Auto DQM in GEM detector

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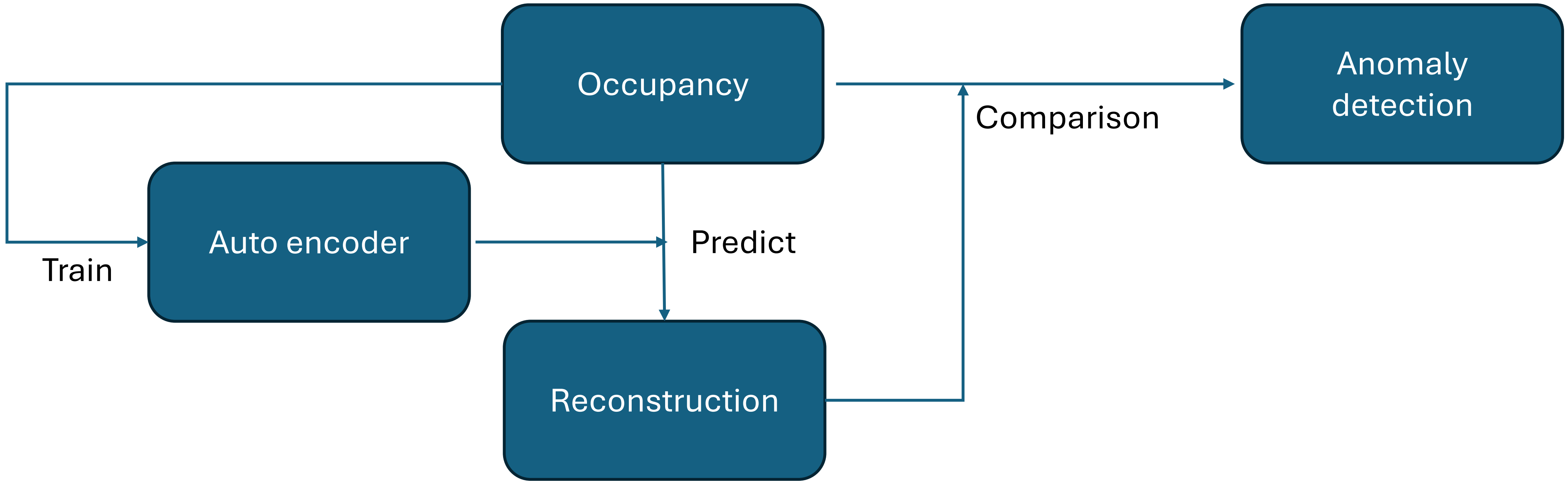
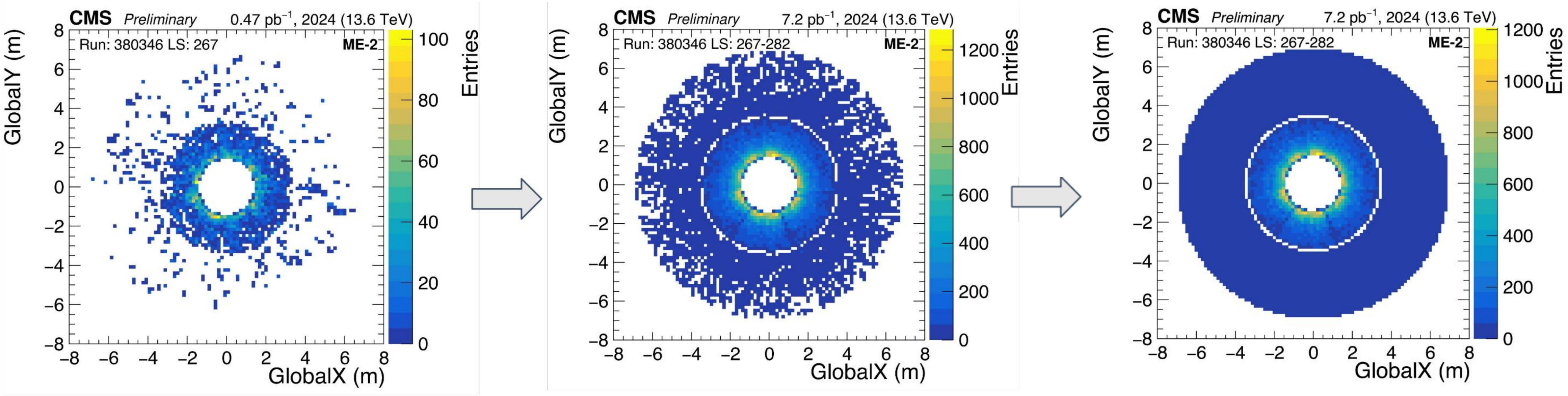
Task overview

- This study aims at train an AutoDQM program for the GEM detector anomaly detection.
- The tool need to observe the offline GEM detector monitoring elements, using a trained auto encoder to reconstruct the occupancy image, and via comparison to the original occupancy image reporting the anomaly.



Review of AutoDQM in CSC

- This idea comes from the CSC AutoDQM project https://cds.cern.ch/record/2916189/files/DP2024_095.pdf
- The GEM AutoDQM task starts from the CSC code https://github.com/Ma128-bit/ML4DQM.
- The CSC data processing of stacking the lumi sections to receive enough occupancy, and smear the images in ϕ direction are also referred to.



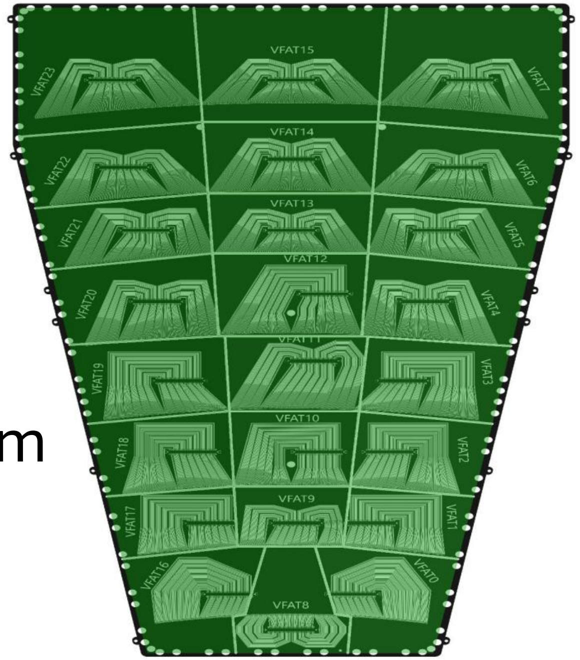
Plots from https://cds.cern.ch/record/2916189/files/DP2024_095.pdf

