Anomaly detection for ECAL DQM

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for
ML4DQM team

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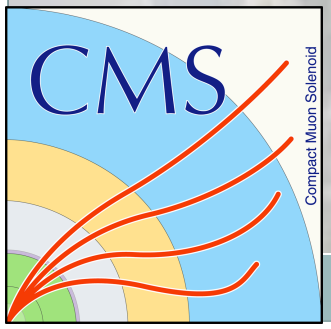


Introduction

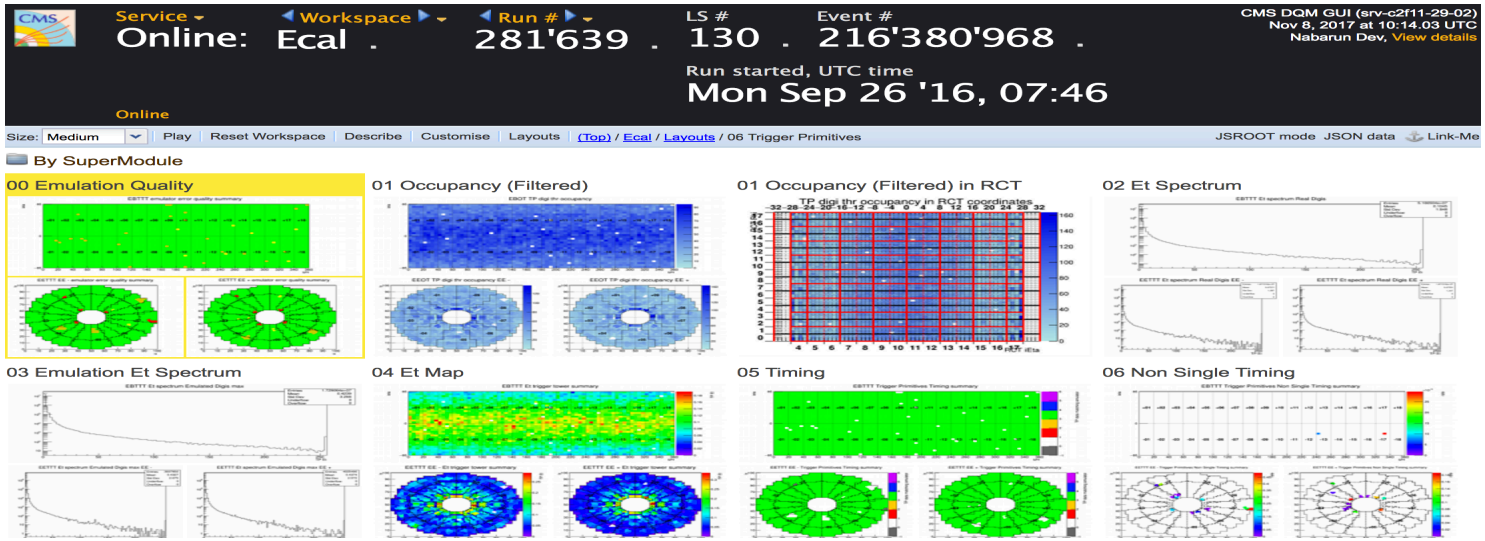
- DQM (data quality monitoring) system is an important tool to ensure high quality data-taking for analyses purposes. It is used both online and offline.

- In real time data quality is currently assessed by looking at a dashboard containing a set of histograms which are compared to a reference set of histograms according to certain set of instructions.

- By spotting **anomalies** in these images (plots/histograms) it is possible to identify problems that appear in the detector, flag poor quality data and/or take steps towards fixing these issues.

ECAL DQM

- The ECAL DQM consists of a set of several histograms that help us monitor the running condition of the ECAL subdetector. DQM GUI shown below:



- The histograms are usually redrawn every lumisection. By monitoring these the shifter is able to spot problems in real time.

Avenues of improvements

- Although the DQM system has been performing well over the years there are areas which can be potentially improved.
- The number of plots to monitor can be overwhelmingly large which can cause delay in spotting a problem or cause a transient problem to be overlooked.
- Lot of manpower is needed to constantly monitor these systems during data-taking.
- There is a possibility that the monitoring decisions can vary from shifter to shifter.

Machine Learning techniques can help reduce these issues.

Current Strategy

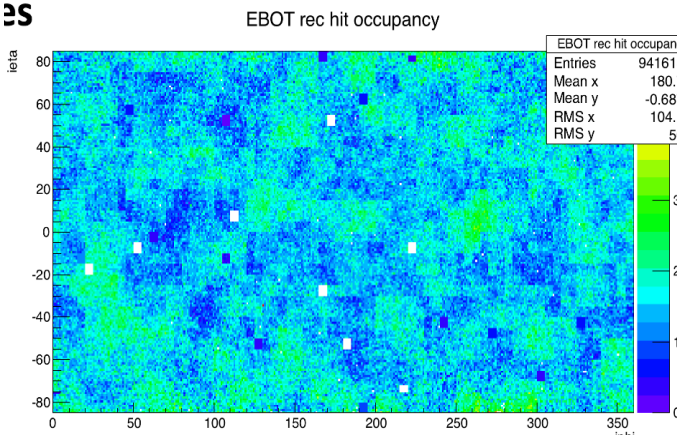
- Use only normal instances (semi-supervised learning) to train an autoencoder (input is mapped to ouput, the system learns to reconstruct the input with minimum loss) [1] to minimize the loss function.

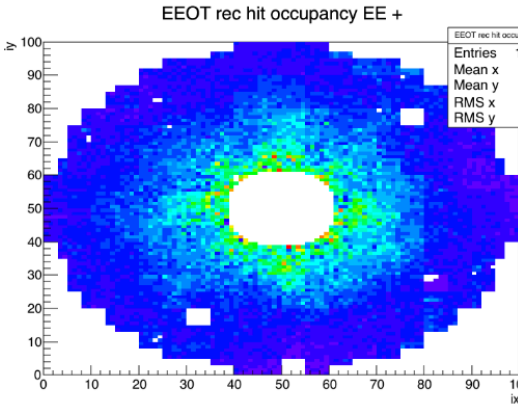
- The loss can then also serve as a discriminant:
  - Good instances should be reconstructed with low loss
  - Bad instances should be reconstructed with higher loss

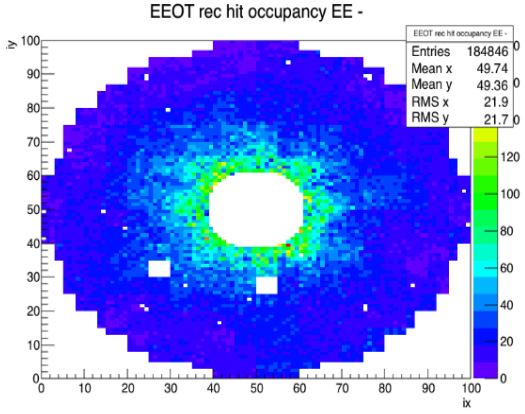
[1]:http://ufldl.stanford.edu/tutorial/unsupervised/Autoencoders/ ,
http://www.deeplearningbook.org/contents/autoencoders.html

Dataset

- Current dataset consists of ~40000 samples from 2016 data from lumisections marked as good. (2016 goldenjson , CMSSW_9_2_11)
- The dataset (SingleElectron/RAW) is processed to emulate the online DQM running conditions and produce one sample (set of images) per lumisection (40k sets of images from 2016, 70k from 2017)
- The current image set per sample consists of rechit occupancy and timing plots: one for barrel and one each for both endcaps.

