Optimizing ANN-Based Triggering for BSM events with Knowledge Distillation

Marco Lorusso[1,2]

[1]Department of Physics, University of Bologna, Bologna, Italy
[2]Bologna Division, Istituto Nazionale di Fisica Nucleare, Bologna, Italy

E-mail: marco.lorusso11@unibo.it

Abstract. In recent years, the scope of applications for Machine Learning, particularly Artificial Neural Network algorithms, has experienced an exponential expansion. This surge in versatility has uncovered new and promising avenues for enhancing data analysis in experiments conducted at the Large Hadron Collider at CERN. The integration of these advanced techniques has demonstrated considerable potential for elevating the efficiency and efficacy of data processing in this experimental setting. However, an often overlooked aspect of utilizing Artificial Neural Networks is the imperative of efficient data processing for online applications, crucial for selecting interesting events at the trigger level, such as Beyond Standard Model (BSM) events. This study explores Autoencoders (AEs), unbiased algorithms capable of event selection based on abnormality without theoretical priors. The unique latency and energy constraints within a trigger domain necessitate tailored software and deployment strategies to optimize on-site hardware, specifically Field-Programmable Gate Arrays (FPGAs). The strategy followed to distill the teacher model will be presented, together with consideration on the difference in performance of applying the quantization before or after the best architecture of the student model has been found.

1 Introduction

In order to increase the discovery potential of the Large Hadron Collider (LHC) at CERN, as well as to improve the precision of Standard Model physics measurements, the High Luminosity LHC (HL-LHC) Project was setup in 2010 to extend its operability by another decade and to increase its luminosity (and thus collision rate) by a factor of ~ 10 beyond its design value.

With the purpose of fully exploiting the HL-LHC running period, major consolidations and upgrades of all four main detectors at LHC are planned. The collision rate and level of expected pileup imply very high particle multiplicity and an intense radiation environment and imposes serious challenges to the Trigger system requirements in order to maintain performance, which pushes the need for technological advances at the hardware level of the data acquisition system, as well as new software ones to increase the physical acceptance of interesting events, while intensifying the efforts to identify and analyze events which are not explainable with the Standard Model theory.

One of the most popular type of algorithms proposed to tackle these needs is the one commonly known as Machine Learning, with a major focus on Artificial Neural Networks. In recent years, Machine Learning has become one of the pillars of Computer and Data Science and it has been introduced in almost every aspect of everyday life. This spread of learning algorithms in many sectors finds its roots mainly in an increased quantity of data available, combined with a technological progress in storage and computational power, which can nowadays be exploited with lower maintenance and material costs.

However, the latency and energy constraints of the first line of data acquisition at LHC experiments are quite unique and create the necessity of specific software development and strategies to deploy Machine Learning models efficiently on the hardware available on-site, like FPGAs.

Field Programmable Gate Arrays (FPGAs) combine the benefits of hardware and software by implementing circuits for high performance and efficiency while being reprogrammable for various tasks. They perform millions of operations simultaneously across a silicon chip, making them significantly faster than microprocessor-based designs, and can be reprogrammed multiple times, unlike ASICs.

A candidate for using Machine Learning as a triggering mechanism at LHC is the research for Beyond Standard Model events. The trigger selection algorithms are designed to guarantee a high acceptance rate for certain physics processes under study. When designing ways to search for new physics kinds of collisions (e.g., dark matter production), physicists typically consider specific scenarios motivated by theoretical considerations. This approach may become a limiting factor in the absence of a strong theoretical prior. This is why unsupervised ML techniques, like Autoencoders, can be useful for new physics mining. By deploying an unbiased algorithm which selects events based on their degree of abnormality, rather than on the amount of energy present in the event, data can be collected in a signal-model-independent way. Such an anomaly detection (AD) algorithm is required to have extremely low latency because of the restrictions imposed by the frequency of new events at LHC, and this is why there is a need to optimize and compress these kind of algorithm to make them suitable for trigger environments.