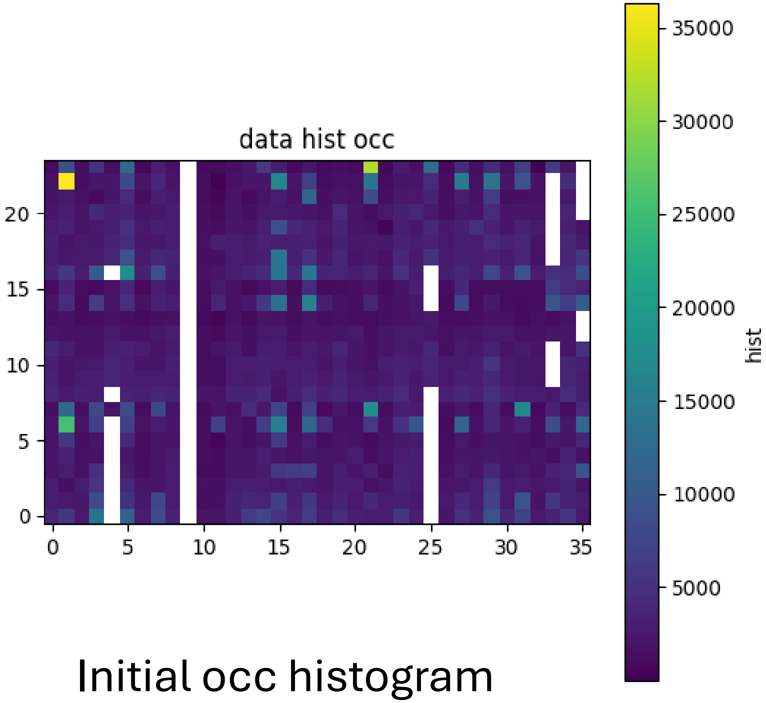
Dataset for GEM AutoDQM

- Using the Run2025C monitoring elements dataset
- ME of interests:
  - `GEM/Digis/occ_GE11-M-L1`
  - `GEM/Digis/occ_GE11-M-L2`
  - `GEM/Digis/occ_GE11-P-L1`
  - `GEM/Digis/occ_GE11-P-L2`
  - Downloaded from `/StreamExpress/Run2025C-Express-v1/DQMIO` on dial.
- Run2025C selection
  - Starting from Run 392174.
  - Currently the study uses Run number up to 392542 (will increase as accumulating on dial).
  - Require Collision25 run without GEM standby/bad/empty.
- The demonstrated train in these slides based on `GEM/Digis/occ_GE11-P-L1`.

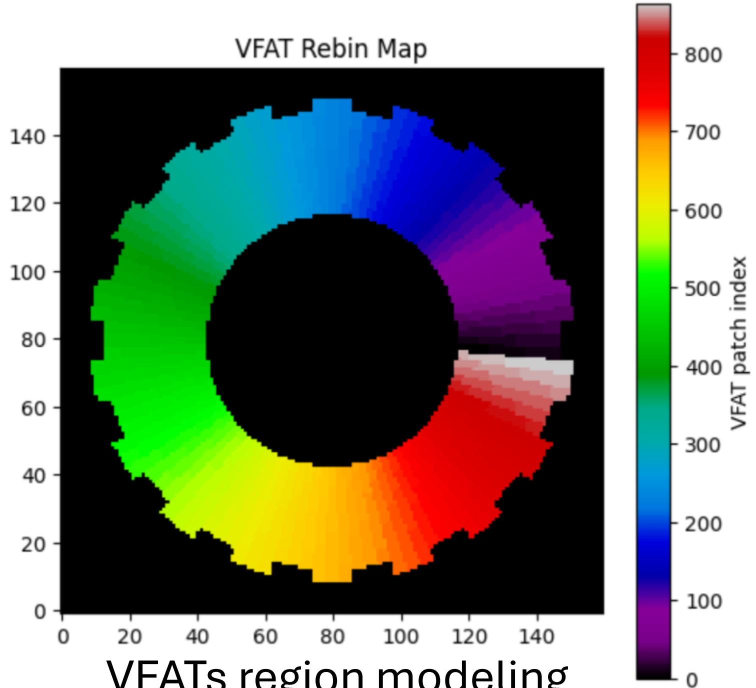
Image converting

- The initial occupancy is recorded in 24*36 histograms, 24 for VFATs in a chamber, 36 for 36 chambers.
- Converting to 160*160 pixels image for x and y both in [-280, 280] cm ranges.
- Assigning the pixels with VFAT-wise occupancy mean value.

