

Lovely Report

Patomporn (Jab)

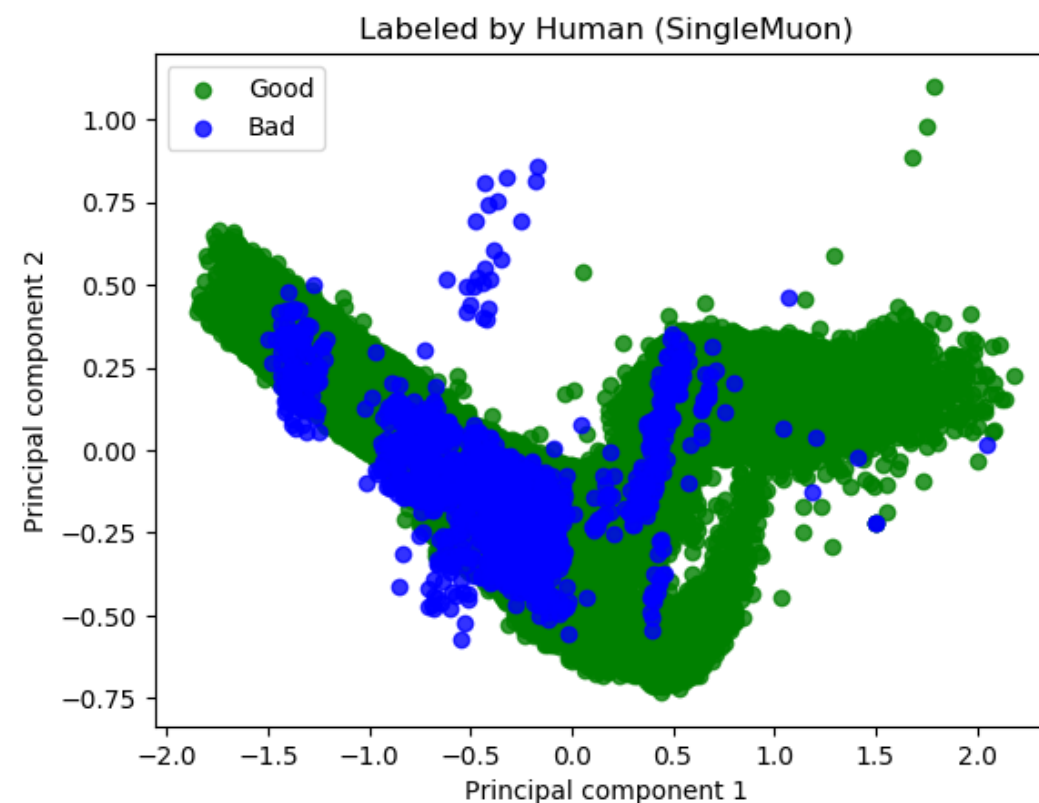
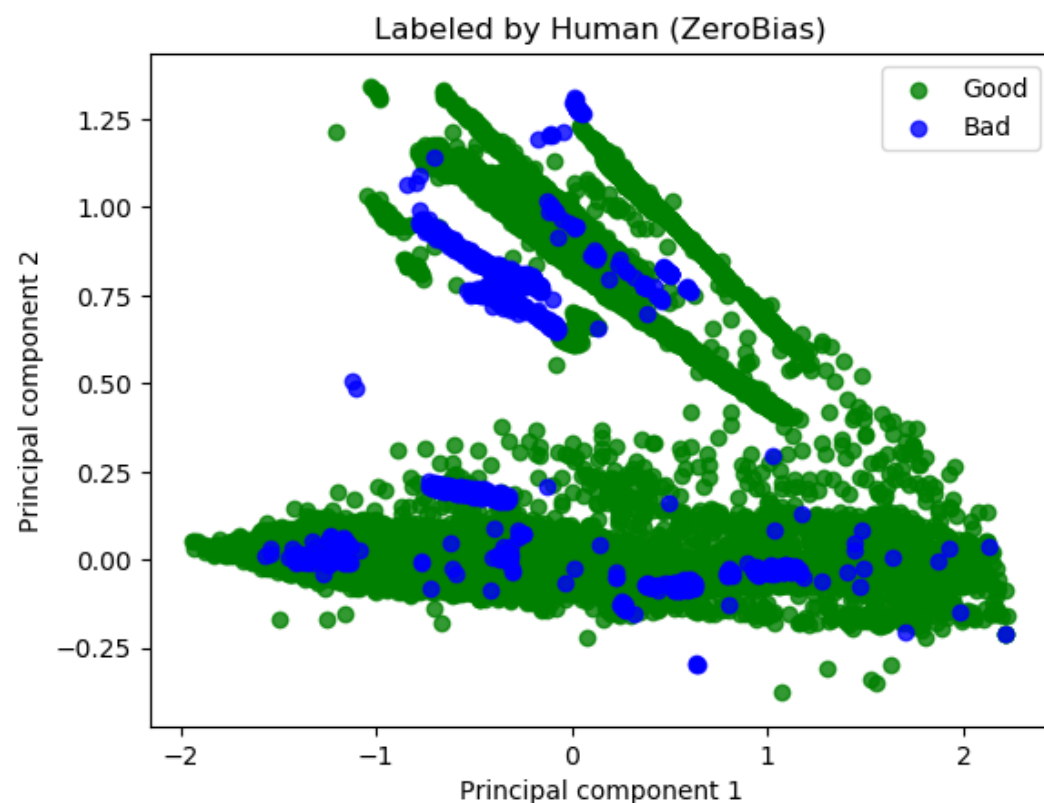