2 Anomaly Detection with Autoencoders

Anomaly detection (AD) aims to identify instances containing patterns that deviate from those observed in normal instances [1]. This task is crucial in various vision applications, such as manufacturing defect detection, medical image analysis, and video surveillance. Unlike typical supervised classification problems, anomaly detection presents unique challenges. Primarily, it is difficult to obtain a substantial amount of anomalous data, whether labeled or unlabeled. Additionally, the differences between normal and anomalous patterns are often fine-grained, as defective areas can be small and subtle in high-resolution images. Since the distribution of anomaly patterns is unknown in advance, models are trained to learn the patterns of normal instances.

In practice, an instance is determined to be anomalous if it is not well-represented by these models. Considering the peculiarities of this kind of task, AD is one of the popular application for Autoencoders [2].

2.1 Autoencoders

An Autoencoder (AE) is a type of Neural Network that is trained to attempt to copy its input to its output [3]. Internally, it usually comprises of a hidden layer h that describes a code used to represent the input. The network can be viewed as made up of two parts: an encoder function $\mathbf{h} = f(\mathbf{x})$ and a decoder that produces a reconstruction $\mathbf{r} = g(\mathbf{h})$. This architecture is presented in Figure 1. If an Autoencoder succeeds in simply learning to set $g(f(\mathbf{x})) = \mathbf{x}$ everywhere, then it is not especially useful. Instead, Autoencoders are designed to be unable to learn to copy perfectly. Usually they are restricted in ways that allow them to copy only approximately, and to copy only input that resembles the training data. Because the model is forced to prioritize which aspects of the input should be copied, it often learns useful properties of the data.

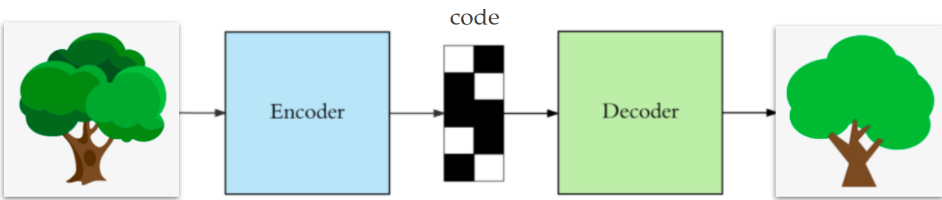


Figure 1: The general structure of an autoencoder, mapping an input to an output (called reconstruction) through an internal representation or code. The autoencoder has two components: the encoder and the decoder.

Autoencoders with nonlinear encoder functions f and nonlinear decoder functions g can learn a more powerful nonlinear generalization of Principal Component Analysis [4]. In other words, it is able to simplify the data while preserving its essential patterns and structures.

3 Knowledge Distillation

Deploying large, accurate deep learning models to resource-constrained environments like FPGAs, mobile phones, and smart cameras presents significant challenges. These models often have millions of parameters requiring substantial storage, while on-device memory is limited. Additionally, a single model inference can involve billions of memory accesses and arithmetic operations, which consume power, generate heat, and drain battery life, or test the device's thermal limits. To address these issues, research is focused on compressing neural network models to reduce memory and computation demands while maintaining model quality. Model compression not only reduces energy-intensive memory accesses but also improves inference time by increasing effective memory bandwidth. Knowledge Distillation, a key approach in this research, involves training a smaller student model to mimic a larger, complex teacher model, aiming to achieve competitive performance with fewer resources [5], [6].