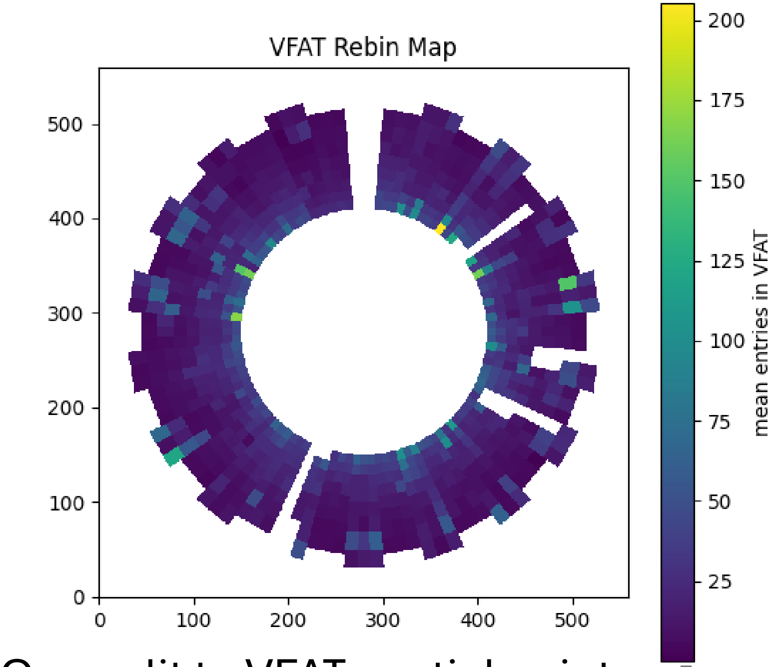




Initial occ histogram

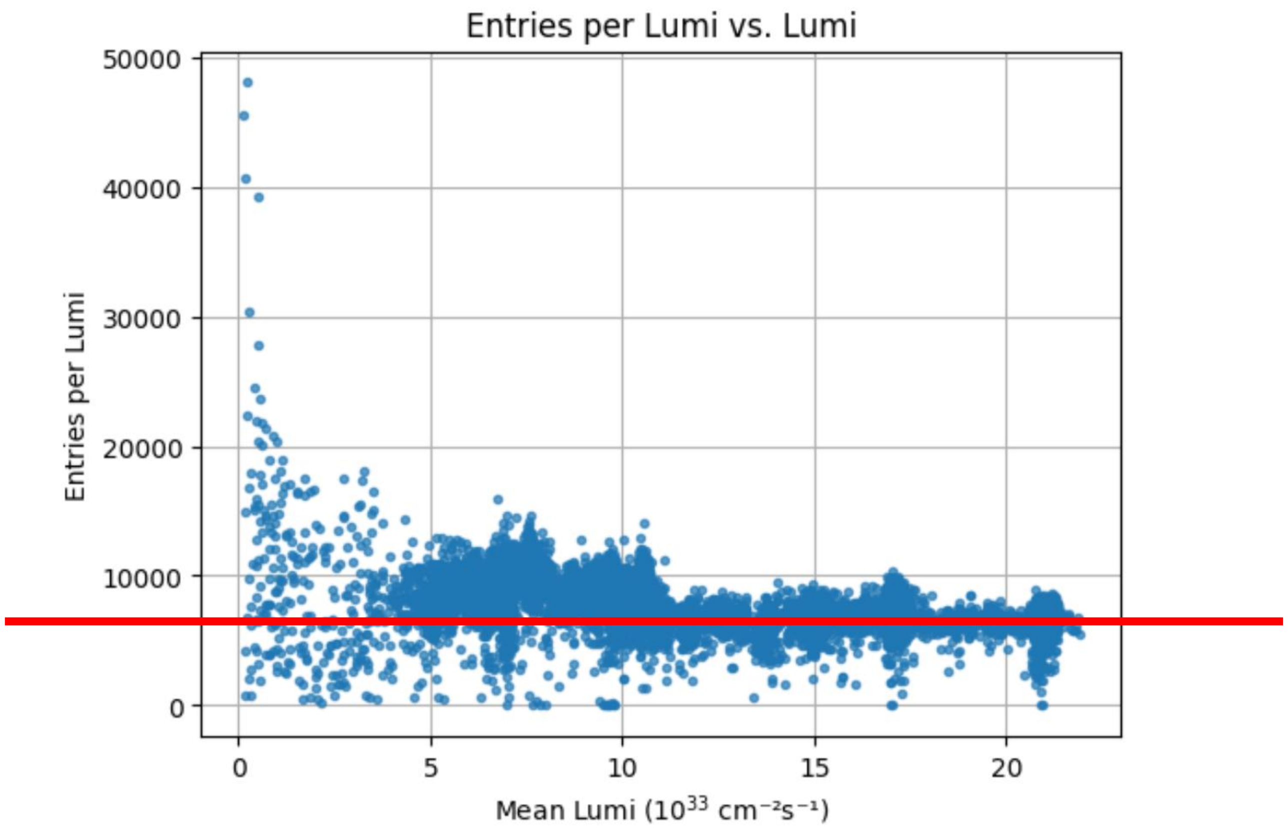


VFATs region modeling



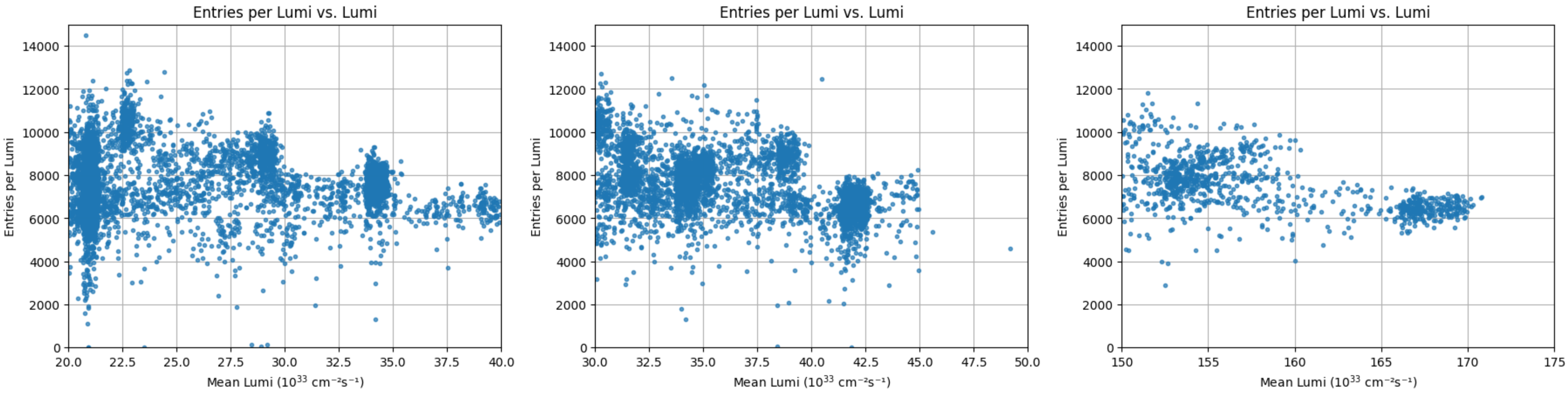
Occ split to VFAT spatial points

Entries and instataneous luminosity in lumi sections



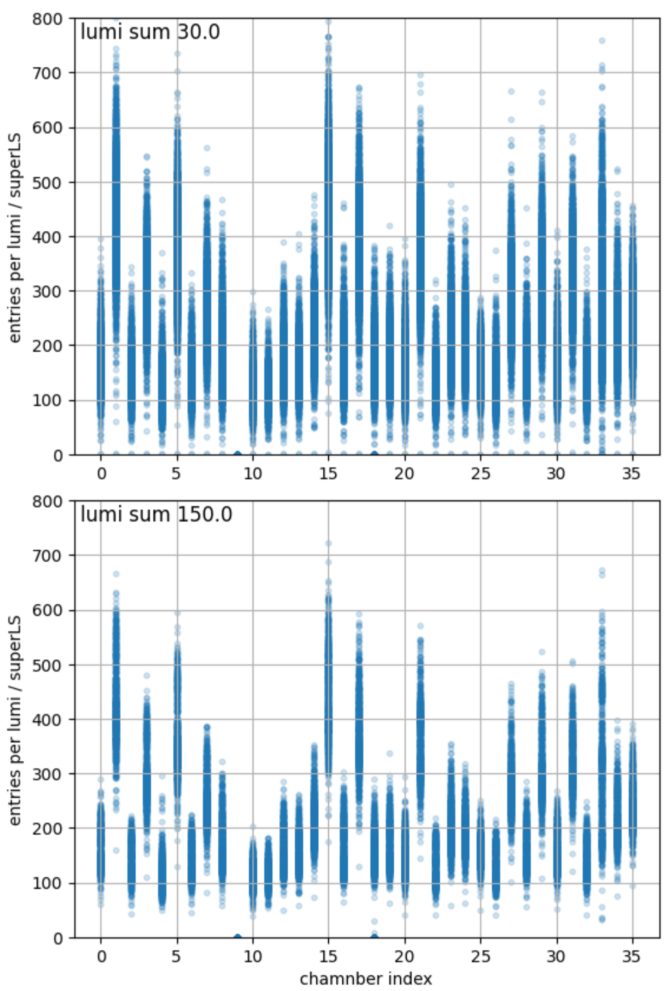
- Mean lumi = (init lumi+end lumi)/2
- The total entries in one lumi section over the mean lumi in $10^{33}\mathrm{cm}^{-2}\mathrm{s}^{-1}$ should be around a constant.
- It has median around 7000 and most lumi sections around 7000.
- The lumi-sections with too low mean lumi (<0.1) is exclude.
- The lumi sections can be merged to get more stable entries per lumi.