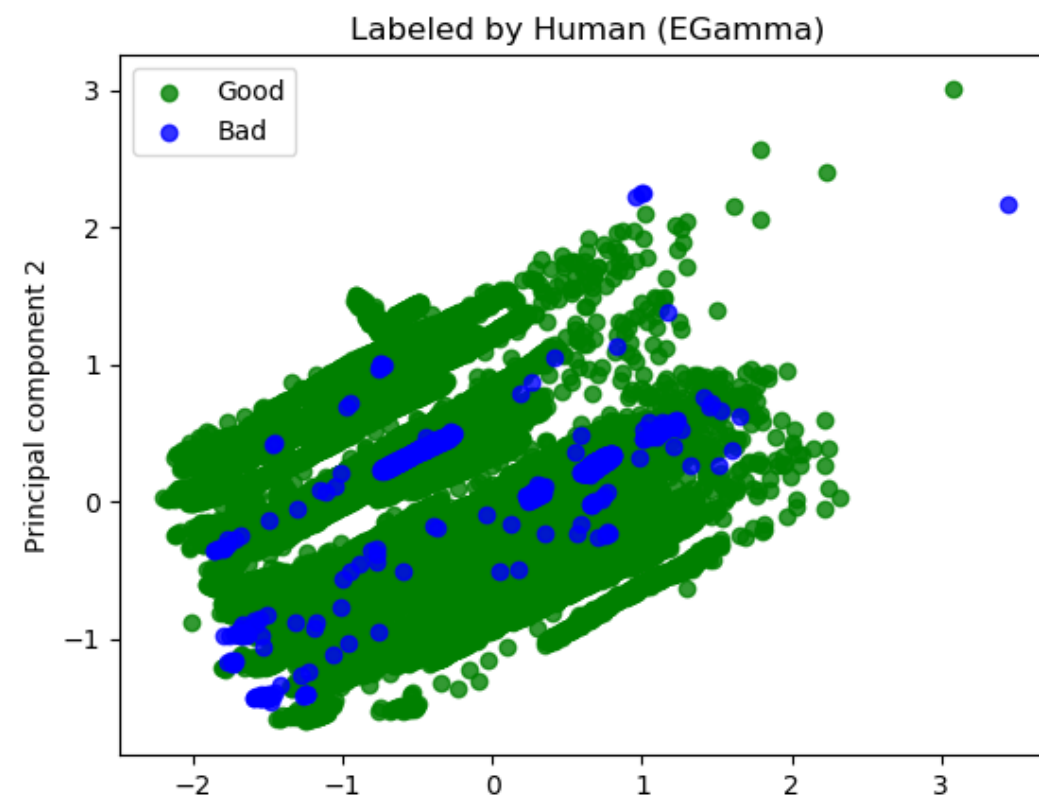
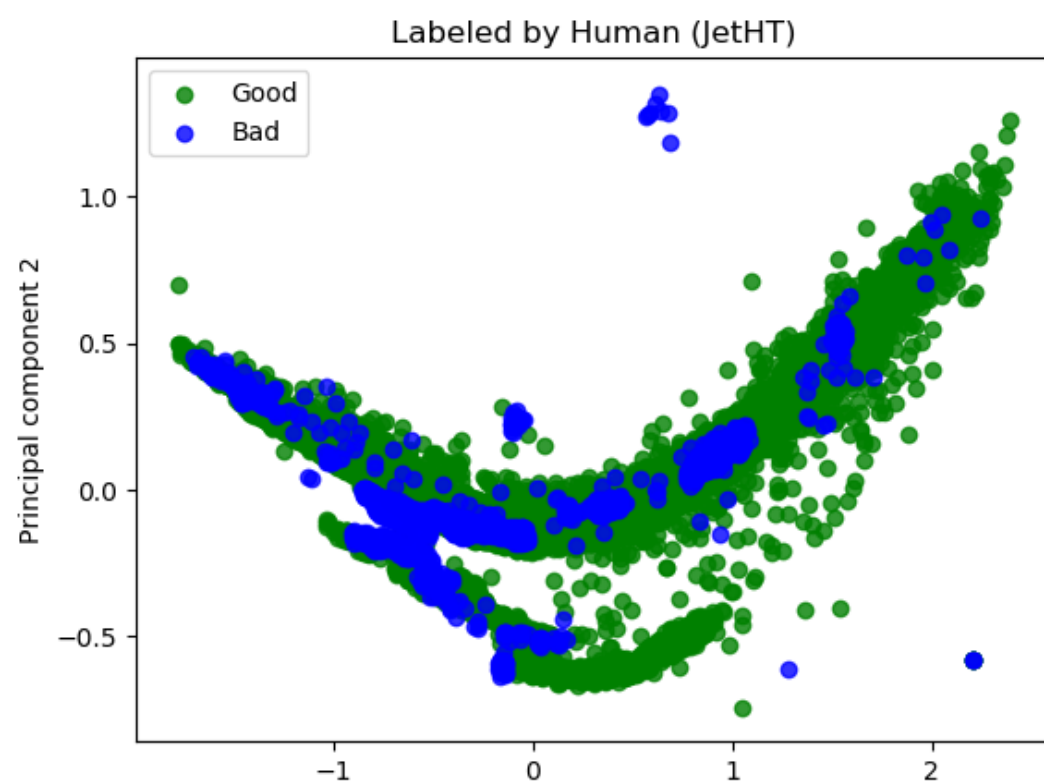
CMS-DQM-WHATEVER4DC

