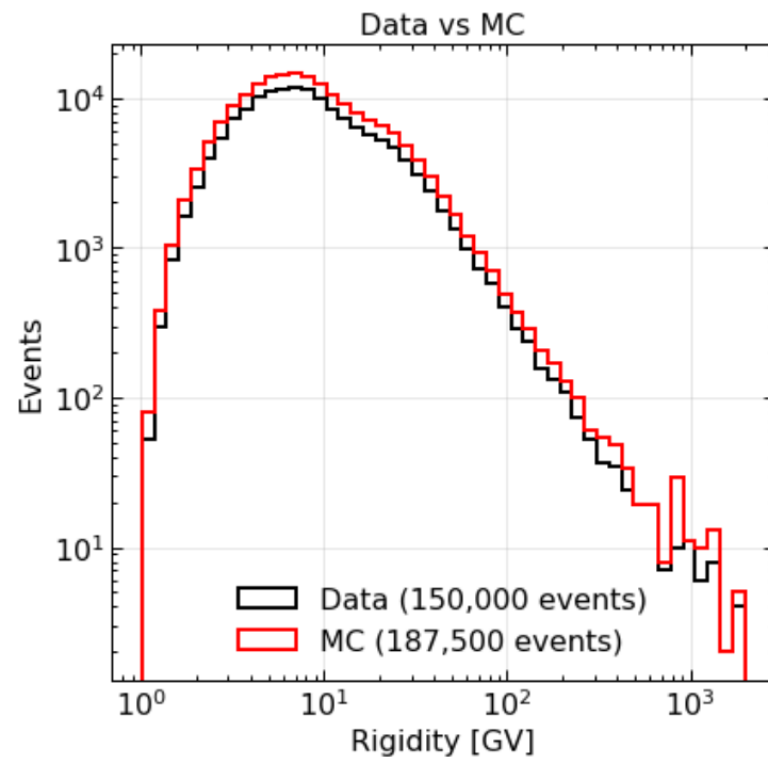
## Definition:

- Signal/Background: MC truth
- **Fragmented\_belowL1: true only if primary survived at L1** (need to rename)
  1. MC truth: TrackMCHits on L1 Charge == Primary Z
  2. MC truth: Primary particle Position is in L1 fiducial volume



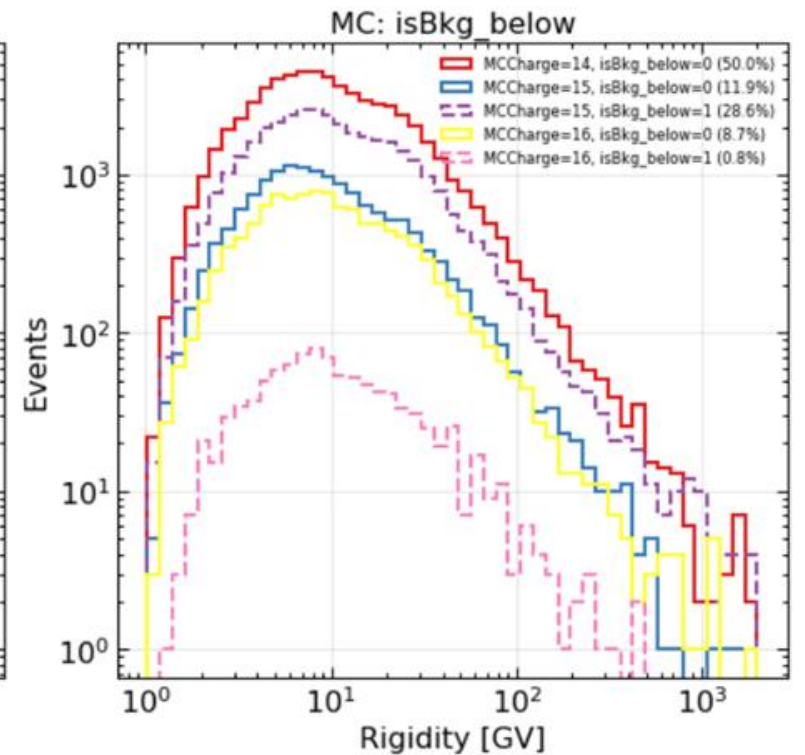
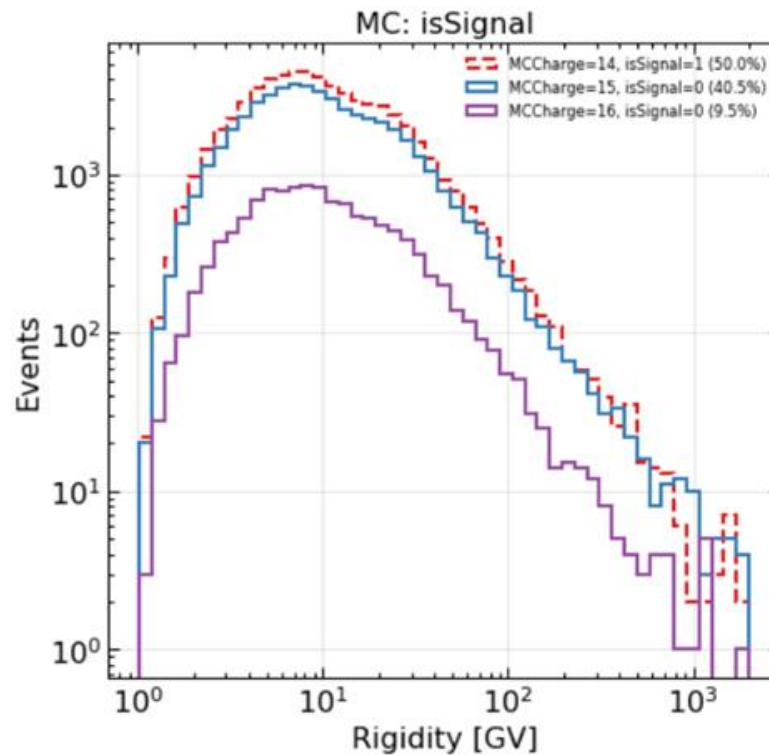
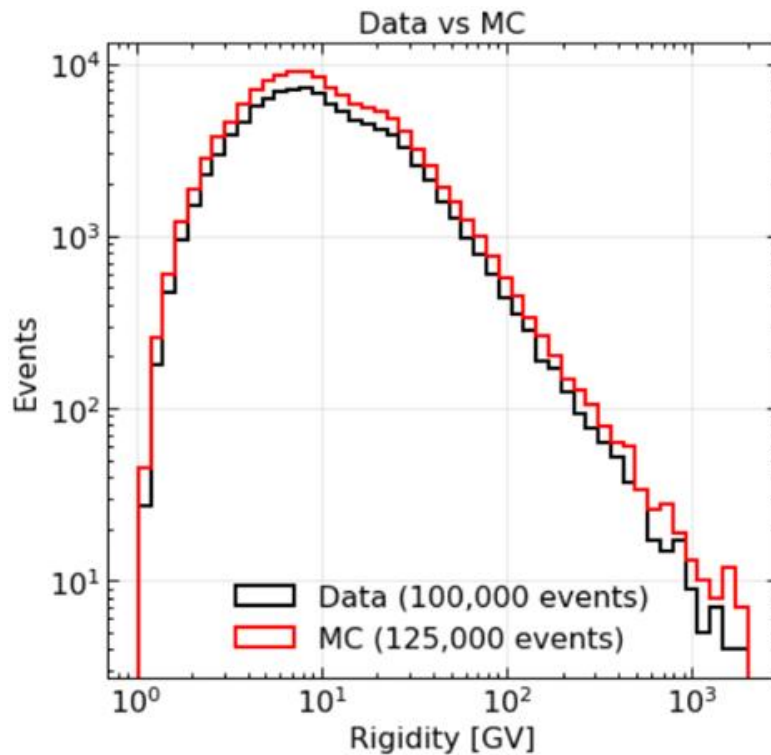
# Samples (P event selection):