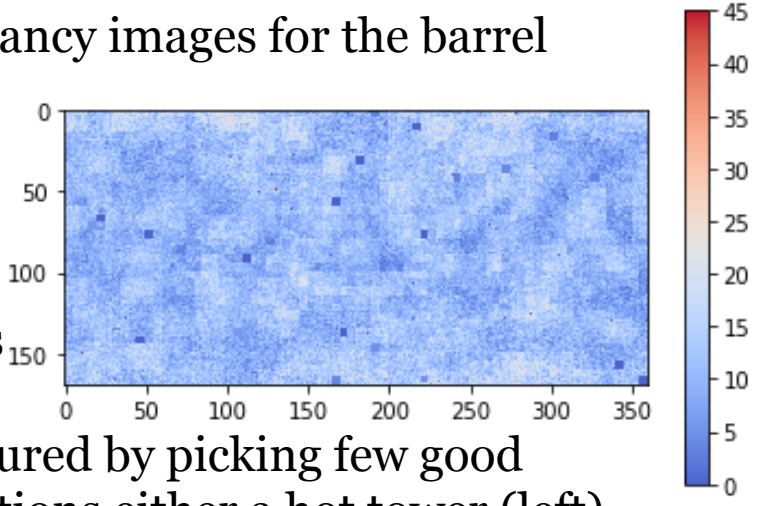






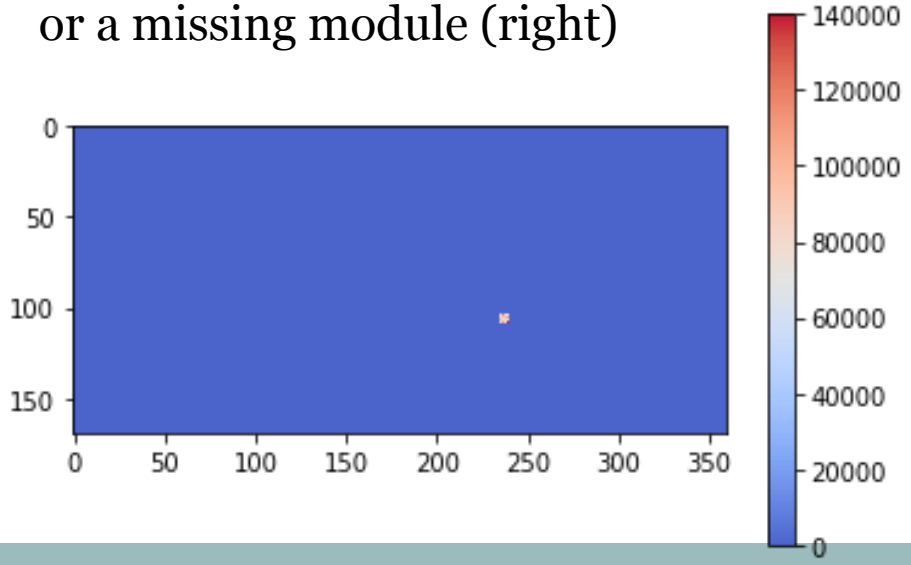
Dataset

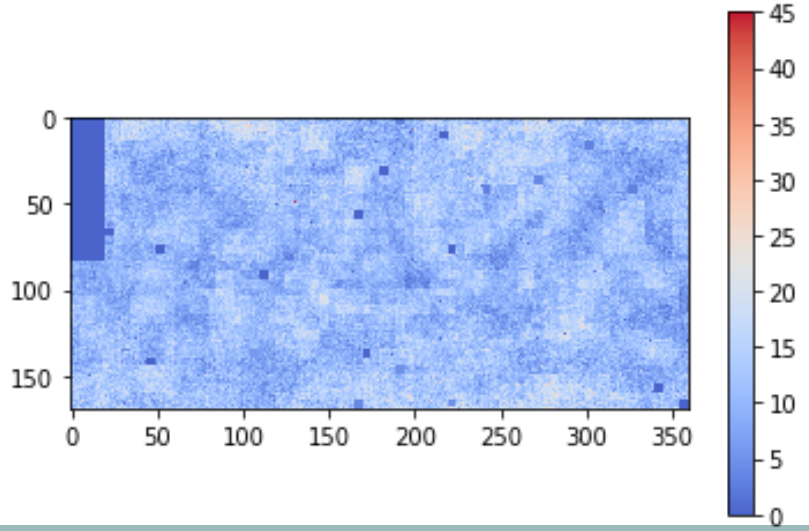
- The following study only uses the rechit occupancy images for the barrel as normal images:



- Was able to acquire very few anomalous images

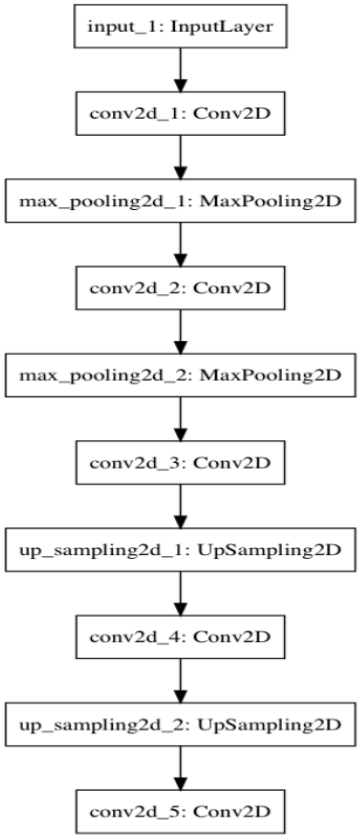
- Two types of anomalous images were manufactured by picking few good images and artificially inserting at random positions either a hot tower (left) or a missing module (right)





