# Adaptive Anomaly Detection in LHC Triggers

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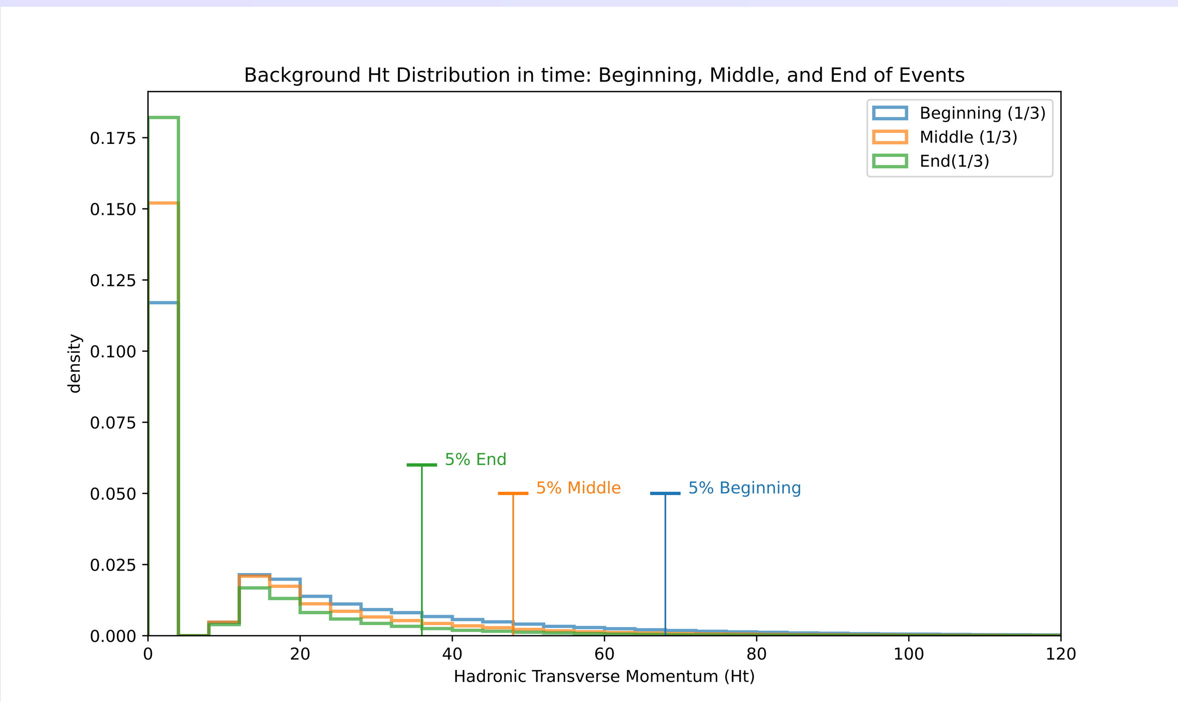
## LHC Trigger System

The **LHC** generates vast amounts of data, with proton-proton collisions occurring at rates of 40 MHz. Due to bandwidth and storage limits, the LHC trigger system reduces this data by more than 10,000x, selecting only the most relevant events for potential new physics.

**Trigger Menu**: The trigger system selects events according to a "menu" of algorithms, including traditional strategies based on specific particles such as muons, or using more advanced methods like anomaly detection (AD).

