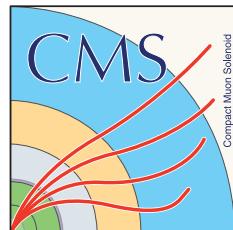


CERN Summer Student Report 2019

# Machine Learning Based Outlier Detection for Data Certification



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A report submitted in partial fulfilment of the requirements  
for the CERN summer student programme 2019

August 20, 2019

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## Abstract

Compact Muon Solenoid (CMS) detector was built in the middle of collision from Large Hadron Collider (LHC) which is one of the most particle accelerator in the world. The mission is to collect the product from collision and decaying which happens 40 million times each second. The data taking in CMS experiment is reconstructed to become physics quantity 48 hours after collision. The certification of data quality is made on run and lumisection levels. The criteria to certify are both from an automatic system as well as manual work from untrackable misbehaving of detector which are marked by offline shifter and detector experts. Approximately 95% of data are good and the rest of them are bad. The phenomenon that cause the data be marked as bad are still not well known. Then the aim of this work is to reduce the manual work for data qualification by exploiting various types of semi-supervised learning by treating the outlier as bad in lumisection granularity.

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# Chapter 1

## Overview

Before the whole data be feeding to physics analysis, there are a procedure to certify the data quality in run and lumisection granularity. Data quality monitoring (DQM) team provide the tools and workflow where there are offline and online section to consider which basically online is a real time and the data that we get 2 days after collision would be inspected in offline section. There are the person who looking at a dozen of histogram that demonstrate the occupancy of detector in each sub-system and also the physics quantities in various perspective of information. Most of Bad lumisection (LS) are automatically came from run tagged as bad by human for the whole run and DCS bits in lumisection levels. In some cases, there are a small fraction bad LS that are manually marked as bad by data certification experts in lumisection levels because some kind of detector malfunction isn't tracable from the previous process. On the other hand, good LS are defined in Golden JSON which are literally taken from data that passes of of those bad criteria.

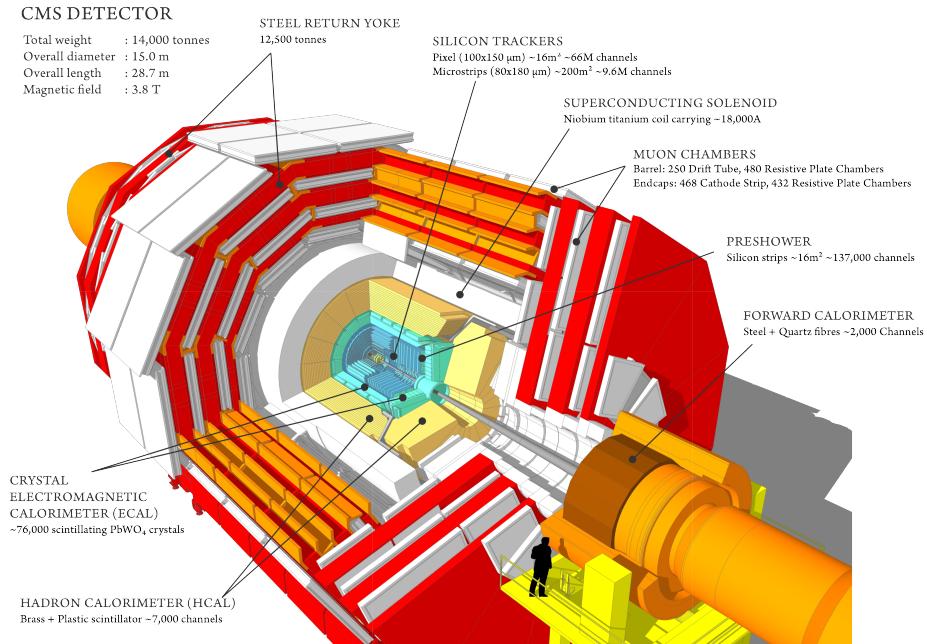
The main objective of this work is to find a mathematical way to certify data quality in lumisection granularity to reduce the mannal work of data certification experts. As you might have seen that there are only a small fraction of data. Moreover, the bad data that are marked by the expert are relatively small compare to a good data. Then we have to face to the imbalance class problem and it is the reason why we choosing semi-supervised learing where we feed only good data to train the unsupervise model and testing with both kind of data. Consequently, the data that are mark as bad by the model would be consider as outlier where model does not familier with. The more explicit analysis would be provided in this report.