- Data: 150k
- MC: 187.5k (150k(80%) for training, 20% for testing)
  - Signal: 50%
  - Background-Si: 1.1%
    - AboveL1: 100%
  - Background-S: 48.9%
    - Above: 24.2% of S



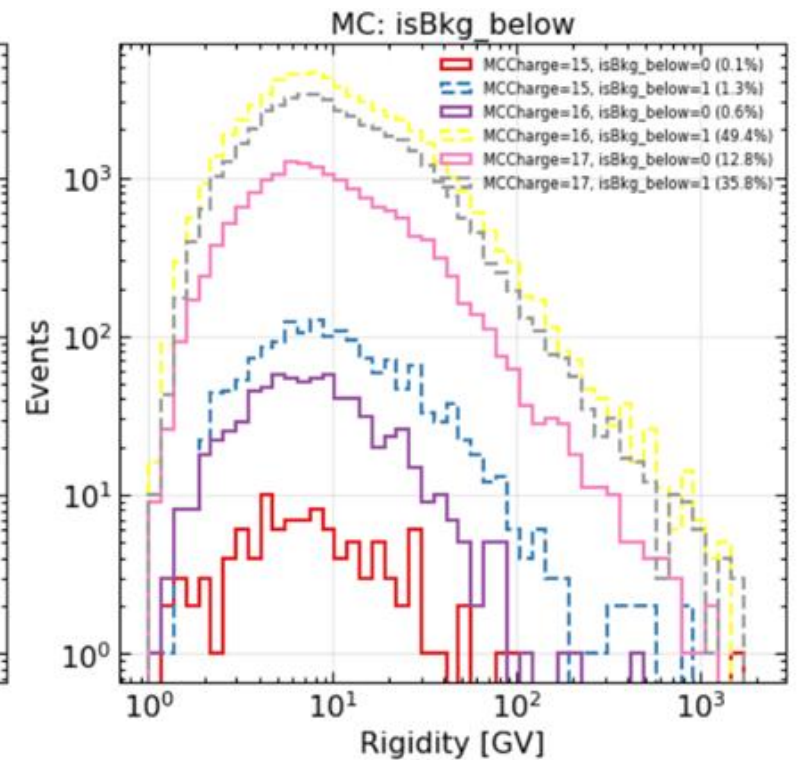
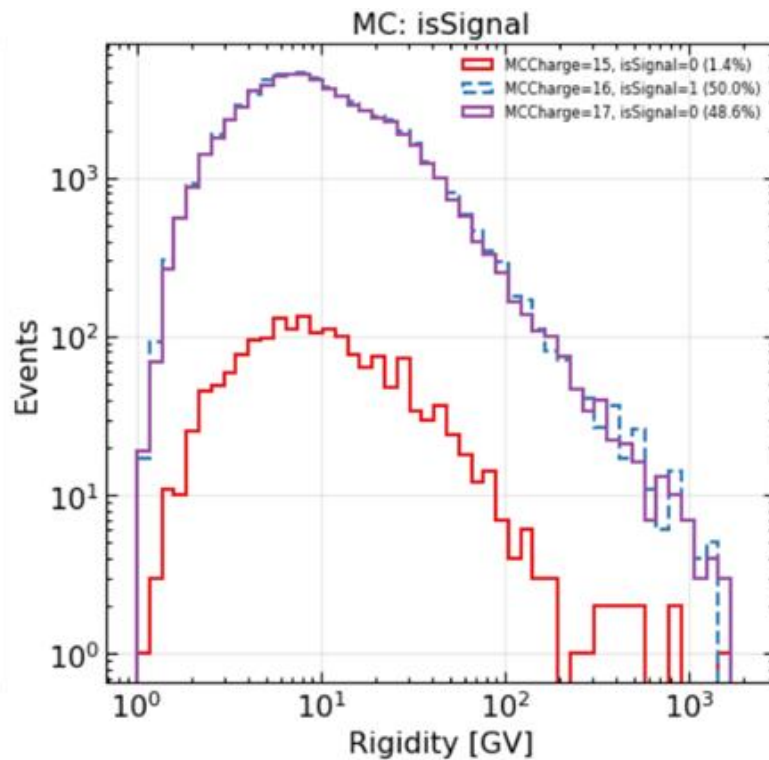
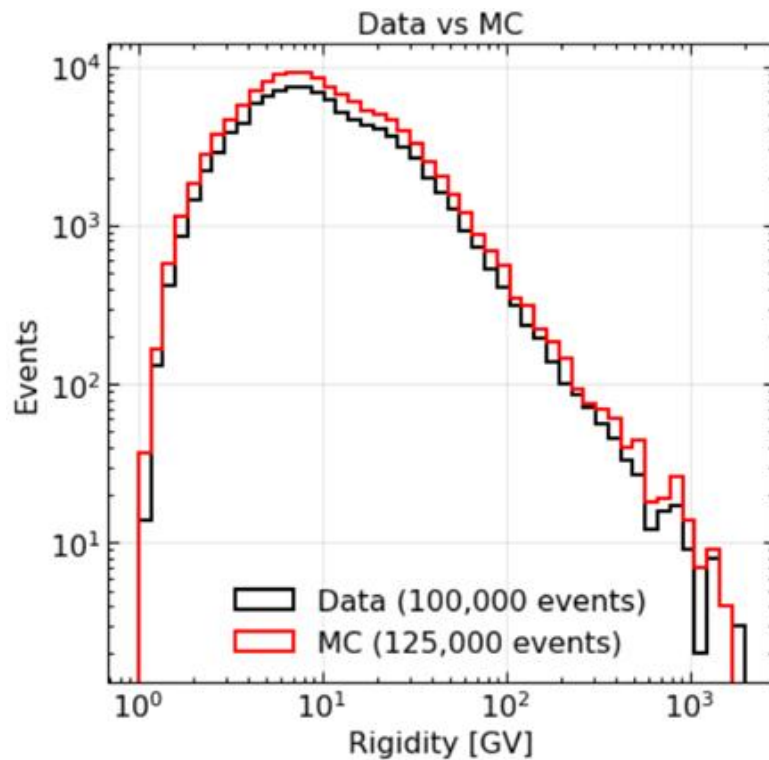
# Samples (Si event selection):

- Data: 100k
- MC: 125k (100k for training)
  - Signal: 50%
  - Background-P: 40.5%
    - AboveL1: 26.9% of P
  - Background-S: 9.5%
    - Above: 91.6% of S



