## Weekly Report

CMS DQM-ML4DC Patomporn (Jab) 22 July 2019

#### Outline

- My Pointless Experiment
  - Extended AE
    - Sparse + Contractive AE
    - Sparse + Variational AE
    - Contractive + Variational AE
    - The Standard AE
  - Results
- Simplest prototype of Malfunction Spotter

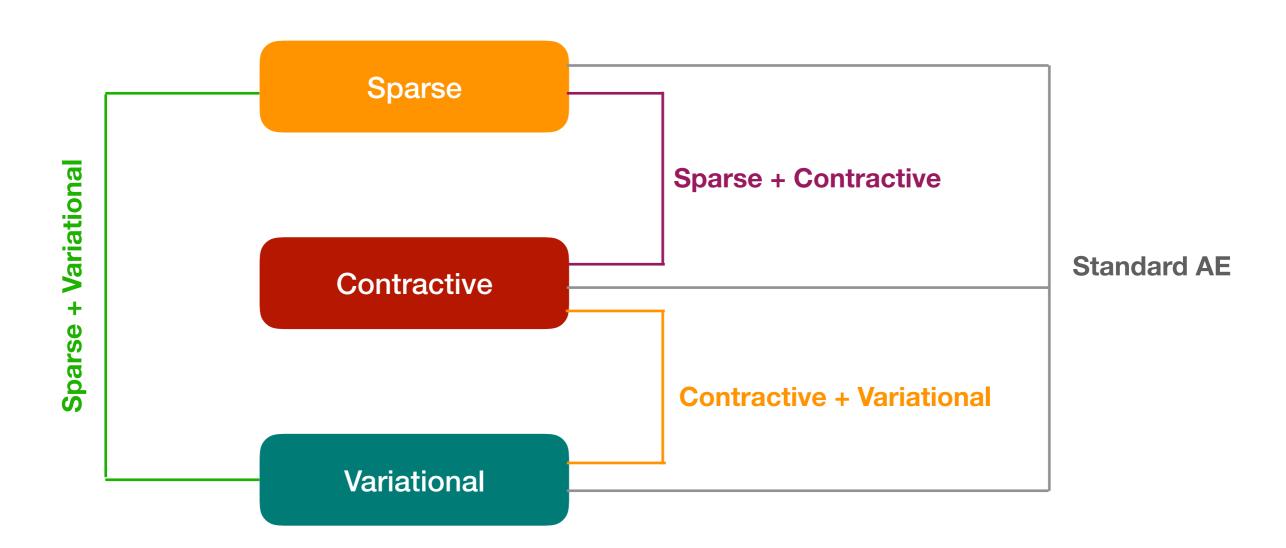
## My Pointless Experiment

#### **Extended Model**

- Simple idea: could we combine those technique?
- Add independent constrain into the same model and then we could consider loss function as

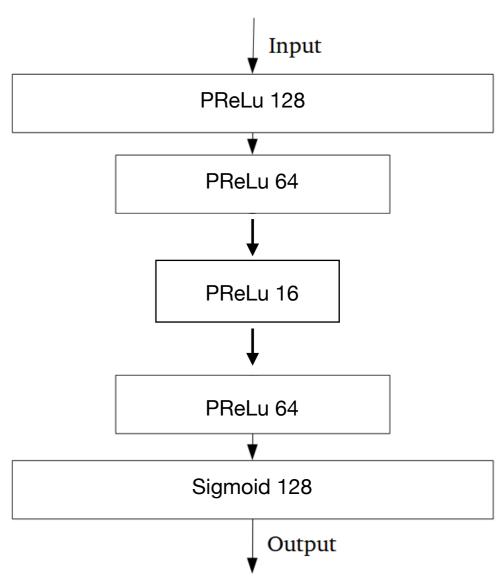
$$\mathcal{L}_{ ext{tot}} \equiv \mathcal{L}_{ ext{MSE}} + \sum_{i} \mathcal{L}_{ ext{Constrain}_{i}}$$

#### Combination of Constrain



## Sparse + Contractive AE

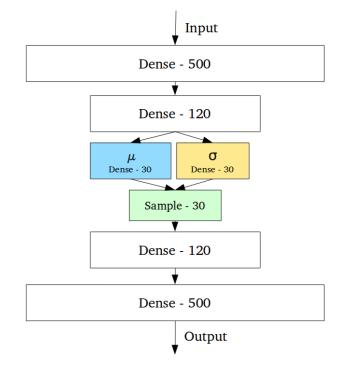
- Combine
  - Prevent overfitting
  - Prevent variation in data



$$\mathcal{L}_{\text{tot}} \equiv \frac{1}{N} \sum_{i}^{N} |x_i - \tilde{x_i}|^2 + \lambda_{\text{s}} \sum_{j} ||w_j|| + \lambda_{\text{c}} ||J_h(x)||^2$$