Architecture

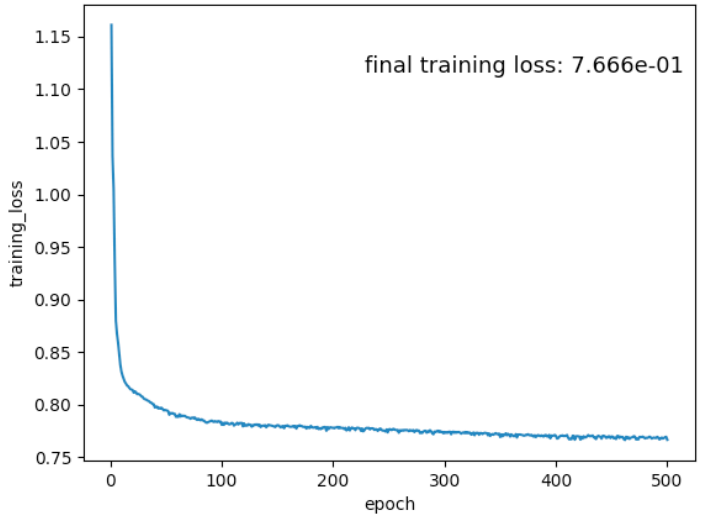
- Models with several architectures were trained
- All models so far are (plain) autoencoders with convolutional layers
- Conv2D (6 channels,(5x5) patches)→
  MaxPooling2D(5, 5)→Conv2D (6 ,(4x4))→
  MaxPooling2D(2, 2)→Conv2D (4 ,(2x2))→
  MaxPooling2D(2, 3)→Conv2D (4 ,(2x2))→
  UpSampling2D(2, 3)→Conv2D (4 ,(2x1))→
  UpSampling2D(2, 2)→Conv2D (6 ,(4x4))→
  UpSampling2D(5, 5)→Conv2D (6 ,(5x5))→
  Conv2D(1,(5x5))
- All Conv layers are 'padded' to keep size of output channels same as input.
- FrameworkUsed:
  Keras library using tensorflow backend

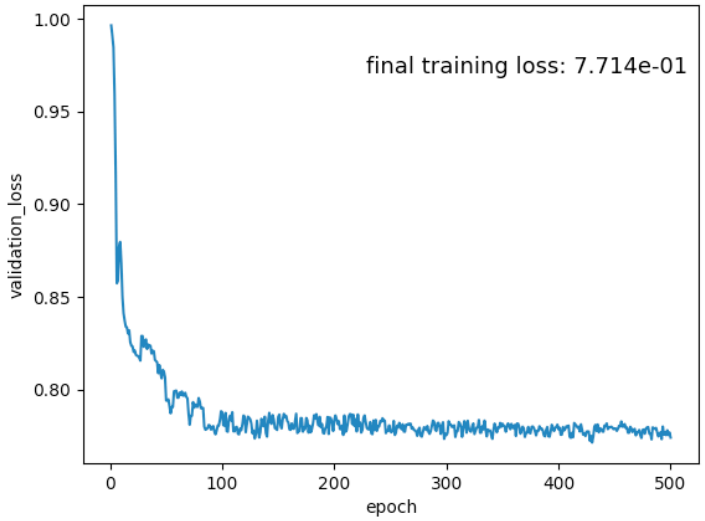


Model 1

- Preprocessing scale to 0 mean and standard deviation of 1: $X = \frac{X - \mu}{\sigma}$
- Input-to-hidden and all hidden-to-hidden layers have LeakyRelu activations.
- Hidden to output layer has linear activation.
- Optimizer: AdaDelta; Loss : MSE loss.
- Regularization: Dropout (10-15%)

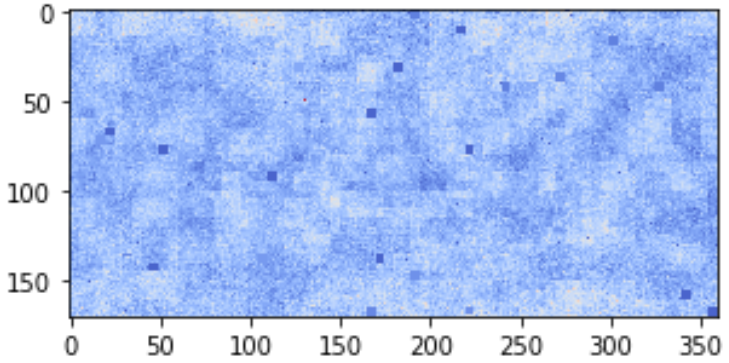
Other optimizers, regularization methods were tried with similar results