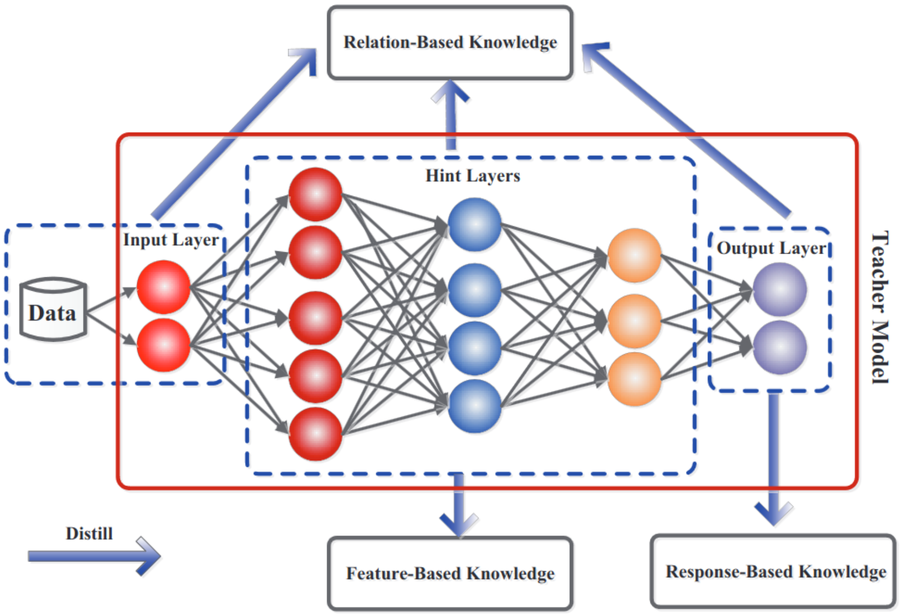


Figure 2: A schematic illustration of three different types of knowledge that can be transferred from a deep teacher network: response-based knowledge, feature-based knowledge and relation-based knowledge.

Knowledge types, distillation strategies and the teacher-student architectures play a crucial role in the student learning [7]. Indeed, there are three different categories of knowledge (see Figure 2):

Response-based It usually refers to the neural response of the last output layer of the teacher model. The main idea is to directly mimic the final prediction of the teacher model. The response-based knowledge distillation is simple yet effective for model compression, and has been widely used in different tasks and applications;

Feature-Based Deep neural networks are good at learning multiple levels of feature representation with increasing abstraction. This is known as representation learning. Therefore, both the output of the last layer and the output of intermediate layers, i.e., feature maps, can be used as the knowledge to supervise the training of the student model. Specifically, feature-based knowledge from the intermediate layers is a good extension of response-based knowledge, especially for the training of thinner and deeper networks;

Relation-Based Both response-based and feature-based knowledge use the outputs of specific layers in the teacher model. Relation-based knowledge further explores the relationships between different layers or data samples.

There are three main ways to transfer knowledge from a teacher to a student model. Offline Distillation involves transferring knowledge from a pre-trained teacher model to a student model in two stages: the teacher is first trained on a dataset, then it guides the student model's training using extracted knowledge.

Online Distillation updates both the teacher and student models simultaneously in an end-to-end trainable framework. Self-Distillation uses the same network for both teacher and student models by transferring knowledge, for example, from deeper sections of a network to its initial sections.

4 The Case study

In order to test this approach to model compression, the aforementioned use of an Autoencoder to perform physics mining of events not explainable using the Standard model was chosen [8]. A data sample was selected that represents a typical proton-proton collision dataset that has been pre-filtered by requiring the presence of an electron or a muon with a transverse momentum $p_T > 23$ GeV and a pseudo-rapidity $|\eta| < 3$ and $|\eta| < 2.1$, respectively. This is representative of a typical trigger selection algorithm of a multipurpose LHC experiment. In addition to this, four benchmark new physics scenarios discussed were considered [9]:

- A *Leptoquark* (LQ) with a mass of 80 GeV, decaying to a b quark and a τ lepton;
- A Neutral scalar boson (A) with a mass of 50 GeV, decaying to two off-shell Z bosons, each forced to decay to two leptons: $A \to 4$;
- A Scalar boson with a mass of 60 GeV, decaying to two tau leptons: $h_0 \to \tau\tau$;
- A charged scalar boson with a mass of 60 GeV, decaying to a tau lepton and a neutrino: $h_\pm \to \tau\nu$.

In total, the background sample consists of 8 million events. Of these, 50% are used for training, 40% for testing and 10% for validation. The new physics benchmark samples are only used for evaluating the performance of the models.

The architecture of the teacher model was an AE using convolutional layers (more details can be found in [8]). The inputs consisted in p_T, η, ϕ (azimuthal angle w.r.t. the LHC beam pipe) values for 18 reconstructed objects (ordered as 4 muons, 4 electrons, and 10 jets), and the ϕ and magnitude of the missing transverse energy (MET), forming together an input of shape (19, 3) where MET η values are zero-padded by construction (η is zero for transverse quantities). For events with fewer than the maximum number of muons, electrons, or jets, the input is also zero-padded.

