Using Machine Learning Techniques for Data Quality Monitoring at CMS Experiment

by

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Abstract

The Data Quality Monitoring (DQM) of CMS is a key asset to deliver high-quality data for physics analysis and it is used both in the online and offline environment. The current paradigm of the quality assessment is labor intensive and it is based on the scrutiny of a large number of histograms by detector experts comparing them with a reference. This project aims at applying recent progress in Machine Learning techniques to the automation of the DQM scrutiny. In particular the use of convolutional neural networks to spot problems in the acquired data is presented with particular attention to semi-supervised models (e.g. autoencoders) to define a classification strategy that doesn't assume previous knowledge of failure modes. Real data from the hadron calorimeter of CMS are used to demonstrate the effectiveness of the proposed approach.

Keywords: [DQM, online, offline, Machine Learning]

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Chapter 1

Introduction

The work for this thesis was performed at CERN on CMS Experiment. CERN stands for European Organization for Nuclear Research. It was founded in 1954 and is located at the Franco-Swiss border near Geneva. At CERN, physicists and engineers are probing the fundamental structure of the universe. They use the world's largest and most complex scientific instruments to study the basic constituents of matter – the fundamental particles. The instruments used at CERN are purpose-built particle accelerators and detectors. Accelerators boost beams of particles to high energies before the beams are made to collide with each other or with stationary targets. Detectors observe and record the results of these collisions. The accelerator at CERN is called the Large Hadron Collider (LHC), the largest machine ever built by humans and it collides particles (protons) at close to the speed of light. The process gives the physicists clues about how the particles interact, and provides insights into the fundamental laws of nature. Seven experiments at the LHC use detectors to analyze particles produced by proton-proton collisions. The biggest of these experiments, ATLAS and CMS, use general-purpose detectors designed to study the fundamental nature of matter and fundamental forces and to look for new physics or evidence of particles that are beyond the Standard Model. Having two independently designed detectors is vital for cross-confirmation of any new discoveries made. The other two major detectors ALICE and LHCb, respectively, study a state of matter that was present just moments after the Big Bang and preponderance of matter than antimatter. Each experiment does important research that is key to understanding the universe that surrounds and makes us.

Chapter 2 presents a basic description of the Large Hadron Collider and CMS Detector

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The conclusions and results of each chapter are presented in the corresponding chapter.

This thesis work has been presented at several internal meetings of the CMS Experiment and at the following international meetings and conferences:

1. **Andrés Abreu** gave a talk "***Estimation of the Z Invisible Background for Searches for Supersymmetry in the All-Hadronic Channel***" at "APS April 2018: American Physical Society April Meeting 2018, 14-17 Apr 2018", Columbus, OH

2. **Andrés Abreu** gave a talk "***Phase-2 Pixel upgrade simulations***" at the "USLUA Annual meeting: 2017 US LHC Users Association Meeting, 1-3 Nov 2017", Fermilab, Batavia, IL

Chapter 2

The CMS Experiment

The Compact Muon Solenoid (CMS) detector is a general purpose particle detector designed to investigate various physical phenomena concerning the SM and beyond it, such as Supersymmetry, Extra Dimensions and Dark Matter. As its name implies, the detector is a solenoid which is constructed around a superconducting magnet capable of producing a magnetic field of 3.8 T. The magnetic coil is 13m long with an inner diameter of 6m, making it the largest superconducting magnet ever constructed. The CMS detector itself is 21m long with a diameter of 15m and it has a weight of approximately 14,000 tons. The CMS experiment is one of the largest scientific collaborations in the history of mankind with over 4,000 participants from 42 countries and 182 institutions. CMS is located at one of these points and it essentially acts as a giant super highspeed camera that makes 3D images of the collisions that are produced at a rate of 40 MHz (40 million times per second). The detector has an onion-like structure to capture all the particles that are produced in these high energy collisions most of them being unstable and decaying further to stable particles that are detected. CMS detector was designed with the following features (as shown in Figure 2.1) :

1. A **magnet** with large bending power and high performance muon detector for good muon identification and momentum resolution over a wide range of momenta and angles.