Outline

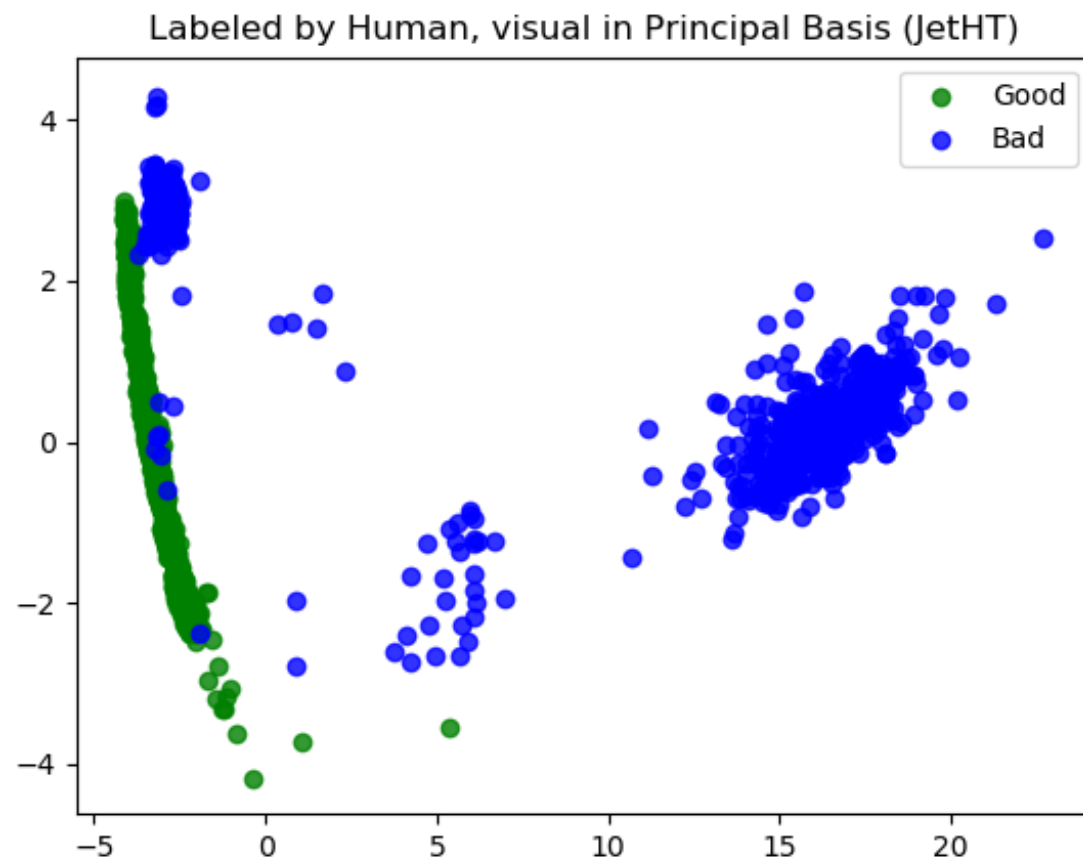
- Similarity of bad and good LS (in 2018)
- Why our model is too aggressive
- Fundamental question
- Solution