Lumi section merging

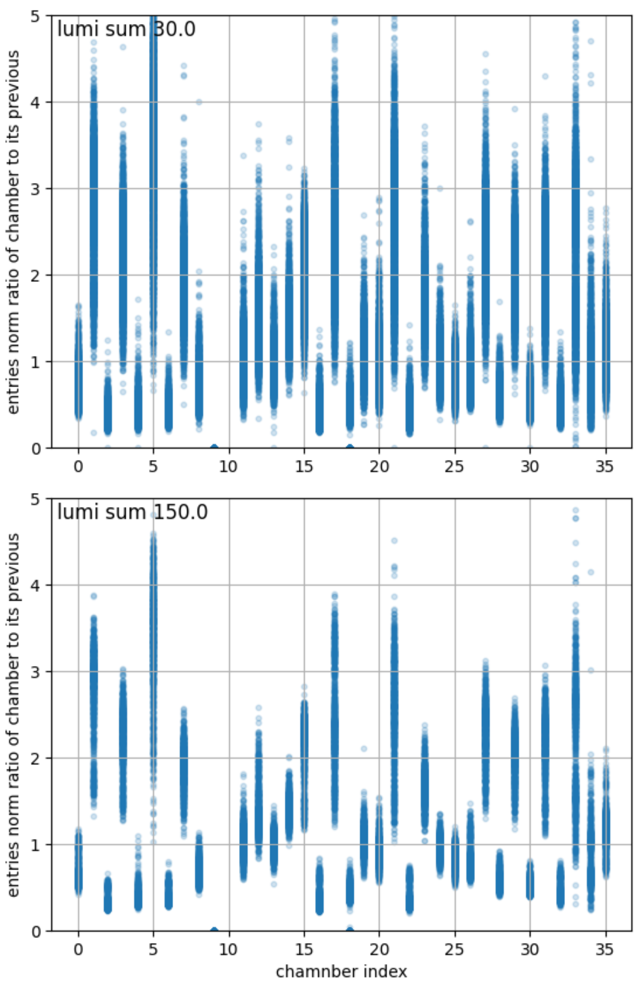


- Lumi sections stacked into superLS up to $\sum \text{mean lumi} = 20{,}30{,}150\ 10^{33}\text{cm}^{-2}\text{s}^{-1}$.
- The higher merging, the superLS has more concentrated entries per lumi. This reduce the difficulties in training due to changed.
- In this study, $\sum \text{mean lumi} = 150\ 10^{33}\text{cm}^{-2}\text{s}^{-1}$ is tested to be a suitable value for training.

Lumi section merging



- Entries per lumi in each chamber varies.
- Merge lumi sections will also decrease the range for each chamber, and make the variation more clear for the model to learn.
- Again, merge up to $\sum \text{mean lumi} = 150\ 10^{33}\text{cm}^{-2}\text{s}^{-1}$ in this study can have a clear enough variation.



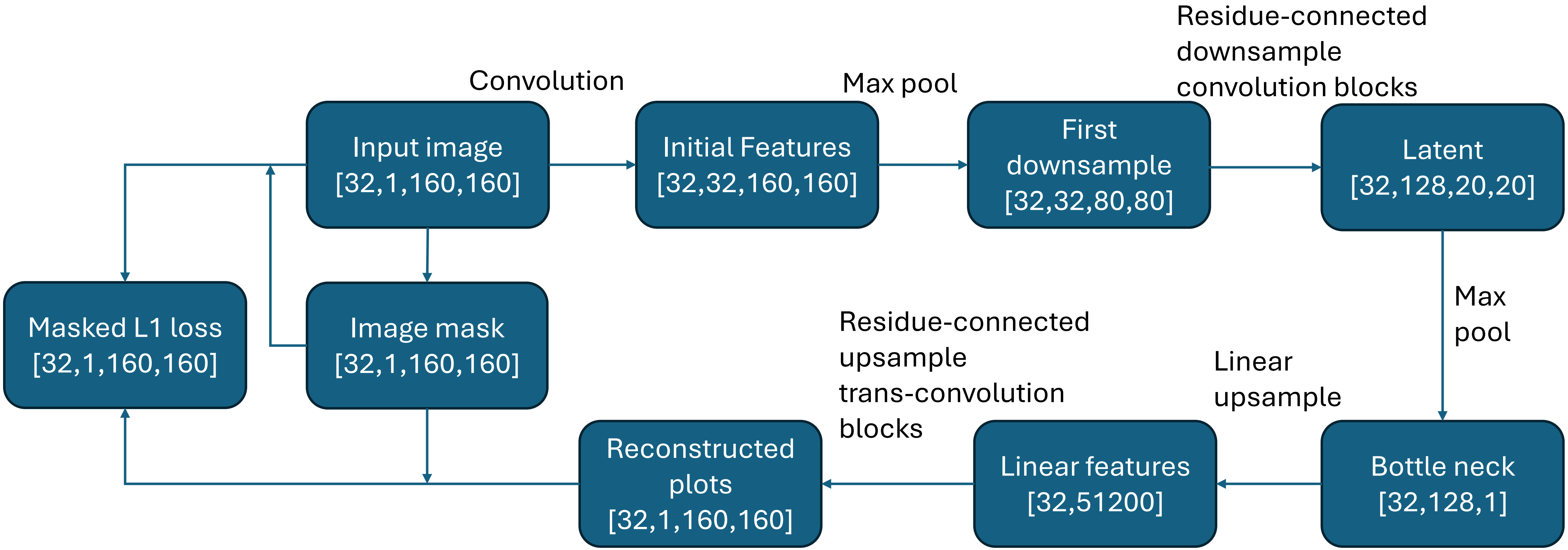
- The relative relation of adjacent chambers would carry information need for image reco.
- The ratio of a chamber's entries to its previous chamber's with 30 and 150 mean lumi sum is demonstrated.

Dataset spliting

- The data are separated based on its anomaly regions.
- The rare anomaly (<10%) are excluded from the dataset.
- The chamber which is off with >10% rate is kept for training, labeling as large off datasets.
- Both images with only common region off and with large ratio off are split into train and validation dataset with 85:15 ratio.

Auto encoder structure

- Input dimension [batch_size=32, channel=1, height=160, width=160]