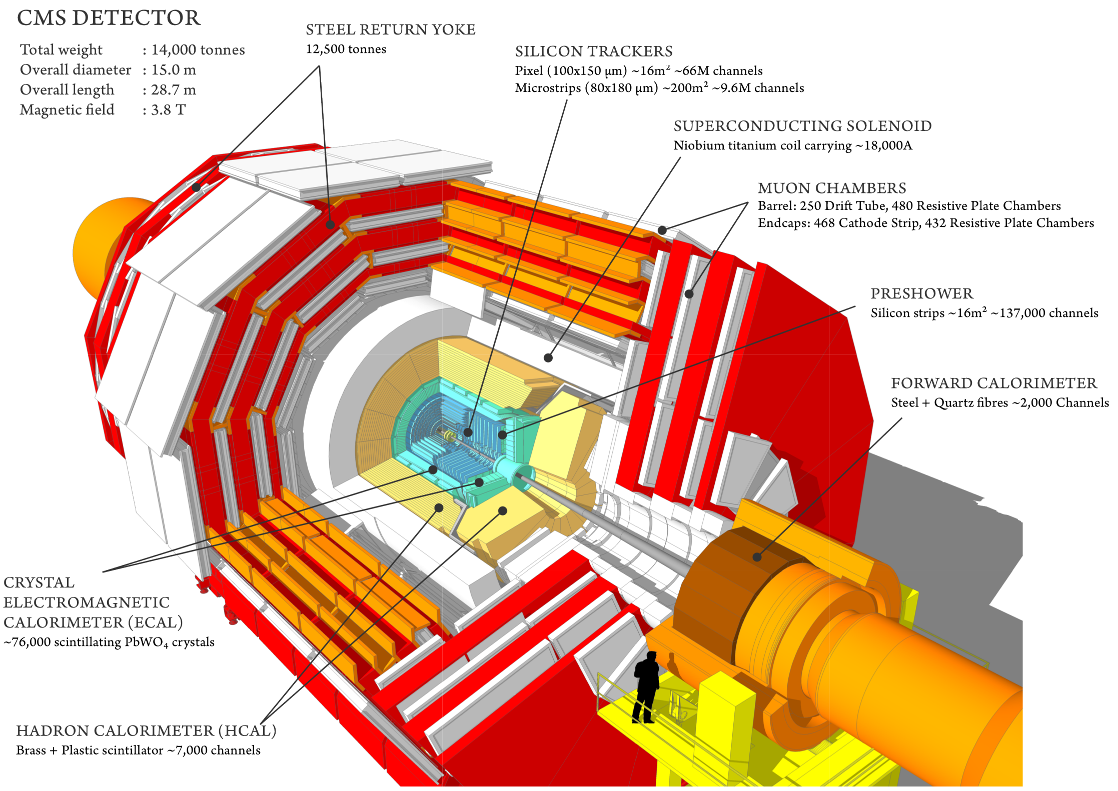


Figure 2.1: CMS Detector

2. An **inner tracking system** capable of high reconstruction efficiency and momentum resolution requiring **pixel detectors** close to the interaction region.

3. An **electromagnetic calorimeter** able to provide good electromagnetic energy resolution and a high isolation efficiency for photons and leptons.