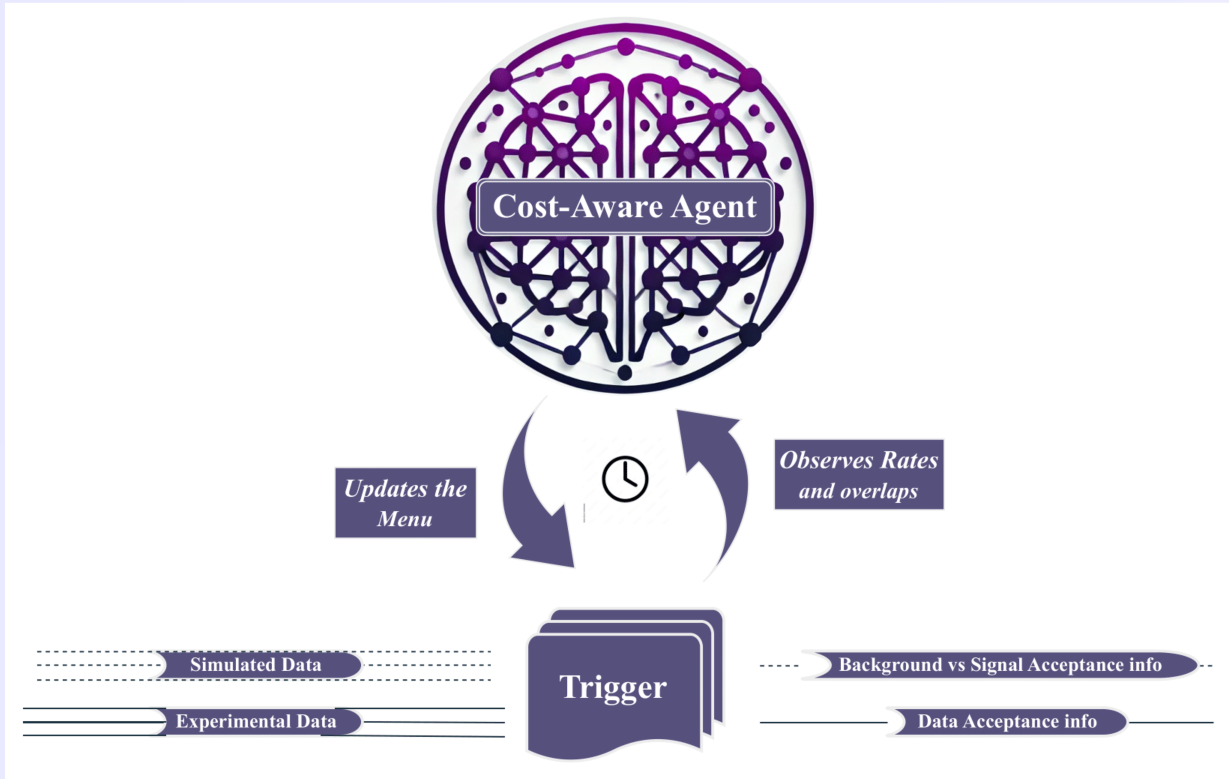
**Cuts and Thresholds**: A key feature of the menu is the set of cuts to accept only events above some limit. For instance, a jet-based trigger would require a threshold for jet energy or transverse momentum ($p_T$), or an AD trigger needs a threshold based on the anomaly score.

**Experiments Dynamics**: Over time, important experimental conditions can change, altering the detector response. For example, the mean number of interactions per event decreases in each LHC fill, necessitating adjustments to the trigger thresholds. For AD triggers, the definition of 'anomalous' events may also change over time. Therefore, an adaptive system capable of observing these changes and updating the trigger menu accordingly is crucial.




## Project Overview

In this work, we introduce a modular ecosystem to develop and assess strategies for autonomous discovery that incorporates diverse components including: datasets with time-dependent effects, complex trigger menus, real-time control mechanisms, and cost-aware optimization criteria. We illustrate this framework with a novel benchmark based on reinforcement learning for traditional and anomaly detection triggers using public CMS datasets, aiming to encourage community-driven development towards a new generation of both intelligent and adaptive triggers.

