Detect New Physics with Deep Learning Trigger at the LHC

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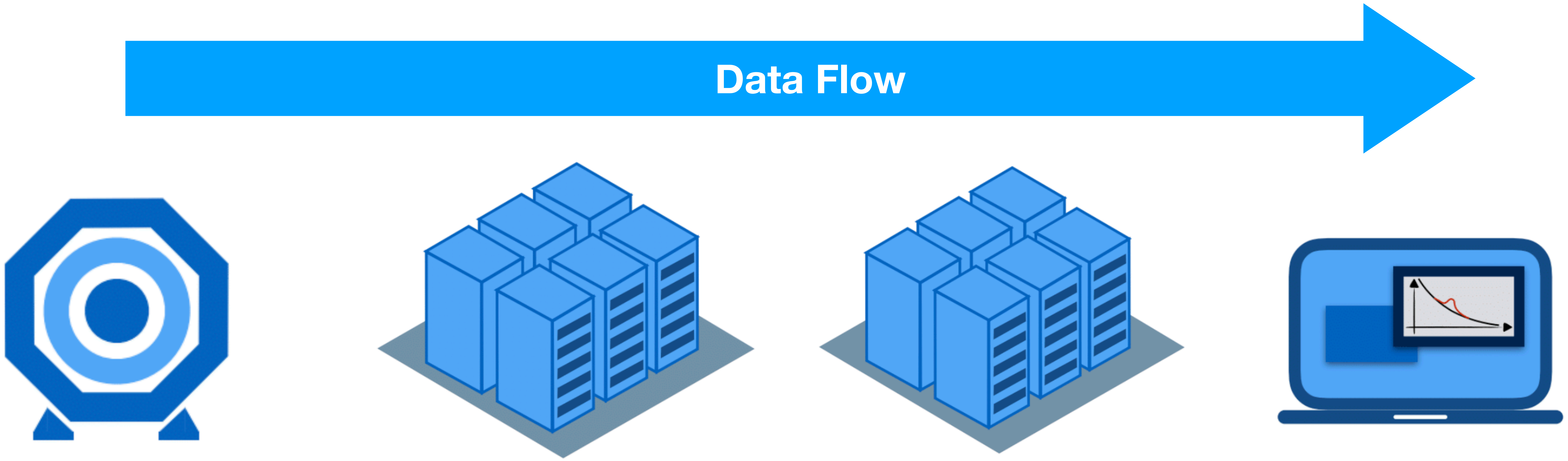
--on behalf of the CMS collaboration

CPAD Instrumentation Frontier Workshop
December 8-10, 2019

The LHC Big Data Problem



L1 Trigger

- **40M** bunch crossing per second
- Logging rate: **~100 kHz**
- Non-zero suppressed RAW data rate ~**1PB/s**
- Zero suppressed data rate is **~20TB/s**
- Coarse local reconstruction implemented on FPGA/hardware.

HLT Farm

- Logging rate ~**1kHz**
- Data rate **~1GB/s** distributed over dozens of primary datasets
- Simplified global reconstructions implemented on CPUs.

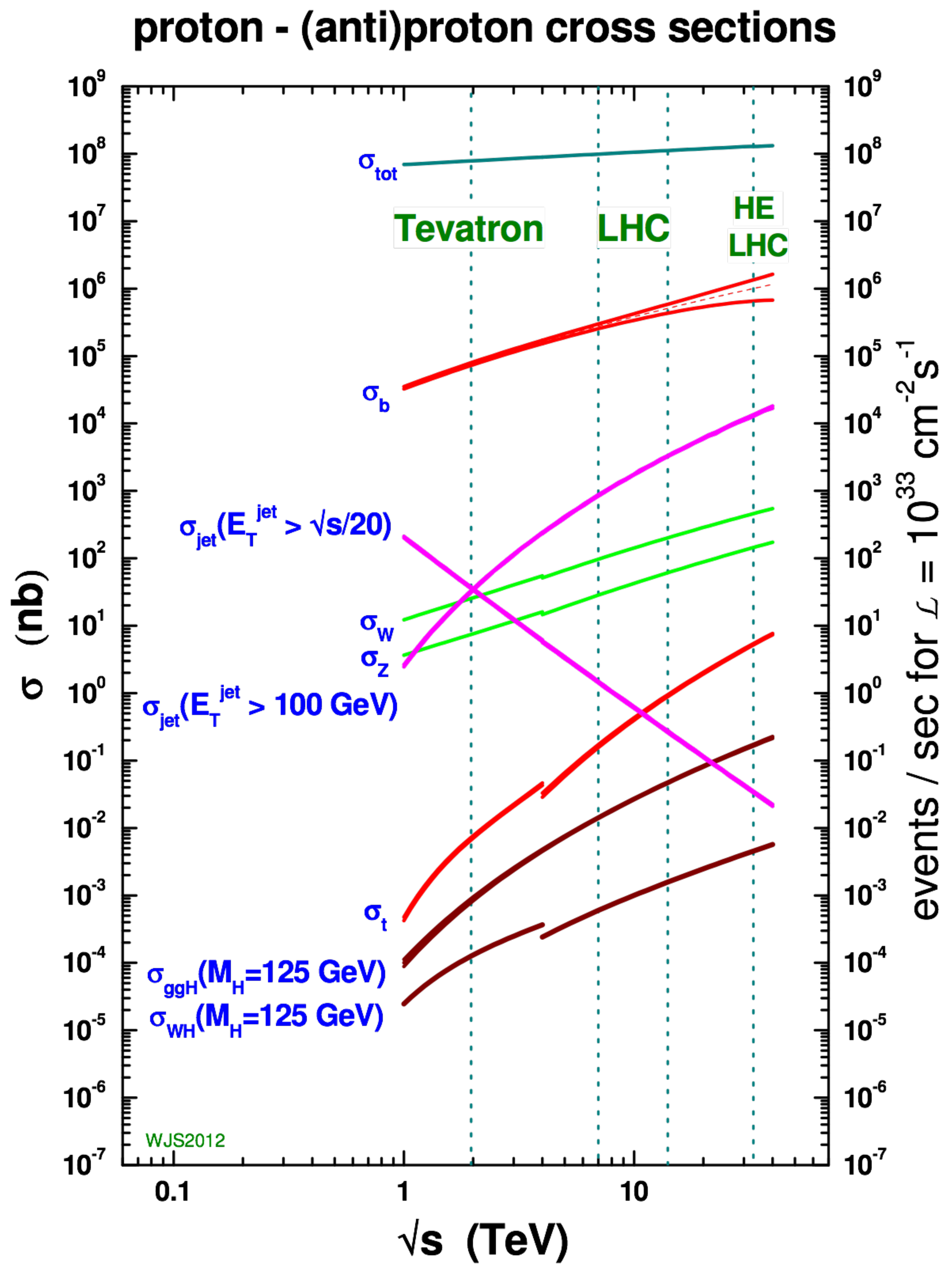
Offline Computing

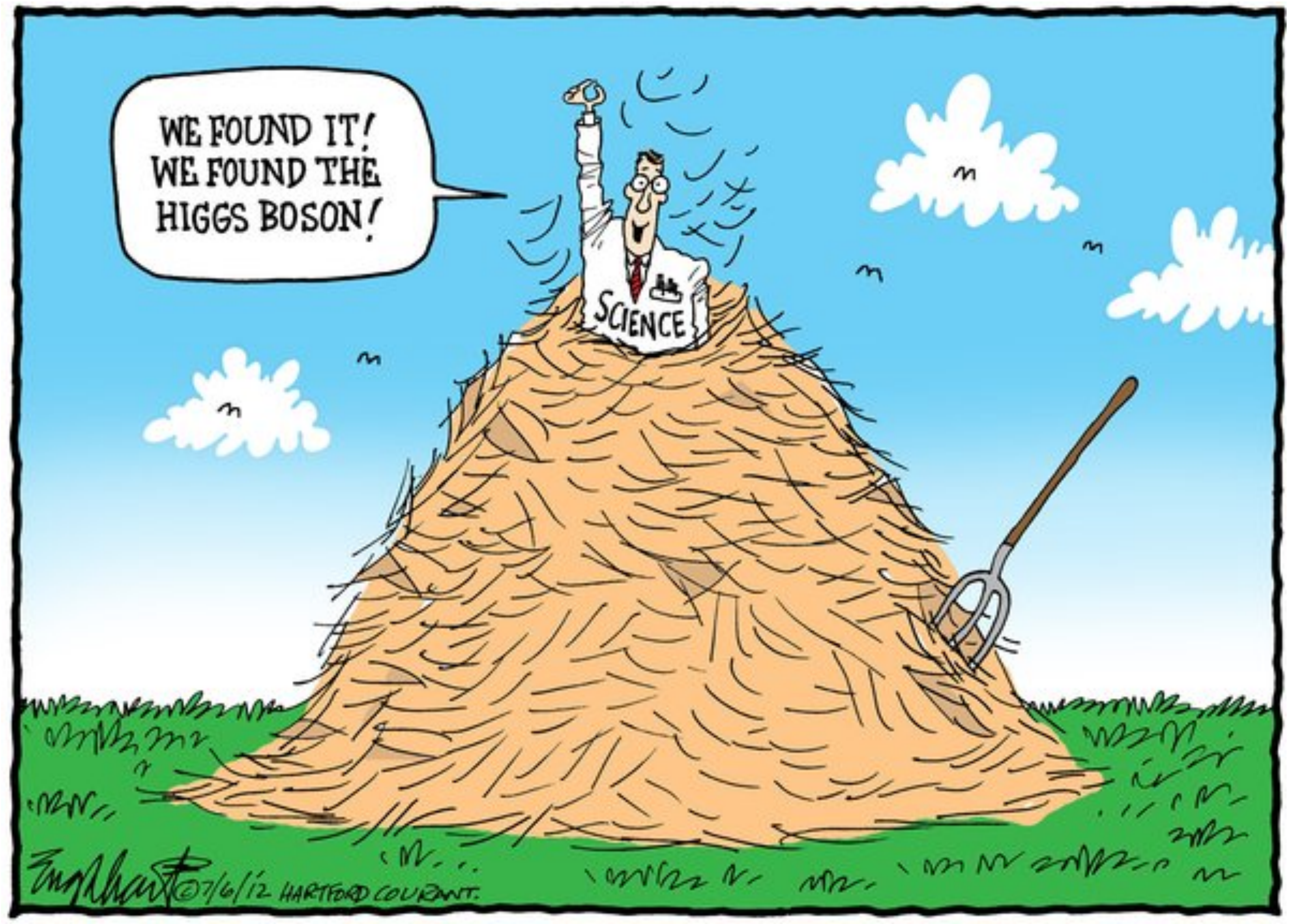
- Roughly **1GB/s** data rate
- Global reconstruction fully optimized for accuracy with software implemented on CPUs.