## Sparse + Variational AE

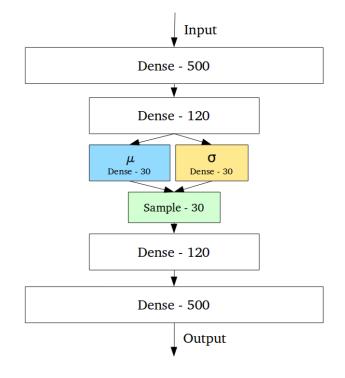
- Combine
  - Prevent overfitting
  - Remove discontinuity in encoding space



$$\mathcal{L}_{\text{tot}} \equiv \frac{1}{N} \sum_{i}^{N} |x_i - \tilde{x_i}|^2 + \lambda_{\text{s}} \sum_{j} ||w_j|| + \mathcal{D}_{\text{KL}}(p|q)$$

#### Contractive + Variational AE

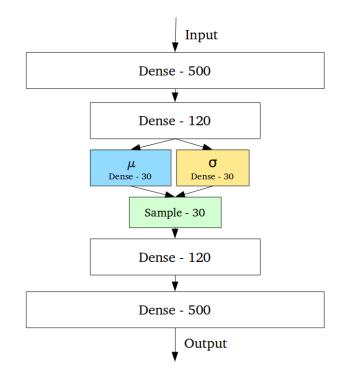
- Combine
  - Prevent variation in data
  - Remove discontinuity in encoding space



$$\mathcal{L}_{\text{tot}} \equiv \frac{1}{N} \sum_{i}^{N} |x_i - \tilde{x_i}|^2 + \lambda_{\text{c}} ||J_h(x)||^2 + \mathcal{D}_{\text{KL}}(p|q)$$

#### The Standard AE

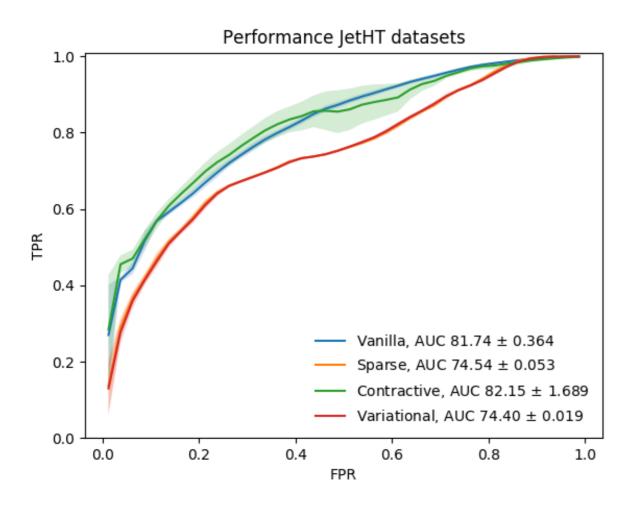
- Combine
  - Prevent overfitting
  - Prevent variation in data
  - Remove discontinuity in encoding space



$$\mathcal{L}_{\text{tot}} \equiv \frac{1}{N} \sum_{i}^{N} |x_i - \tilde{x_i}|^2 + \lambda_{\text{s}} \sum_{j} ||w_j|| + \lambda_{\text{c}} ||J_h(x)||^2 + \mathcal{D}_{\text{KL}}(p|q)$$

### Results

#### JetHT

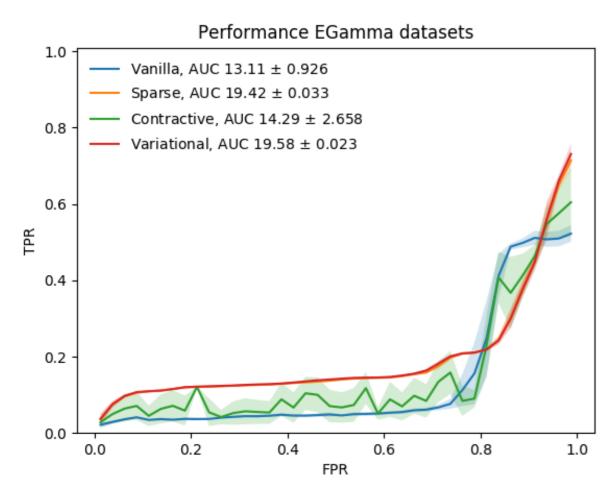


Performance JetHT datasets 1.0 0.8 0.6 TPR 0.4 SparseContractive, AUC 74.49 ± 0.039 0.2 SparseVariational, AUC 74.35 ± 0.343 ContractiveVariational, AUC 74.40 ± 0.020 Standard, AUC 74.32 ± 0.189 0.0 0.0 0.2 0.4 0.8 1.0 0.6 **FPR** 