4.1 Quantization vs architecture

The work in this paper was done not only to simply test KD, but also to try to answer a question related to the actual procedure to follow when trying to obtain a small model implementable on an FPGA. In particular, when optimizing a NN for hardware inference, one must consider not only finding the optimal architecture but also identifying the best quantization. Here for quantization is intended the conversion of all parameters, e.g. weights, of a model to fixed-point numbers, better handled by FPGAs. In this case the quantization is considered before performing the training of the students, falling into the Quantization Aware Training category [10], achieved using QKeras [11].

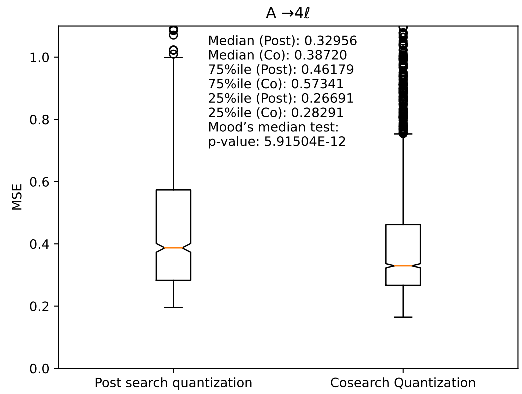
Thus, the question arises: Is there a difference between searching for the best candidate with the quantization process in mind versus without it? In other words, do the results differ when first identifying the optimal architecture and then determining the best quantization compared to performing a hyperparameter search that simultaneously considers both aspects?

The strategy to answer to this was simple. Firstly a simple hyperparameter search with no quantisation was performed to get the best student architecture; then, another search was done for the quantization using the model obtained (Post search quantization). On the other hand, a single search was set up to search the architecture and quantization parameters at the same time (Cosearch quantization).

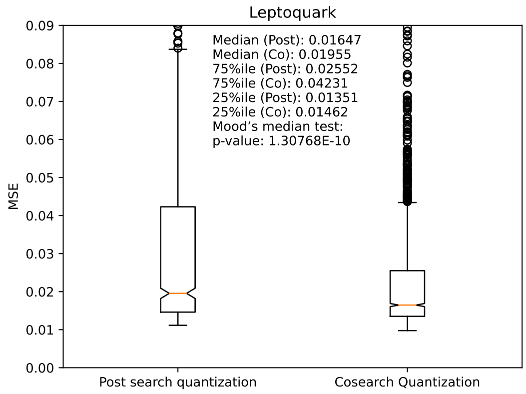
The results of the two search strategies are presented in Figure 3 and 4 for ≈ 1000 student candidates. These figures compare the distributions of the mean squared errors (MSE) of the models with respect to the teacher for the different anomalies the students are expected to detect. It is evident how the Cosearch quantization produces students with lower MSEs more consistently, with minimum values of both searches that are basically the same.

This means that by performing architecture and quantization optimizations as a single hyperparameter search, it is more likely to achieve a good model with fewer attempts, while also ensuring that both procedures will ultimately yield nearly identical optimal candidates.

Finally, in Figure 5 the ROC curves of the best student found with Cosearch quantization are shown. A good and very comparable with the teacher model performance was achieved, making this student a very good candidate for a future implementation on FPGA in order to study its efficiency in latency and hardware footprint.

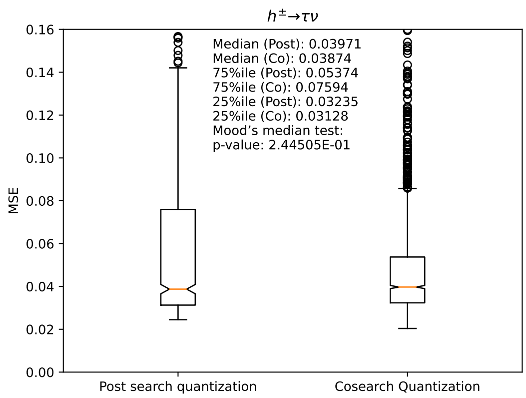


(a) A Neutral scalar boson (A) decaying to two off-shell Z bosons, each producing two leptons: $A \to 4$.