**Similarity of bad and
good LS in 2018 datasets**

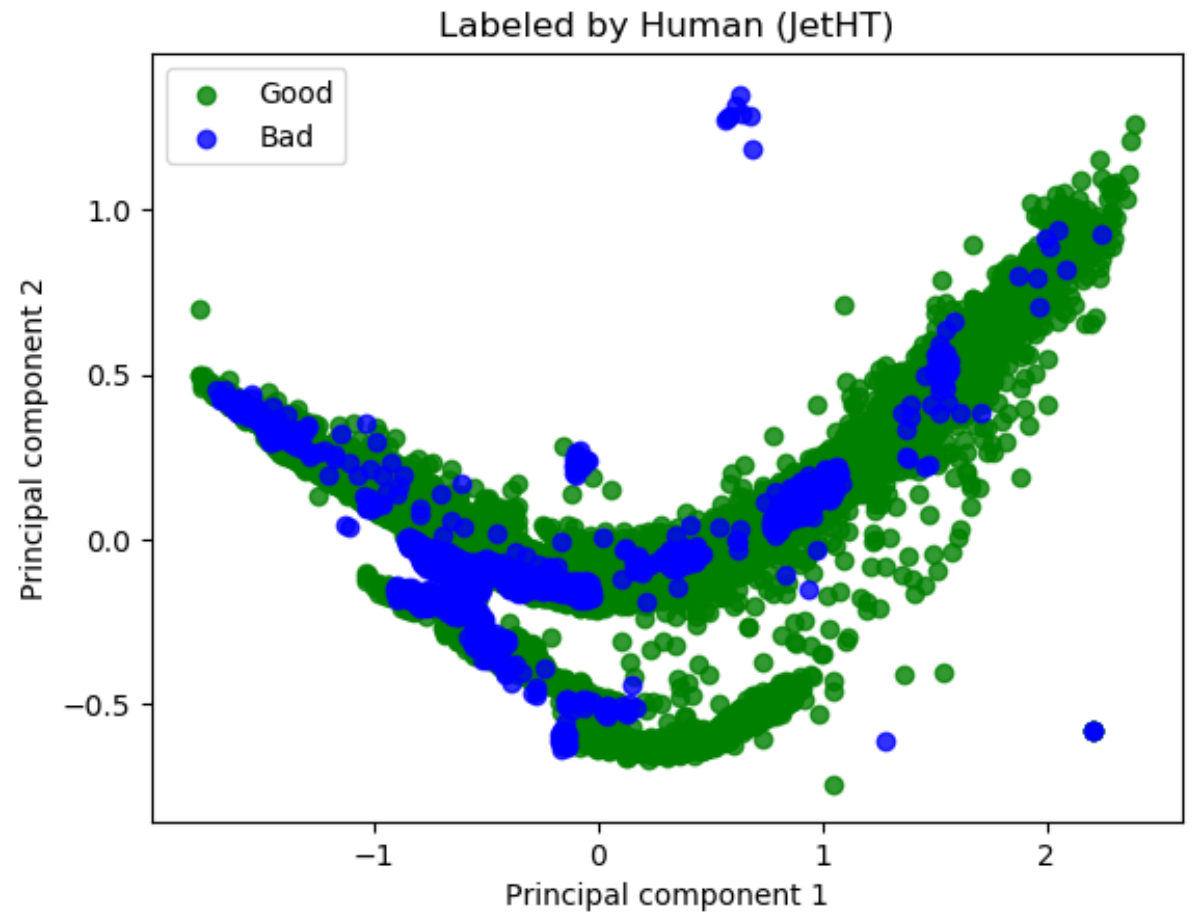
Let's have a look



JetHT 2016 VS 2018



2016



2018

“..Toy’s example vs real life scenario”

Preliminary Results

Model\Channel	ZeroBias	JetHT	EGamma	SingleMuon
One-Class SVM	74.2	74.8 (99.1)	16.4	52.9
Contractive AE	-	83.3 (99.1)	-	-
Vanilla AE	-	81.4 (99.2)	-	-
Sparse AE	-	74.6 (98.9)	-	-
Variational AE	-	74.4 (96.8)	-	-

Table of AUC (for convenient you could consider it as accuracy)