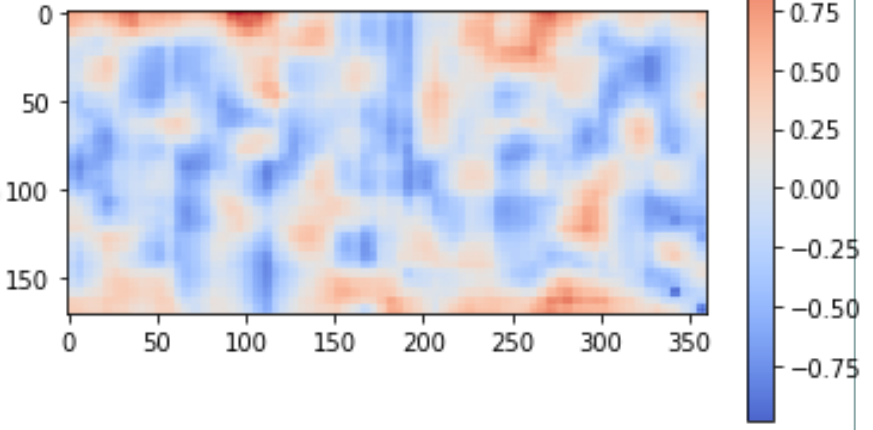


Reconstruction of good LS images: Model I

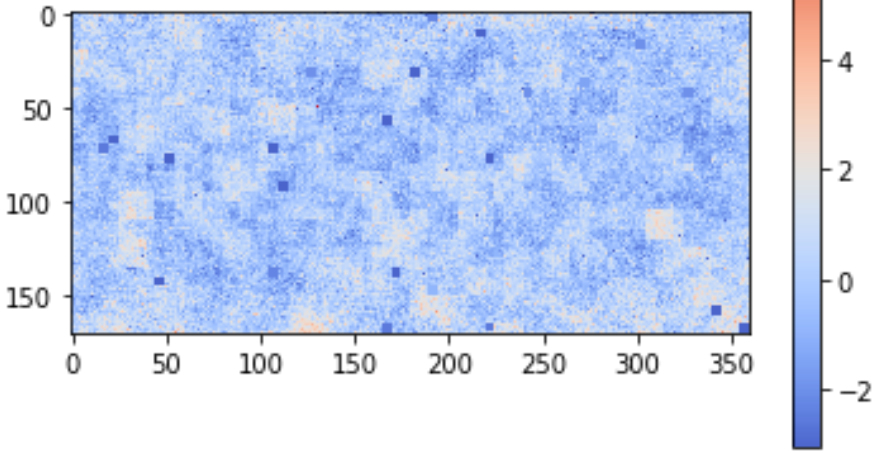
Good Image



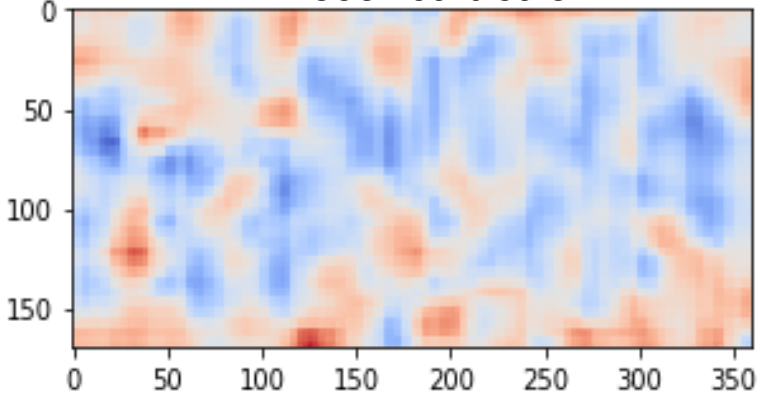
Reconstruction



Good Image



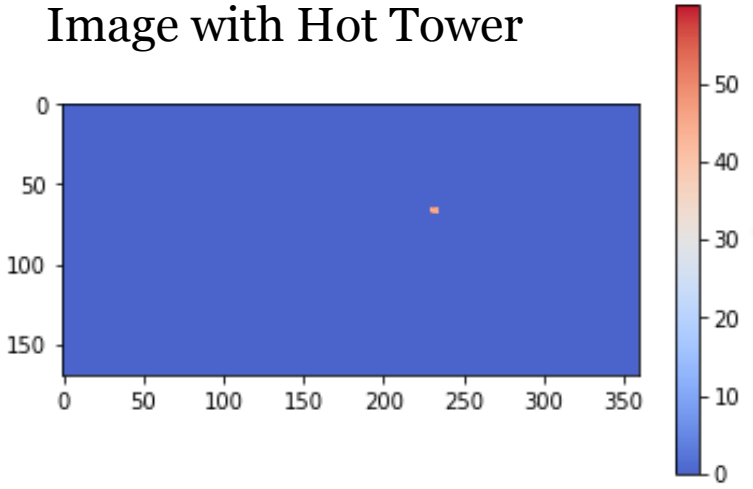
Reconstruction



Code dimension is ~100x smaller than input dimension: undercomplete reconstruction

Reconstruction of anomalous images: Model I

Image with Hot Tower



Reconstruction

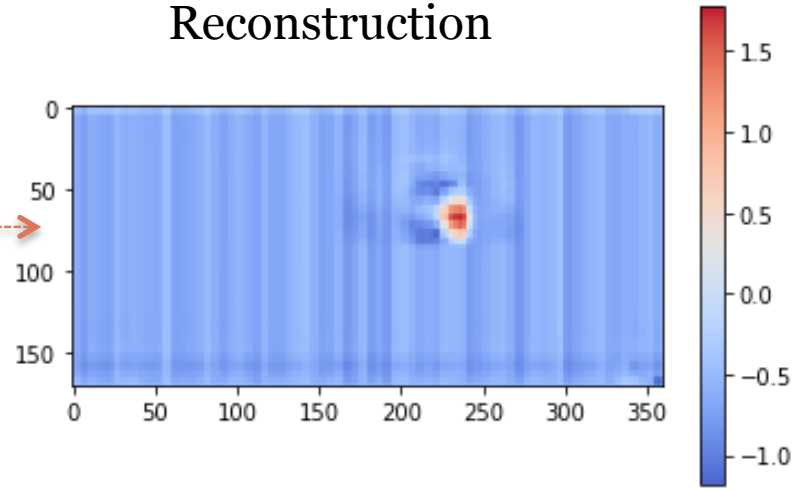
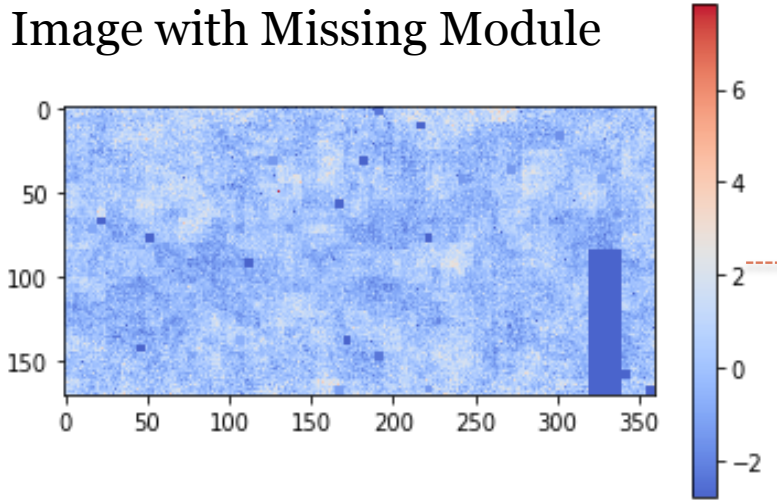
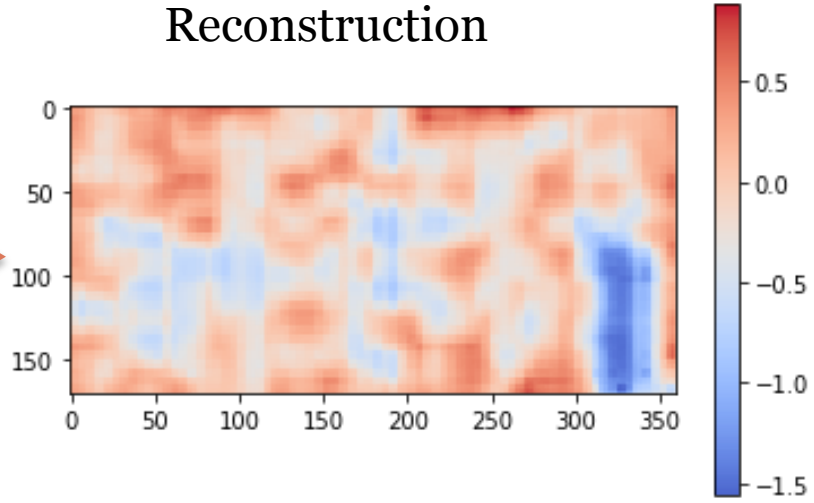