# Chapter 2

## Background

### 2.1 Compact Muon Solenoid (CMS) Detector

The Compact Muon Solenoid (CMS) detector be designed for collect the collision and decaying data in forward and transverse of the beamline. It has more resolution in the transverse direction from the equipment that has been designed to focus in transverse direction as the Figure 2.1. According to [3], The detector itself consist of different sub-detector for their own purpose where the main components are

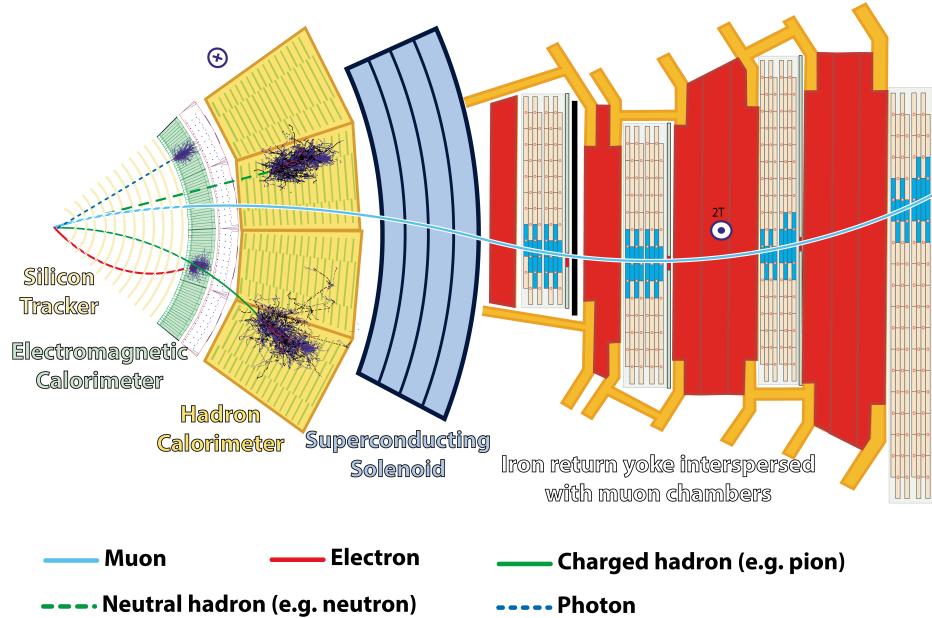


**Figure 2.1:** Sectional view of the CMS detector. The LHC beams travel in opposite directions along the central axis of the CMS cylinder colliding in the middle of the CMS detector. Image retrieved from <http://cms.web.cern.ch/news/cms-detector-design>

1. **Tracker** to trace the footprint of charge particle by beginning at the hitting of the

closest layer which is pixel detector and following by multiple layer of strip detector to gain more precision of particle track that are correspond to momentum of the particle

2. **Electromagnetic Calorimeter (ECAL)** measure the momentum of leptons (especially electron) and photon where the main interaction obviously is electromagnetic interaction
3. **Hadron Calorimeter (HCAL)** has been designed for measure the energy of hadronic particle where it also has QCD interaction rather than only electromagnetic
4. **Superconducting Solenoid** for generate a nearly-uniform magnetic field inside of the cylindrical shape and definitely charge particle turn their heading around where it propagate in the outside of this radius like a muon track in Figure 2.2
5. **Muon Detectors** is one of the most important sub-detector for measuring the muon momentum and the track of them by also take the footprint tracking system into account to get more precise information which is also the most important task of CMS detector