Data Analysis

- User-written code, plots, theses, talks, etc.
- ~100 papers of 10 MB each year, less than **1kB/s**

Trigger at LHC

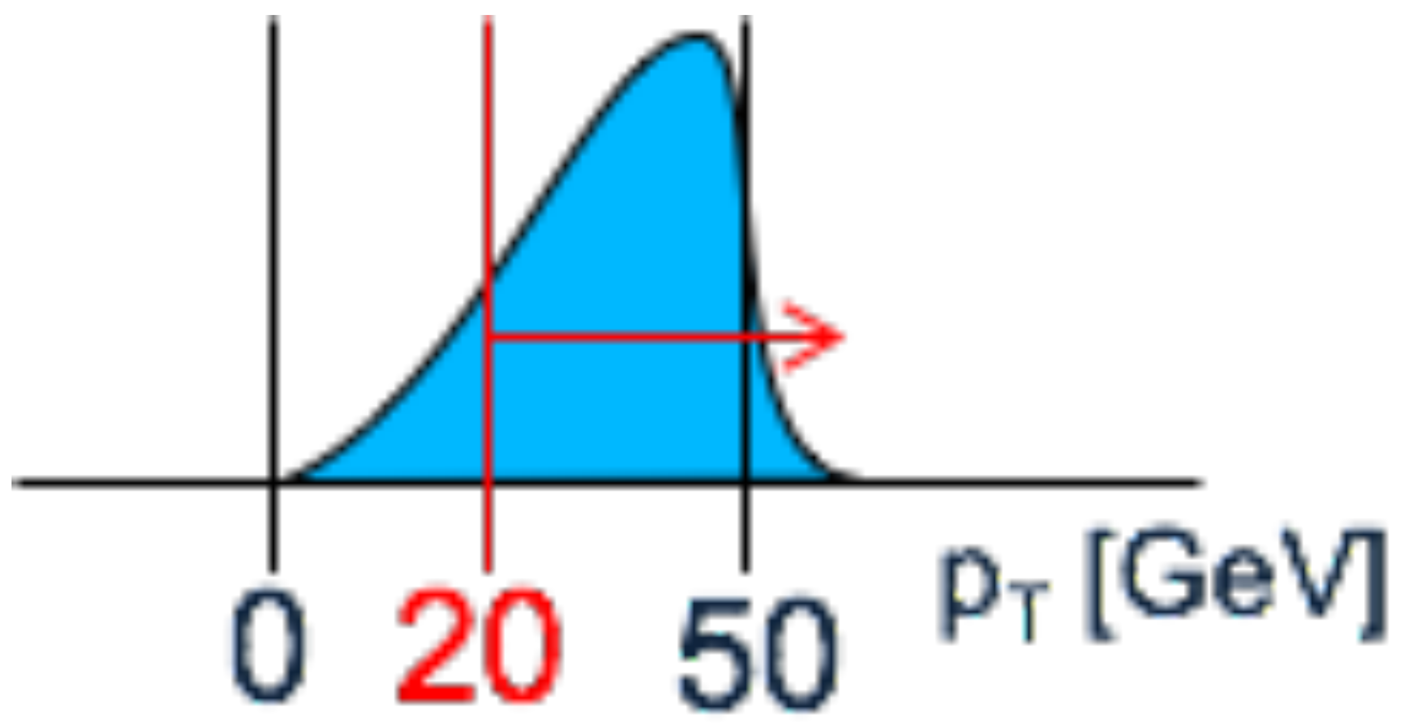




- The interested physics productions are much smaller comparing to inelastic production
- Trigger in LHC: finding a needle in a haystack scenario (anomaly)
- Event not trigger will be lost forever!

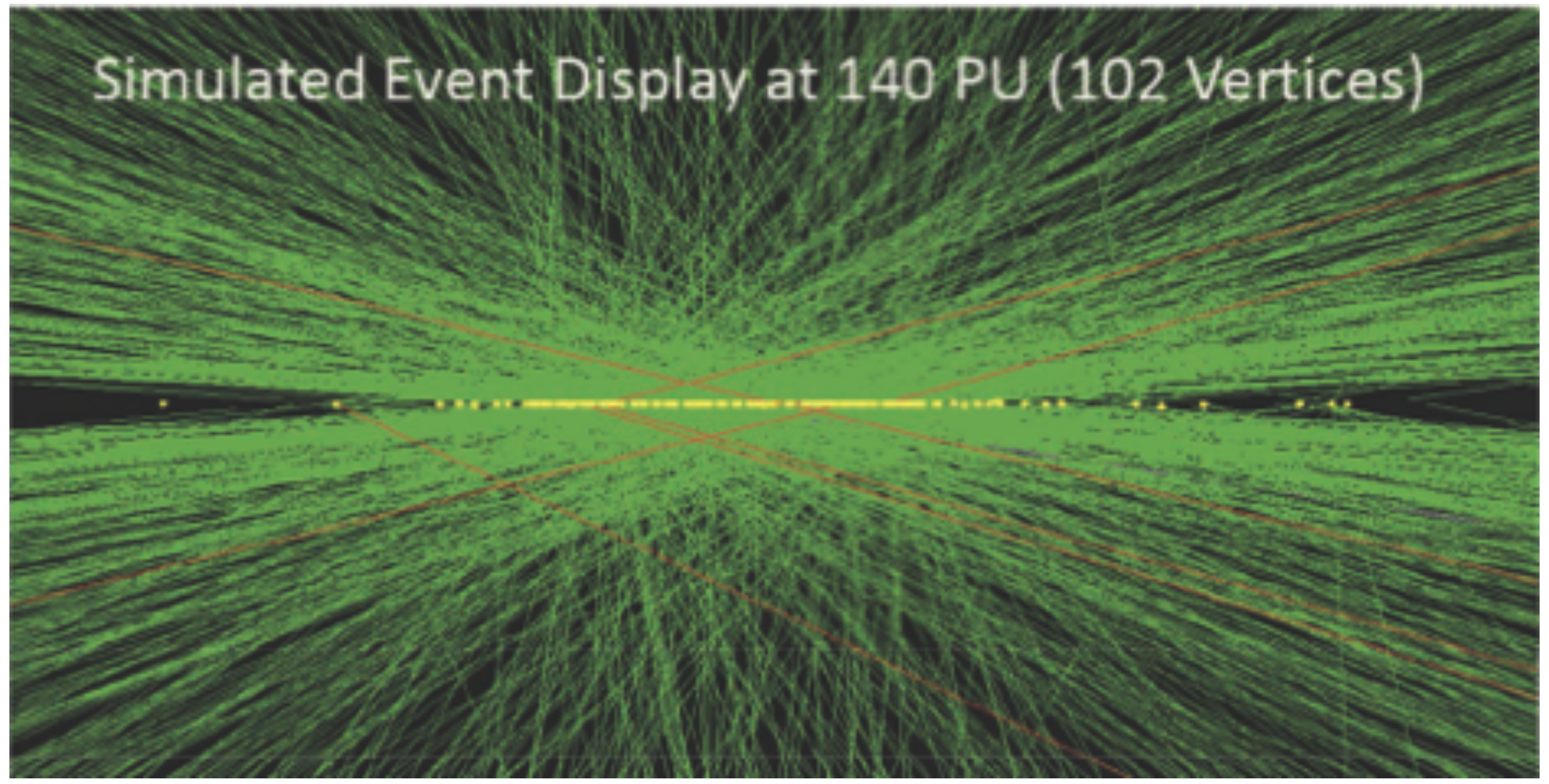
Trigger at HL-LHC

- The High-Luminosity of LHC:
  - Higgs, Flavour, Gauge Hierarchy, Supersymmetry, Dark Matter
  - O(100) GeV mass scales ➞ O(50) GeV endpoints ➞ O(20) GeV thresholds

