Monitoring of Time Evolution of the Trigger Rates Exploiting Deep Representation Learning at the CMS Experiment

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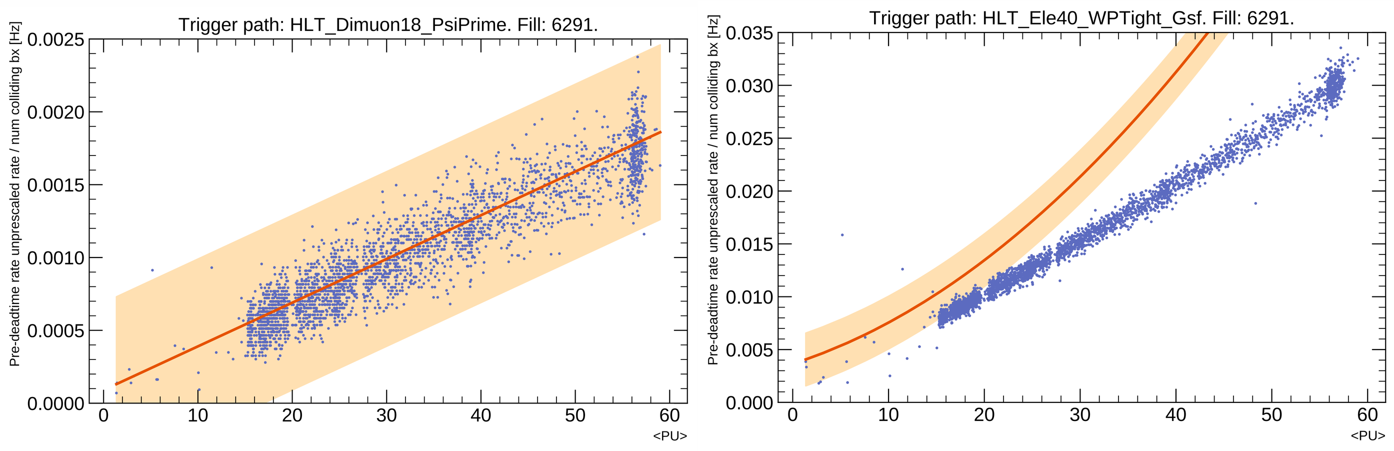
Trigger System at the CMS Experiment

- **Reduces the event rate** from 40 MHz to 1 kHz [1]:
  - **Level 1** (L1) **Trigger**: custom-designed electronics, scaling to 100kHz;
  - **High Level Trigger** (HLT): software, scaling to 1kHz.
- Trigger systems implement configurable rules to perform the selection (*paths*).
- The HLT paths are seeded by the events selected by a configurable set of L1 rules.

Review of CMS Trigger Rate Monitoring Tools

- Rates are monitored as a function of average pile-up (PU) i.e. average number of simultaneous collisions in an LHC bunch crossing.
- Prediction is limited to regression models trained on recent good data.
- Each model for trigger path trained independently from others.
- Monitoring tool compares obtained rates to a set of predictions, [2].



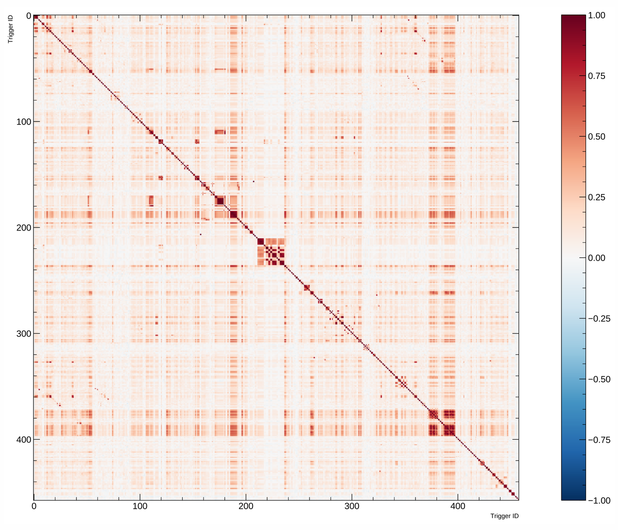
Observed rates as a function of average PU (blue dots), compared to the predicted dependence (red line) and its uncertainty (in orange band) generated using monitoring software. The plots above show an example of well (left) and poorly (right) predicting model.

Why Machine Learning?

The CMS trigger rate monitoring should account for underlying factors of variation. The goal is to **extend** the **anomaly detection** capabilities of the monitoring, exploiting current advances in machine learning and copious CMS data archives.