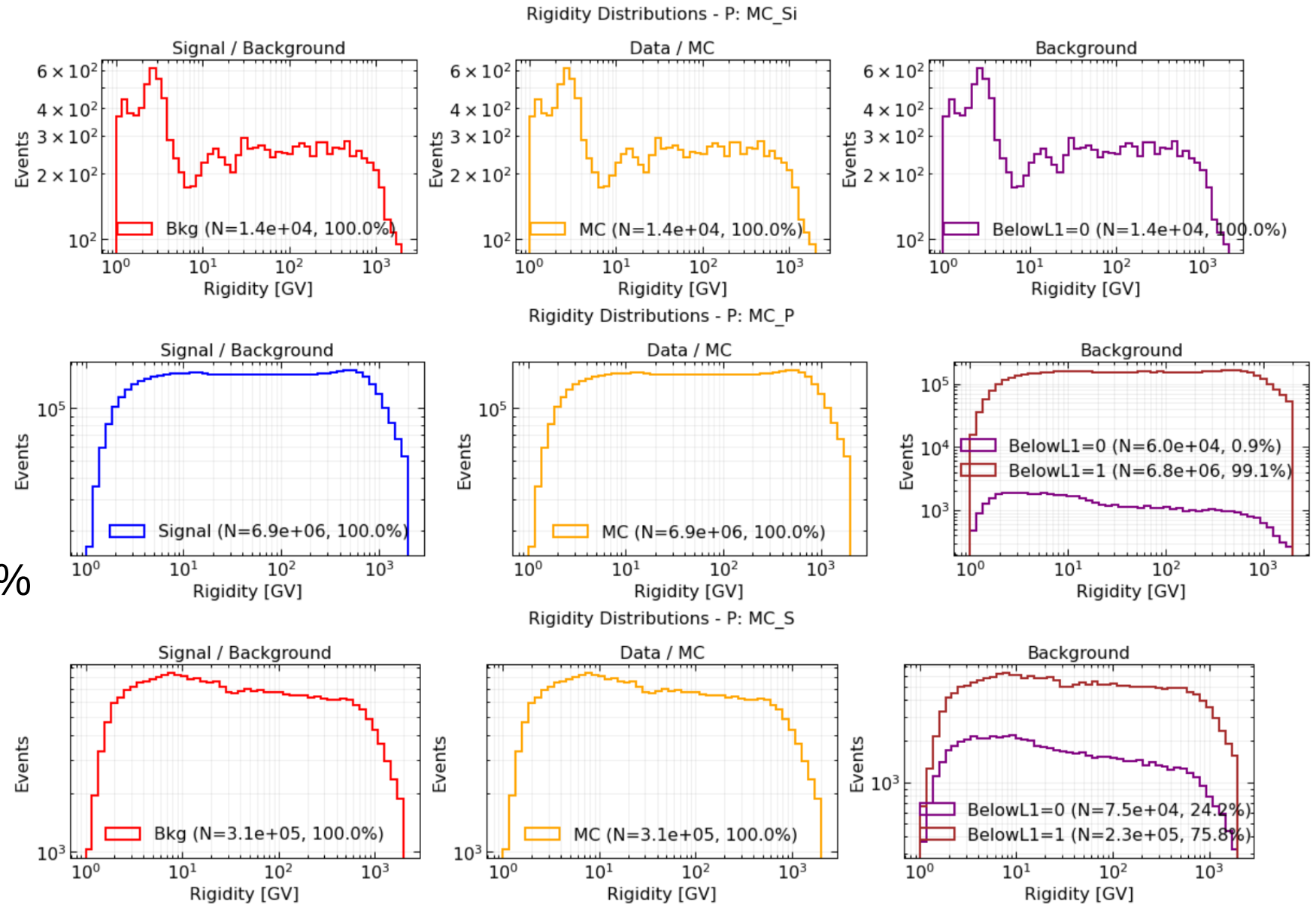
# Samples (S event selection):

- Data: 100k
- MC: 125k (100k for training)
  - Signal: 50%
  - Background-P: 1.36%
    - AboveL1: 6.7% of P
  - Background-CI: 48.64%
    - Above: 24.6% of CI



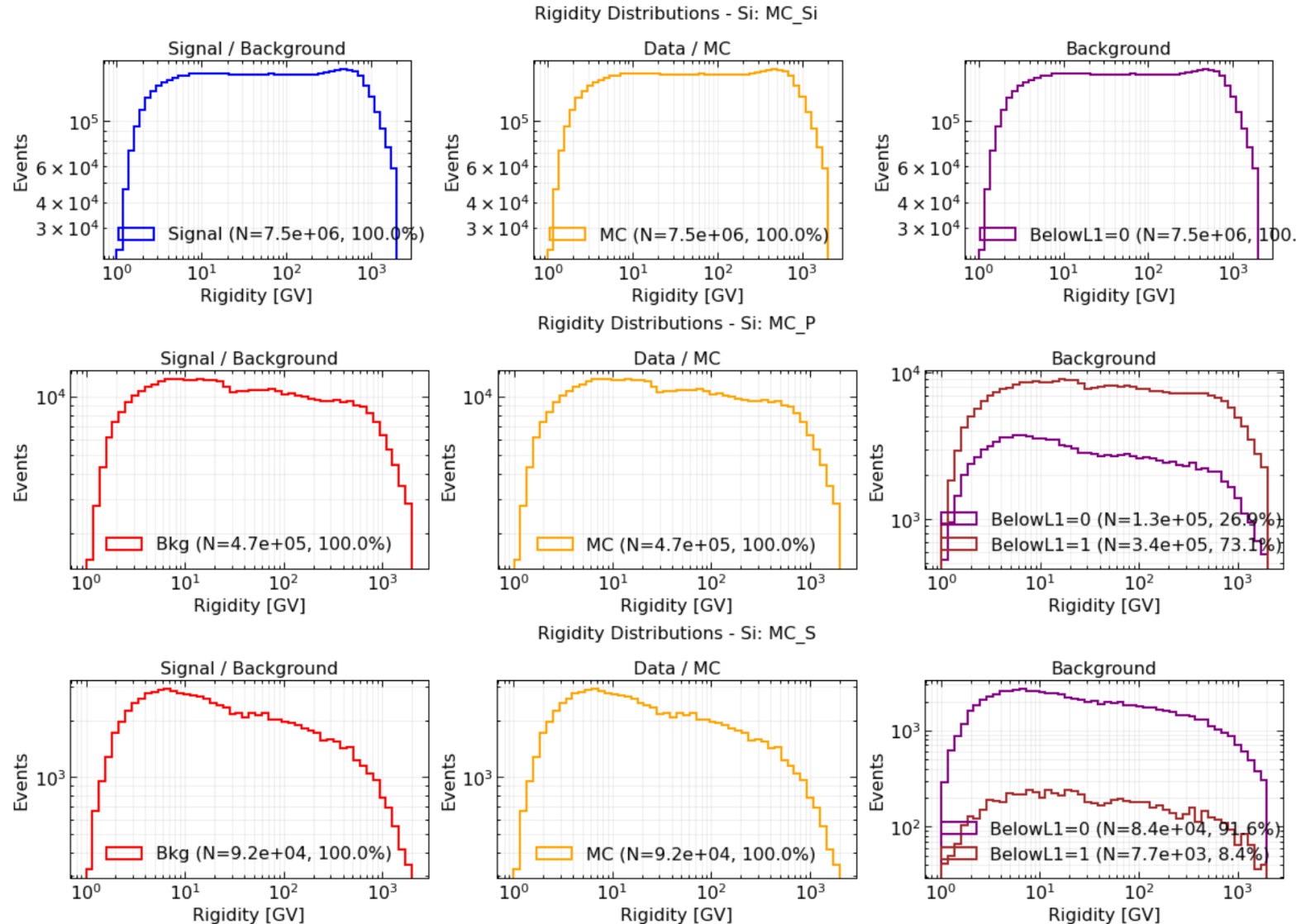
P

- Data: 150k
- MC: **187.5k**
  - Signal: 93.75k
  - **Background-Si**
    - AboveL1: 100%
  - Background-S: 48.9%
    - Above: 24.2%