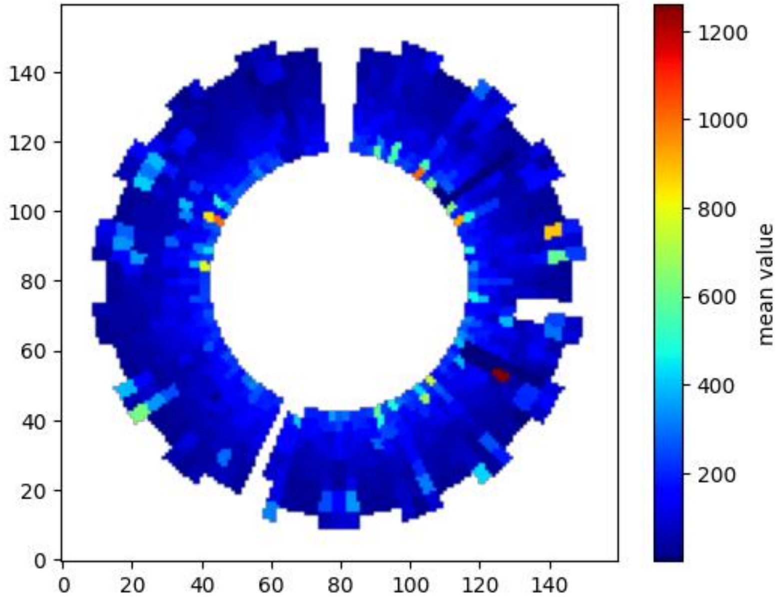


Auto encoder structure

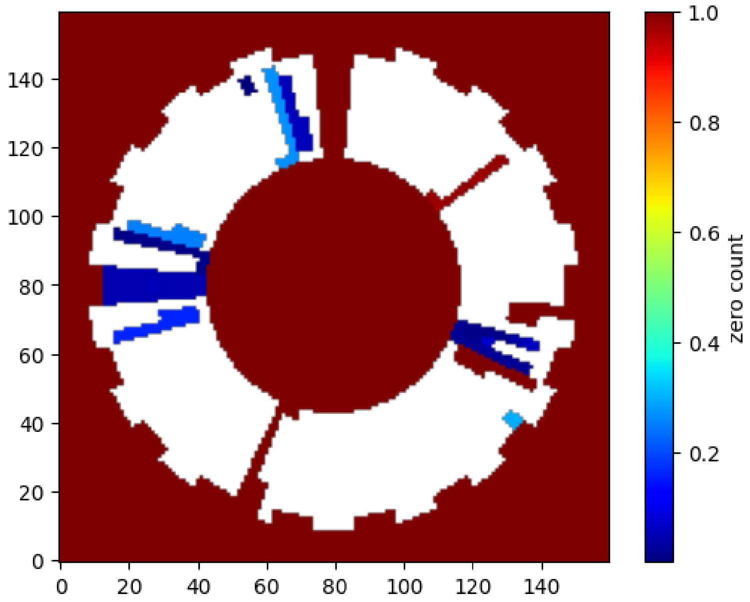
- Encoder
  - Initial feature extraction: Conv2d layer with kernel_size=3, activation=ReLU, 32 channels.
  - 3 Encoding blocks:
    - 3 stacked residue connection blocks with 2 Conv2d layers
    - Down sampling and doubled features residue block with 3 Conv2d layers
  - Compress latent space to 128-dimensional bottleneck
- Decoder
  - Linear layer upsampling to 51200-dimensional linear features.
  - 3 Decoding blocks:
    - 3 stacked residue connection blocks with 2 ConvTranspose2d layers
    - Up sampling and reduce features residue block with 3 ConvTranspose2d layers.
  - Merge features using activation=ReLU.

Anomaly masking

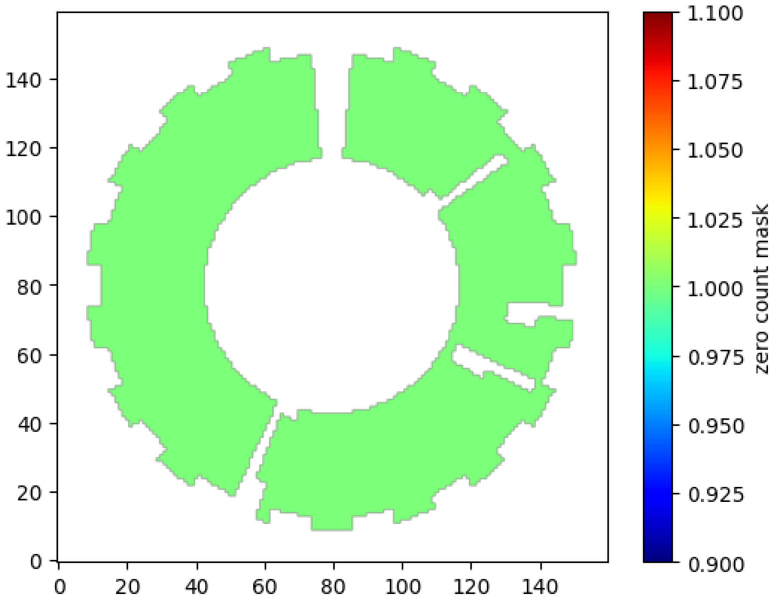
- The input figures contains anomaly regions, in such region, the auto-encoder should not learn the corresponding features.
- There are regions not considered as anomaly but mostly 0, should learn
  - Outside the detector
  - Always fail regions



Mean image
Some regions always fail



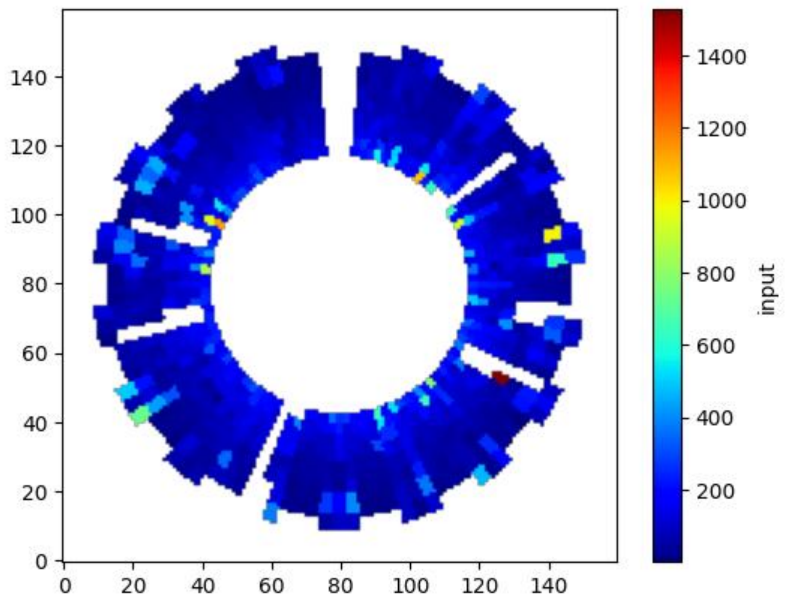
Failure rate of regions
Some regions almost fail



