



Contribution ID: 42

Type: **not specified**

Anomaly Detection in High Energy Physics via Non-Gaussian Variational Autoencoders

Thursday 9 November 2023 16:30 (15 minutes)

In particle physics, the search for phenomena outside the well-established predictions of the Standard Model (SM) is of great importance. For more than four decades, the SM has been the established theory of fundamental particles and their interactions. However, some aspects of nature remain elusive to the explanatory power of the SM. Thus, researchers' attention turns to the pursuit of new processes that can shed light on missing pieces of the model, potentially unveiling entirely new fundamental particles [1].

Within the context of the CERN Large Hadron Collider (LHC), most efforts to unveil new physics are directed toward specific experimental signatures. This strategy has proven exceptionally effective when hunting for preconceived, theoretically motivated particles. However, in cases where a predefined target is absent, the strength of this approach can also become its limitation. To overcome this potential hurdle, researchers engage in model-independent searches, and machine learning (ML) has emerged as the favored path for these explorations [2].

In the vast landscape of ML, Variational Autoencoders (VAEs) have emerged as a powerful tool for detecting anomalies across diverse domains. Their ability to capture the underlying data distribution and reconstruct input samples makes VAEs adept at identifying anomalies or outliers. Nonetheless, the conventional Gaussian distributions that underpin traditional VAEs may not be well-suited for the intricate nature of High Energy Physics (HEP) data. To address this challenge, we propose alternative VAE implementations, including [3]:

1. Multi-mode Non-Gaussian VAE (MNVAE):

This approach, previously used on complex electromechanical equipment, enhances the encoder's architecture to generate a latent variable governed by a Gaussian mixture model (GMM). The GMM is a linear combination of multiple Gaussian distributions, and it can characterize arbitrarily complex distributions if the number of Gaussian components is large enough. Subsequently, the Householder flow (HF) is employed to endow the latent variable with the full covariance matrix. [3].

2. Monte Carlo-based Approach:

In this method, the latent vector can assume a non-Gaussian distribution, offering a broader range of choices for the posterior distribution while ensuring a tighter Evidence Lower Bound (ELBO). This can result in VAEs capable of capturing finer details within the data distribution, thereby enhancing their generative capabilities and data reconstruction prowess [4].

Our aim is to thoroughly examine the underlying data distributions and subsequently introduce suitable modifications to the VAE framework. Creating a latent space that closely mirrors the data's shape holds the potential to enhance the VAE's ability to capture semantic content, making it better suited for anomaly detection purposes [5]. Later, hls4ml may be employed to synthesize VHDL code, enabling the implementation of the network on an FPGA.

References

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Session Classification: Anomalies