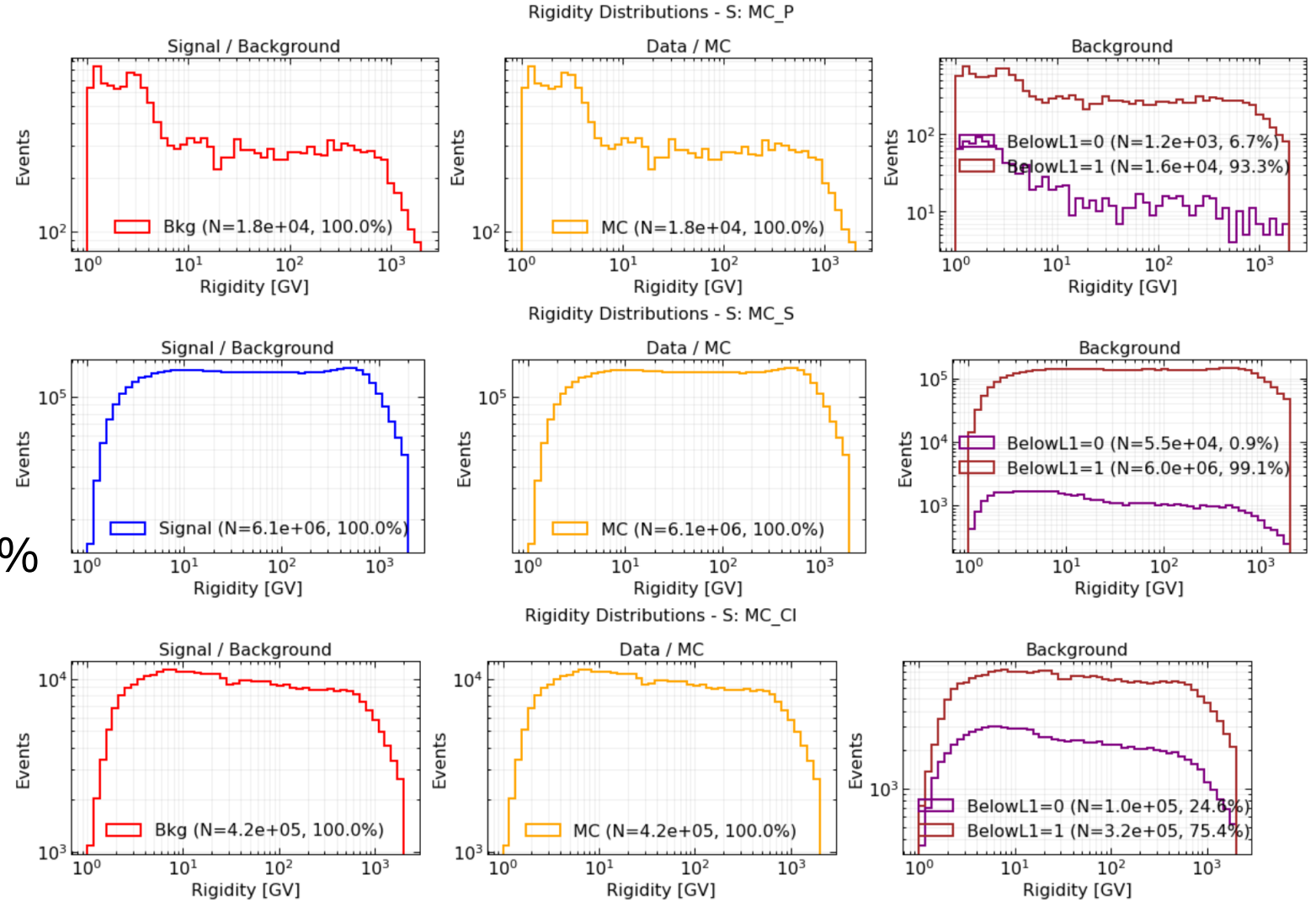
# Si

- Data: 100k
- MC: **125k**
  - Signal: **62.5k**
  - Background-P: 40.5%
    - AboveL1: 26.9%
  - Background-S
    - Above: 91.6%



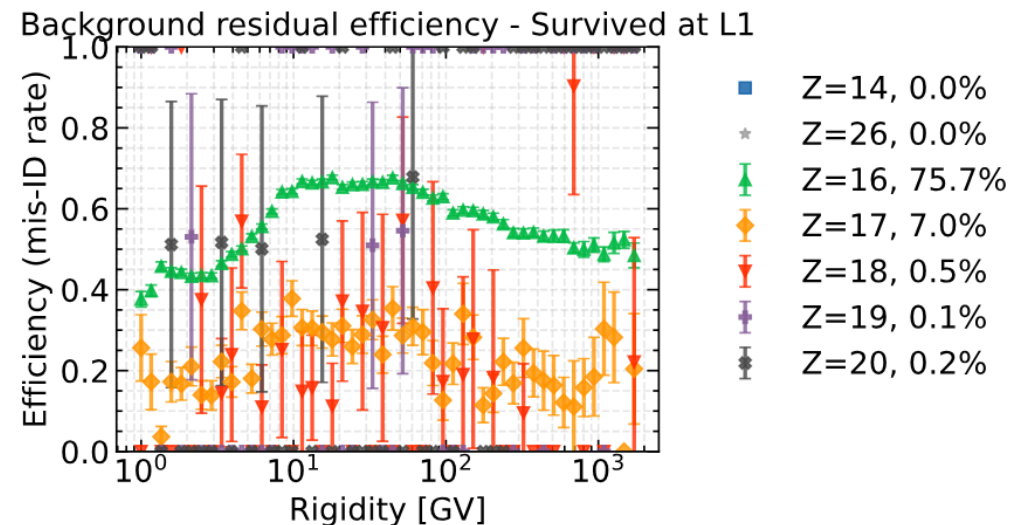
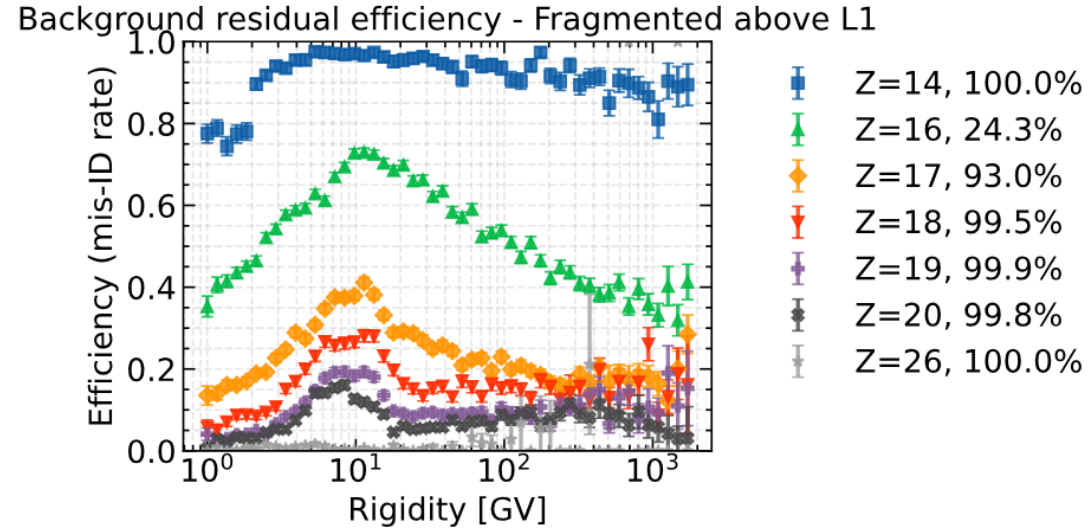
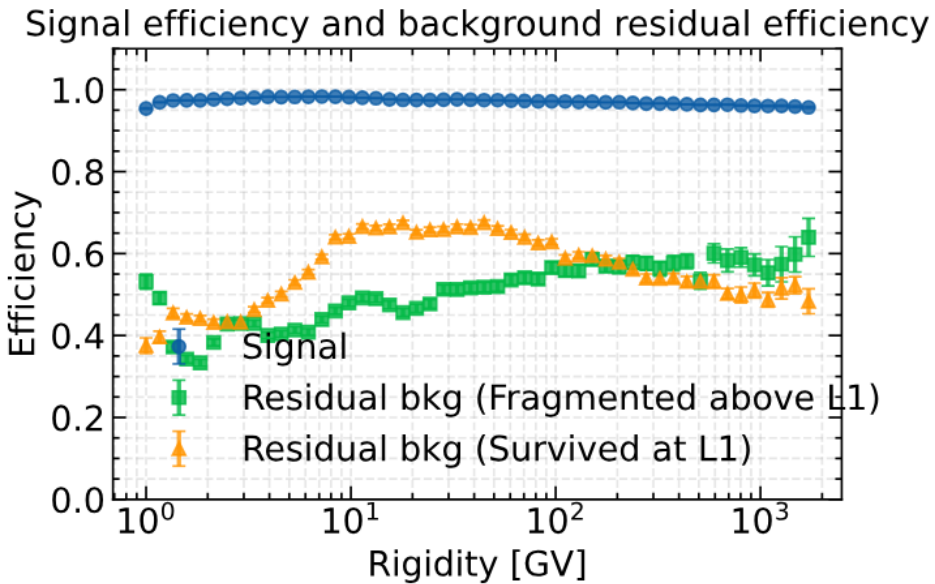
# S