- 2018 datasets , 2016 datasets
- Exact same algorithm

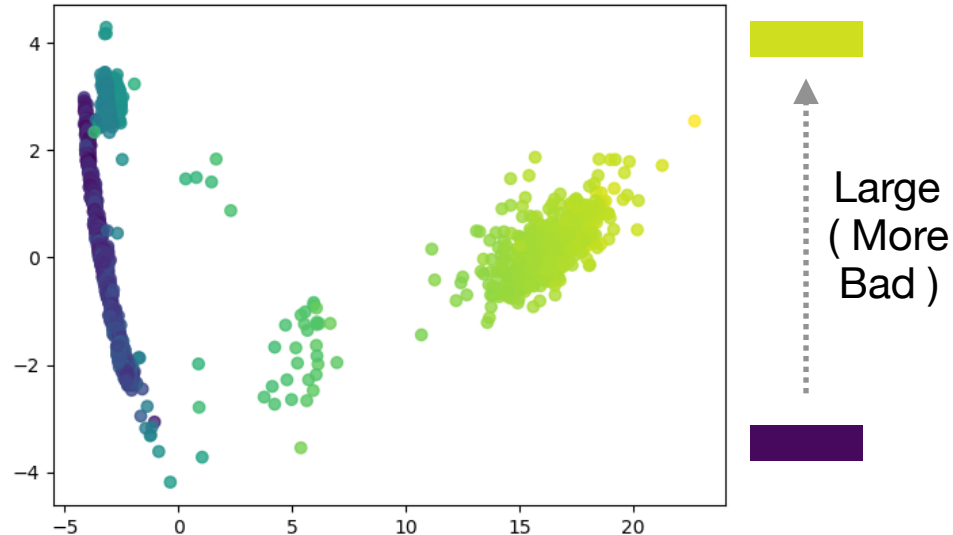
Why it's aggressive

With a choice of Semi-supervised is **too aggressively** mark bad LS

Loss value from Vanilla AE