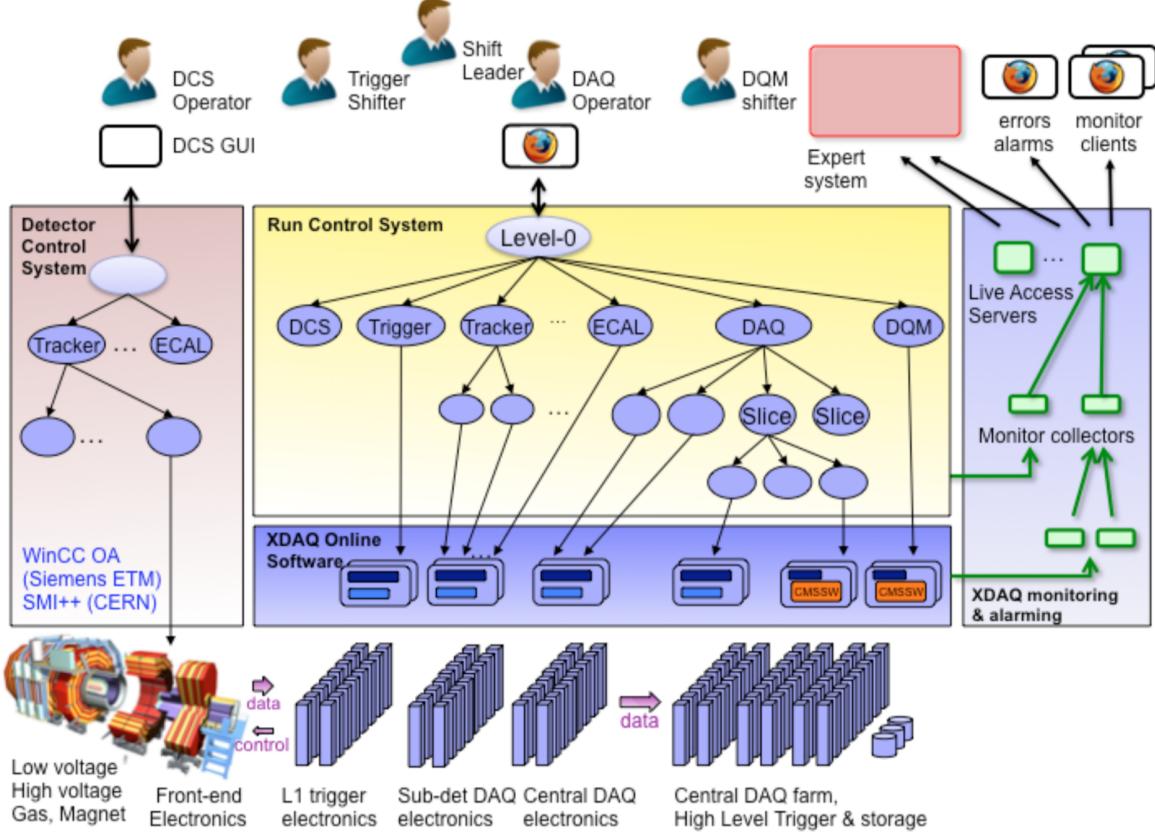
**Figure 2.2:** Onion-like crosssection of CMS. Image retrieved from [1]

## 2.2 Data Acquisition (DAQ)

According to [2], the collision rate takes around 40Mhz (100 Tbyte/s) which is impossible for the instrument to collect all of those signal that happen at a time. The harvested signal that CMS detector select are determined from low level trigger where the detector frontend (electronic circuit determination) process to select an interesting signal. The level-1 (L1) trigger filter and produce the signal at 100 kHz (100 Gbyte/s). Then it has been send to high level trigger (HLT) where we could start to really see the interpretable physical quantities from here.

### 2.2.1 CMS Online System

CMS team also provide the tools for automate data acquisition as [7] where the big picture has been demonstrated in Figure 2.3. Apparently, the system still need some people to double check by using various tools e.g. Web GUI and so on during the running process of beam collider in LHC from the low level system to high level system.