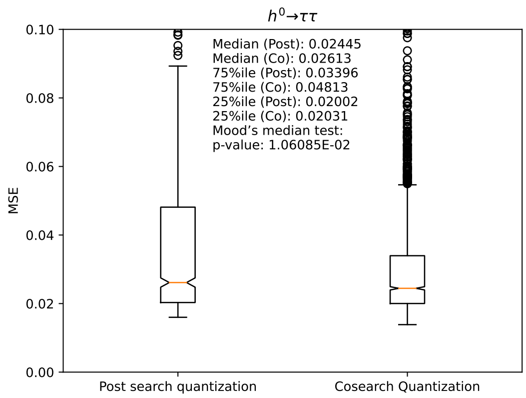


(b) A *Leptoquark* decaying to a b quark and a τ lepton.

Figure 3: MSE loss distribution of student models w.r.t. a teacher model built using Post search and Cosearch quantization for two of the 4 signals used for testing.



(a) A charged scalar boson decaying to a τ lepton and a ν.



(b) A Scalar boson decaying to two τ leptons.

Figure 4: MSE loss distribution of student models w.r.t. a teacher model built using Post search and Cosearch quantization for two of the 4 signals used for testing.

5 Conclusions

In conclusion, this study addressed the critical aspect of efficient data processing for online applications when utilizing Artificial Neural Networks, particularly for selecting interesting events at the trigger level, such as Beyond Standard Model (BSM) events. By focusing on Autoencoders (AEs) — unbiased algorithms capable of event selection based on abnormality without theoretical priors — this research tackled the unique latency and energy constraints within the trigger domain, necessitating tailored software and deployment strategies to optimize on-site hardware, specifically Field-Programmable Gate Arrays (FPGAs). The study compared two different strategies for optimizing Neural Networks obtained from the Knowledge Distillation of an Autoencoder, examining the performance differences between applying quantization during the phase of identifying the best architecture and after. The results show that it is more probable to find a good model by performing a combined hyperparameter search for both aspects of the optimization, while also confirming that the best models in both cases are comparable.

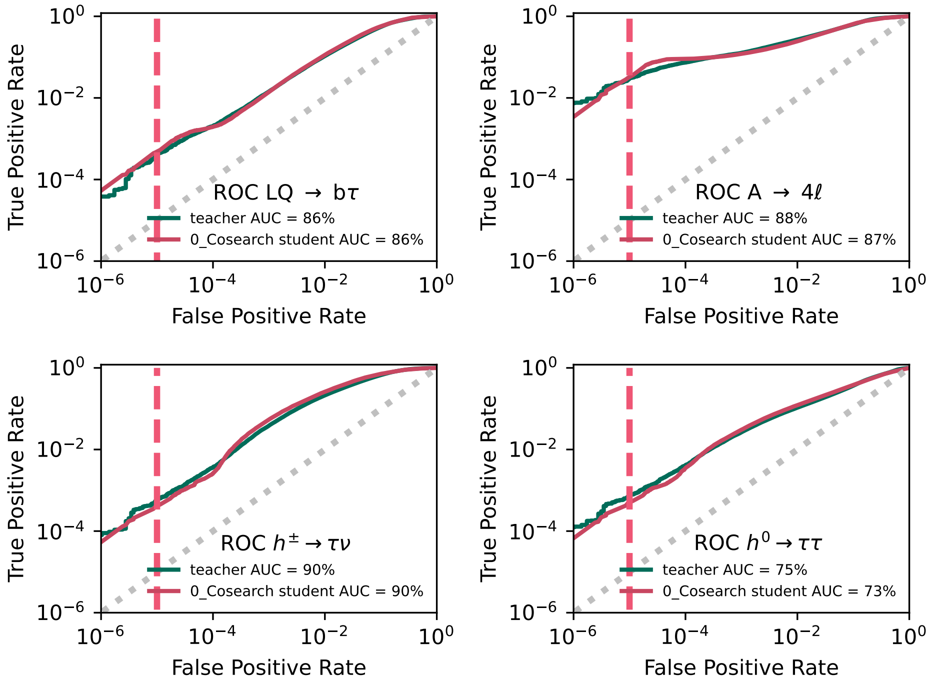


Figure 5: ROCs displaying the ability of the best student model (red) built with Cosearch quantization to detect the 4 test signals, compared with the performance of the teacher model (green).

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