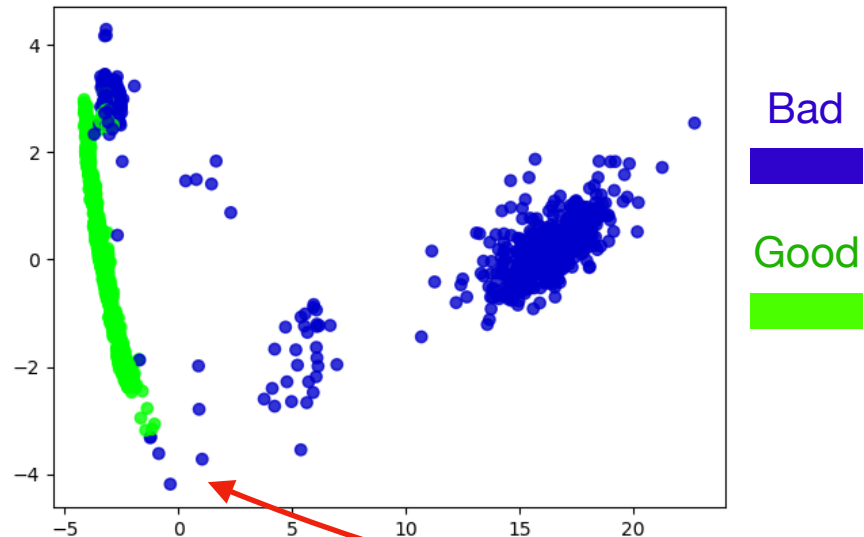
Loss as color shading

Loss from AE data, testing set visual in Principal Basis (JetHT)



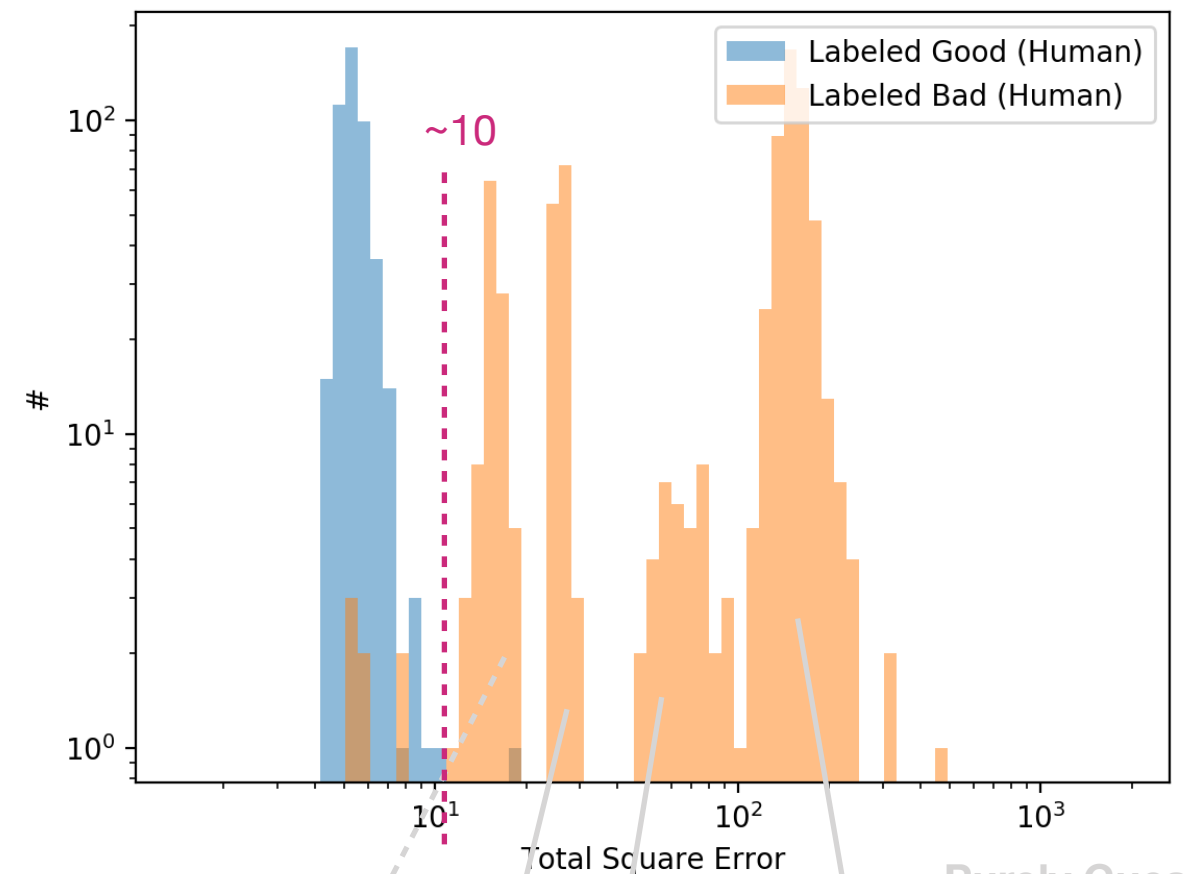
Applying cutoff ($MSE > 10.0$ is bad)