**Original AE** 

**Extended AE** 

#### **EGamma**

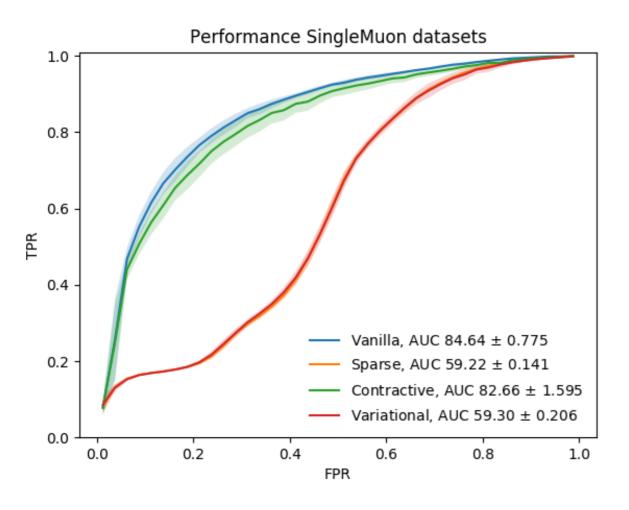


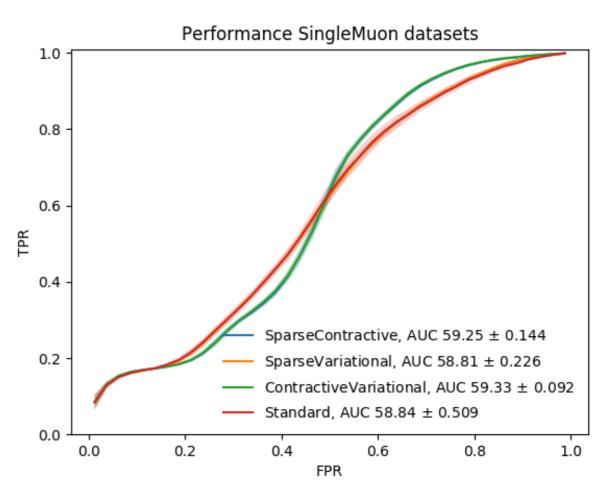
Performance EGamma datasets 1.0 SparseContractive, AUC 19.46 ± 0.031 SparseVariational, AUC 19.85 ± 0.147 ContractiveVariational, AUC 19.57 ± 0.012 0.8 Standard, AUC 19.92  $\pm$  0.192 0.6 0.4 0.2 0.0 0.2 0.4 0.6 0.8 1.0 **FPR** 