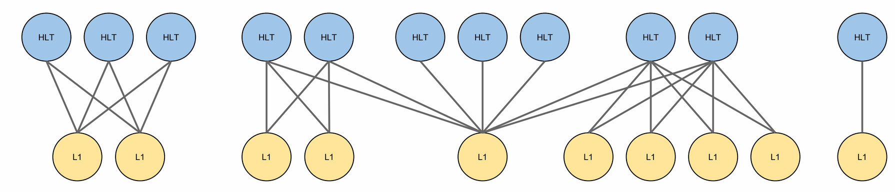
Extended Monitoring: Exploring Similarities

- Are trigger paths correlated?



Correlations between 458 HLT paths rates of LHC fill 6291. The calculation is performed after preprocessing the trigger rates using first differences ($\hat{x} = x_t - x_{t-1}$) and z-score normalization to account for different scales.

Extended Monitoring: Exploring Causality



Simplified, schematic graph inspired by the trigger system configuration. Blue nodes represent HLT paths while yellow L1 trigger paths. Each link is unidirectional starting from yellow nodes. The graph has few hundred nodes for each LHC fill, spread approximately equally between HLT and L1 triggers paths.

Background

- A variety of algorithms, based on autoencoder architecture, were proposed to explore the hierarchical organization and disentanglement of latent features [3, 4].
- Disentangling factors becomes easier under strong supervision [5].
- We denote generative modeling as $p(x, z) = p_\theta(x|z)p(z)$, where:
  - x random observable variable;
  - z independent random latent variables;
  - $p(z)$ is the prior distribution over the latent variables (e.g. spherical Gaussian $N(0, I)$);
  - $p_\theta(x|z)$ is a conditional likelihood function: a non-linear transformation with parameters θ.
- **Variational Autoencoder (VAE)**:
  - learns approximate inference using stochastic gradient descent [6];
  - learns approximate inference posterior distribution $q_\phi(z|x) = N(\mu, \sigma I)$ with a neural network ϕ (encoder) and mean μ;
  - minimizes the upper-bound on the expected negative log-likelihood of x:

$$\mathbb{E}_{q(z|x)}[-\log p_\theta(x|z)] + D_{\mathrm{KL}}(q_\phi(z|x)||p(z))$$

  first term is a reconstruction error, second is the additional regularizer.

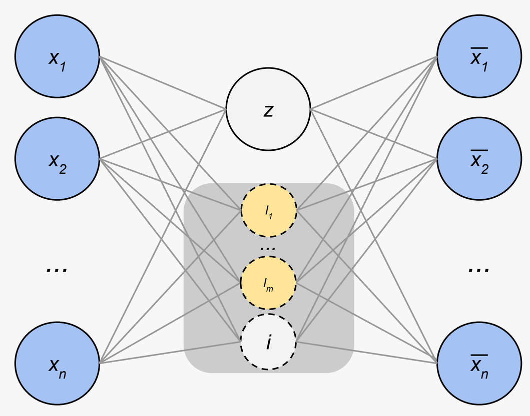
Composite VAE (CompVAE)

- Independent sources of variation in data: observed variable a describing known factors and a latent variable z that characterizes remaining variability.
- To generate new instance of x: $z \sim p(z) = N(0, I); x \sim p_\theta(x|z, a)$.
- We introduce two encoders:
  - deterministic encoder that links HLT rates to the corresponding L1 rates;
  - encoder that parametrizes the posterior $q_\phi(z|x, a)$.
- To prevent all information be stored in z, we introduce additional objective $\mathcal{L}_a$:

$$\mathbb{E}_{q(z|x,a)}[-\log p_\theta(x|z, a)] + D_{\mathrm{KL}}(q(z|x)||p(z)) + \lambda\mathcal{L}_a,$$
$$\mathcal{L}_a = \mathbb{E}_{q(a|x)}[-\log p_\phi(a|x)]$$