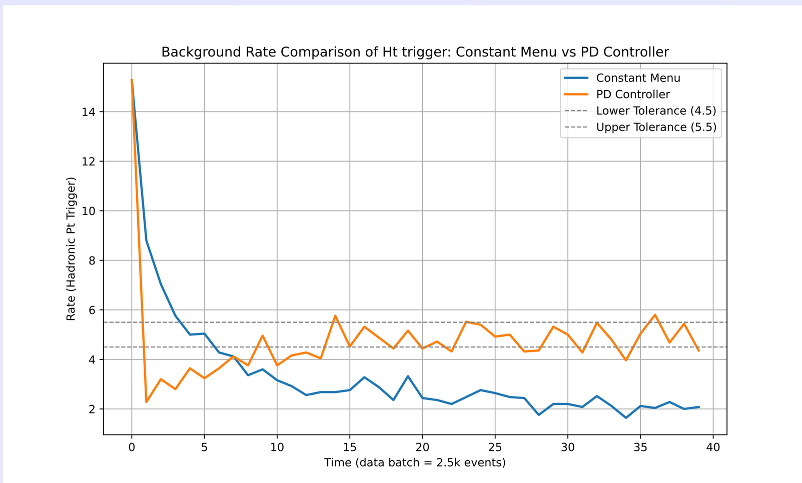


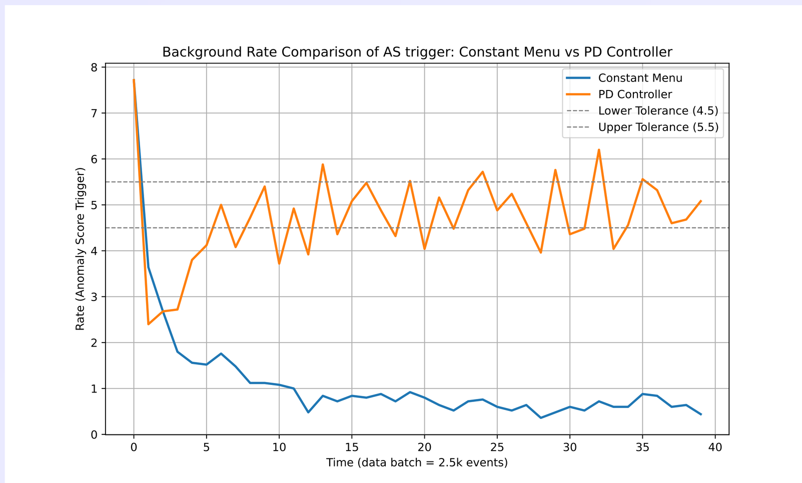

## Single-Path Trigger

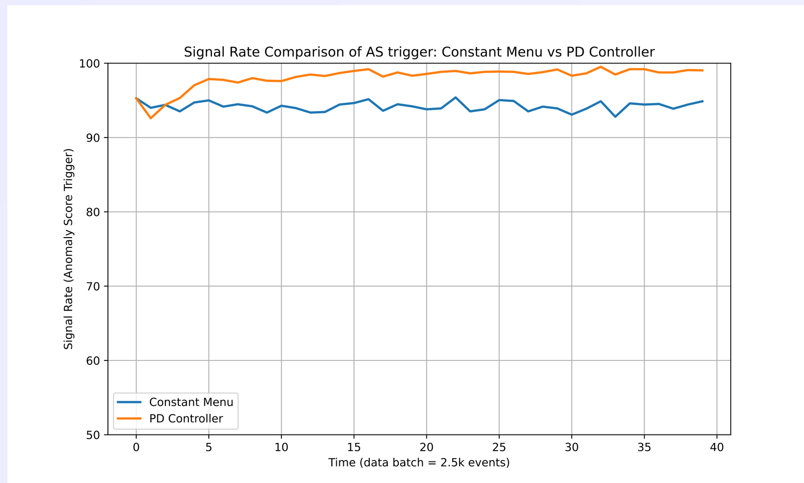
To illustrate how characteristics of the data evolve over time, consider a trigger requiring large $H_T$ (hadronic transverse momentum of an event). The distribution of $H_T$ varies between the beginning, middle, and end of a typical LHC fill from the 2015 CMS data. To maintain a constant selection rate, time-dependent cuts are necessary.