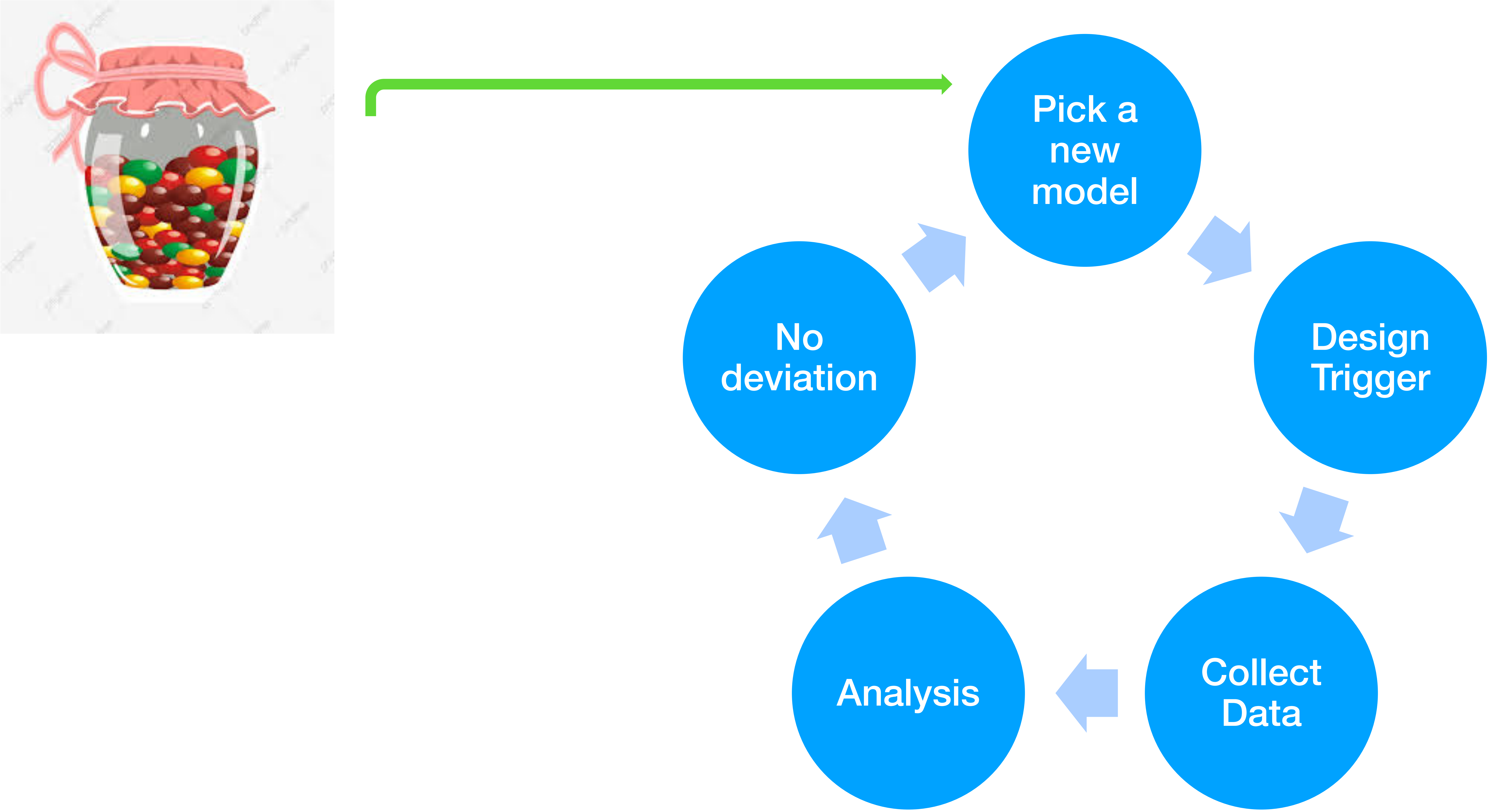


- Weak-scale physics ➞ Large statistics ➞ High luminosity ➞ Harsh environment!
- Great effort on upgrading Phase 2 Trigger system at HL-LHC

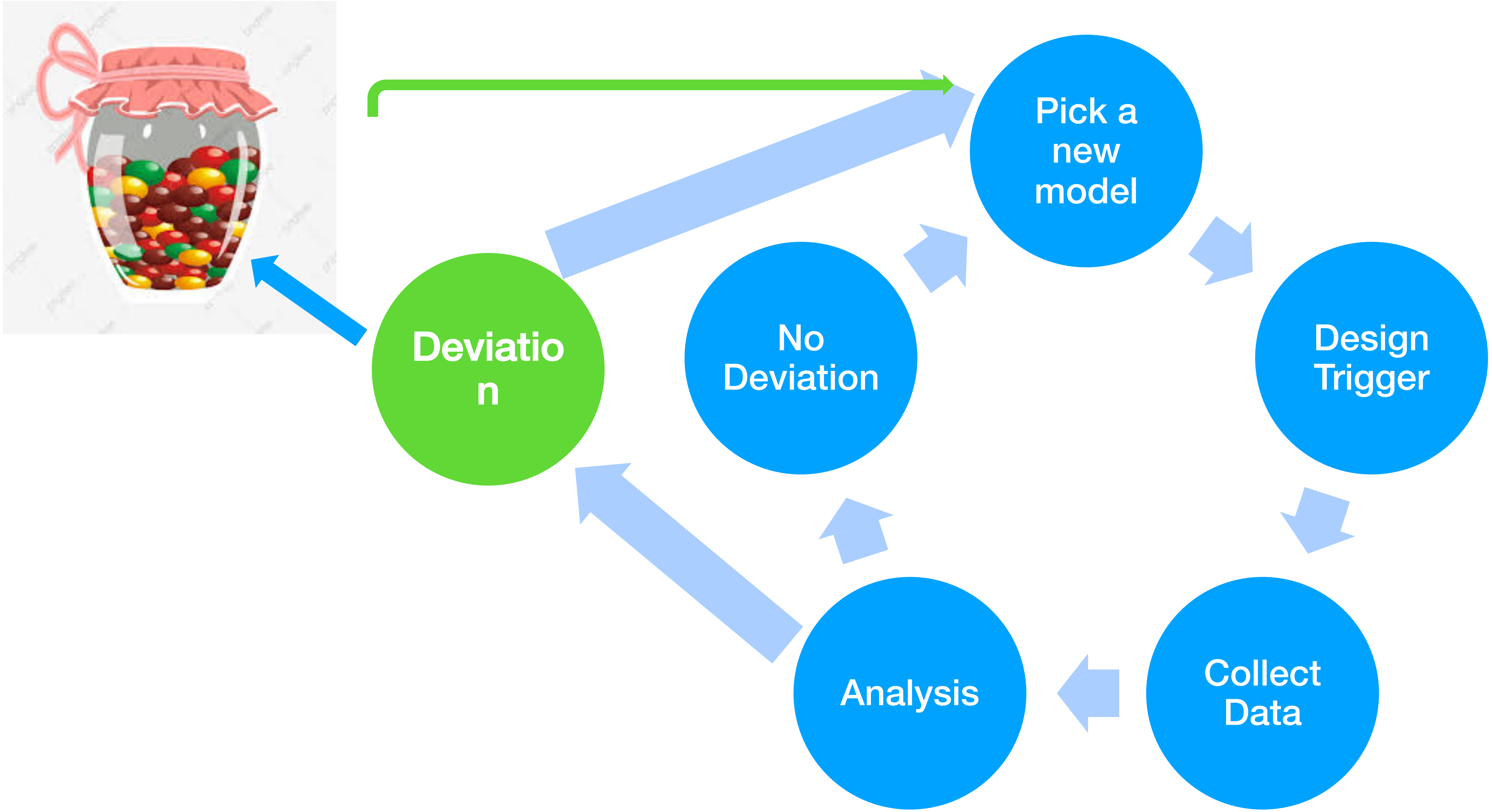
- Science potential of HL-LHC determined by datasets it collects