Image with Missing Module



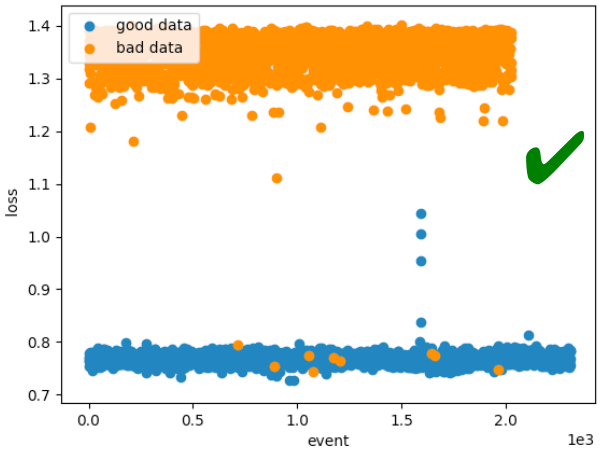
Reconstruction



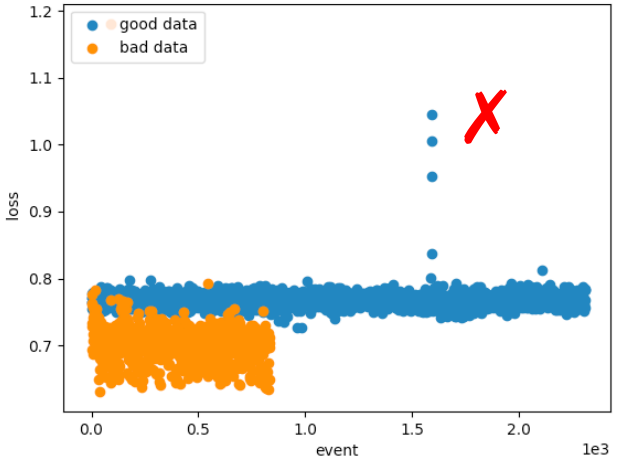
Code dimension is ~100x smaller than input dimension: undercomplete reconstruction

Reconstruction loss as discriminant: Model I

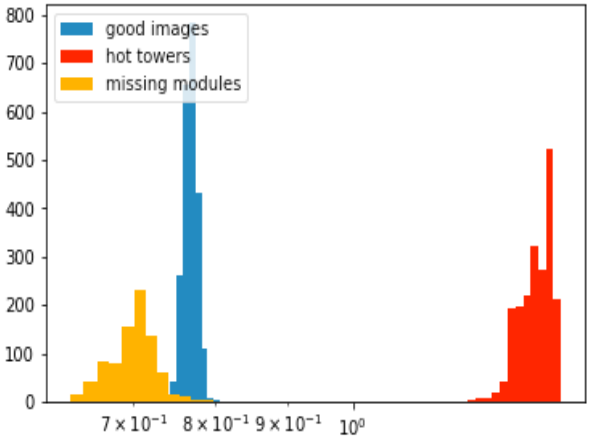
Hot Towers V. Good



Missing Modules V. Good



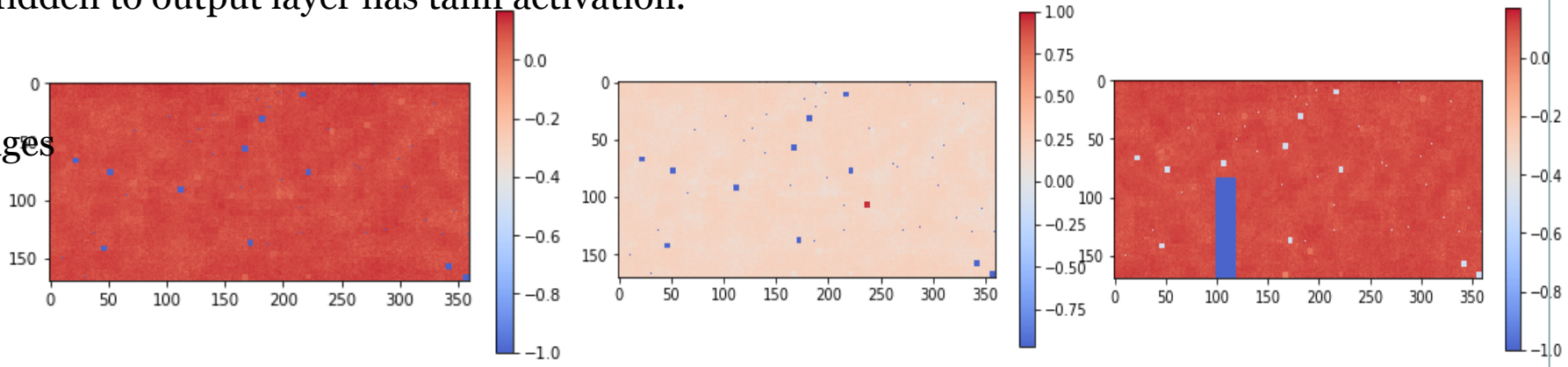
- works well with hot towers: the higher reconstruction loss can be seen as coming from the 'spread' around the hot tower.
- doesn't work with missing modules: It seems to reconstruct the missing module quite well and there is minimal spread around it with well defined edges.



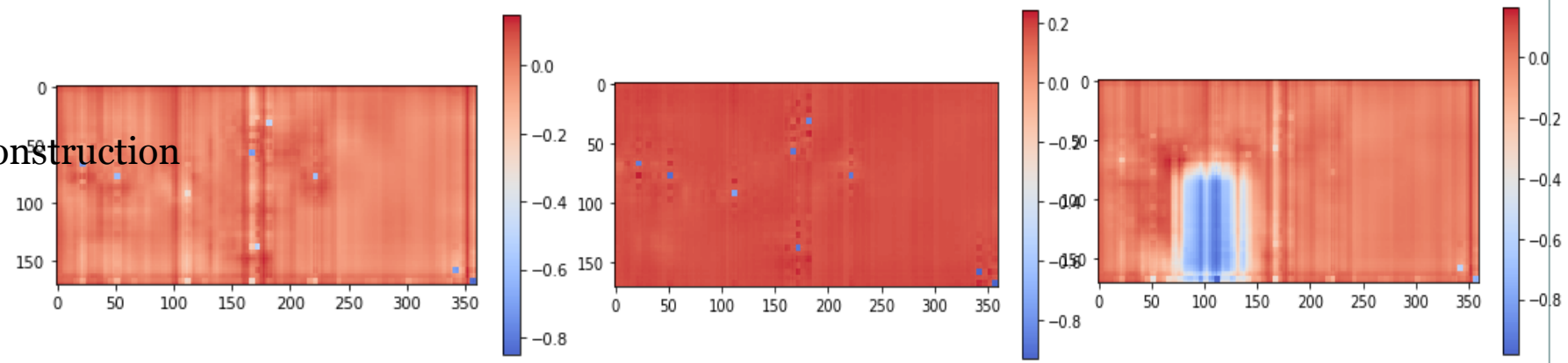
Model 2

- Preprocessing : log followed by max_absolute_scaling
- Hidden to output layer has tanh activation.