**Original AE** 

**Extended AE** 

## SingleMuon

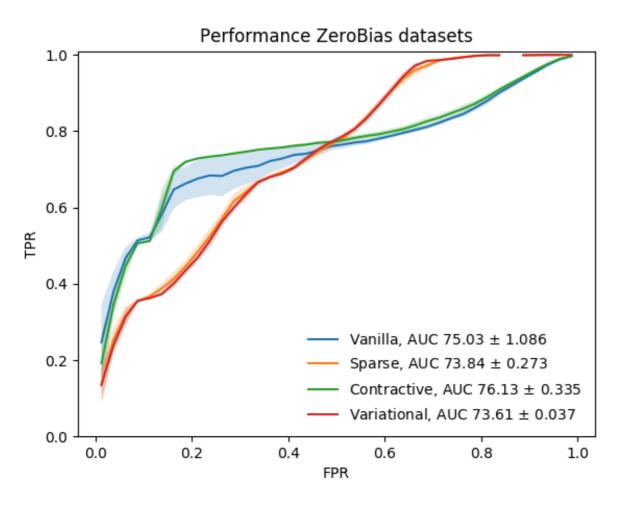


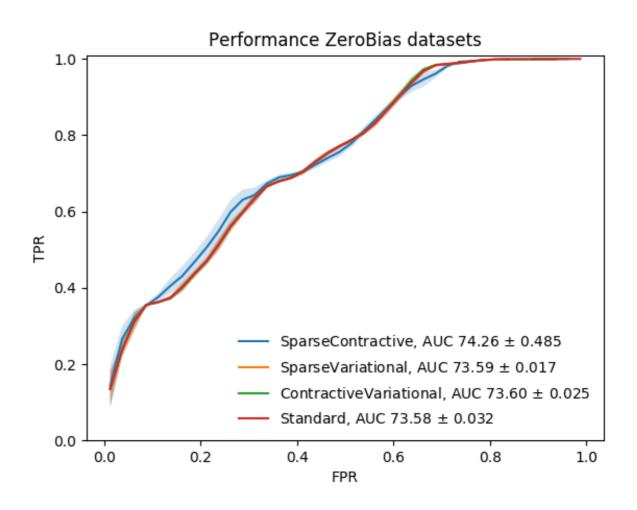


**Original AE** 

**Extended AE** 

#### ZeroBias





**Original AE** 

**Extended AE** 

### To sum up

- Summary:
  - Too many constrain is fairly more robust but the accuracy still unremarkable
- To do:
  - Re-evaluate ROC after all of Failure Scenario has been process

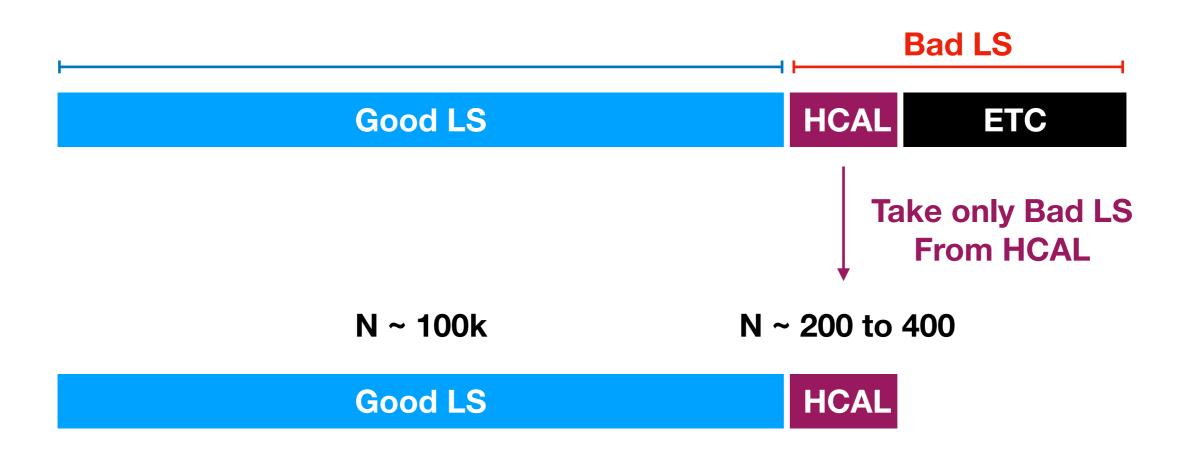
# Simplest Prototype of The New Approach

## Simplest prototype of Malfunction Spotter

- Simpler Objective: Spot the HCAL malfunction from 4 channels of 2018 datasets
- Supervised
- Input (x): Physics objects
- Label (y): HCAL status => GOOD or ELSE (NOT GOOD)
  - Combine all of those status
    ['hcal-hb', 'hcal-he', 'hcal-hf', 'hcal-hcal']
  - In the future, we could extend to identify ECAL and so on.

