INTER-UNIVERSITY MASTER'S DEGREE PROGRAMME

Università degli Studi di Milano

Università degli Studi di Milano - Bicocca

Università degli Studi di Pavia

Master's Degree Programme

Artificial Intelligence for Science and Technology

Unsupervised Anomaly Detection for High-Energy Physics Using VAEs

Class: AI Model For Physics

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Academic Year 2023/2024

Repo:https://github.com/herormo/anomaly-detection-HEP

Project Overview

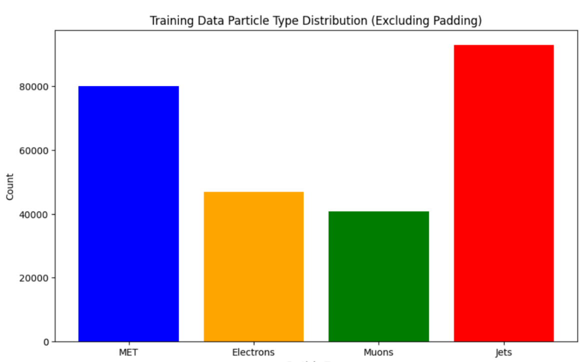
This project aimed to detect anomalies in particle physics data using unsupervised learning techniques more specifically using Variational Autoencoders, focusing on identifying events that deviate from the Standard Model (SM) in high-energy physics. The dataset used in this project was generated and published by CERN for the LHC 2021 Anomaly Detection Challenge, and it included a mixture of SM processes and Beyond the Standard Model (BSM) events. The dataset contained a "blackbox" dataset with new physics events. The primary challenge was to build a model capable of identifying these anomalies, which may indicate new physics phenomena.

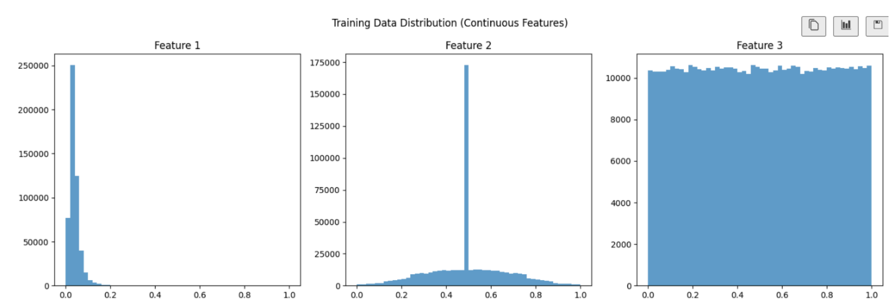
Data Description

The datasets were provided in Hierarchical Data Format version 5 (HDF5) and contained three main components: "Particles", "Particles_Classes", and "Particles_Names". The "Particles" dataset had a shape of (N, 19, 4), where N was the number of events. The second index represented the various physics objects such as MET, electrons, muons, and jets. The events were zero-padded, meaning that fewer objects were filled with zeros to maintain consistency across the dataset.

The physics objects in each event were characterized by their transverse momentum (pT), pseudorapidity (η), and azimuthal angle (ϕ), along with an additional particle type index to distinguish between MET, electrons, muons, and jets.

This is how the distribution of the different features looks like:





Methodology

1. **Data Preprocessing**: The data preprocessing stage involved loading the dataset and normalizing it to prepare for model training. The continuous features were normalized using min-max scaling, ensuring values were between 0 and 1. Categorical features, such as particle type, were one-hot encoded, resulting in four separate features representing the

different particle types. After preprocessing, the dataset contained seven features, excluding the original particle type index.

Zero-padded events (those with no particles) were removed, as they contributed no information to the VAE. The preprocessed data was then split into training, validation, and testing sets, which were used as follows:

- **train_loader**: Used to train the VAE on SM data.
- **val_loader**: Used to validate the model during training, assisting in hyperparameter tuning.
- **test_loader**: Contained BSM data for testing the model's anomaly detection performance.
- **blackbox_loader**: Contained blackbox data for the final evaluation of the model's ability to detect unknown anomalies.