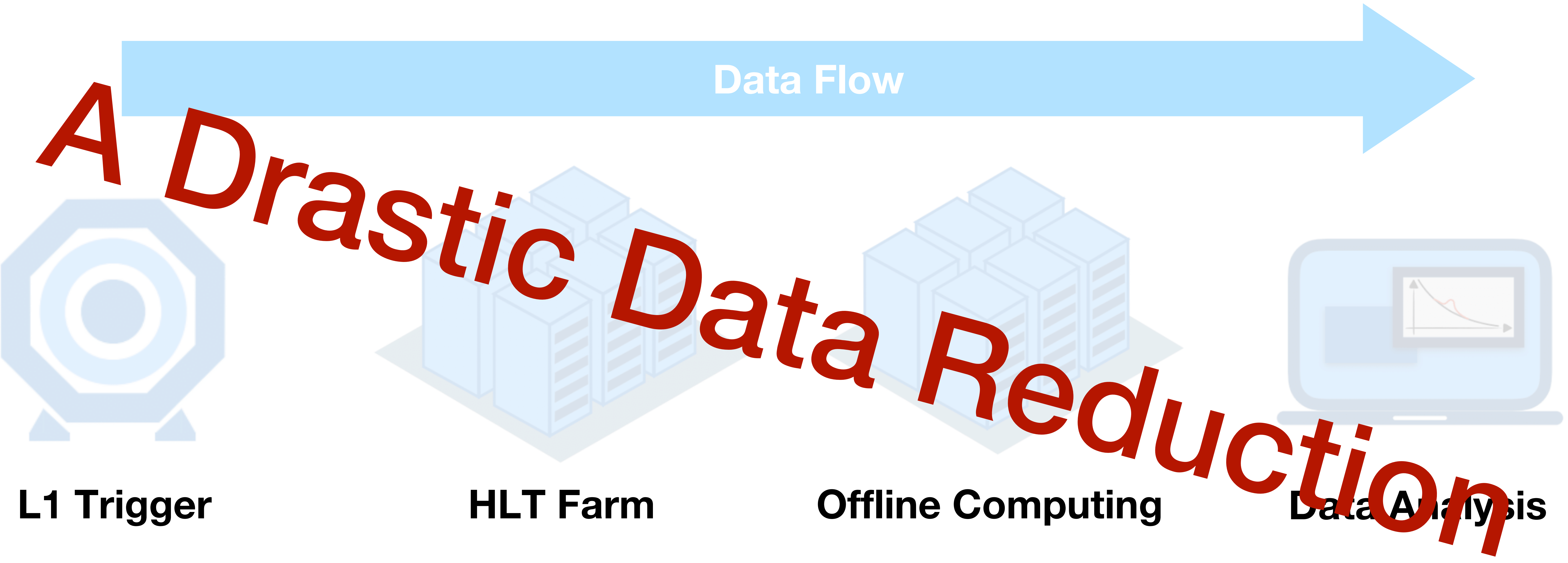
Workflow of Searches



Workflow of Searches



The LHC Big Data Problem



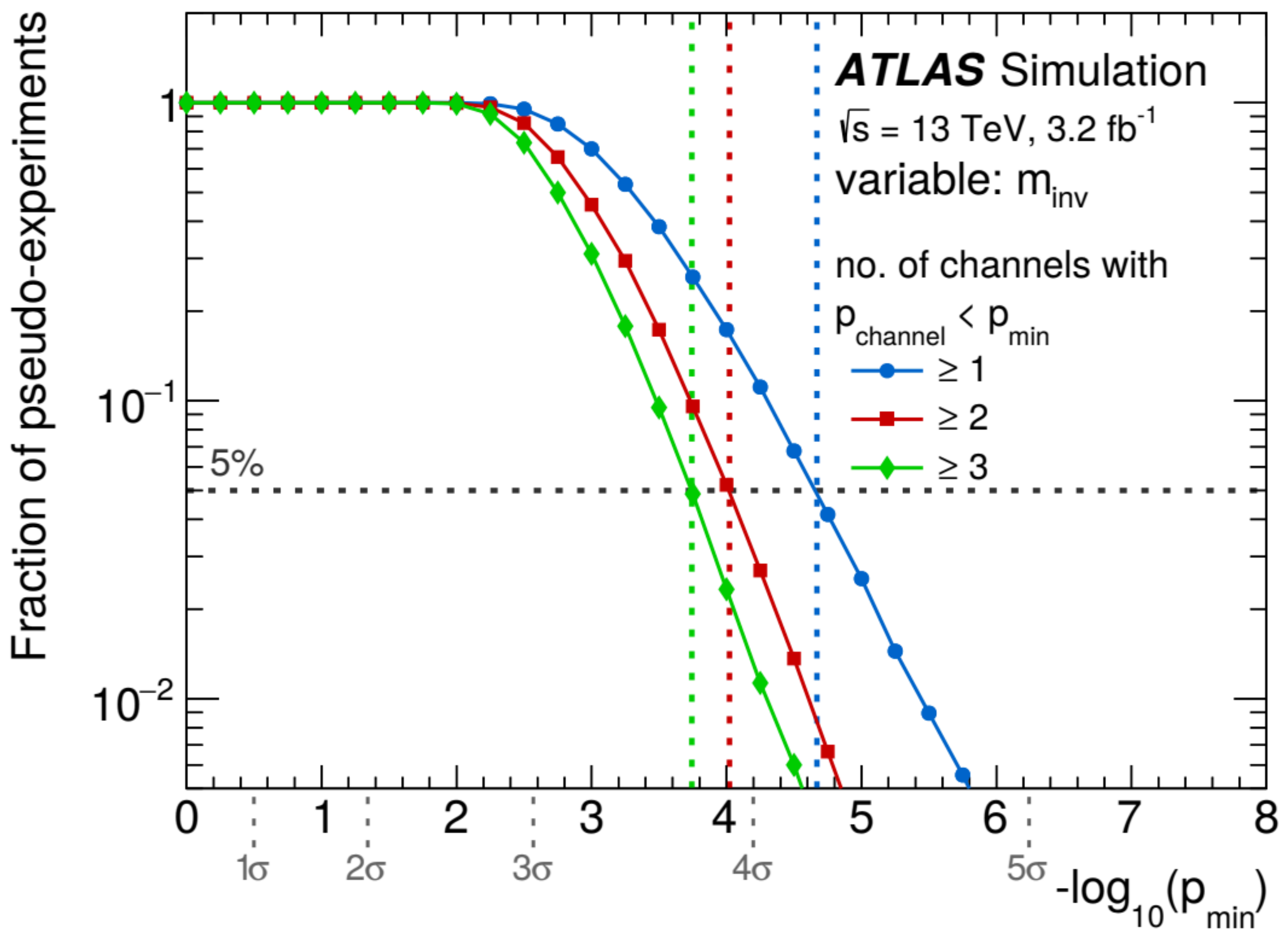
Could new physics have been discarded somewhere in this process?

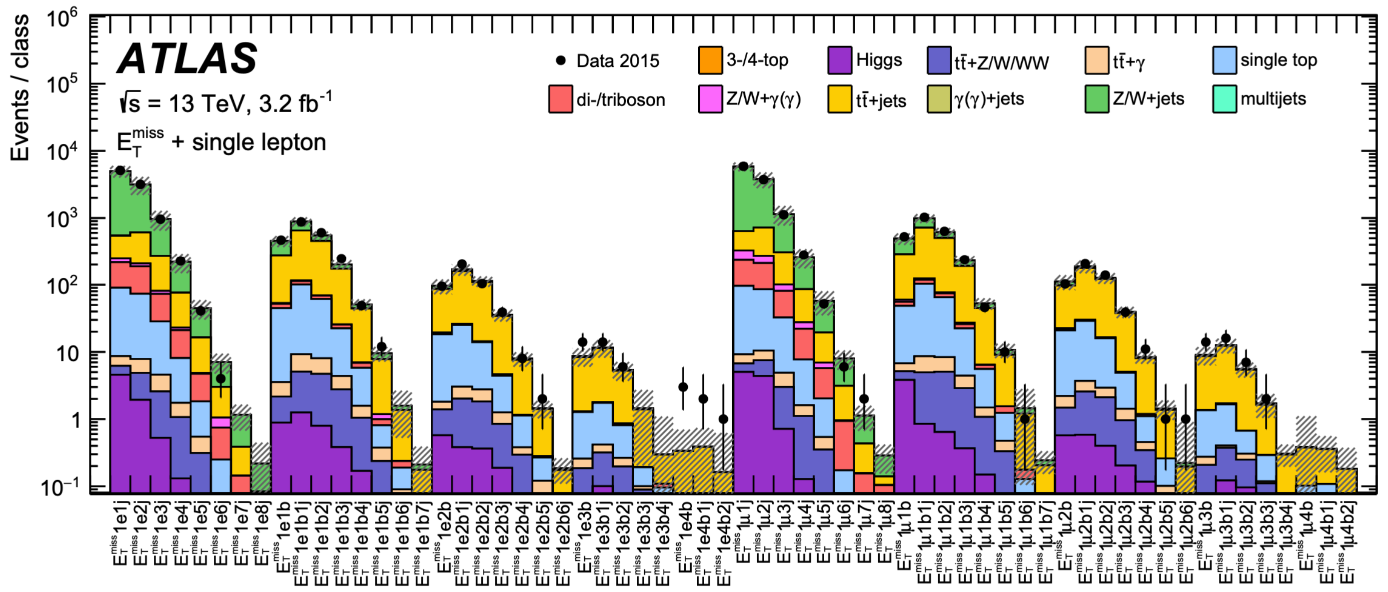
Model-Independent Searches in HEP

- Traditional new physics search relies on hypothesis testing with specific alternative models.
- Motivated multiple attempts for model-independent searches in high-energy physics over the years.