- Data: 100k
- MC: **125k**
  - Signal: **62.5k**
  - Background-P
    - AboveL1: 6.7%
  - Background-CI: 48.64%
    - Above: 24.6%



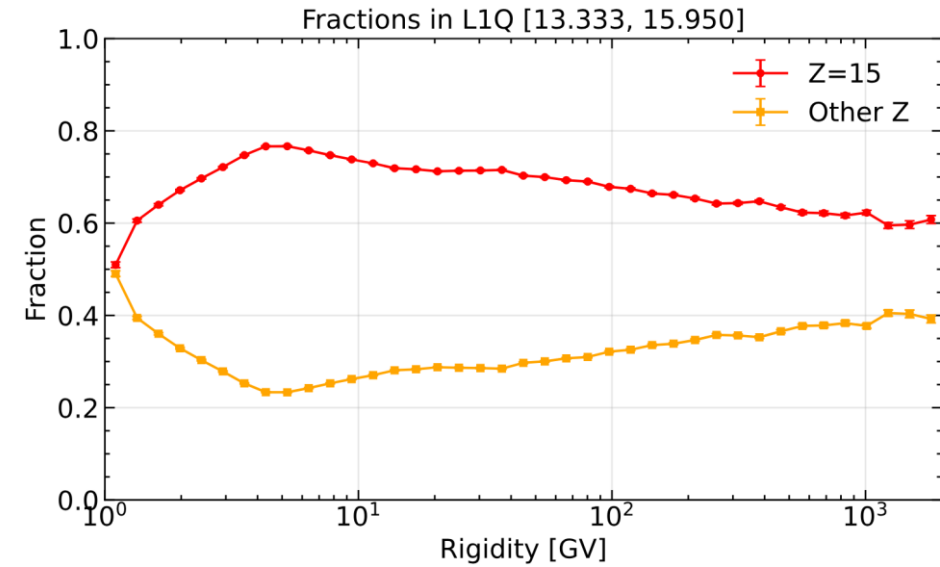
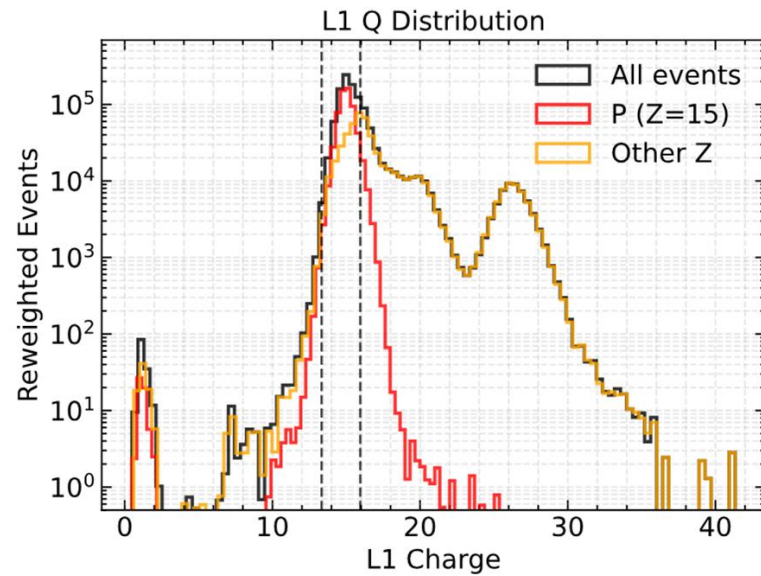


# Test with **P** global MC: Efficiency (for events passed event selection in L1 cut range)

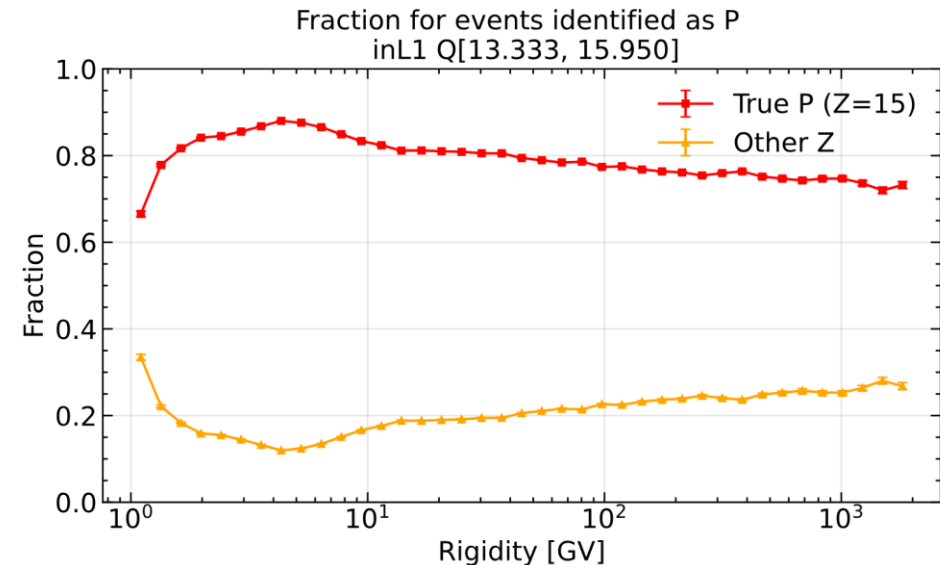
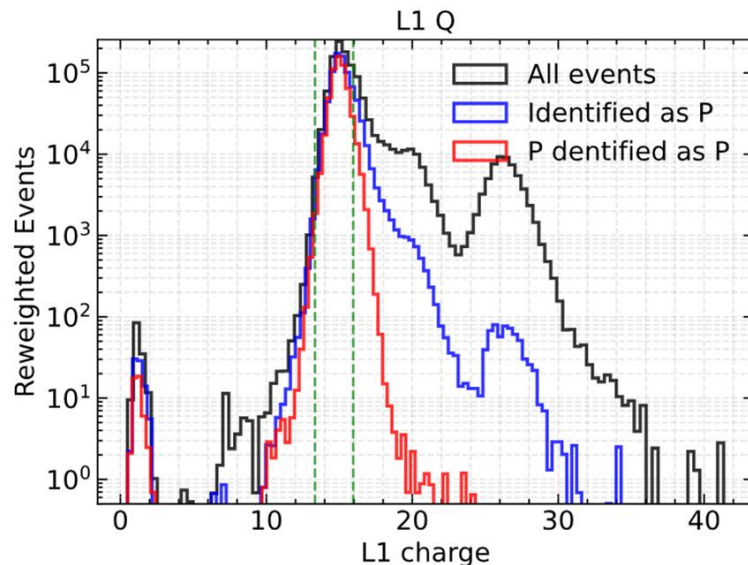