4. A **hadron calorimeter** capable of providing precise missing-transverse-energy and dijet-mass resolution.

A property from these particles that is exploited is their charge. Normally, particles produced in collisions travel in a straight line, but in the presence of a magnetic field, their paths are skewed and curved. Except the muon system, the rest of the subdetectors lie inside a 3.8 Tesla magnetic field . Due to the magnetic field the trajectory of charged particle produced in the collisions gets curved (as shown in Figure 2.2) and one can calculate the particle's momentum and know the type of charge on the particle. The Tracking devices are responsible for drawing the trajectory of the particles by using a computer program that reconstructs the path by using electrical signals that are left by the particle as they move. The Calorimeters measure the energy of particles that pass through them by absorbing their energy with the intent of stopping them. The particle identification detectors work by detecting radiation emitted by charged particles and using this information they can measure the speed, momentum, and mass of a particle. After the information is put together to make the “snapshot” of the collision one looks for results that do not fit the current theories or models in order to look for new physics.

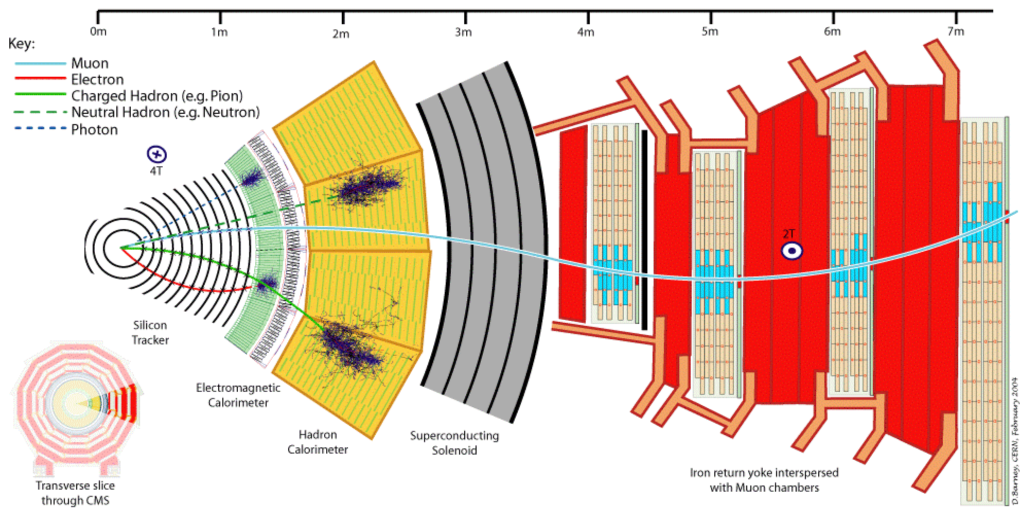


Figure 2.2: The trajectory of a particle traveling through the layers of the detector leaving behind it’s signature footprint

The project focusses specifically on data collected from one of the Calorimeters, - the Hadron Calorimeter (HCAL). The HCAL, as its name indicates, is designed to detect and measure the energy of hadrons or, particles that are composed of quarks and gluons, like protons and neutrons. Additionally, it provides an indirect measurement of the presence of non-interacting, uncharged particles such as neutrinos (missing energy) . Measuring these particles is important as they can tell us if new particles such as the Higgs boson or supersymmetric particles (much heavier versions of the standard particles we know) have been formed. The layers of the HCAL are structured in a staggered fashion to prevent any gaps that a particle might pass through undetected. There are two main parts: the barrel and the end caps. There are 36 barrel wedges that form the last layer of the detector inside the magnet coil, there is another layer outside this, and on the endcaps, there are another 36 wedges to detect particles that come out at shallow angles with respect to the beam line.

Chapter 3

Data Collection and Data Quality Monitoring

3.1 What is Data Collection for CMS?

During data taking there are millions of collisions occurring in the center of the detector every second. The data per event is around one million bytes (1 MB), that is produced at a rate of about 600 million events per second [1], that's about 600 MB/s. Keeping in mind that only certain events are considered "interesting" for analysis, the task of deciding what events to consider out of all the data collected is a two-stage process. First, the events are filtered down to 100 thousand events per second for digital reconstruction and then more specialized algorithms filter the data even more to around 100 200 events per second that are found interesting. For CMS there is a Data Acquisition System that records the raw data to what's called a High-Level Trigger farm which is a room full of servers that are dedicated to processing and classify this raw data quickly. The data then gets sent to what's known as the Tier-0 farm where the full processing and the first reconstruction of the data are done. [2]