An Alternative Approach

- General approach by model-independent searches:
    - Look for discrepancy from the kinematic distribution of data versus expectation from Monte Carlo, taking into account of detector's effects.
- **Look-elsewhere effect** dilutes the discovery power with large number of bins.
- ATLAS' proposal: use the analysis to **identify** an excess, but establish the **significance** with a **traditional method** (supervised) on an **independent dataset**.





Same spirit we have in mind for what follows…

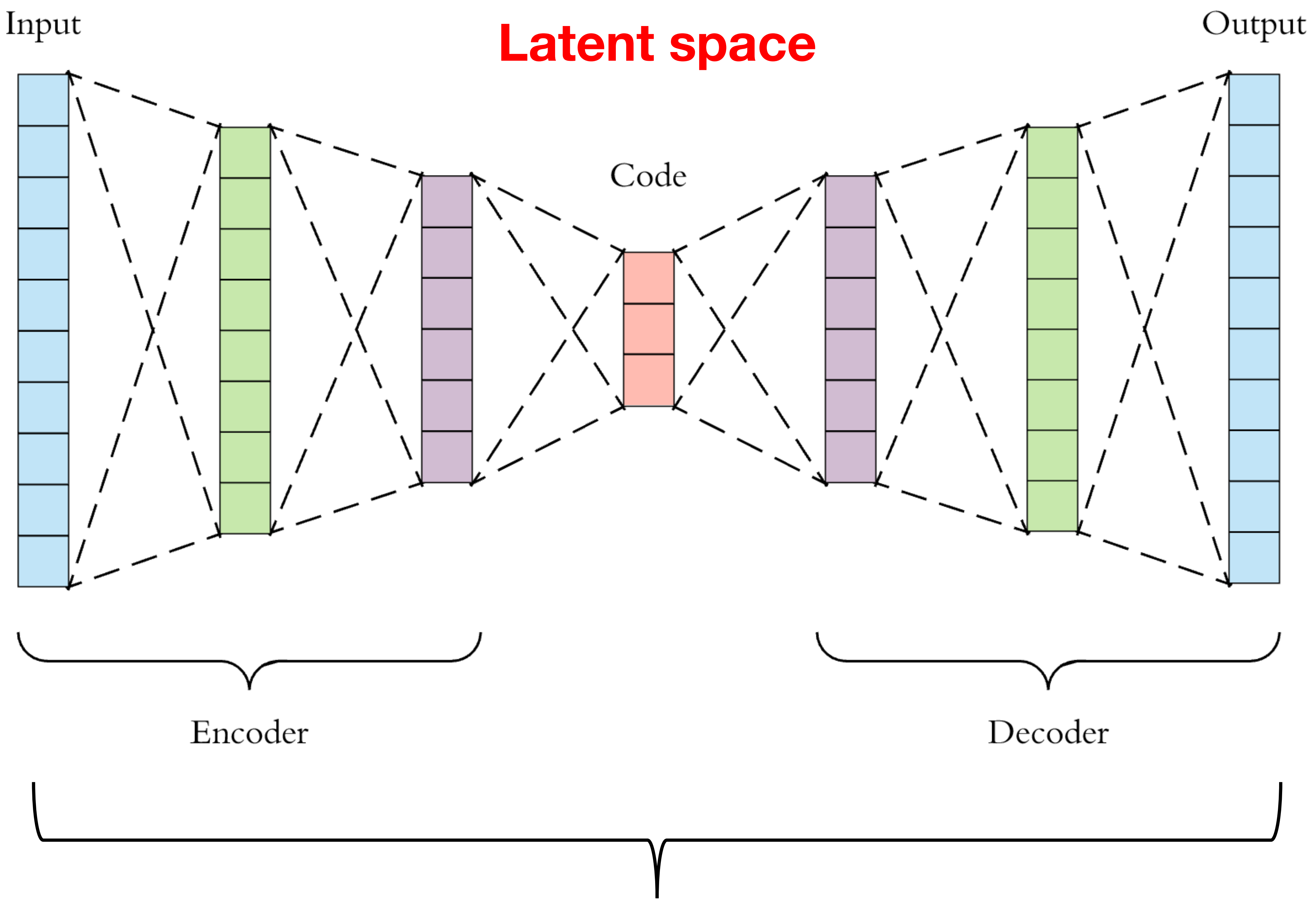
CERN-EP-2018-070

Autoencoders in a Nutshell

- Compression-decompression algorithm that learns to describe the a given dataset in terms of point in lower-dimension *latent space*, from which it reconstructs the original data.

- **Unsupervised learning**, used for data compression, generation, clustering, etc.

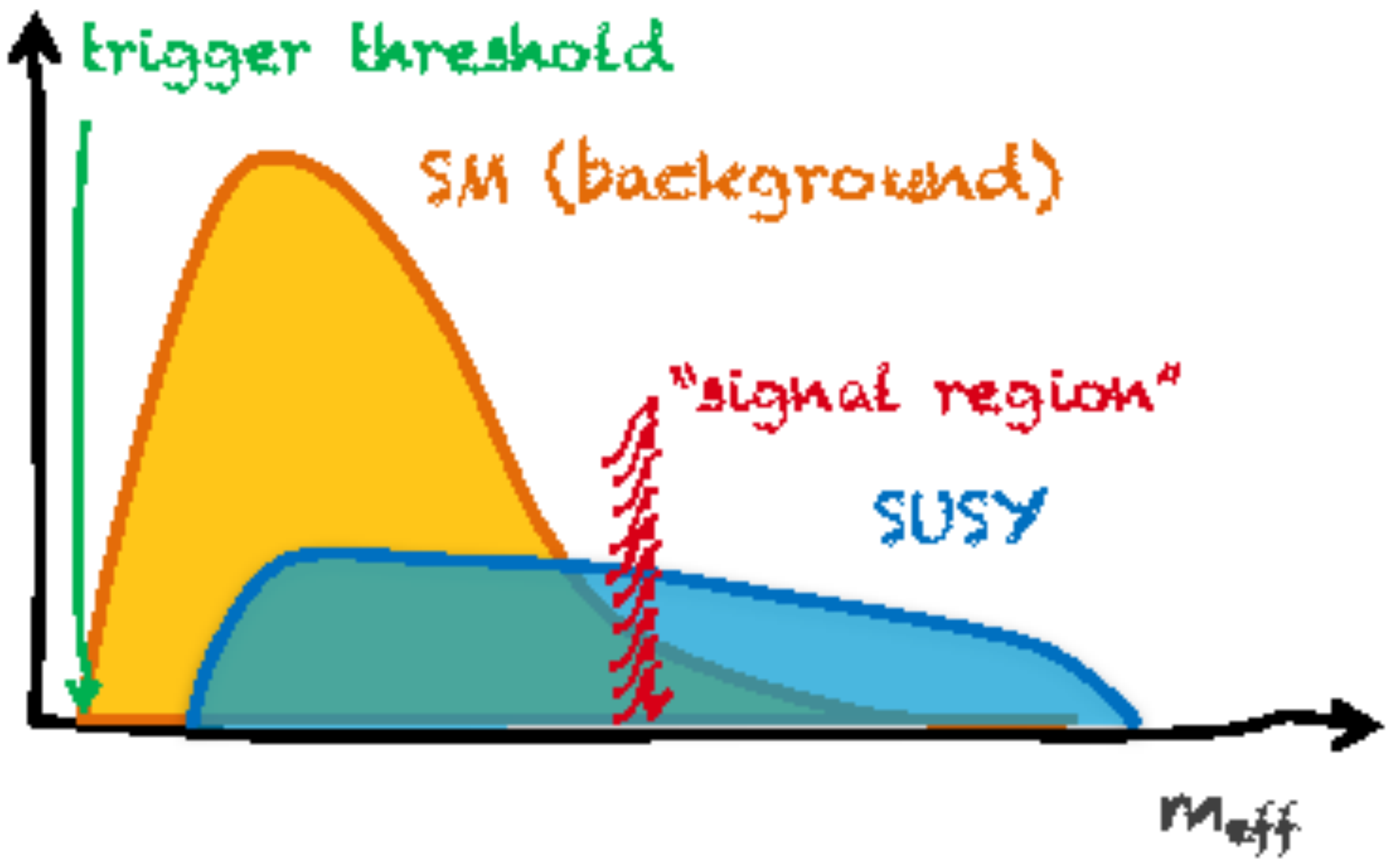
- Anomaly: any event whose decompressed output is "far" from the input, in some metric of the autoencoder loss.