# Test with **P global MC**: Fraction of events in L1 Q range with ML identification

MC L1 Q  
distribution  
(MC truth)



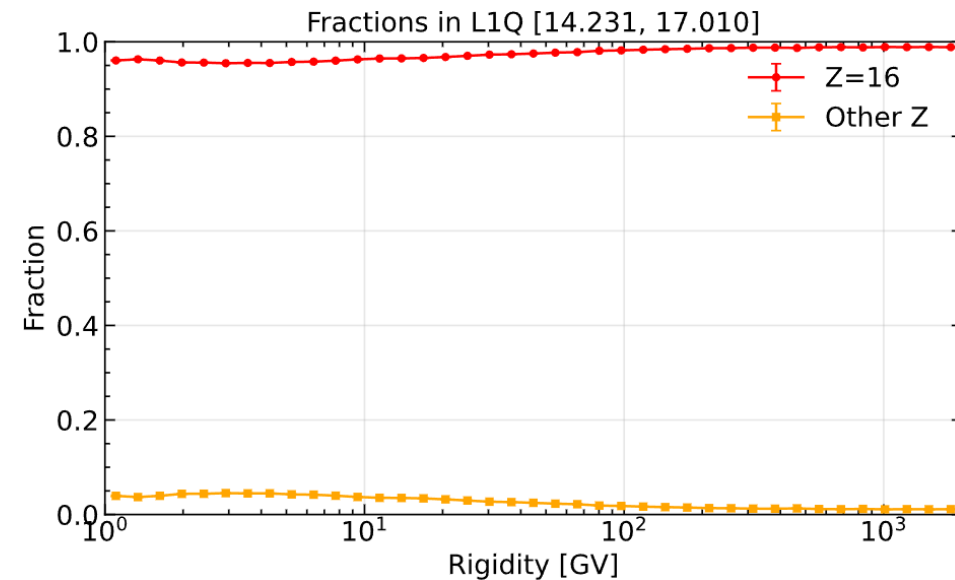
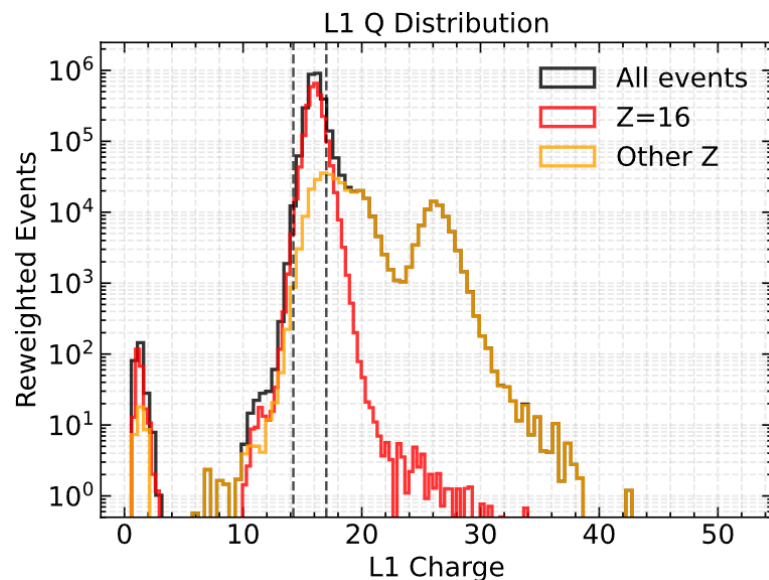
MC L1 Q  
distribution:  
**Before and after  
ML identification**



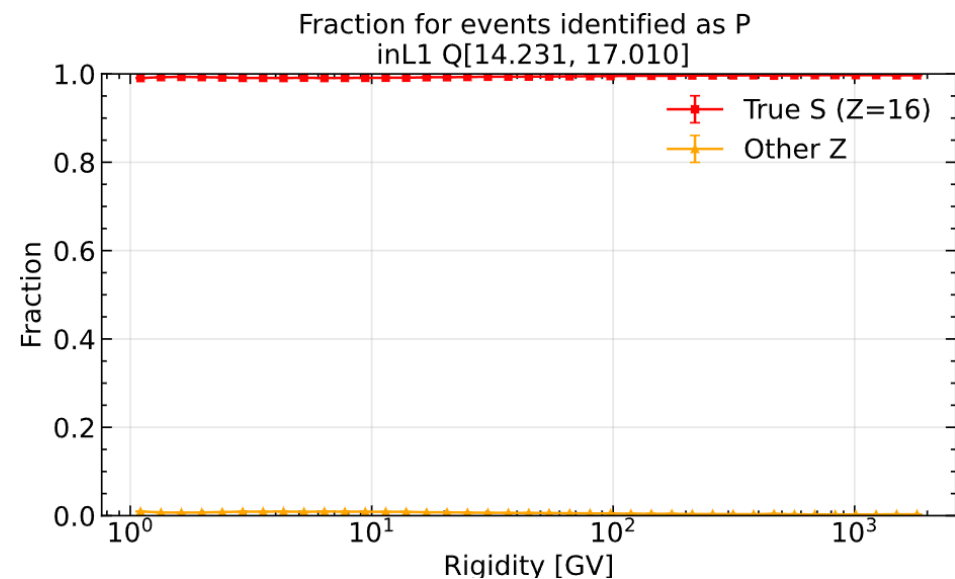
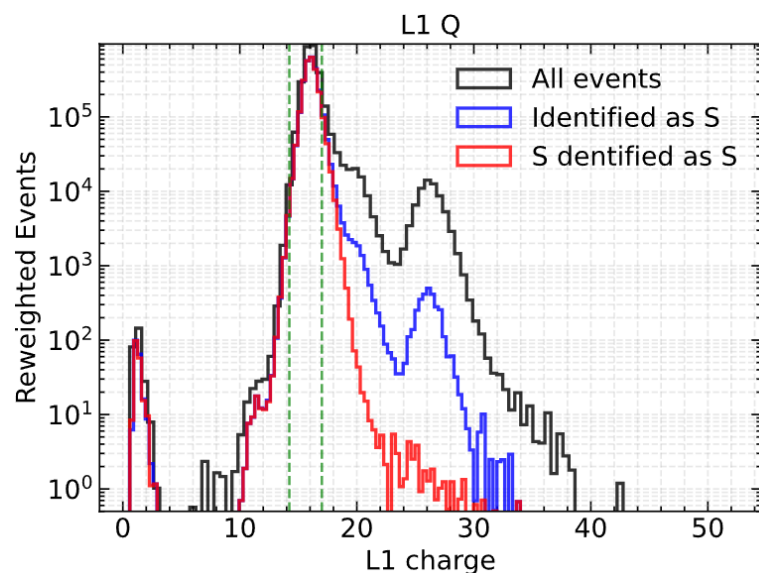