**Figure 2.3:** Overview of the CMS online systems. Image retrieved from [7]

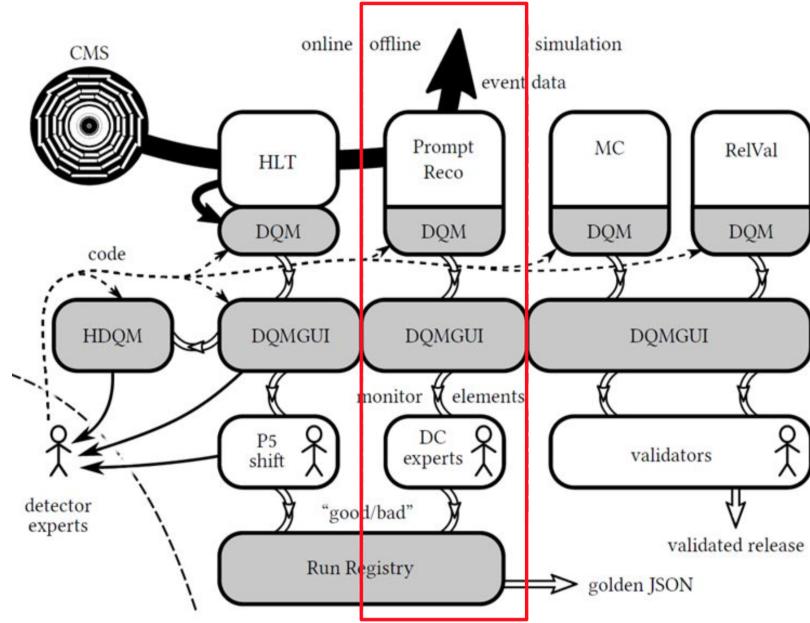
### 2.2.2 Data Granularity

We decide to divide a big chunk of data into one run and each run contain multiple lumisection which has an 23 seconds of interval due to the beam does not change much where we consider a 23 seconds of time. Moreover, each lumisection contain multiple events. If we consider in term of time to reconstruction, there are Express and PromptReco where data are reconstructed at nearly real-time and two days after collision.

## 2.3 Data Quality Monitoring (DQM)

In order to make sure that data quality is nearly perfectly well collected, there is another story called DQM where it's actually the subset of the run control system in the Figure 2.3. CMS DQM team provide the tool where there is online and offline shifter checking the result

from beam collision real-time and 48 hours after collision orderly. Figure 2.4 is the schematic of DQM workflow where including the tools and person who responsible for each module. If some sub-system went weird such as peak of the histogram drastically increase with no physical sense or some part of the detector turnoff, they will report in the log of the system in running process and calling detector experts to inspect the problem. In this work, we will only focus on the red box which is the offline world.



**Figure 2.4:** Tools and Processes of DQM. Image retrieved from M. Schneider, CHEP 2018

Regarding the scope that we want to mimic, offline shifter and detector experts check a multiple distribution histogram to inspect and certify data quality. The certification is made run and lumisection granularity. The procedure to certify the data are the following list

1. Runs tagged as bad by human (whole run)
2. Automatically filter by DCS bits, beam status and etc. (LS levels)
3. In rare cases are marked by DC experts (LS levels)

Then the rest of them that pass all of those criteria are defined in Golden JSON which are all of good LS.