Applying cutoff in AE, testing set visual in Principal Basis (JetHT)



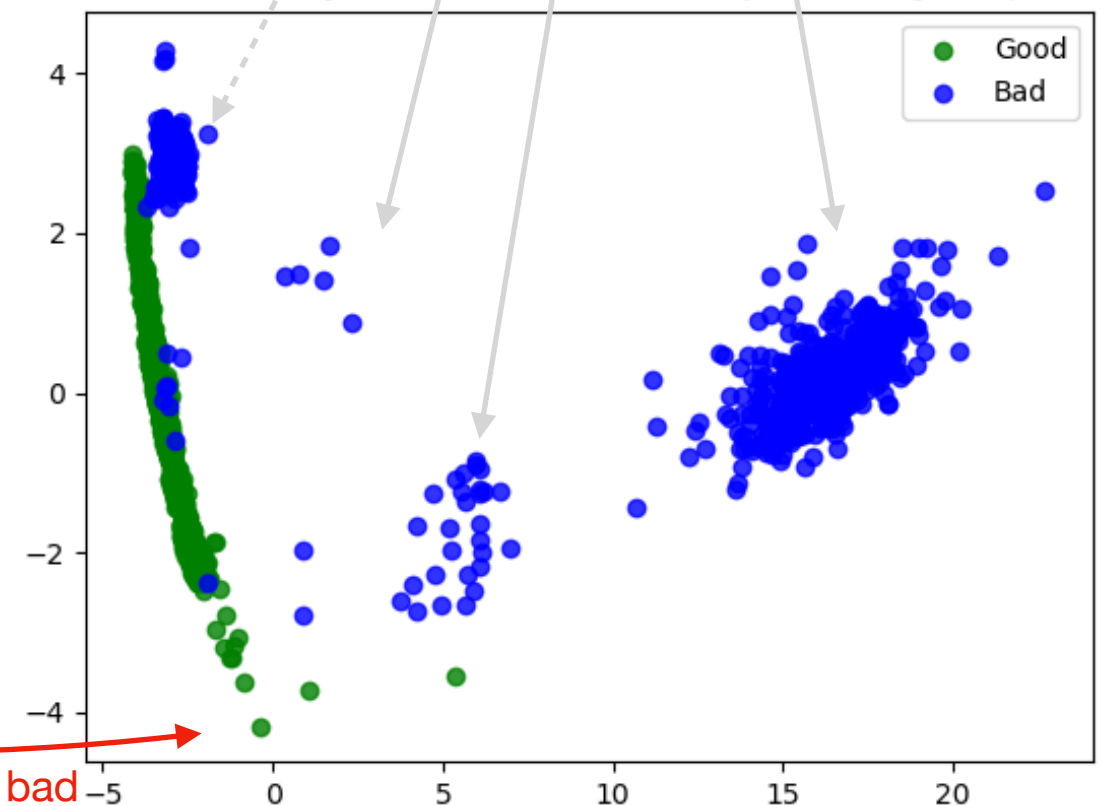
Consequently, something rarely happen would mark as bad

Distribution of Total Error



Purely Guess

Labeled by Human, visual in Principal Basis (JetHT)



Consequence

- Our machine determine something that it's not familiar with by marking as bad LS
- As the time evolving, configuration of CMS also evolve then it's quite dangerous

Fundamental question

But wait

- The accuracy has computed by reference from DCs bit then
- If we trust DCs bit to be a “ground truth”:
 - why we need Autoencoder
- else:
 - Require datasets from simulation of known bad scenario that DCs bit couldn't do
 - If we could provide simulation of bad scenario data to model:
 - When it's disagree with DCs bit when we implemented, how could we trace back to prove

Solution ?

Malfunction Spotter

- Objective
 - Inspect detector malfunction in lumisection granularity which shifter does inspect in run granularity
- Supervised
- Input (x):
 - Physics object
 - Occupancy of sub-detector
- Label (y): status of detector which we could get from RR

Malfunction Spotter

- Model Candidate
 - Decision Tree
 - Random Forest
 - Neural network with **probabilistic output** such as sigmoid to tell “level of confidence” for malfunction in each sub-detector
- And again!
- If model prediction and RR is disagree:
 - Of course we have to call the expert as shifter does