Factors of Variation in the Trigger System

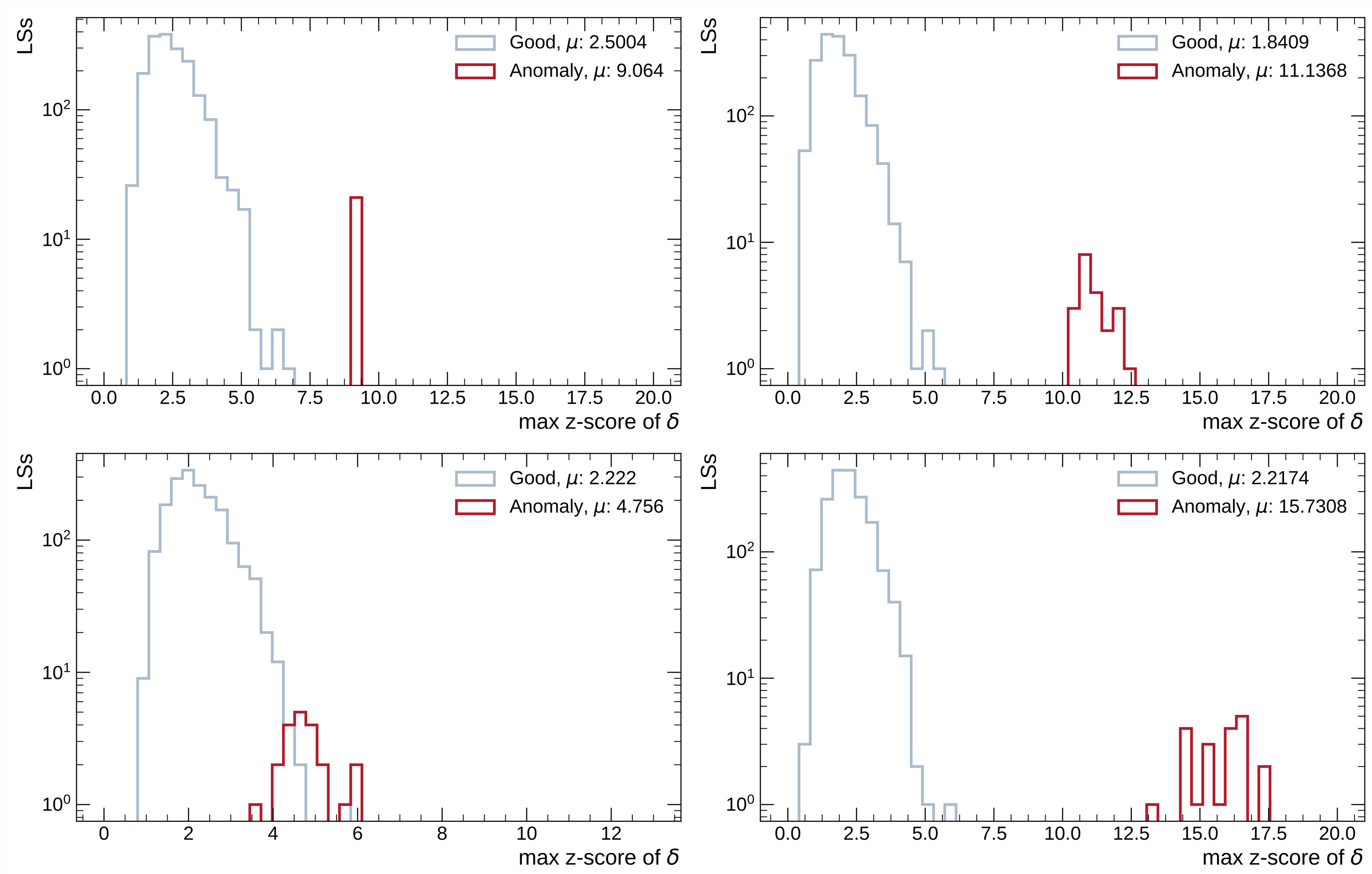
- HLT trigger rate x depend on some latent features $X = f(a, z)$, where:
  - values of a correspond to average PU and L1 trigger rates;
  - values of z are characterizing the remaining variability.
- Anomalies are going to be spotted in incorrect reconstruction of x or encoding of a.



Architecture of our CompVAE model. Yellow nodes l correspond to L1 rates and i to average PU. l and i constitute a vector a. Node z is the variable that aims to describe the variability of the HLTs that is not captured by a. In our experiment we use 15 HLT and 4 L1 paths.

Experiments

- **Real dataset**: trigger rates recorded in the past labelled by detector experts.



Reported max z-score (to account for different scales) of the distances between predicted and recorded rates for each data point (LS). Results from left to right, top to bottom: model currently used in production, extended regression (with L1 trigger rates), non-regularized AE and CompVAE.

- **Synthetic dataset**: four artificial benchmark scenarios and reported p-values

Description	Label	Production	Extended	CompVAE	CompVAE ϕ
3σ deviation form trend on 3 correlated triggers	Anomaly	.090	.037	.162	**.027**
5σ deviation form trend on 1 of the trigger paths	Anomaly	.017	.001	**<.001**	.465
3σ deviation form trend on 3 random triggers	Good	.294	.037	.031	.346
3σ deviation form trend on 1 of the trigger paths	Good	.459	.037	.031	.773

The performance of CompVAE on anomalous samples is higher compared to regression model used in *Production* and extended regression (with L1 trigger rates).

Summary and Outlook

- A successfully tested prototype for extending current trigger rate monitoring.
- The model should be further refined, e.g. verify if it scales to high luminosity runs.
- Ongoing work to extend the algorithm for full trigger configuration.
- Cooperation with trigger and computing experts to test this strategy in production environment.

References

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