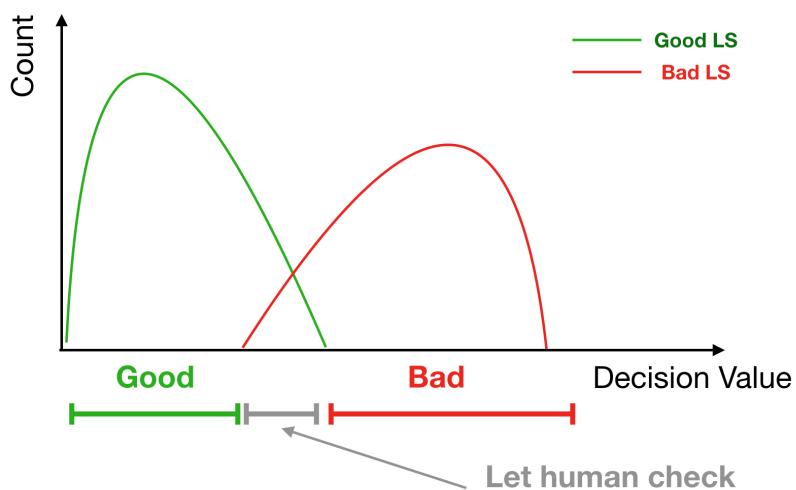
# Chapter 3

## Objectives

- Certify data quality in lumisection granularity
  - Classification on the basis of actual data distributions per LS
- Reduce manual work of DC Experts

### 3.1 Expectation

The most important aim of this work is to reduce the offline shifter work where we should provide the tools to reduce their work if some data are totally bad or perfectly good and let them inspect only for a few grey zone. To separate the kind of data quality, we have to define some decision value from some mathematical model to determine the data quality by finding some threshold to separate them. For the ideal case, we might see the good lumisection that looks perfectly good, bad lumisection that looks terribly skew and the grey zone where some of those two kind of lumisection are overlapping.



**Figure 3.1:** Three possible regions of prediction

### 3.2 Proposal For an Alternative Approach

Again, the purpose of this work is not to redefine the certification process but mimic a shifter and reduce their work if there is an obvious case. Then the automatic DCS bit flagging will stay but we apply the algorithm on top of it rather than remove and redefine as we mentioned. The quantity value of each data point are physical quantities such as

1. **Features** transverse momentum, azimuth angle from the beamline, etc.
2. **Objects** Mapped to the relevant primary dataset (i.e. tracks to ZeroBias, muons to SingleMuon and so on)

Since each run contain a lot of lumisection which probably too much for processing the certification, [4] offers a way to certify data by run and lumisection levels where there is a supervised learning apply in the whole run and feeding only the grey zone to inspect by lumisection to investigate the outlier on the step 2 as in the Figure 3.2.