Images



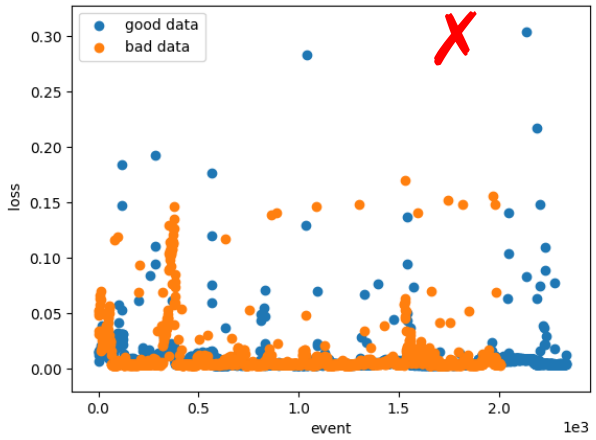
Reconstruction



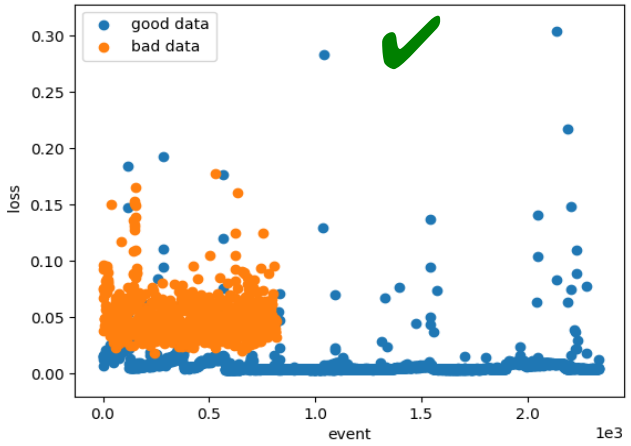
- Unable to reconstruct the hot tower at all.
- Blurs out the edges of the missing module into neighboring areas.

Reconstruction loss as discriminant: Model II

Hot Towers V. Good



Missing Modules V. Good



- It is unable to reconstruct the hot tower at all. It seems to uniformly 'warm' up the whole image rather. But the reconstruction error (sadly and understandably) is similar to that of normal images as it doesn't really have any handle to blow up. A better function as discriminant could help here
- The reconstruction blurs out the edges of the missing module into neighboring areas. This leads to a higher loss. .

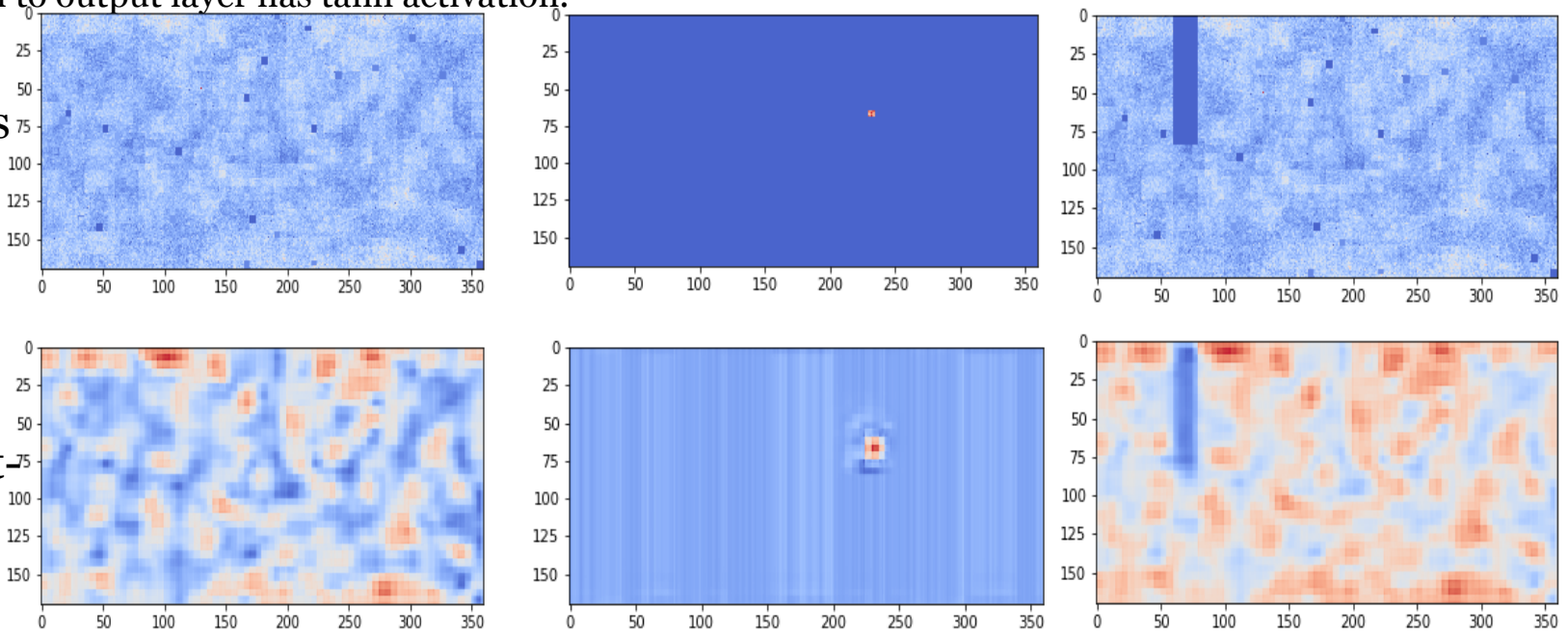
Other strategies

- Preprocessing : (x-mean)/sigma followed by MaxAbsScaling
- Hidden to output layer has tanh activation.

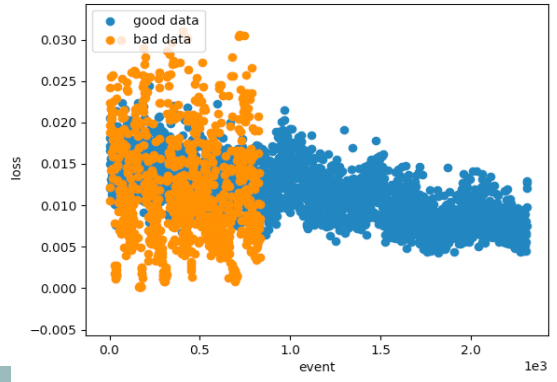
- Preprocessing : log followed by max_abs_scaling
- Hidden to output layer has tanh activation.