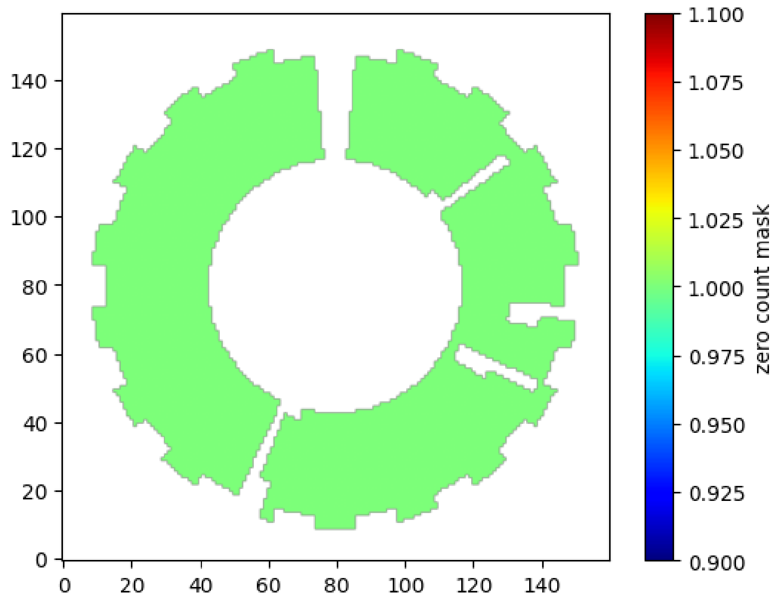
Mask exclusion
>90% rate fails

Anomaly masking

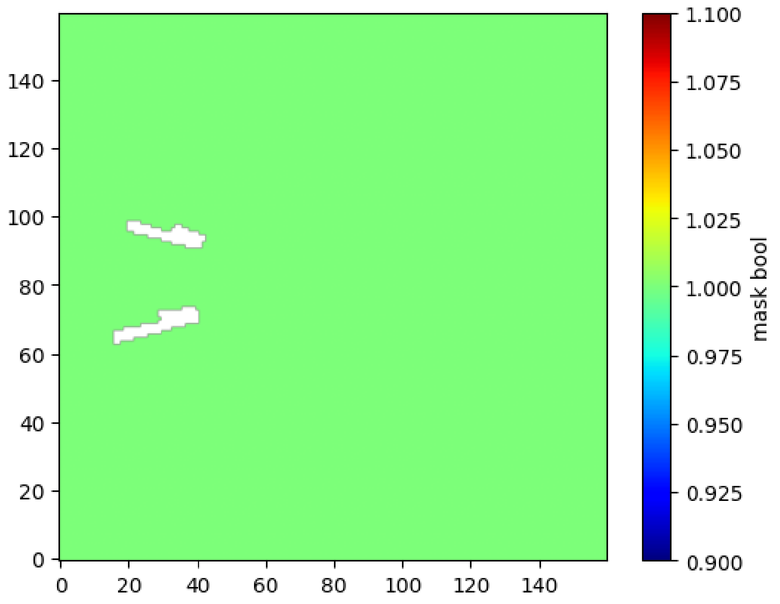
- The example of one image mask creation.
  - The not almost fail region is an anomaly.
  - The anomaly feature should be excluded from learning.
  - Mask created combine the image input and mask exclusion.



One image input



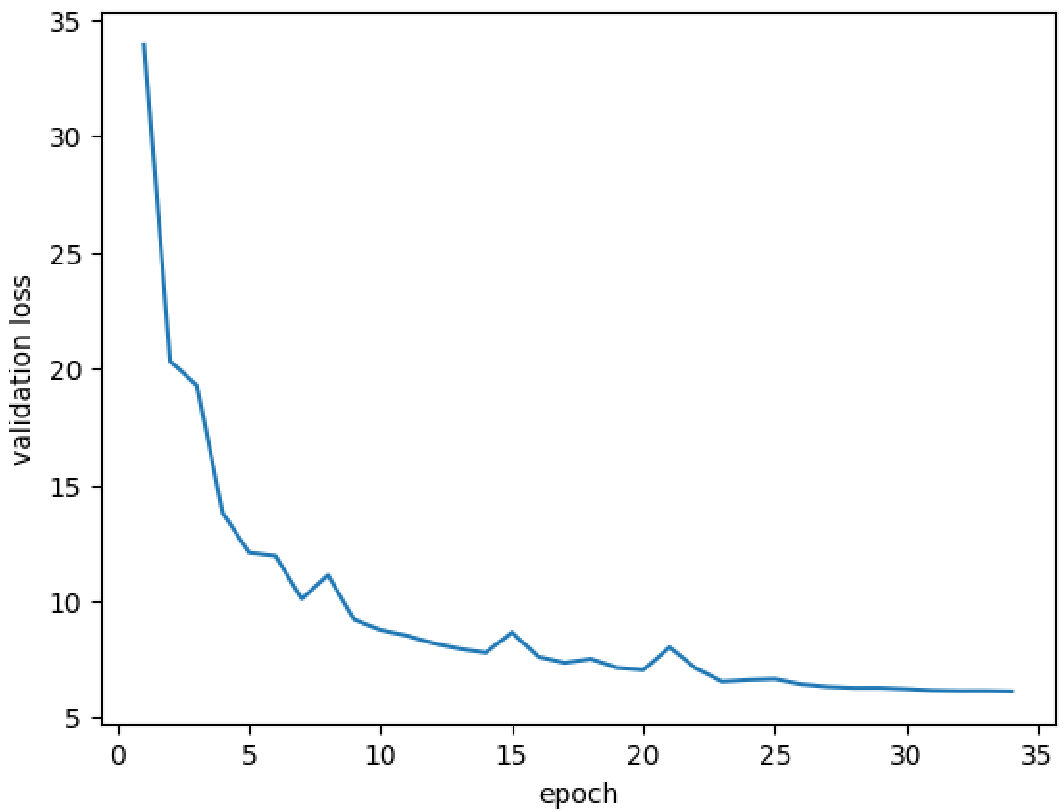
Mask exclusion
From global behavior

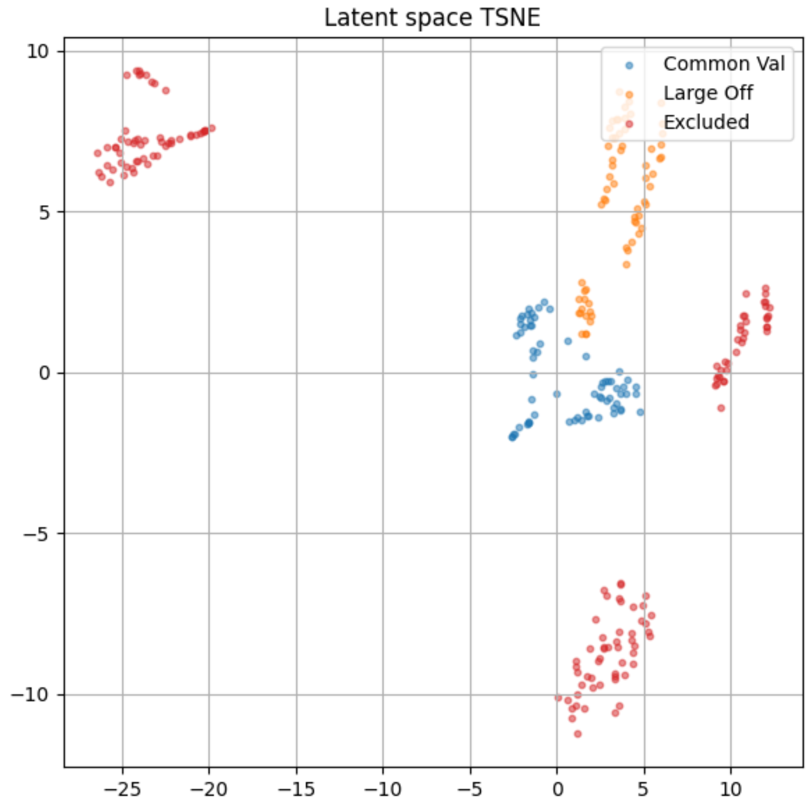


Mask for corresponding image

Training performance

- L1 loss in validation dataset decrease to saturation with epochs.
- The latent space visualization using TSNE method.
    - Good identification of anomaly for the excluded batches.
    - Large off batches chamber 11 and chamber 16 also separated.