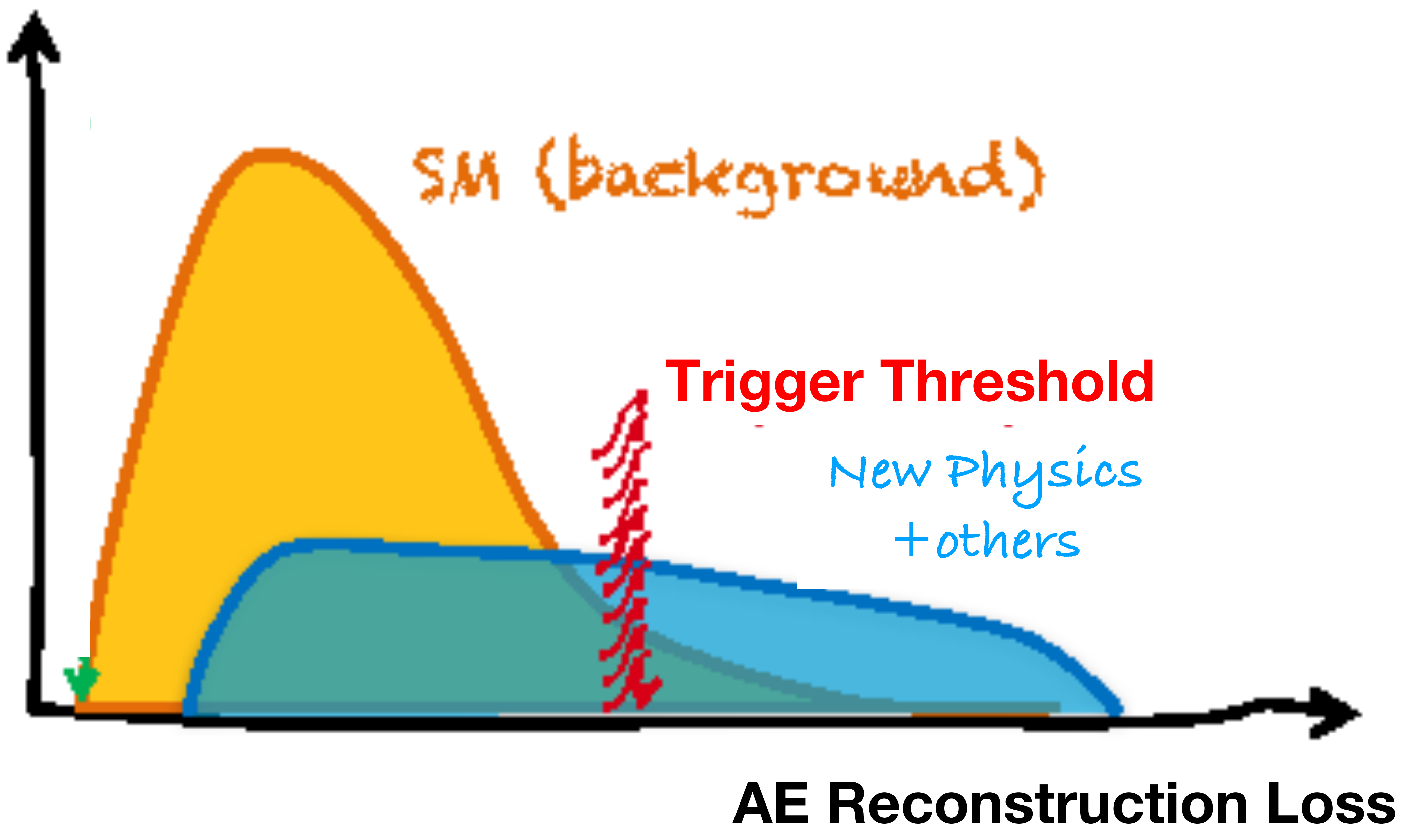
Loss = f(input – output)

Autoencoders @ Level-1 Trigger

Standard Triggers

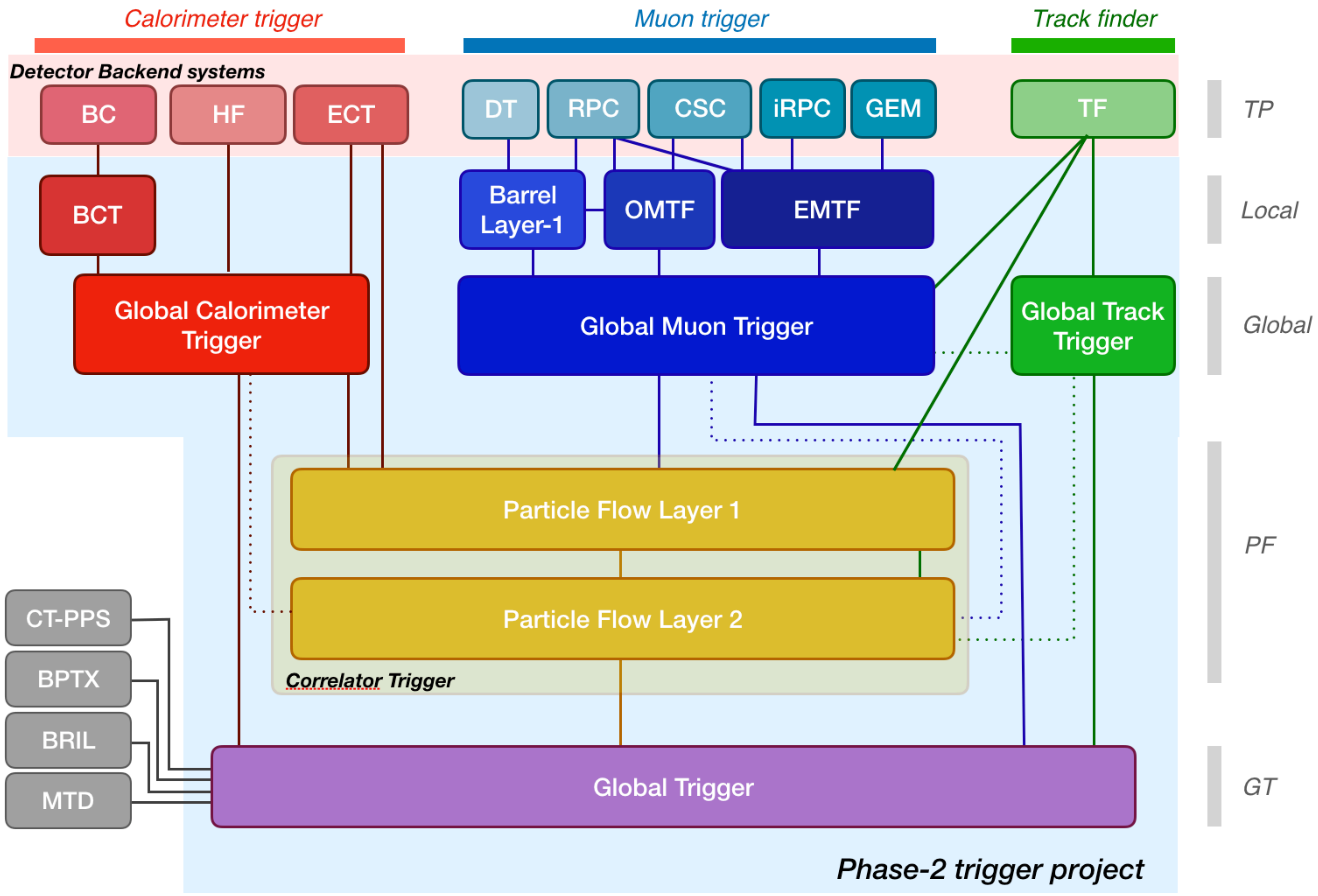


AE Triggers



- A Model-Agnostic Trigger for anomaly events with autoencoder (AE) model
- Deployment at Level-1 trigger to avoid any bias from upstream
- But limited by the resource and latency requirement on the Level-1 trigger system