Images

Reconst-ruction

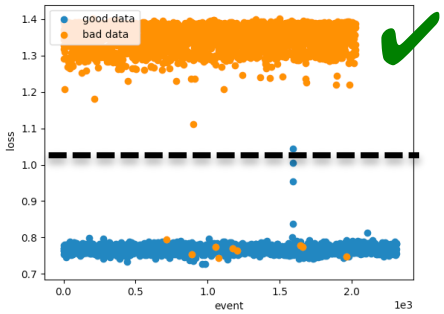


- Reconstructs too well, or at least reconstructs anomalous images as well as good ones. This doesn't help as we are not looking for a generative model
- Loss spectrums of good and bad images not different to allow good discrimination

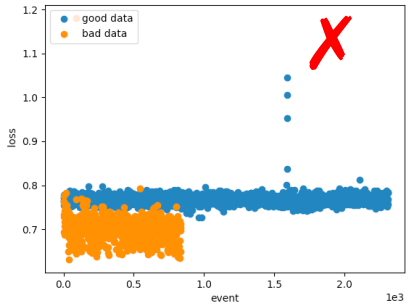


Current best startegy

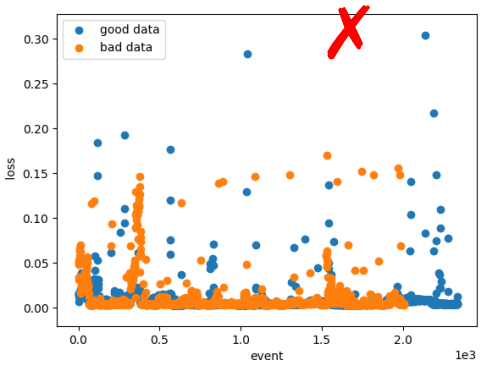
- Current best strategy is to use a mixture of experts: Classify an image as an anomaly if either model 1 or model 2 calls it an anomaly.



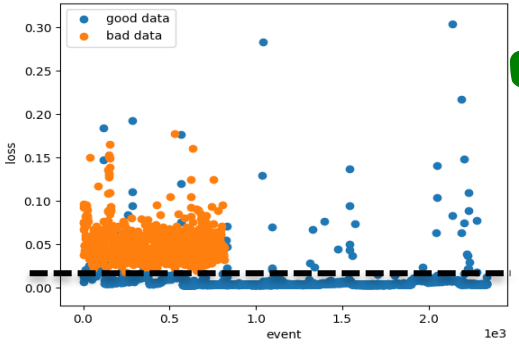
Model 1



OR



Model 2



- Needs lot of improvement!
- A supervised learner based on the same dataset does almost perfectly. (backup)

Conclusion and next steps

- A first demonstration of semi-supervised approach is made. There is a lot of room for improvement. Supervised approach (see backup) slides works very well. However we lose the potential benefit of detecting anomalies unseen during training.

Next Steps

- Use KL divergence as regularization. The magnitude of loss in the regularization (KL) term has potential to act as better discriminant.

- Try generative models:
  - VAE for anomaly detection[1]
  - Another idea is to train a GAN to generate good images. The discriminator network of such a trained GAN learns to identify out of domain images and can potentially spot anomalies well.

- Train Model for endcap detectors

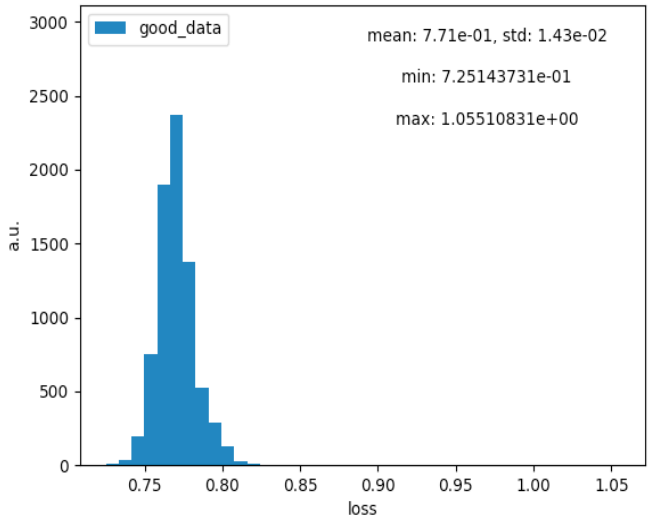
- Use timing information to train a parallel model.

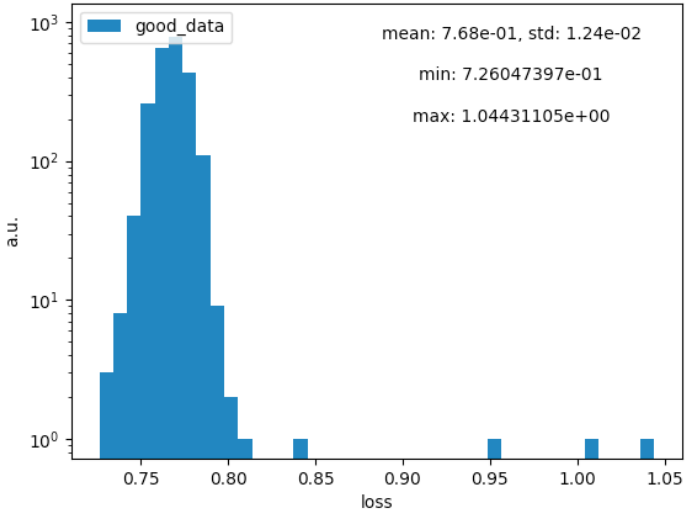
Thank you!

BACK UP

Training /Test Loss Spectrum: Model 1

- Evaluate trained model over (each sample) training and test sets and histogram the reconstruction loss



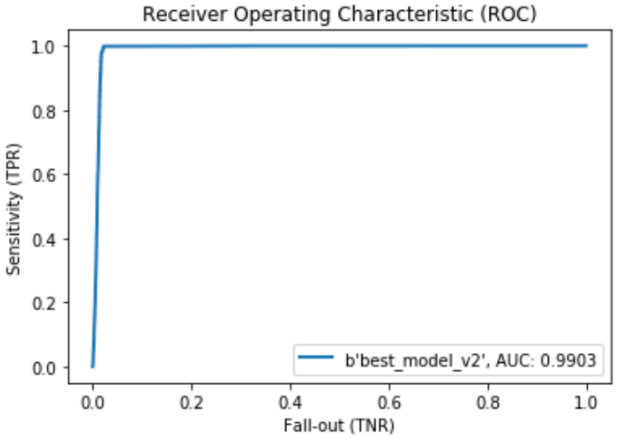


- Training and test sets have similar performance.

