ME0 Segment Reconstruction using Deep Leaning

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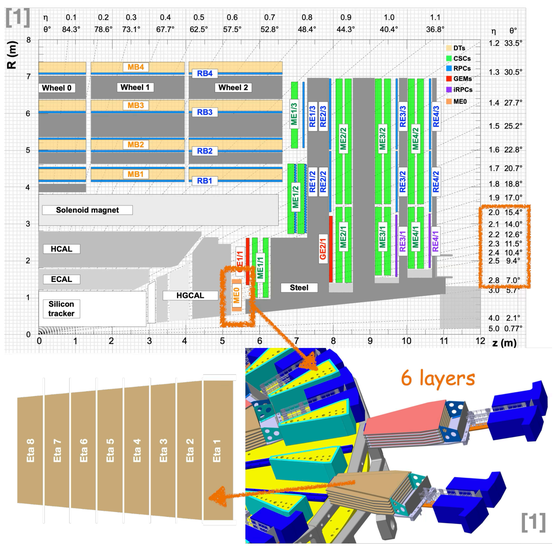
Motivation and Goal

- **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**
  - Investigates the use of **deep learning techniques to improve local muon reconstruction** within the ME0 detector
  - We aim to **enhance reconstruction accuracy and efficiency** in the face of **high background particle rates**

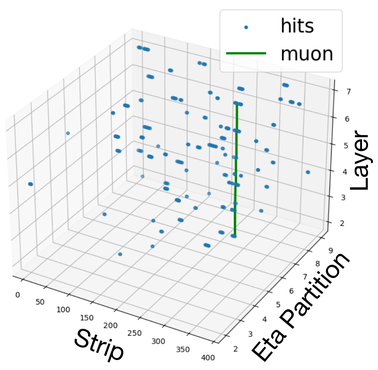
	LHC		HL-LHC	
	Nominal	Run3	Run 4	Run 5
Inst. lumi. [Hz/nb]	10	20	50	75
Average pileup	20	50-60	150	200

ME0 Station

- Based on Gas Electron Multiplier (GEM) technology, a forthcoming component of the CMS experiment
- High pseudorapidity coverage
  $(2.0 < |\eta| < 2.8)$
- Each region has 18 superchambers, each of which has 6 layers
- Every layer contains 8 eta partitions, with the largest eta partition having 374 strips and the others having 384 strips



Muon Local Reconstruction



When a muon passes through the multi-layer detector, it leaves **a track inside the detector, which is called a segment.**

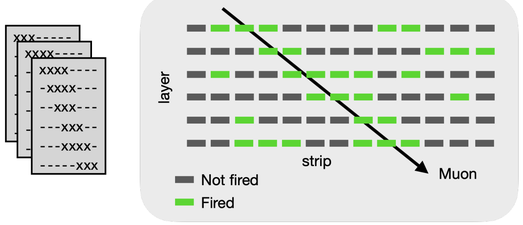
The muon local reconstruction process builds segments, which are used as input for the seed/track reconstruction.

There are two ways to build segments. The pattern matching is **used in hardware based L1 trigger.** The Road Usage algorithm[2] is for **offline reconstruction.**