3.2 What is Data Quality Monitoring?

To operate a sophisticated and complex apparatus as CMS, a quick online feedback on the quality of the data recorded is needed to avoid taking low quality data and to guarantee a good baseline for the offline analysis. Collecting a good data sets from the collisions is an important step towards search for new physics as deluge of new data poses an extra challenge of processing and storage. This all makes it all the more important to design algorithms and special software to control the quality of the data. This is where the Data Quality Monitoring (DQM) plays a critical in the maintainability of the experiment, the operation efficiency and performs a reliable data certification. The high-level goal of the system is to discover and pinpoint errors, problems occurring in detector hardware or reconstruction software, early, with sufficient accuracy and clarity to maintain good detector and operation efficiency. The DQM workflow consists of 2 types: **Online** and **Offline**.

The **Online** DQM consists of receiving data taken from the event and trigger histograms to produce results in the form of monitoring elements like histogram references and quality reports. This live monitoring of each detector's status during data taking gives the online crew the possibility to identify problems with extremely low latency, minimizing the amount of data that would otherwise be unsuitable for physics analysis. The scrutiny of the Online DQM is a 24/7 job that consists of people or shifters that work at the CMS control center constantly monitoring the hundreds of different plots and histograms produced by the DQM software. This consumes a lot of manpower and is strenuous work.

The **Offline** DQM is more focused on the full statistics over the entire run of the experiment and works more on the data certification. In the offline environment, the system is used to review the results of the final data reconstruction on a run-by-run basis, serving as the basis for certified data used across the CMS collaboration in all physics analyses. In addition, the DQM framework is an integral part of the prompt calibration loop. This is a specialized workflow run before the data are reconstructed to compute and validate the most up-to-date set of conditions and calibrations subsequently used during the prompt reconstruction.

This project aims to minimize the DQM scrutiny by eye and automate the process so that there is a more efficient process to monitor the detector and the quality of the data by implementing Machine Learning techniques.

Chapter 4

What is Machine Learning?

Machine Learning (ML) can be defined as an application of Artificial Intelligence that permits the computer system to learn without being told explicitly. In ML a computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E [3]. ML has made tremendous strides in the past decades and has become very popular recently due to its multifaceted applications. It is being used on social media, marketing, and in the scientific community as well. Some examples of ML applications are: the algorithms used on application in smartphones to detect human faces, self-driving cars, computer games, stock prediction, and voice recognition. An interesting characteristic of ML algorithms is that the more data one inputs the better is the performance. The ML application has a very wide spectrum covering almost every aspect of human endeavor that involves a lot of data. Scientific analysis today generates enormous data and is a hence is a perfect used case to apply ML techniques. In this work we use enhanced ML techniques based on progress in the recent past.

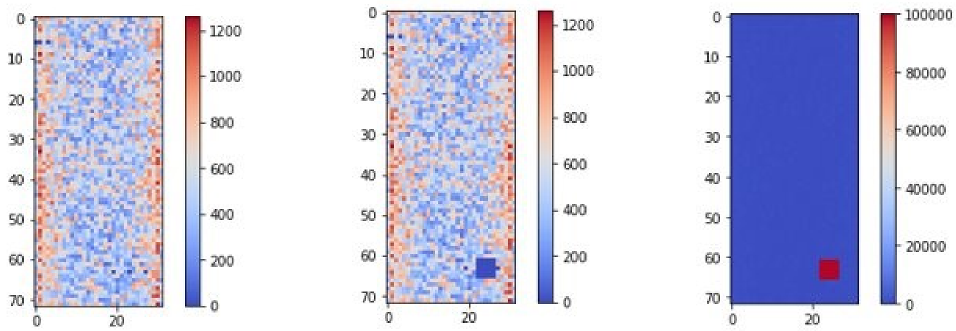
In general, there are two main categories to classify machine learning problems: **Supervised Learning** (SL) and **Unsupervised Learning** (UL). SL is the most used ML approach and has proven to be very effective for a wide variety of problems. Examples of common SL problems are: spam filters, predicting housing prices, identifying a malignant or benign tumor, etc. These types of problems are characterized by providing a "right answer" as a reference. For example, spam filter algorithms identify emails that are spams by training on a dataset that has examples of such emails. In case of predicting house prices, the algorithm is trained on a dataset of houses involving features like the area of the house, number of rooms, and the selling price of the house.