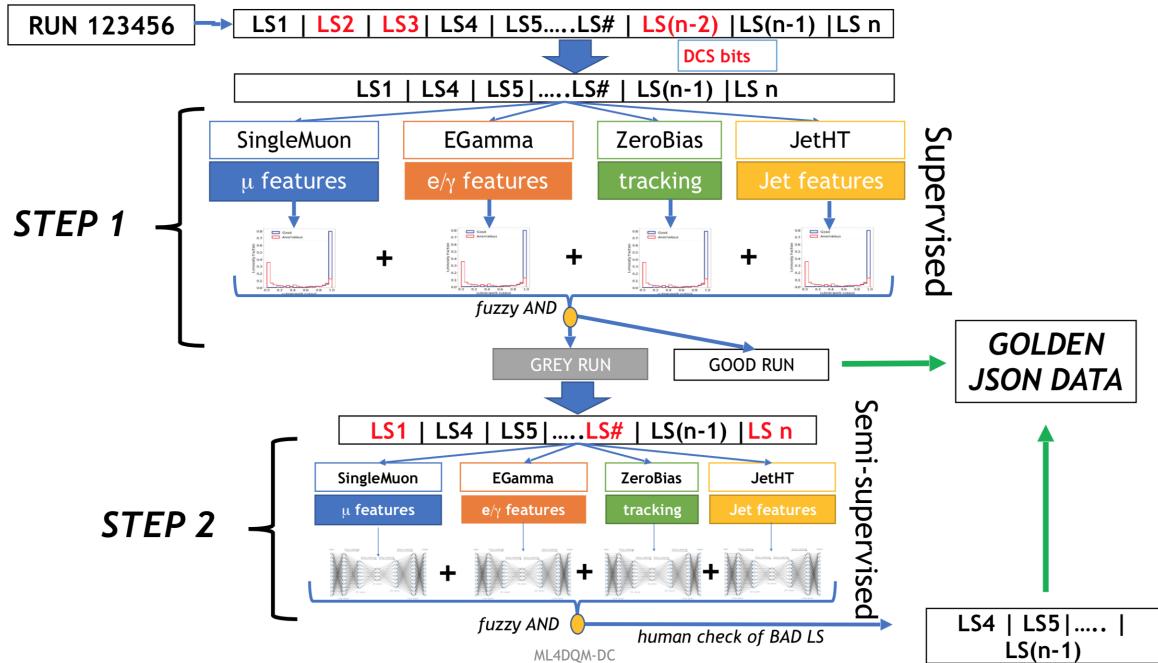


Figure 3.2: ML certification procedure, Image taken from [4]

# Chapter 4

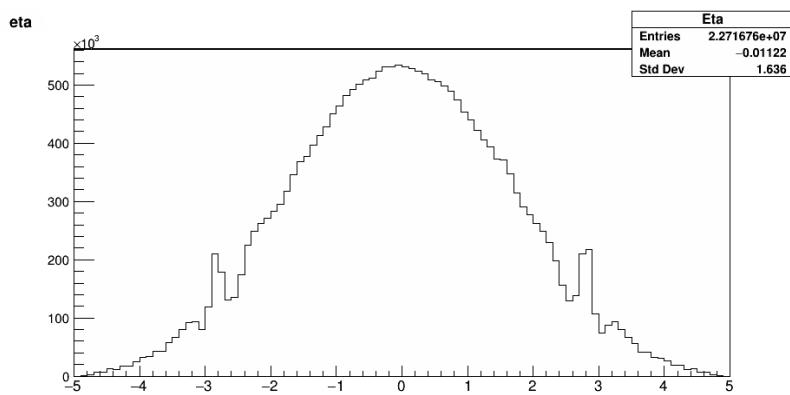
## Methodology

### 4.1 Datasets

#### Offline (PromptReco)

- pp collisions (Separately study 2016 and 2018 data)
- 4 different primary datasets: ZeroBias, JetHT, EGamma, SingleMuon
- Each lumisection (datapoint) contains
  - Selected  $n$  histograms of physics quantity e.g. JetPt, JetEta, JetPhi, etc.
  - Represent one histogram with 7 numbers
  - $n \times 7$  Features
- Good LS defined in Golden JSON else Bad LS

#### 4.1.1 Histogram Representation



**Figure 4.1:**  $\eta$  distribution, Image taken from DQM GUI

In order to mimic the offline shifter that looking at the histogram and certify data by that. Then we decided represent a single histogram with seven quantities instead of feeding

all of those to the model because it would be an overwhelming large features. The explicit example is to consider one histogram as Figure 4.1

Here are the simple step for picking up our represented vector

- Quantize [10%, 30%, 50%, 70%, 90%] of the histogram (For 2016 data, we quantize [0%, 25%, 50%, 75%, 100%] of the histogram)
- Combine mean and rms
- Use these 7 values to represent one histogram

#### 4.1.2 Data Preprocessing

For numerically convenient, we transform the each data point by using

**MinMaxScalar Transformation** The mathematical expression are represented by consider lumisection  $i$  and features  $j$

$$x'_{ij} \leftarrow \frac{x_{ij} - \min_{\forall i \in S_{\text{train}}} \{x_{ij}\}}{\max_{\forall i \in S_{\text{train}}} \{x_{ij}\} - \min_{\forall i \in S_{\text{train}}} \{x_{ij}\}} \quad (4.1)$$

In principle, each feature in our data should be in range zero to unity.

## 4.2 Semi-Supervised Learning

We exploidng a various unsupervised model from a beautiful simple one to more complicate neural network which are

- Schölkopf's One-Class SVM
- Isolation Forest
- 4 Flavours of Autoencoder

For training the model by feeding only good LS as well as validate it with good LS to ensure the learning curve is the appropriate for hyper-parameters configurations. After the training process is done, we test it with both good and bad LS. Consequently, it's falling into **Semi-supervised Learning** category.