For a single trigger item, this issue can be resolved using a Proportional-Derivative (PD) controller, which dynamically adjusts the cuts to maintain a constant background rate. The results below demonstrate how the PD controller effectively stabilizes the background rate over time for 2 items in the menu. PD controller adjusts the menu based on the difference between current rate and target rate:

$$e = \text{rate - target} \rightarrow \Delta H_T - cut = K_p e + K_d \frac{de}{dt}$$

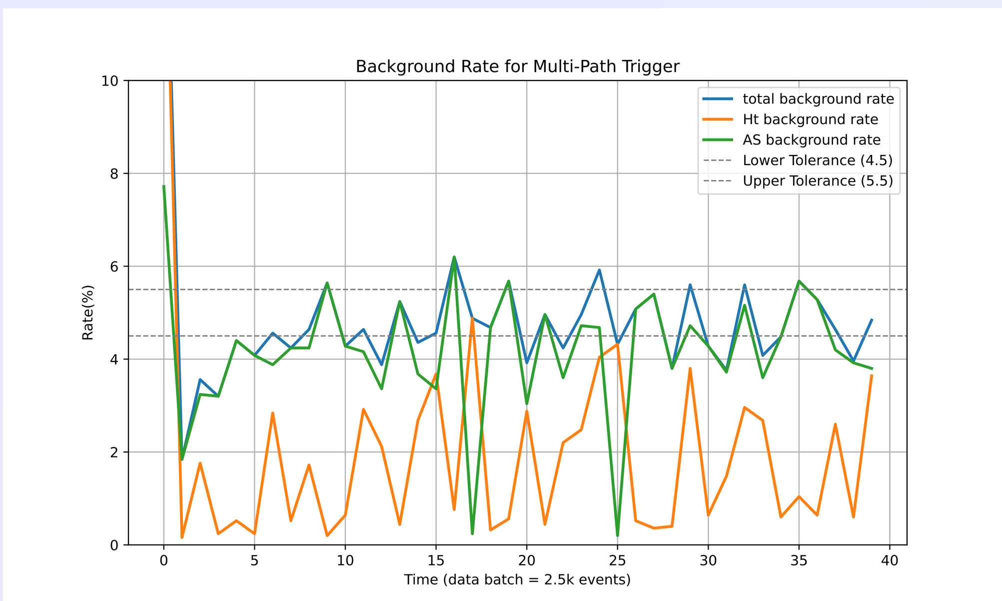


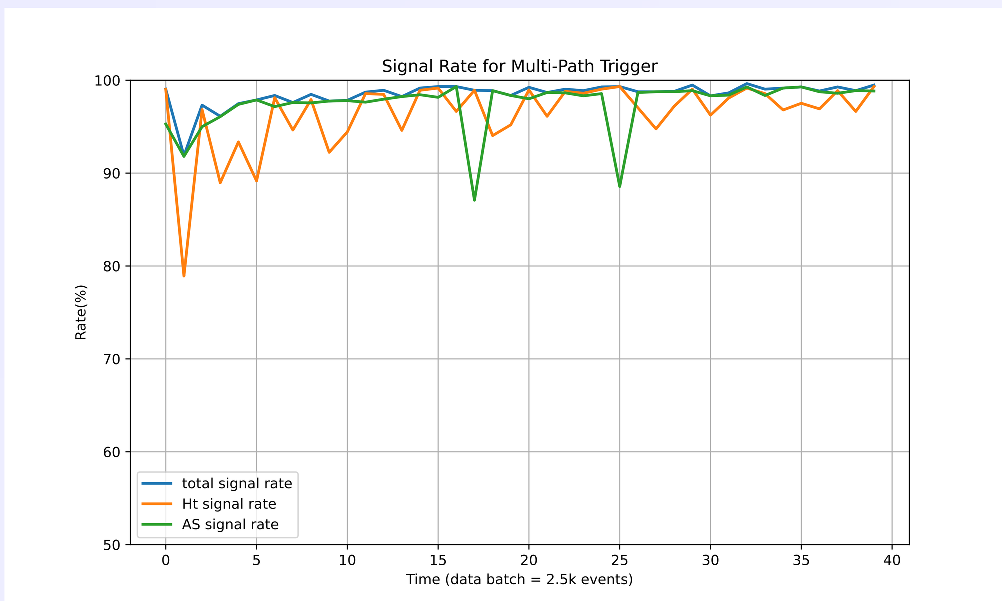




## Multi-Paths Trigger

$$\text{Cost} = \text{a}_1(rate_b - t_b)^4 + a2|rate_s - 1|$$

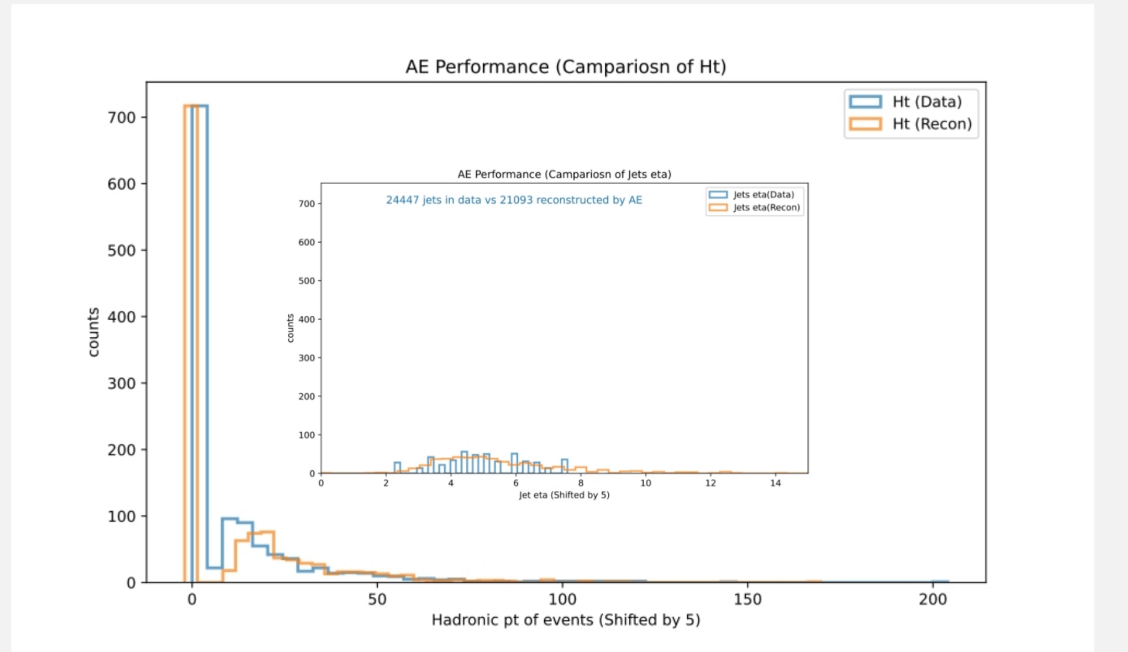



## Toy Model

**Data** : We use the 2015 CMS open data and MC simulation, focusing on jets reconstructed by the Level 1 trigger. The key processes are minimum bias (background) and $t\bar{t}$ (signal) datasets, and to mimic the time variation effects in these samples, events are sorted by a smeared estimate of the interaction multiplicity

**Anomaly Detection**: Anomaly Detector is a Variational Autoencoder (VAE), trained on known physics (background) to capture anomalous events that may indicate new discoveries. Our anomaly detection model focuses on hadronic signatures which are traditionally most challenging to collect with traditional trigger strategies. We trained an autoencoder using 8 jets from each event (with $p_T$, $\eta$, $\phi$, $Npv_{smeared}$) from MinBias events. The autoencoder compresses this data into lower dimensions, learns the typical background behavior, and assigns an anomaly score to each event based on the difference between the reconstructed output and the original data.




**Single vs Multi Paths**: Currently, we are focusing on two triggers in the menu: $H_T$ and the AD. A single-path trigger operates based on just one of these, while a multi-path trigger uses both. Single triggers work based on PD loop, while for multi-path, we introduce a cost function to optimize the system in real time, and minimizing the cost function based on the set of criteria is the key to control rates over time. For high-energy signals like $t\bar{t}$, the AD trigger is expected to behave similarly to the $H_T$ trigger. Therefore, incorporating new types of signals is one of the goals for future analyses ...