2. **Model**: The primary model used for anomaly detection was a Variational Autoencoder (VAE). Unlike traditional autoencoders, VAEs take a probabilistic approach, learning the parameters of a probability distribution (mean and variance) from which latent vectors are sampled. This structure provides a smoother and more continuous latent space, which is crucial for effective anomaly detection.

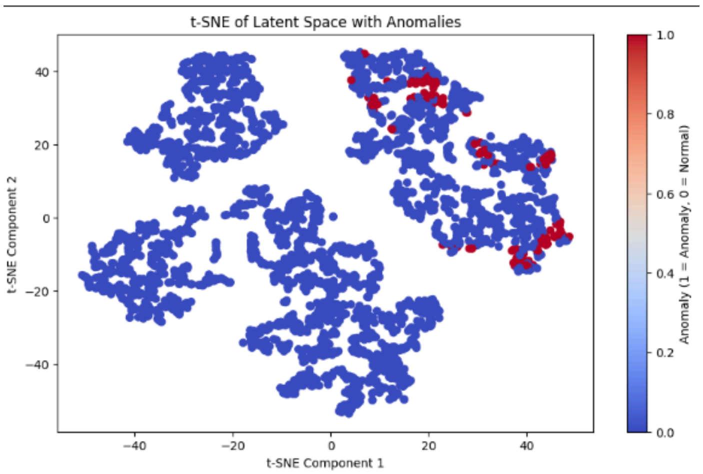
   VAEs use a regularization term known as the Kullback-Leibler (KL) divergence, which ensures the latent space approximates a normal distribution. This regularization, combined with the reconstruction loss that penalizes deviations from the original data, helps the model generate a well-structured latent space for anomaly detection.

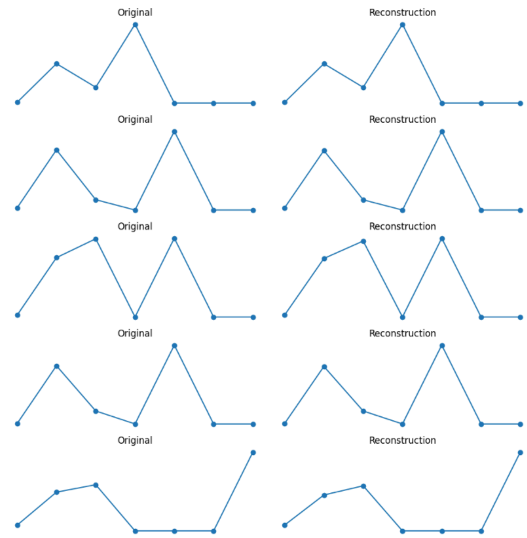
   Hyperparameter tuning was performed using Optuna, an optimization framework. The model was trained to minimize reconstruction errors, and high reconstruction errors were flagged as potential anomalies.

3. **Evaluation**:
   After training, the model's ability to detect anomalous events was assessed by calculating the reconstruction error for each event. Events with high errors were flagged as potential anomalies. The black box dataset, which contained new physics events, was particularly of interest as it was used to test the model's ability to detect BSM events.

Results

The Variational Autoencoder (VAE) effectively reconstructed normal events, forming well-defined clusters in the latent space, as shown in the t-SNE visualization. However, the anomalies, represented by red points, are scattered within the clusters rather than appearing as distinct outliers. While this indicates the model detected some level of anomalous behavior, the anomalies are not entirely separated from normal events. Due to the lack of access to ground truth labels for the black box data, we were unable to fully evaluate the accuracy of these detected anomalies, which limits the overall assessment of the model's performance in identifying potential Beyond the Standard Model (BSM) phenomena.





Disclaimer: I have used ChatGPT to review and refine my sentences and paragraphs in this document.

References:

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3. CERN Indico: Event overview from the Anomaly Detection workshop, 2020. [Indico - CERN Event Overview]
4. GitHub repository: "Anomaly Exercise" by the UHH-PD-ML team. [GitHub - UHH-PD-ML Anomaly Exercise]
5. Arxiv paper: "Exploring Anomalies in Physics: A Case Study" (arXiv:2107.02157). [arXiv.org]