#### 4.2.1 Schölkopf's One-Class SVM

Support vector machine (SVM) is one of the most popular machine learning model since it has no randomness and beautiful straightforward way to express. There is a way to tweak the original one to interpret as the radius-like hyperplane where the inlier of data are feeding and mapped to more than one radius with a soft margin controlled by factor  $\nu$  as interpret in [8]. By minimizing

$$\frac{\|w\|^2}{2} + \frac{1}{\nu l} \sum_{i=1}^l \xi_i - \rho \quad (4.2)$$

Subject to

$$w \cdot \Phi(x_i) \geq \rho - \xi_i, \quad \xi_i \geq 0 \quad (4.3)$$

With Gaussian Base Radial function (GBF) as a kernel like equation 4.4

$$k(\mathbf{x}, \mathbf{y}) = \exp(-\gamma \|\mathbf{x} - \mathbf{y}\|^2) \quad (4.4)$$

#### 4.2.2 Isolation Forest

The idea of bagging the sample and construct a tree are incredibly beautiful are interpreted and adapt in a way that unsupervised learning are come to the place are study by [6]. Forest are construct by picking up subsampling ( $\Psi$ ) and Iteratively picking up features and random value to construct the node (equivalent to step function), then Anomaly score evaluate from average depth of the instance over forest

$$s(x, \Psi) = \exp^{-\langle h(x) \rangle / c(\Psi)} \quad (4.5)$$

where

- $h(x)$  is the depth in tree  $h$
- $c(\Psi)$  normalization factor growing as  $\log_2(\Psi)$  from branching

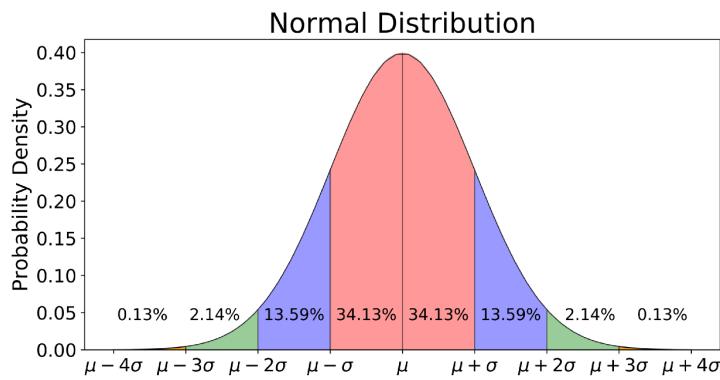
#### 4.2.3 Autoencoder (AE)

Let start with the hyper-parameters and configurations of our model

##### Truncated normal initializer

For model weight initializer, we are using truncated normal initializer which basically you take a gaussian distribution and putting the cutoff only inside  $\pm 2\sigma$  as in the Figure 4.2 to prevent some high absolute value that might leading to divergence of model in the training process.

In our case, we set up  $\sigma = 1$  and  $\mu = 1$



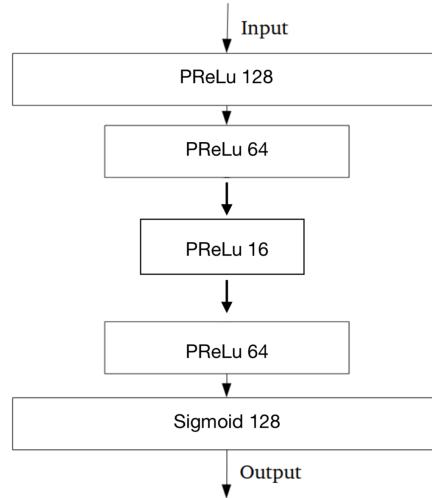
**Figure 4.2:** Gaussian distribution, retrieved from <https://towardsdatascience.com/understanding-the-68-95-99-7-rule-for-a-normal-distribution-b7b7cbf760c2>

### Adam Optimizer

Adam stands for **adaptive moment estimation** [5]. Basically, it's combine Momentum optimization and RMSProp to keep the residue of the gradients decaying from the previous update. We set up  $lr = 10^{-4}$  (learning rate),  $\beta_1 = 0.7$  and  $\beta_2 = 0.9$ .