CMS Phase 2 Level-1 Trigger

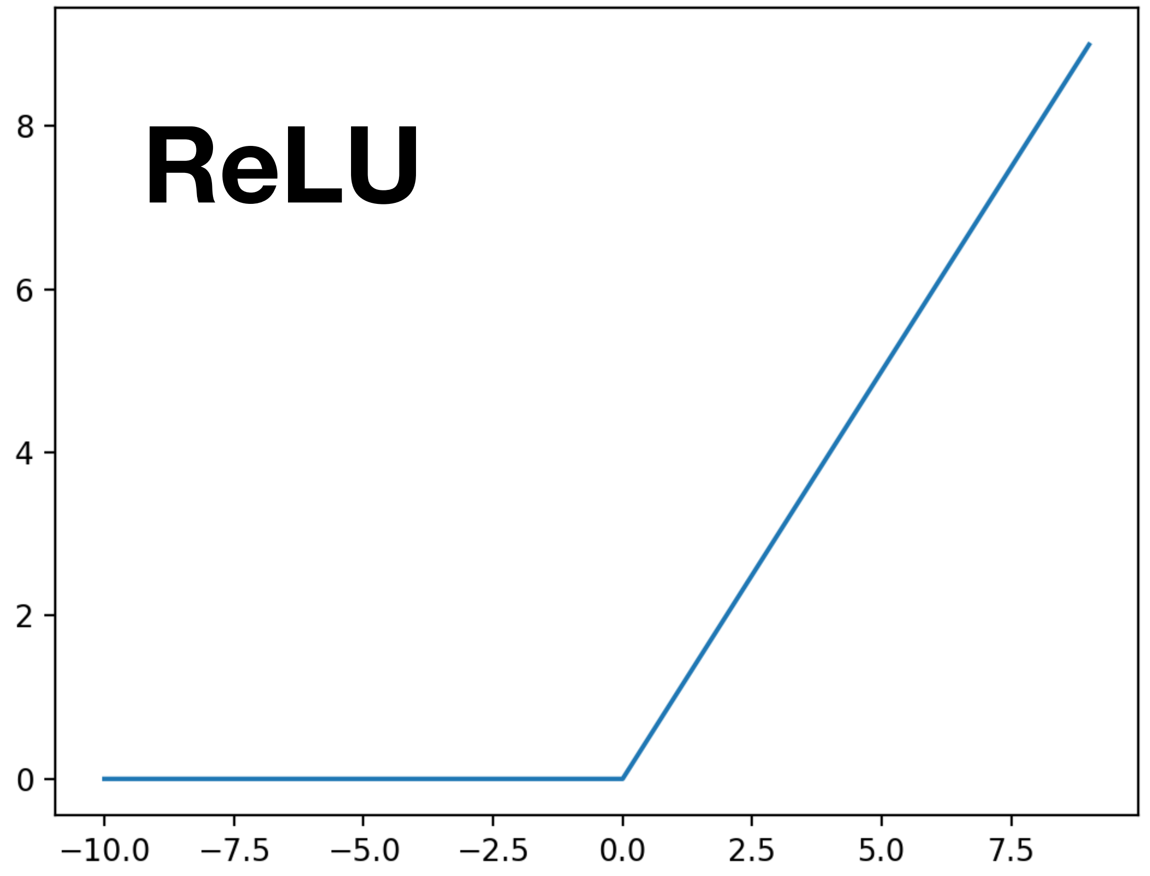


- Sketch of upgraded CMS Phase 2 Level-1 Trigger system
- Produce Particle Flow particles, combining Calo/Muon/Tracker information
- Produce PUPPI weight of each particles for pileup mitigation
- Outputs of each trigger systems send to Global Trigger for Level-1 decision

Example AE Model

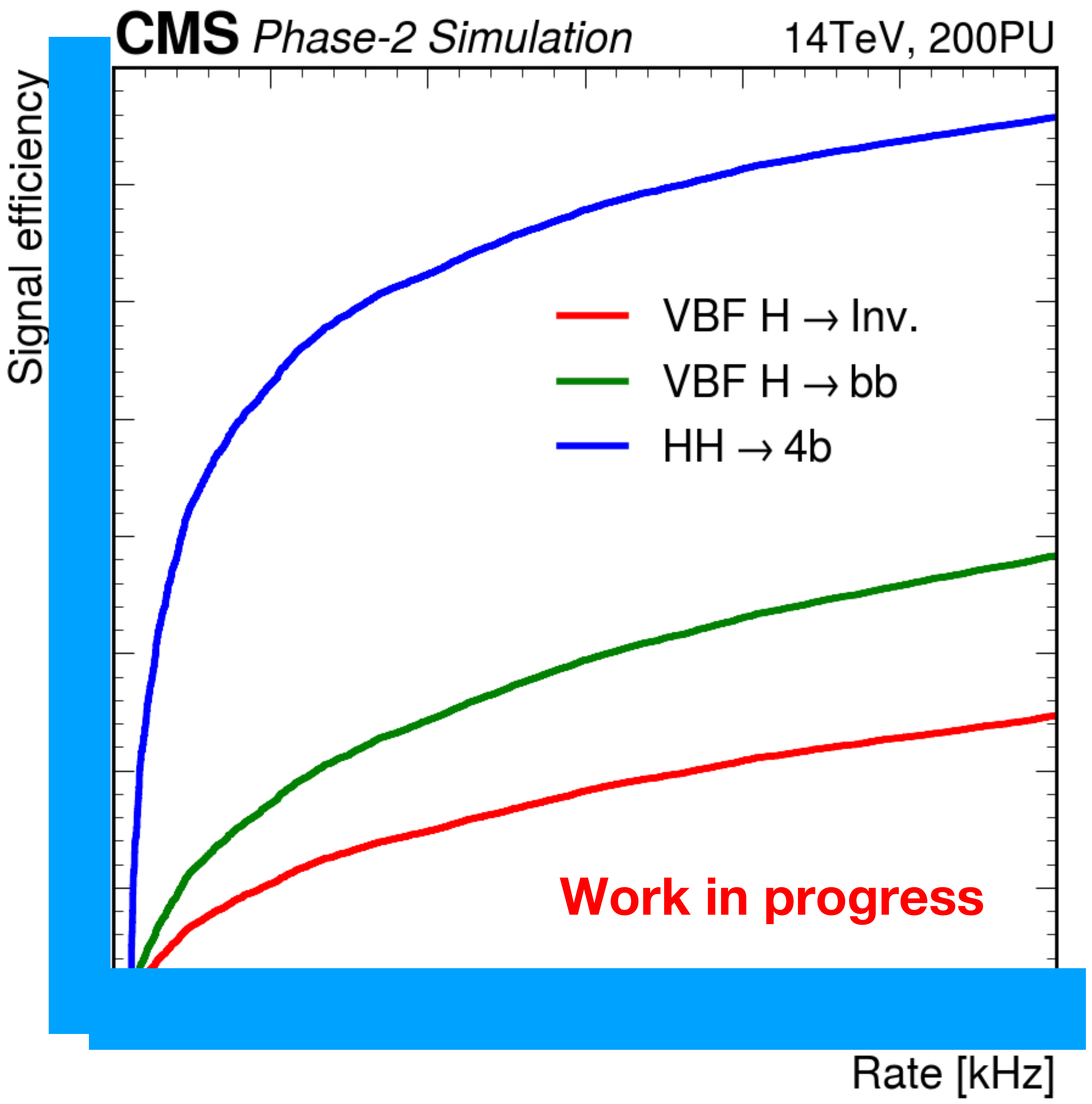
- Train with simulated ZeroBias event at 200 pileup
- Use simulated Puppi Jet/MET/MHT inputs (18 inputs) with preprocessing

- Activation function: ReLU
- Loss function: L1Loss $\ell(x,y) = L = \{l_1, \ldots, l_N\}^\top, \quad l_n = |x_n - y_n|,$
- Training - validation ratio : 0.8
- Number of epochs: 100-200 epochs
- Number of layers: 8 layers



- Model is designed with simplicity for firmware implementation and resource/latency requirement

AE Performance



- Model was trained and validated with simulated Zerobias events, no knowledge of signal during training
- Use the reconstruction loss of AE inputs and outputs as discriminator
- Inference with signal samples show the separation power

AE Implementation

- Use the hls4ml package to implement the AE model into FPGA firmware
  - With additional logic for L1Loss function calculation
- Fully unroll AE with minimal latency, well within the Phase 2 Global Trigger latency budget
- With Xilinx Virtex UltraScale+ (VU9P) FPGA, the AE consumes ~10% of DSP resource, ~1% of Filp Flop and LUT
- To be included in the upcoming CMS Phase 2 Level-1 Trigger TDR