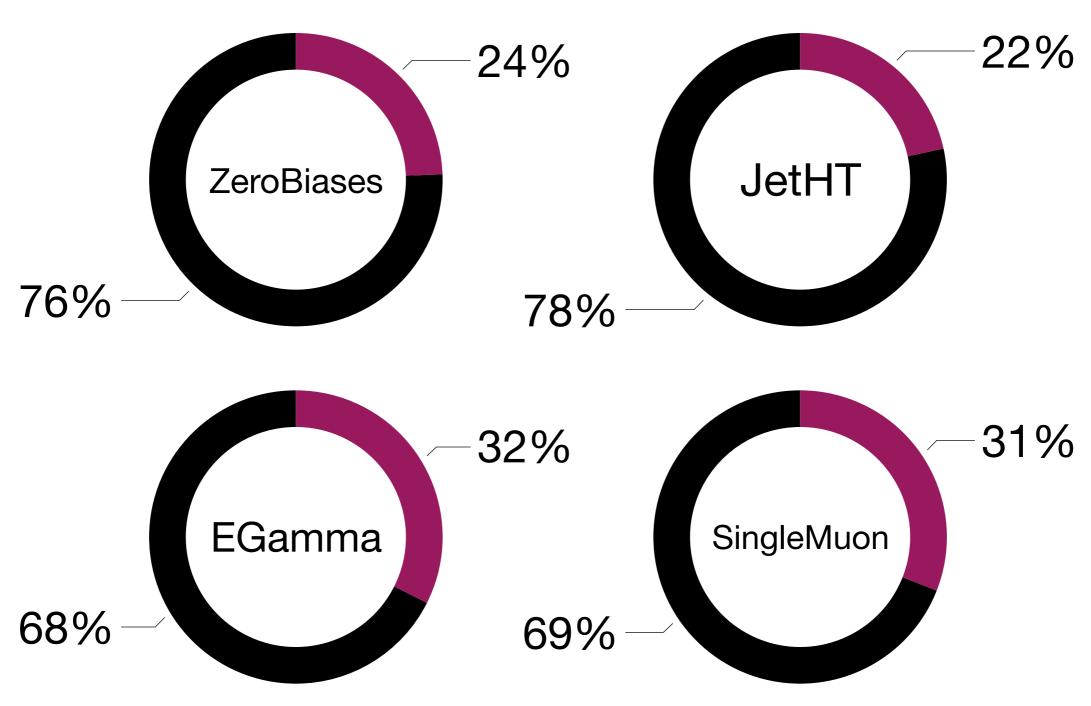
## Dataset preparation

 Extract the sub-detector status in LS granularity from Fabio's API



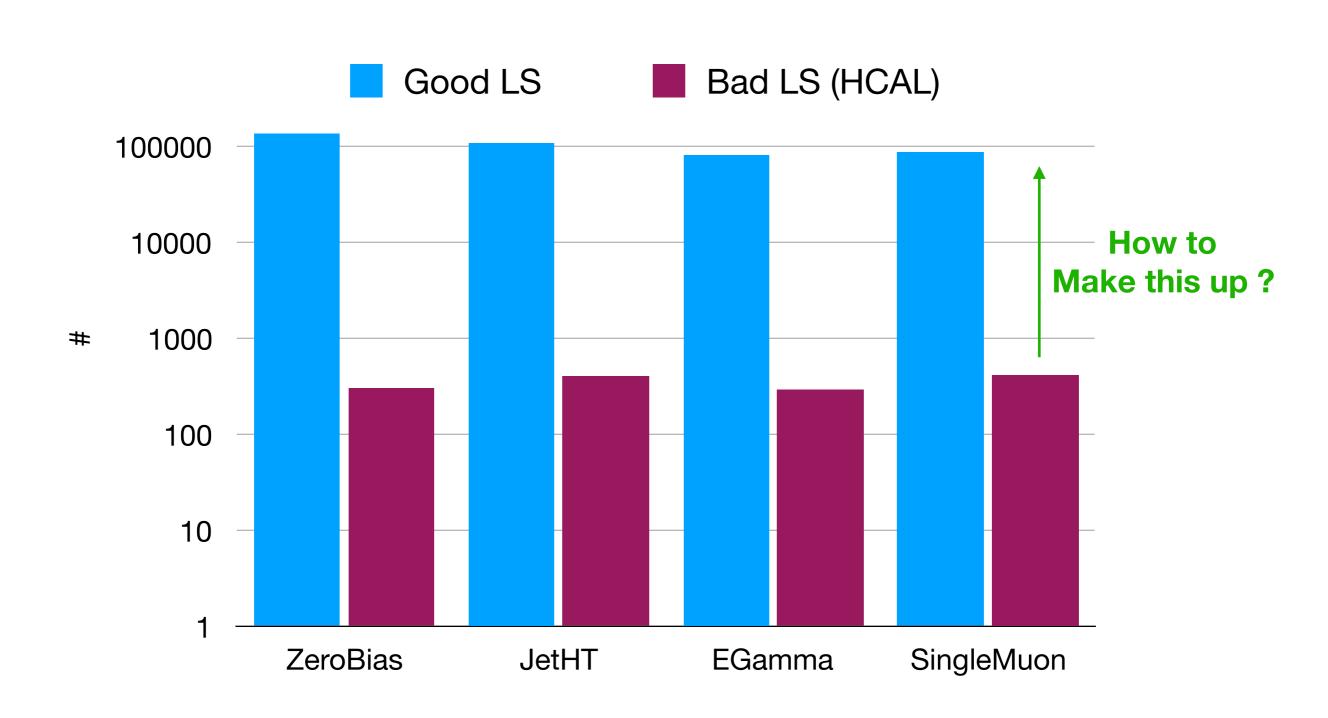
Imbalanced Class! We have a very few bad LS but plenty of good LS

## Malfunction of Bad LS in 2018 dataset



Color: HCAL, Other

#### Imbalanced Class



#### Make it Pseudo-balanced class

Our Choices

1.Replicate bad LS

2. Replicate bad LS with gaussian noise

Any comment for this idea are totally welcome