There are 4 flavours of our autoencoder that we contructed

### Vanilla AE



**Figure 4.3:** Body of Vanilla AE

- Concise the information into small latent space and reconstruct
- Loss function is defined by

The loss function is designed by taking the square different reconstructed vector from the latent space and origin vector as 4.6

$$\mathcal{L}_{\text{tot}} \equiv \frac{1}{N} \sum_i^N |x_i - \tilde{x}_i|^2 \quad (4.6)$$

### Sparse AE

- Similar to Vanilla AE
- Tweak by L1 Regularizaion (Prevent overfitting)
- Loss function

$$\mathcal{L}_{\text{tot}} \equiv \frac{1}{N} \sum_i^N |x_i - \tilde{x}_i|^2 + \lambda_s \sum_j ||w_j|| \quad (4.7)$$

- where  $\lambda_s = 10^{-5}$

### Contractive AE

- Definition

$$\|J_h(x)\|^2 \equiv \frac{1}{N} \sum_{ij} \left( \frac{\partial h_j}{\partial x_i} \right)^2 \quad (4.8)$$

- where  $h_j$  is activation function
- In our cases
  - PReLU activation function

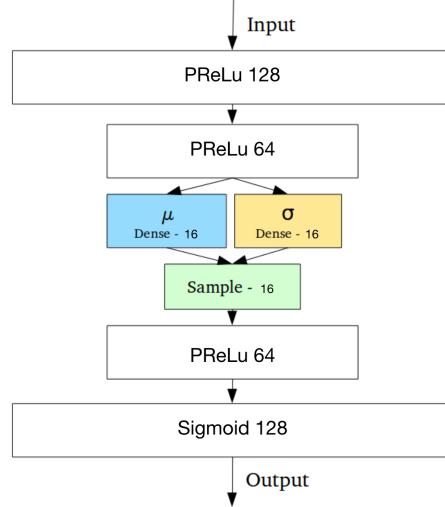
– Sigmoid activation function

$$\|J_h(x)\|^2 = \frac{1}{N} \sum_i^N \sum_j [\alpha_j H(-(w_{jk}x^{ik} + b_j)) + H(w_{jk}x^{ik} + b_j)] \sum_k (w_{jk})^2 \quad (4.9)$$

– Sigmoid activation function

$$\|J_h(x)\|^2 = \frac{1}{N} \sum_{ij} [h_{ij}(1 - h_{ij})] \sum_k (w_{jk})^2 \quad (4.10)$$

### Variational AE



**Figure 4.4:** Body of Variational AE retrieved from <https://towardsdatascience.com/intuitively-understanding-variational-autoencoders-1bfe67eb5daf>

- Random “new sampling” in latent space by gaussian random generator

$$\mathcal{Z} \equiv \mathcal{N}(\mu_i, \sigma_i) \quad (4.11)$$

- Tweak by reduce discontinuity in latent space
- Loss function

$$\mathcal{L}_{\text{tot}} = \frac{1}{N} \sum_i^N |x_i - \tilde{x}_i|^2 + \frac{1}{2N} \sum_i^N \sum_k^{n_{\text{latent}}} (\mu_{ik}^2 + \sigma_{ik}^2 - 2 \log \sigma_{ik} - 1) \quad (4.12)$$

# Chapter 5

## Results and Interpretation

### 5.1 2016 Datasets

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### 5.2 2018 Datasets

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# **Chapter 6**

## **Conclusions**

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# **Appendices**

## Appendix A

# An Appendix of Some Kind

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## Appendix B

### Another Appendix

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