# Test with **S** global MC: Fraction of events in L1 Q range with ML identification

MC L1 Q  
distribution  
(MC truth)



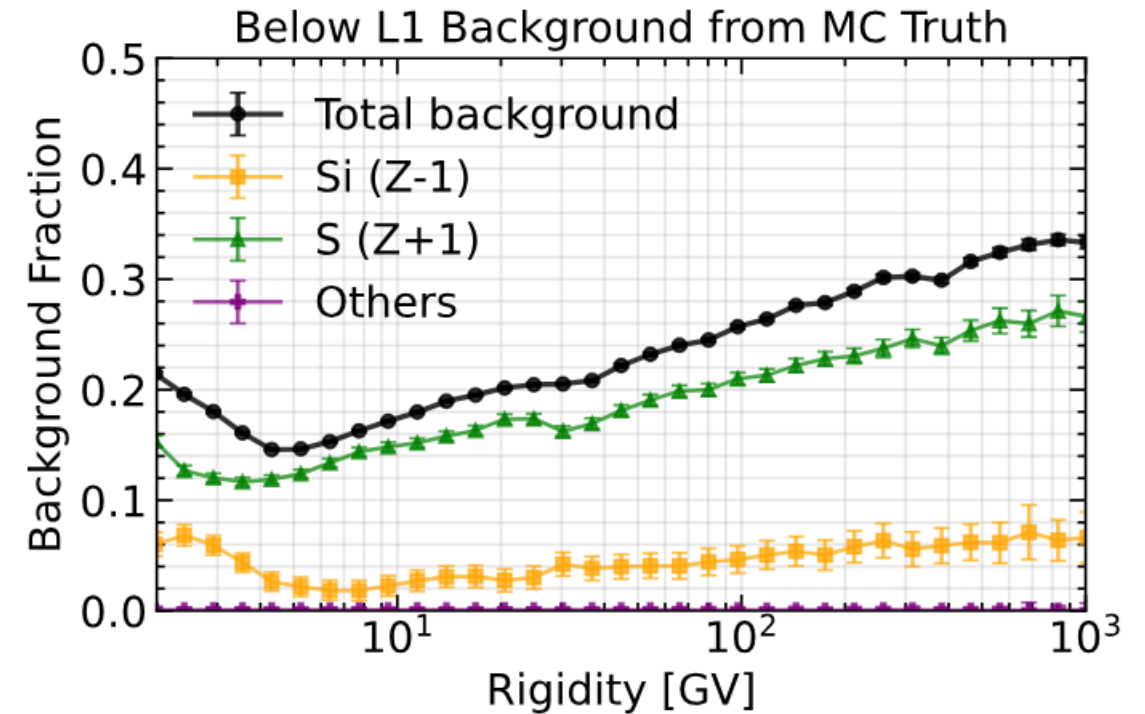
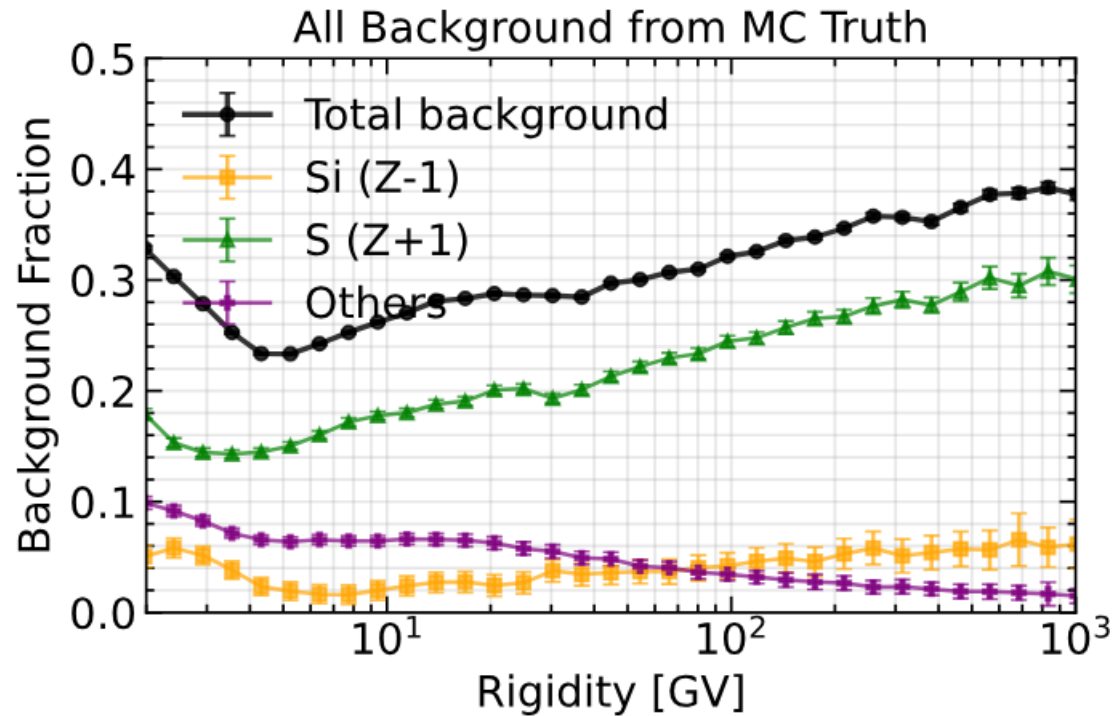
MC L1 Q  
distribution:  
**Before and after  
ML identification**