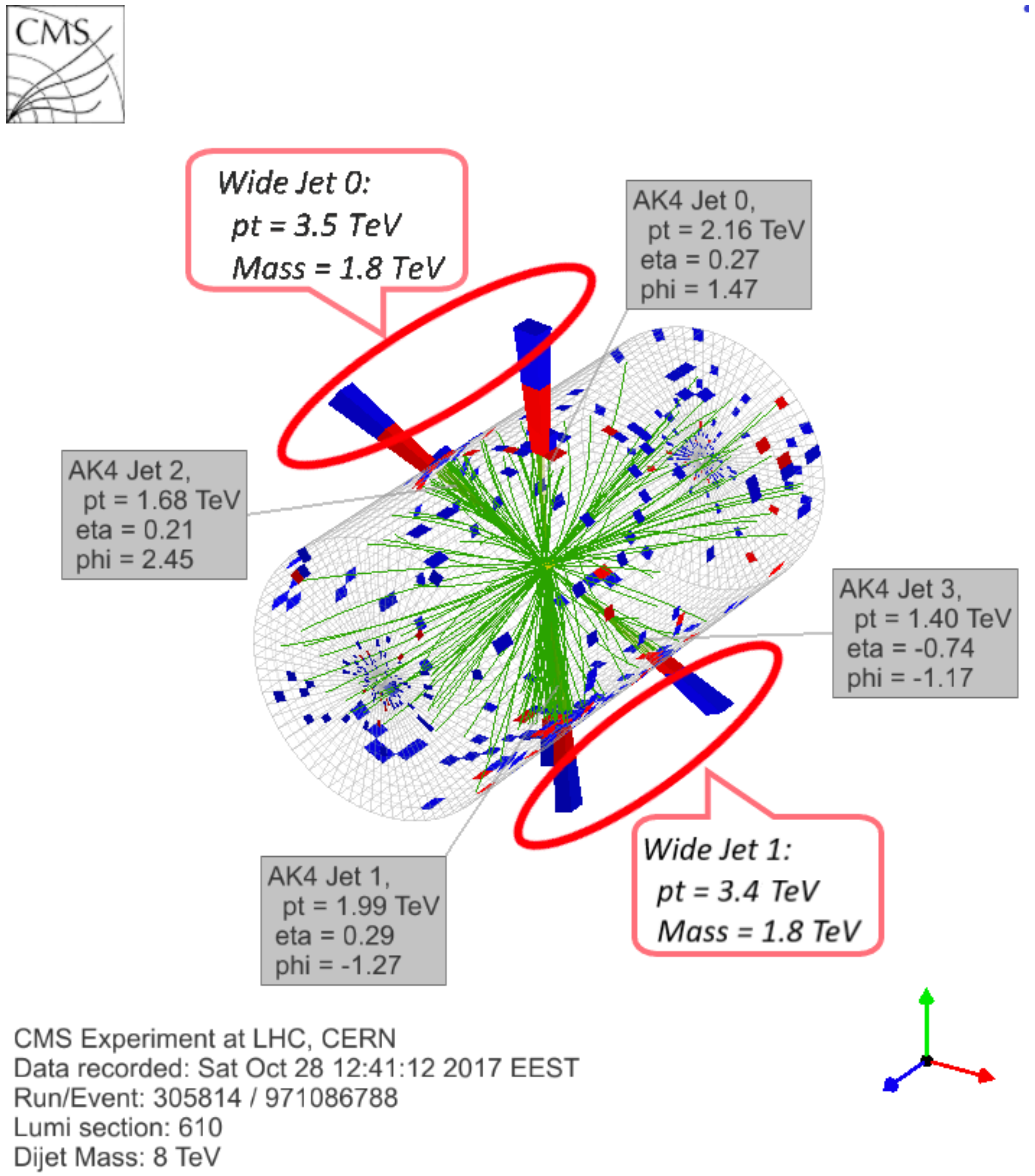
How to use the stream?

Illustration by Jeff Lewonczyk

- **Not to claim a discovery!**
- Use as a resource to guide new physics searches in subsequent data takings, with some extra ingredients:
  - Data mining & visual inspection,
  - BSM-agnostic hypothesis testing.

Data Mining & Visual Inspection

- Macroscopic and microscopic views of the saved data stream.
  - Learn any repeated patterns of events.
  - Select a set of anomalies for visual inspection.



CMS-PAS-EXO-17-026

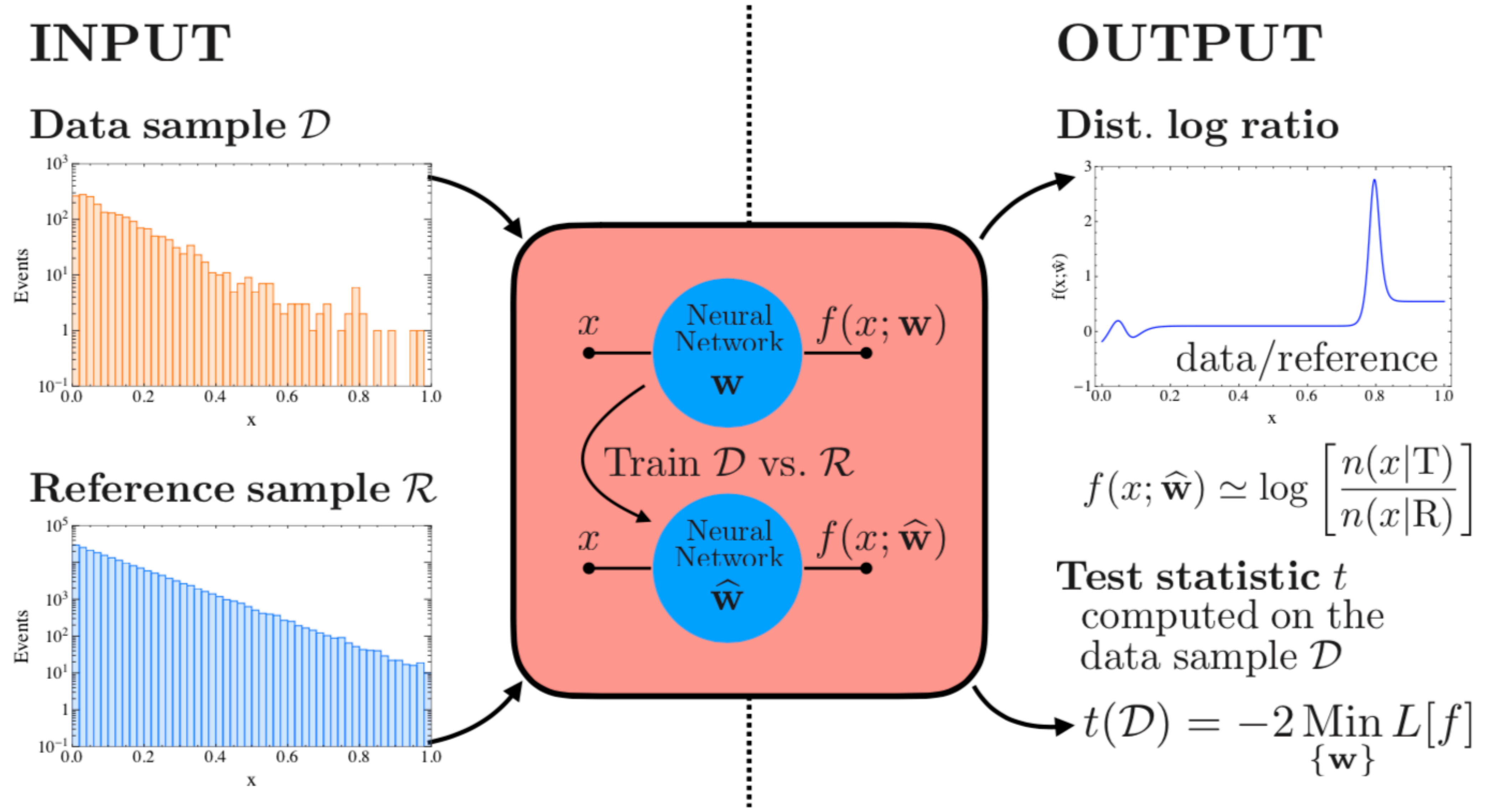
Learning New Physics from a Machine

[Agnolo & Wulzer, arXiv:1806.02350](https://arxiv.org/abs/1806.02350)

- Use SM MC as null hypothesis, run hypothesis testing without specifying alternative hypothesis.

- Allow for isolation of anomalous events by looking at their contribution to the likelihood ratio.

$$t(\mathcal{D}) = 2\log\left[\frac{e^{-N(\widehat{\mathbf{w}})}}{e^{-N(\mathrm{R})}}\prod_{x\in\mathcal{D}}\frac{n(x|\widehat{\mathbf{w}})}{n(x|\mathrm{R})}\right] = -2\,\underset{\{\mathbf{w}\}}{\mathrm{Min}}\left[N(\mathbf{w}) - N(\mathrm{R}) - \sum_{x\in\mathcal{D}} f(x;\mathbf{w})\right]$$



Conclusions

- The LHC has an enormous potential of discovering physics beyond the Standard Model, given the unprecedented collision energy and the large variety of production mechanisms that proton-proton collisions can probe.

- We propose a model-independent anomaly detection technique, based on deep autoencoders, to identify new physics events

- Simple AE model can be implemented at the Level-1 trigger level

- More advanced AE model can be designed for HLT or 40MHz scouting system (arXiv:1811.10276)

- Stay tune for the CMS Phase 2 Level-1 Trigger TDR

BACKUP