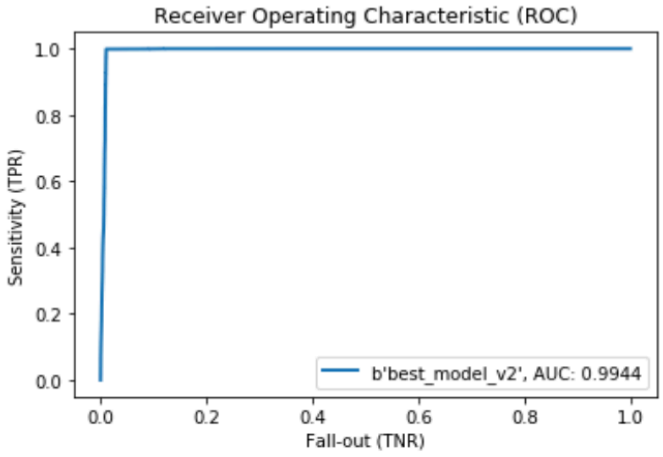
Supervised Approach

- Looked at supervised approach as an exercise.
  - Supervised binary classification
  - All kinds of anomalies are are one negative class
  - Train a net with convolutional layers followed by dense layers.
  - Activation: ReLU (except finaly layer has softmax)
  - ADAM optimizer
  - Binary CrossEntropy loss
  - Net architecture in backup
  - Regularizers: l2, dropout

Training-validation roc



Testing roc

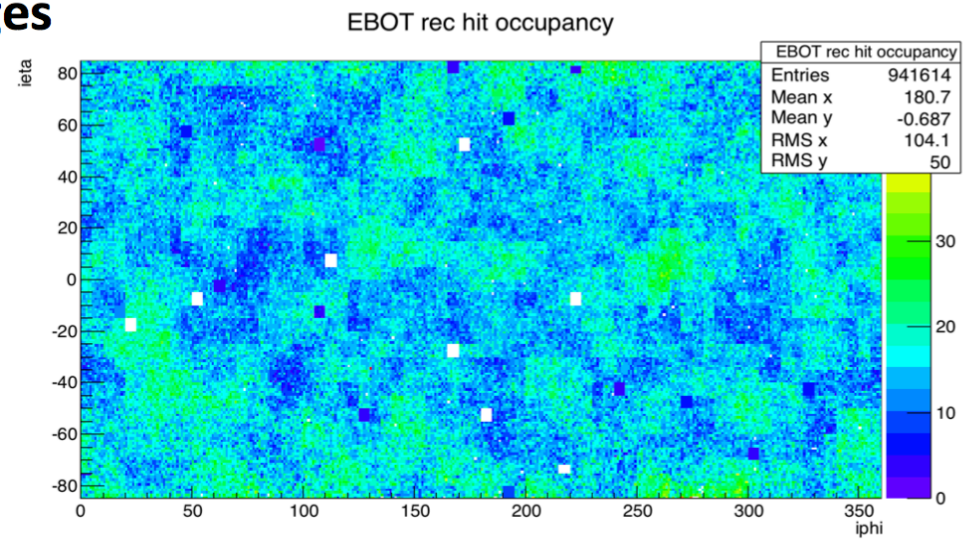


_____
_____ Layer (type) Output Shape Param #
==========
========== input_1 (InputLayer) (None, 1, 170, 360) 0
_____
_____ convA_5x5 (Conv2D) (None, 6, 170, 360) 156
_____
_____ leaky_re_lu_1 (LeakyReLU) (None, 6, 170, 360) 0
_____
_____ pool5x5 (MaxPooling2D) (None, 6, 34, 72) 0
_____
_____ convB_4x4_stride2 (Conv2D) (None, 4, 16, 35) 388
_____
_____ leaky_re_lu_2 (LeakyReLU) (None, 4, 16, 35) 0
_____
_____ convC_4x4_stride2 (Conv2D) (None, 4, 7, 16) 260
_____
_____ leaky_re_lu_3 (LeakyReLU) (None, 4, 7, 16) 0
_____
_____ dropout_1 (Dropout) (None, 4, 7, 16) 0
_____
_____ flatten_1 (Flatten) (None, 448) 0
_____
_____ denseA (Dense) (None, 100) 44900
_____
_____ leaky_re_lu_4 (LeakyReLU) (None, 100) 0
_____
_____ dropout_2 (Dropout) (None, 100) 0
_____
_____ denseB (Dense) (None, 2) 202
==========
========== Total params: 45,906 Trainable params: 45,906 Non-trainable params: 0

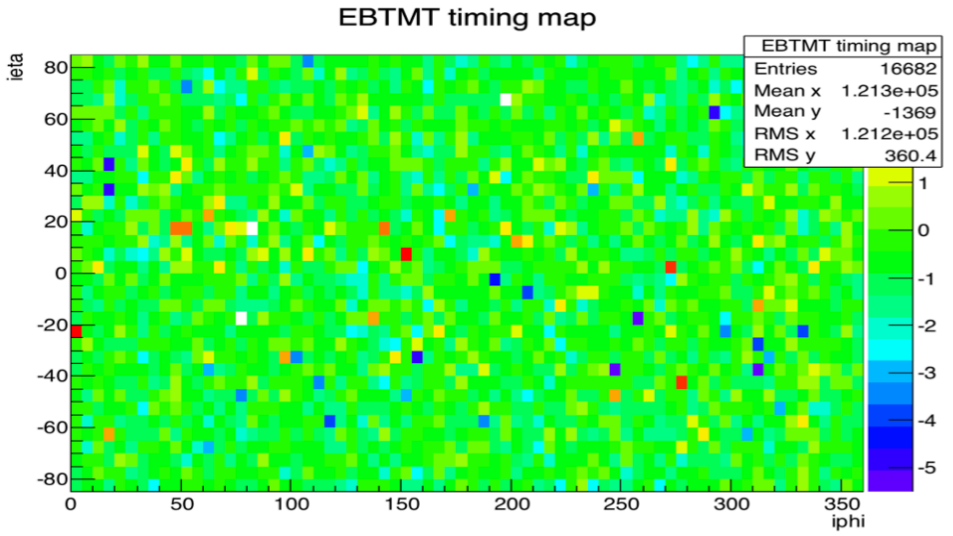
Supervised learning net architecture

Input Images

170, 360



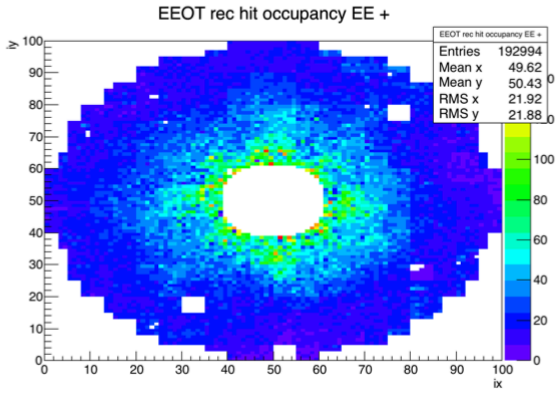
34, 72

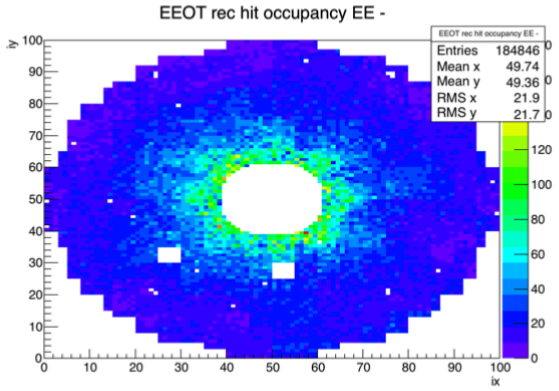


BARREL

Input Images

100, 100





ENDCAPS

20,20