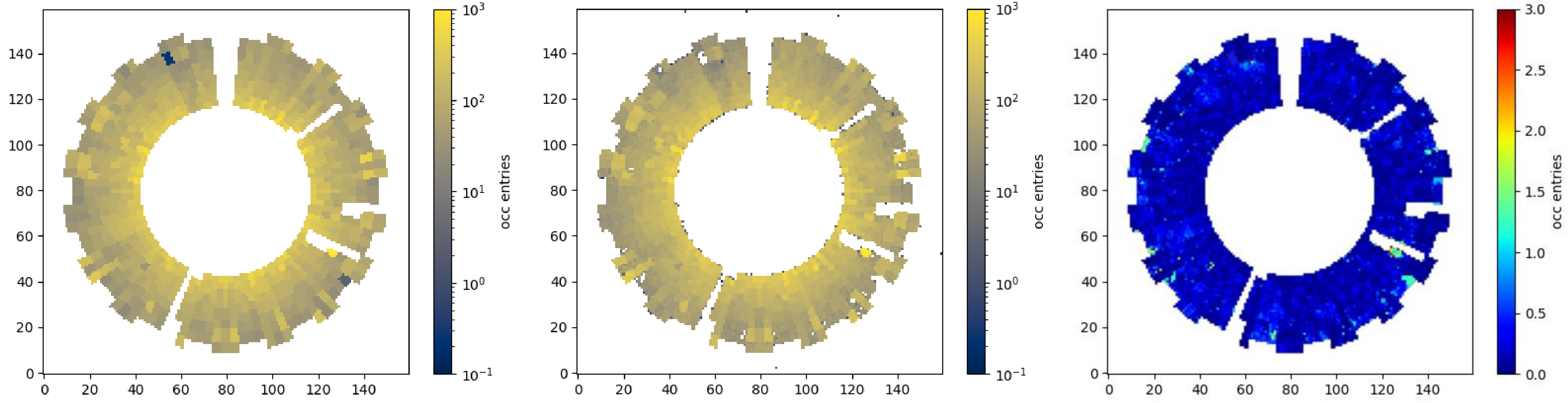




Good image reconstruction

- The model is trained to well-reconstructing the occupancy without anomaly.
- The relative difference is characterized by L1 norm loss over the mean plot for LSs where the region is on rescaled to the image normalization.

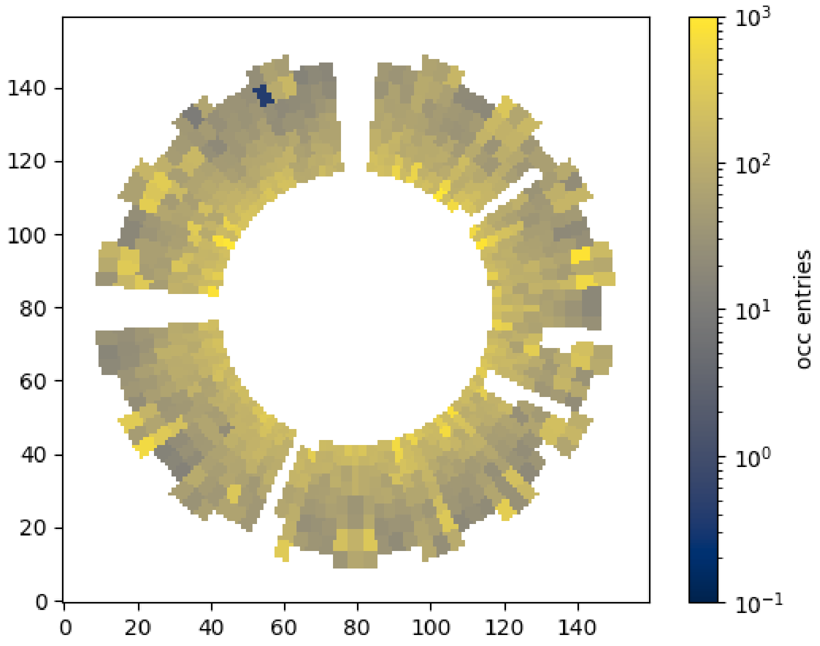
$$\mathrm{diff} = \frac{|\text{reco plot} - \text{input plot}|}{\text{mean plot(region occ>0)} \times \frac{\text{LS total entry}}{\text{mean total entry}}}$$



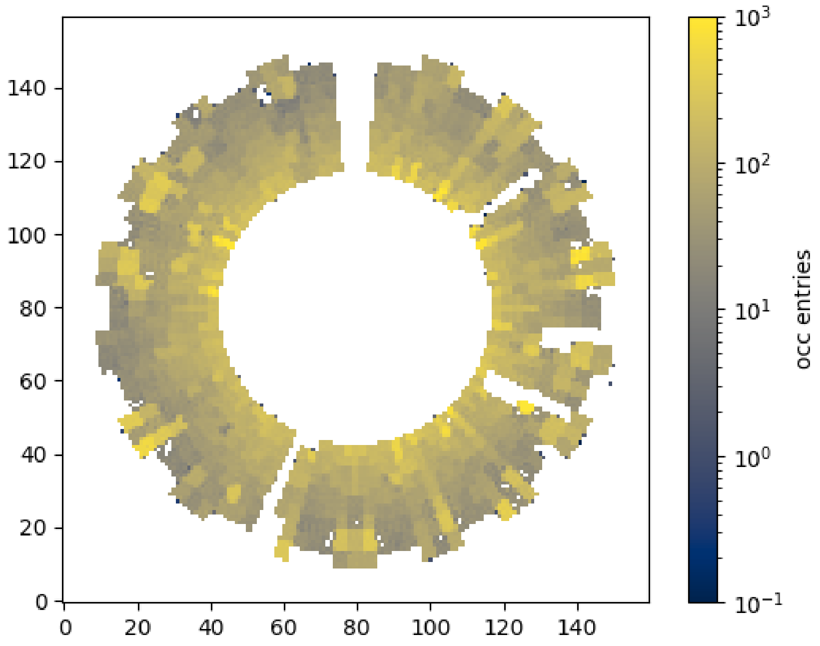
Input occ   Reco occ   Relative difference

Anomaly detection

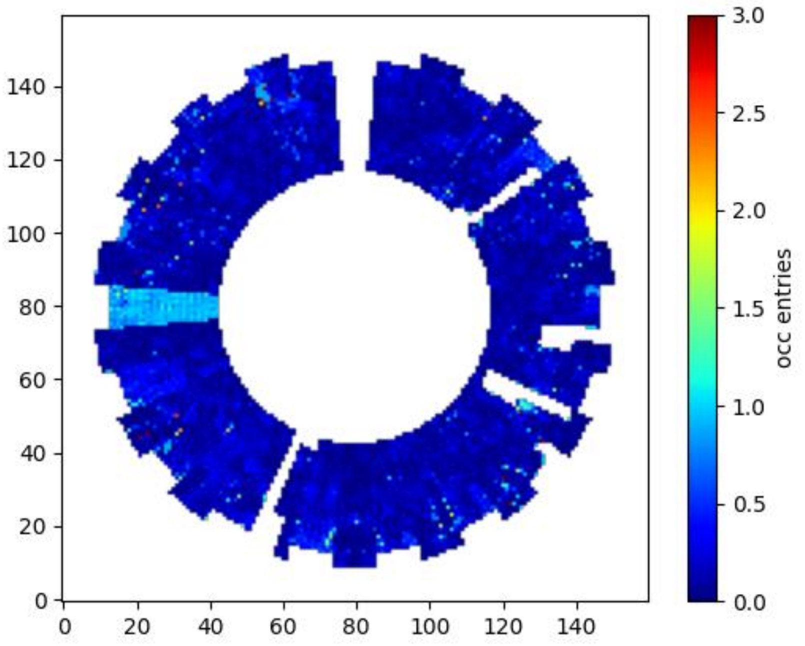
- For the input with anomaly, the reconstructed plot will not have the corresponding anomaly. The auto encoder learnt to reconstruct the chamber from good input.
- The anomaly can be detected with high light stripes on the relative difference plot.