UL algorithms are different in the sense that they do not have the "right answers" given to the machine. Instead, UL algorithms are used for finding patterns and make clusters from the given data. That is what also forms the basis of a search engine (e.g. Google news). Clicking on a link to a news article, one gets many different stories of different journals that have some correlation with the article searched. This happens because the ML algorithm is capable of learning features and shared patterns from a bunch of data without being given any specifics. Another interesting UL problem is the so-called "cocktail party" that involves distinguishing the voice of two people recording on two microphones located at different places. The ML algorithm is able to separate the sources of the voices in the recordings by learning the voice features that correspond to each person, showing the power of the UL algorithm.

In this study, I have focused on an SL approach and a variant of the UL approach, called the **Semi-Supervised Learning** approach (SSL). The SSL is named so because the data involves looking at images that are already known to be "Good" but one doesn't necessarily know every possible situation that produces a "Bad" image. The purpose is to define a metric for a "good" image and subsequently decide if an image is "bad" in case it deviates too much from an acceptable value.

4.1 Developing the Algorithm

To develop an ML algorithm the following are taken into consideration, what is the task? and what is the method to approach the task? In our case, we are looking into images that have information about the activity that the channels in the HCAL are detecting. These images are called "occupancy maps" and they are a visual way of monitoring the health of the detector itself (See Figure 3). There are two common problems that can be identified by viewing occupancy maps which are called ”dead channels” and ”hot towers”. They are referred to as “dead” and “hot” respectively in the rest of this document. Dead channels mean that on a certain place in the occupancy map there is not any readout from the channels on the HCAL and hot channels mean that there are channels that are being triggered by noise or are damaged in a way that makes them readout too much activity.



(a) Good Image **(b)** Dead Image **(c)** Hot Image

Figure 4.1: Occupancy maps with 5x5 affected regions

The problem is the following, to create a model that can detect and classify what type of scenario is occurring on each occupancy map. For this, we want to go with a SL approach which means that we will give the model the images as the input and it will train on these images by learning to identify patterns or features in the image and try to do a “fit” from the images to their corresponding labels. After the training, the algorithm will be given a testing set for us to evaluate the model’s ability to correctly detect if there is a problem with the image and what type of problem is being detected. The output of the model will be the predicted class of the test image. The predictions are based on the labels and their corresponding images that were given to the model during training. This means that if the model was trained with 3 different types of images with their corresponding label the model will only work well for images that present similar patterns or characteristics to those presented in the training. For example, if we only train the model to distinguish between “good” and “hot” then when the model encounters images that aren’t either of these two, like an image labeled “dead”, then the model will not know what to do with this image and will give it an incorrect label. After the SL model has been tested the next step is trying an SSL model. The term semi-supervised simply means that there isn't a ground truth label that is being given to the model during training because either there isn't necessarily a ground truth, or we don't know what the ground truth is. What we do know, is what is considered as a "good" image and what this approach hopes to accomplish is to use the error in the reconstruction of the input image and use that information to discriminate between the "good" vs the "bad" images.

Appendix A

Appendix Title

Appendix B

References

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[2] CMS, “The CMS Computing Project,” tech. rep., CERN, 2005.

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