# P Below L1 background from **P** global MC

All events

- For  $Z > 15$ : Select events survived on L1
- Si: all events

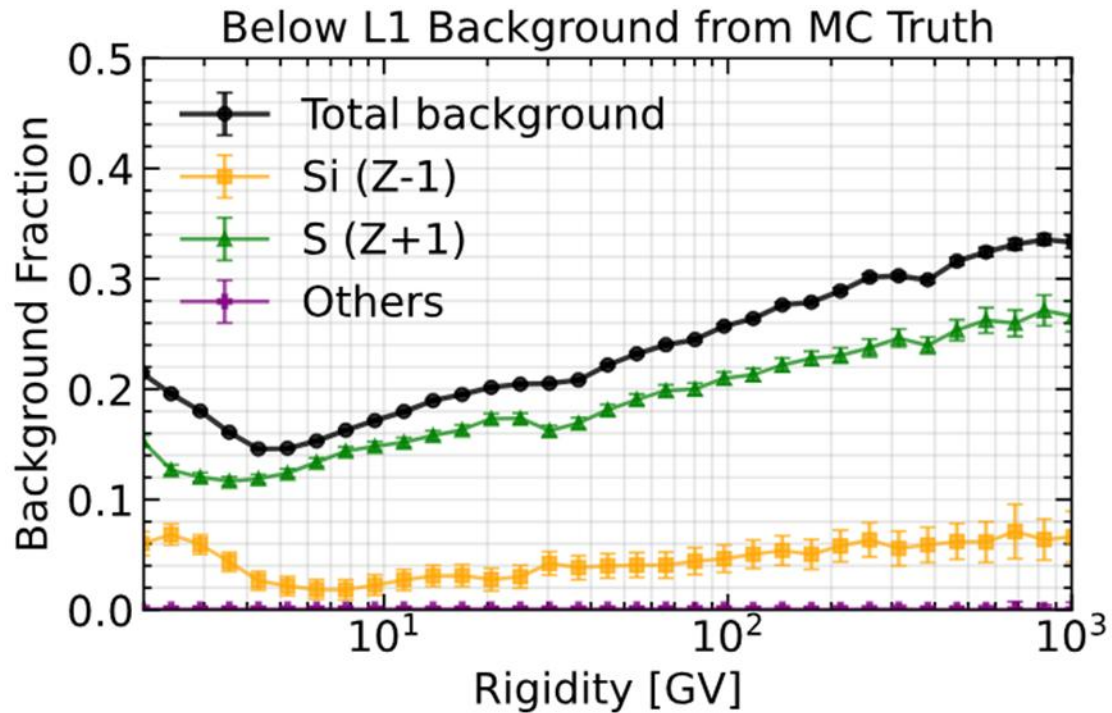


# P below L1 background: check with MC

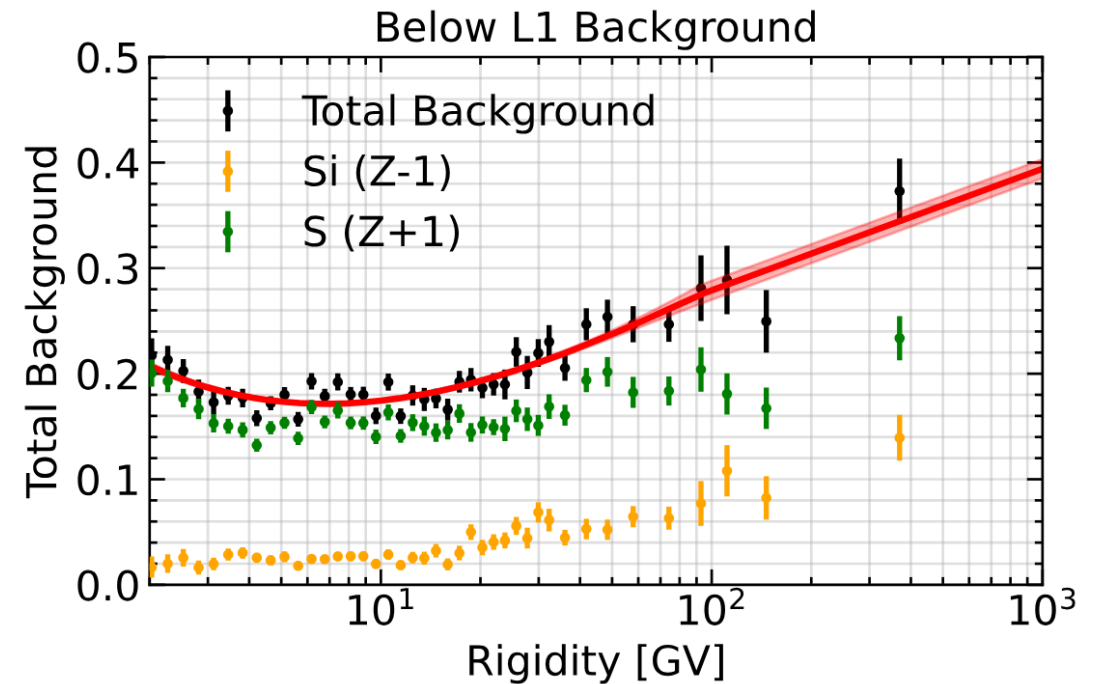
P global MC (Z=14,15,16-20, 26), event selection:

- P event selection
- For Z>15: Select events survived on L1

Background calculated from MC truth.

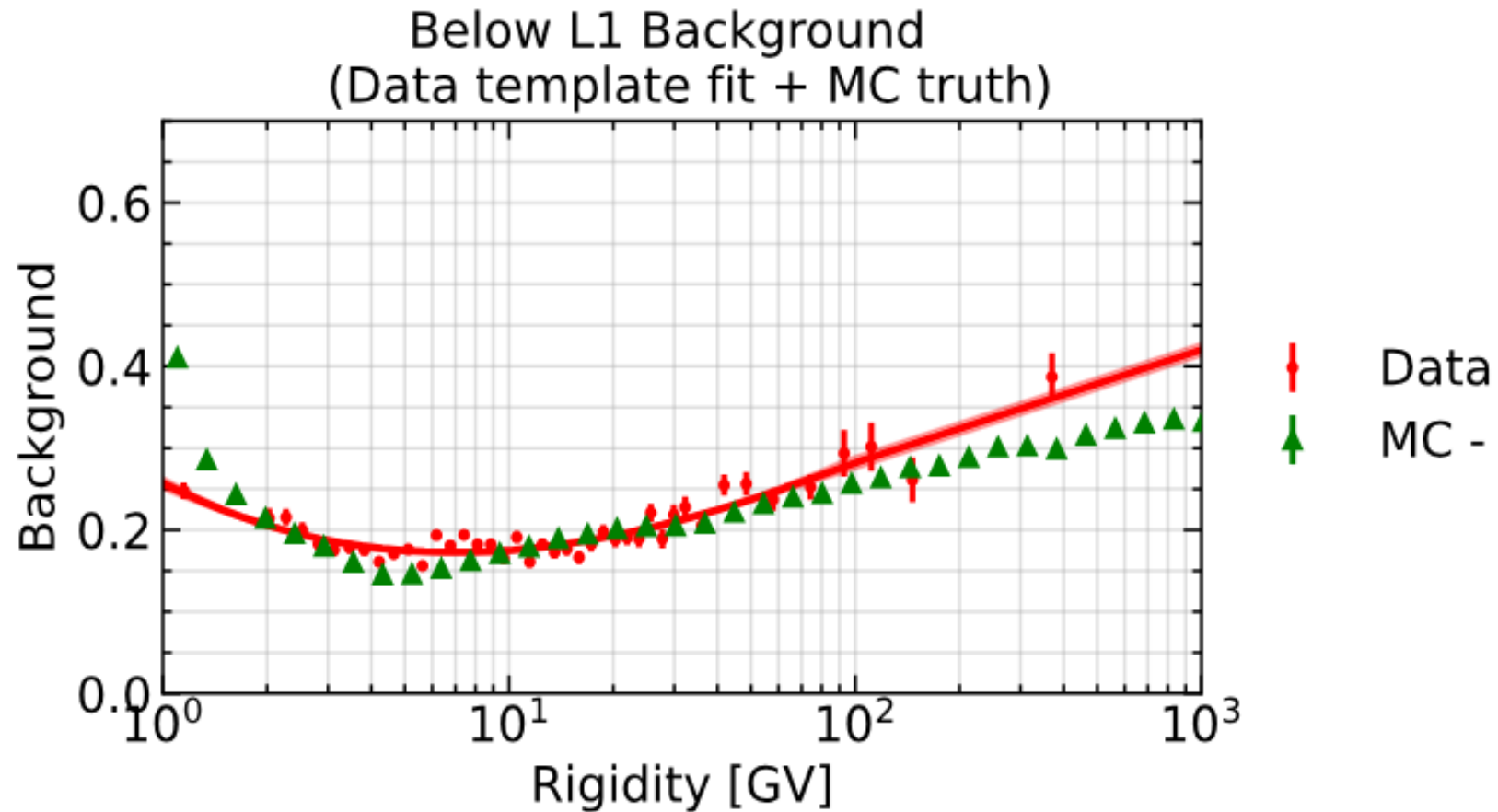


Template fit result from data:



# Below L1 background: P

Comparison between MC truth from global MC and template fit result from Data:



On-going: apply MDA model to data, to compare with MC