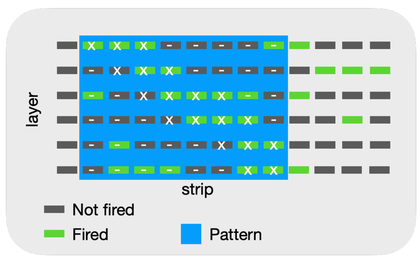
Baseline

Pattern Matching

1. Scan with predefined patterns

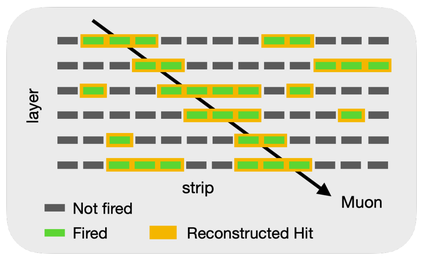


2. Select segments that match the pattern

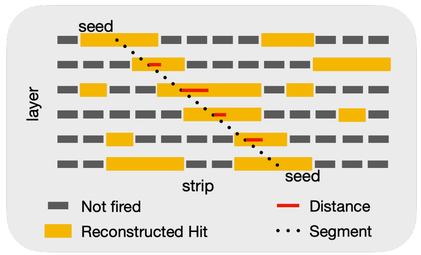


Road Usage Algorithm

1. Hit reconstruction



2. Linear fitting after seed pair selection

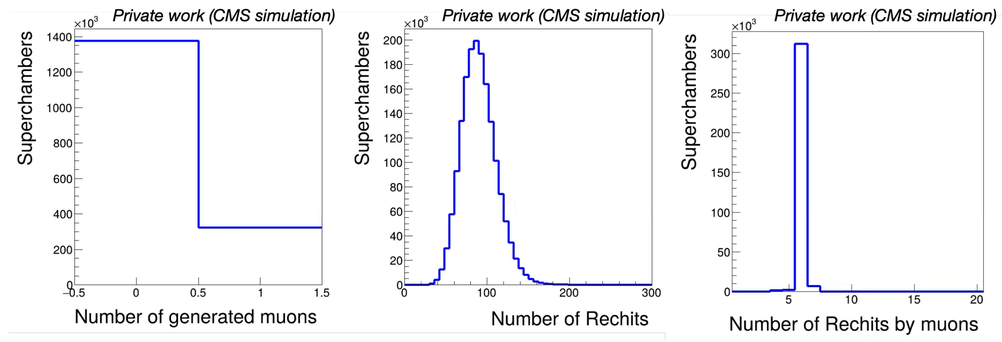


3. Select segment with minimum chi-squared

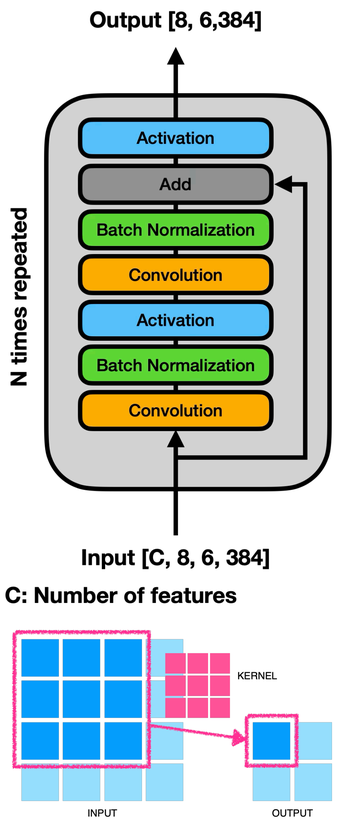
[1] CMS Collaboration, The Phase-2 Upgrade of the CMS Muon Detectors. 9 2017.
[2] CMS Collaboration, Local reconstruction algorithms in the cathode strip chambers of CMS. Technical report, CERN, Geneva, 2019

Dataset

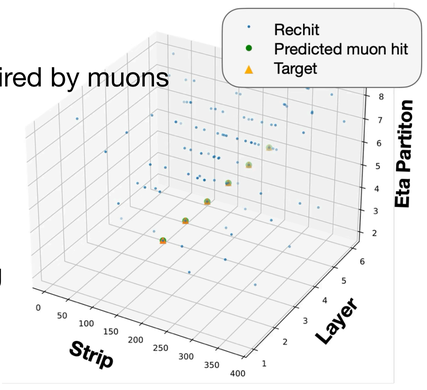
- **Muon gun simulation**
  - Number of generated events: 50k
  - Eight muons per event
    - $10 < p_T < 50$ [GeV]
    - $2.0 < |\eta| < 2.8$
  - The average pileup of 200
- **Data processing**
  - Select superchambers with one or no muons
  - Using Rechit



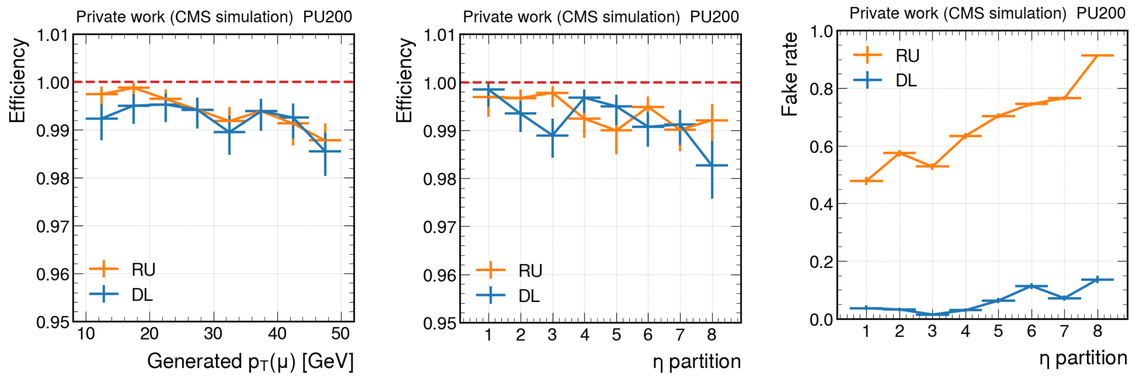
Deep Learning based Reconstruction



- **Data**
  - The input and output are 3-dim images with the same shape as superchamber's geometry
  - Input features:
    - fired or not / bx / cluster size
  - Target:
    - whether each rechit is a muon hit or not
- **Model Architecture**
  - Based on convolution neural network (CNN)
  - Residual connection
- **Training**
  - Loss: Cross Entropy
  - Positive weight on hits fired by muons
  - Optimizer: AdamW
- **Postprocessing**
  - predicted muon hits are reconstructed into one or more segments using a simple clustering algorithm



Results



	Deep Learning (DL)	Road Usage (RU)
Efficiency	0.9922	0.9939
Fake rate	0.0620	0.7373

- **Muon-segment matching criteria**
  - At least 4 layers have muon hits
  - $\frac{\text{number of correct hits in a segment}}{\text{number of hits in a segment}} \geq 0.6$
- **Definition**
  - Efficiency $= \frac{\text{number of matched segments}}{\text{number of generated muons}}$
  - Fake rate $= \frac{\text{number of unmatched segments}}{\text{number of reconstructed segments}}$

Summary and Plan

- We have developed deep learning based muon local reconstruction method
- The deep learning based method **significantly reduces fake rate** compare to Road Usage, while showing **comparable efficiency** in high-pileup environments
- We're planning to add a head to an existing model, using it as the backbone, to replace the role of postprocessing

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