Input occ



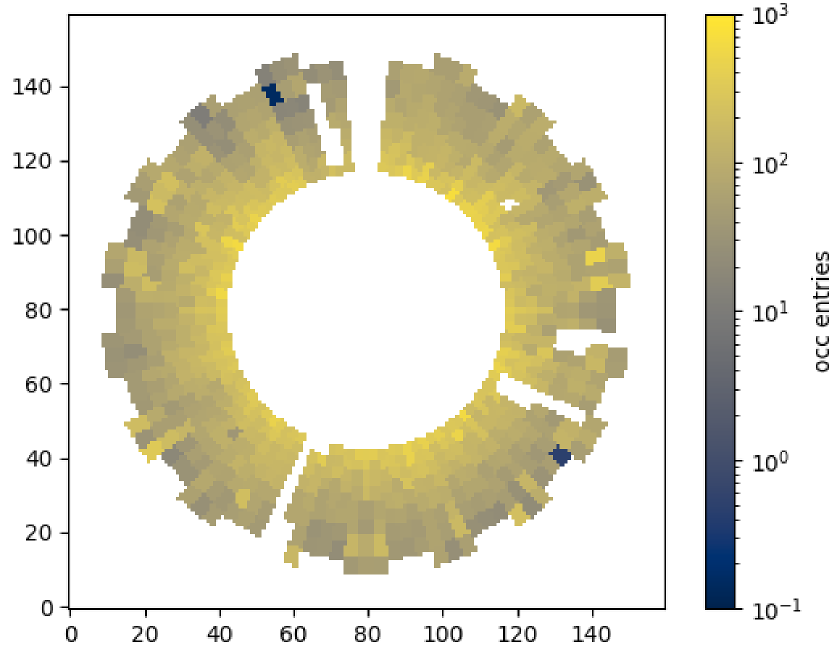
Reco occ



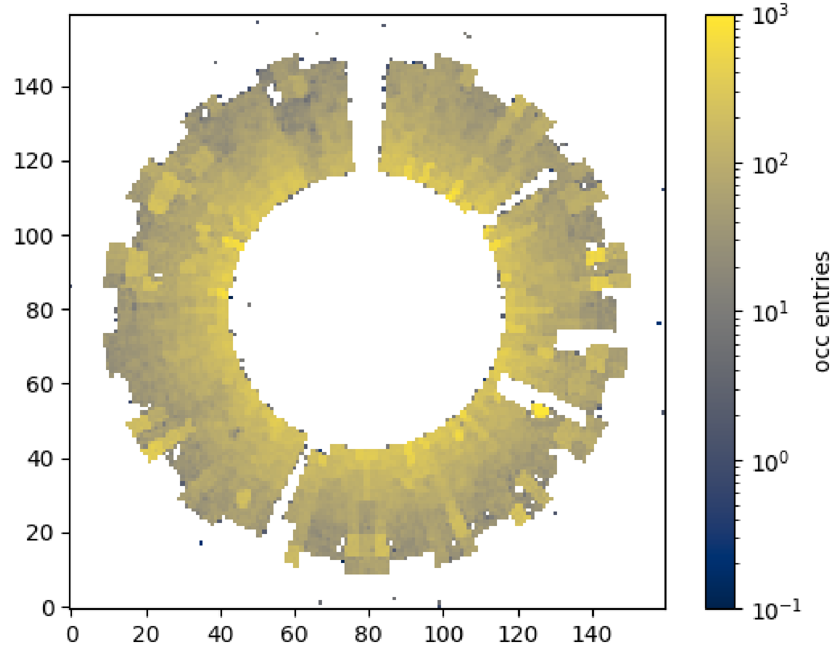
Relative difference

Anomaly mis-detection

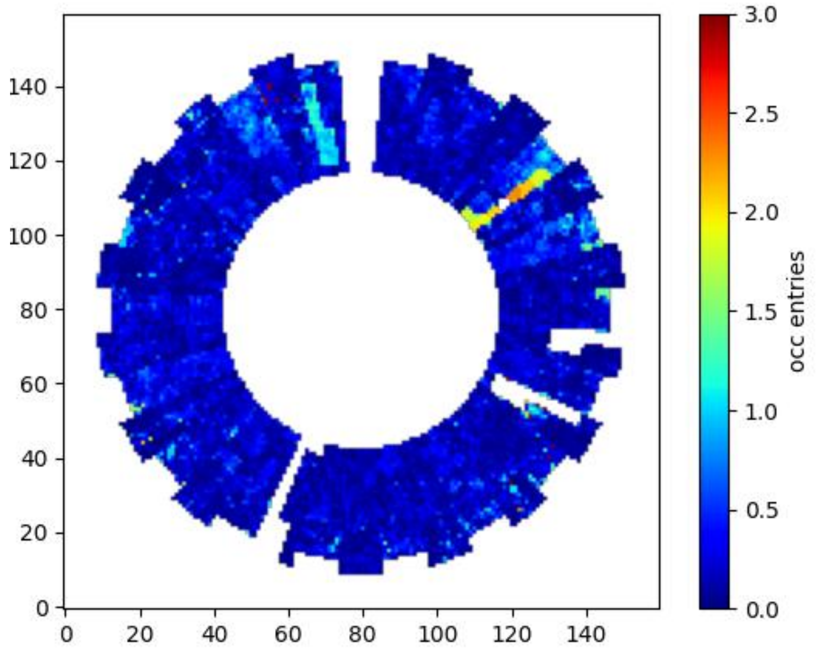
- For the region that is usually (>90%) off in the input, the model would tends to learn the values shall be 0.
- Then for the rare case it works, this would be inversely identified as an anomaly. This seems to be a common feature for auto-encoder.



Input occ



Reco occ



Relative difference

Summary

- These slides show a GEM AutoDQM training using part of Run2025C monitoring element dataset for `GEM/Digis/occ_GE11-P-L1`.
- The lumi sections are merged to reduce the random variations in the chamber occupancy to enhance the training.
- The trained auto encoder has a good reconstruction for most of the good chambers and identify the anomaly chambers well.
- The issue that on a commonly off region, a rare lumi section that has the region on, the auto encoder would mis-report the anomaly.