HEP-ML at the HL-LHC

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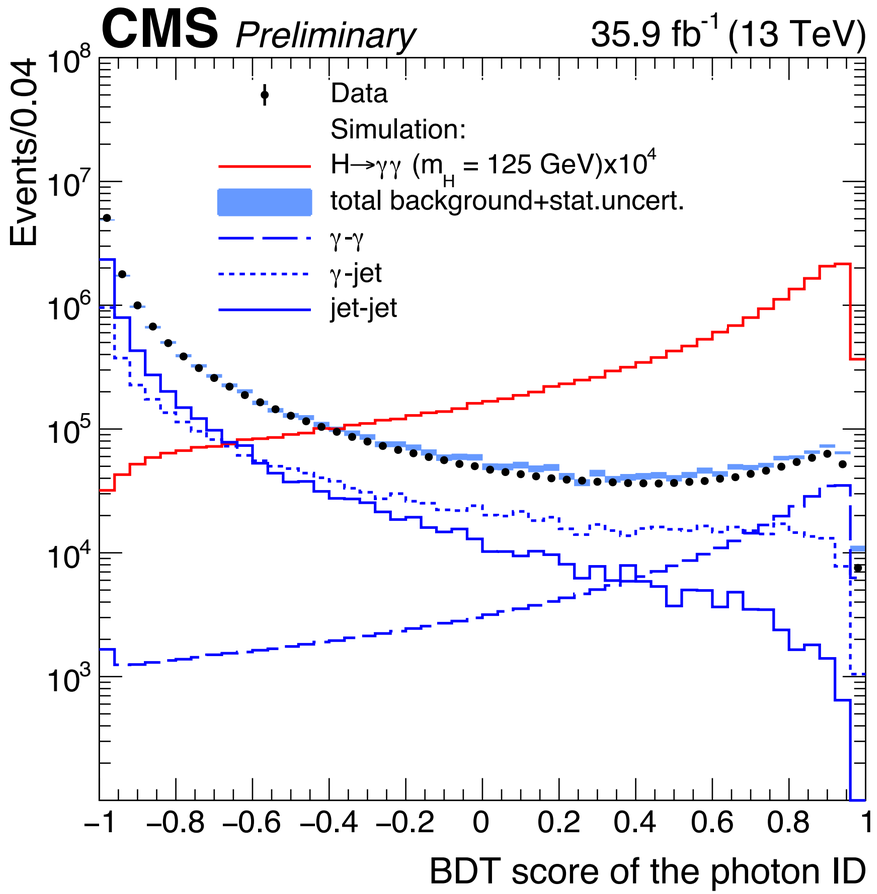
Disclaimer

- *What follows is my personal opinion which is not just mine but, for many aspects, it is not (yet…) mainstream in HEP*
- *I could show you many examples today: there is a lot happening with Machine learning in LHC experiments*
- *I decided to show examples developed by OpenLab summer students in the last two years, to pass two messages*
  - *Thanks to those who sponsor the OpenLab Summer/ technical/doctoral students*
  - *Computer/data scientists, even with little research experience, can be very useful at this stage of things*

What we do with ML today

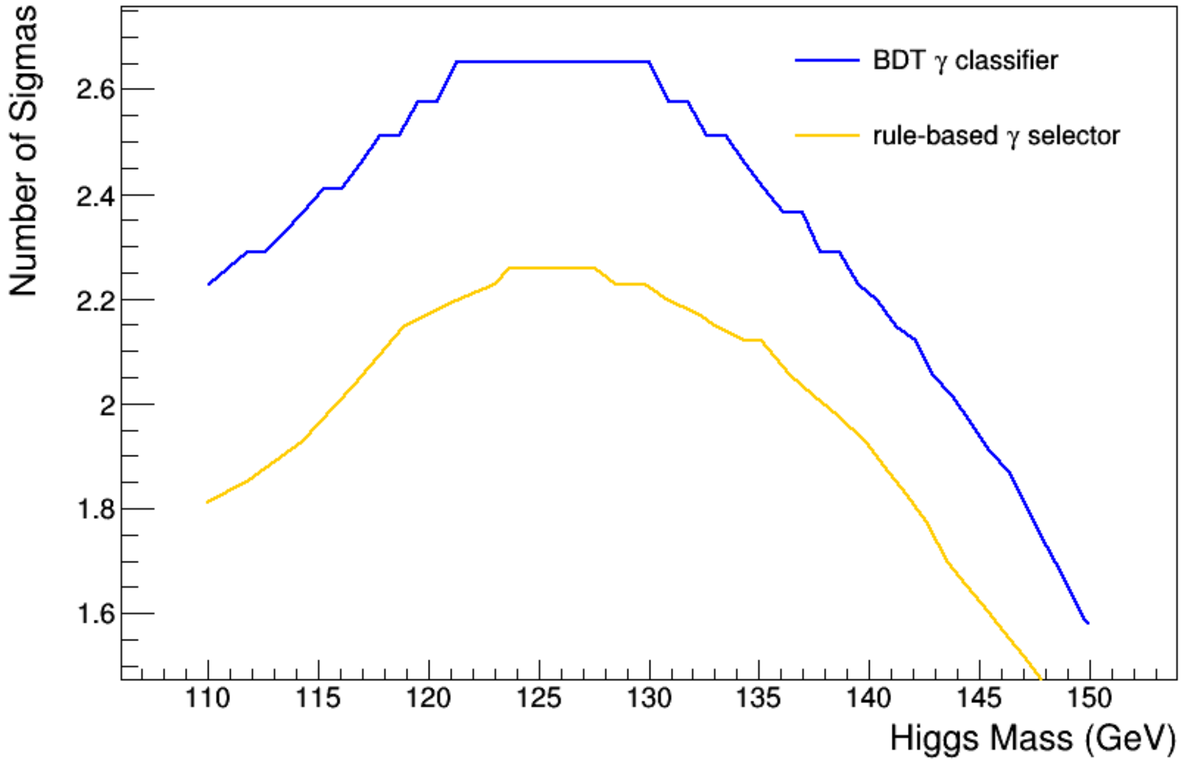
- *Classification:*
  - *identify a particle & reject fakes*
  - *identify signal events & reject background*
- *Regression:*
  - *Measure energy of a particle*
- *We typically use BDTs for these task*
  - *moved to Deep Learning for analysis-specific tasks*
  - *same will happen for centralised tasks (eventually)*

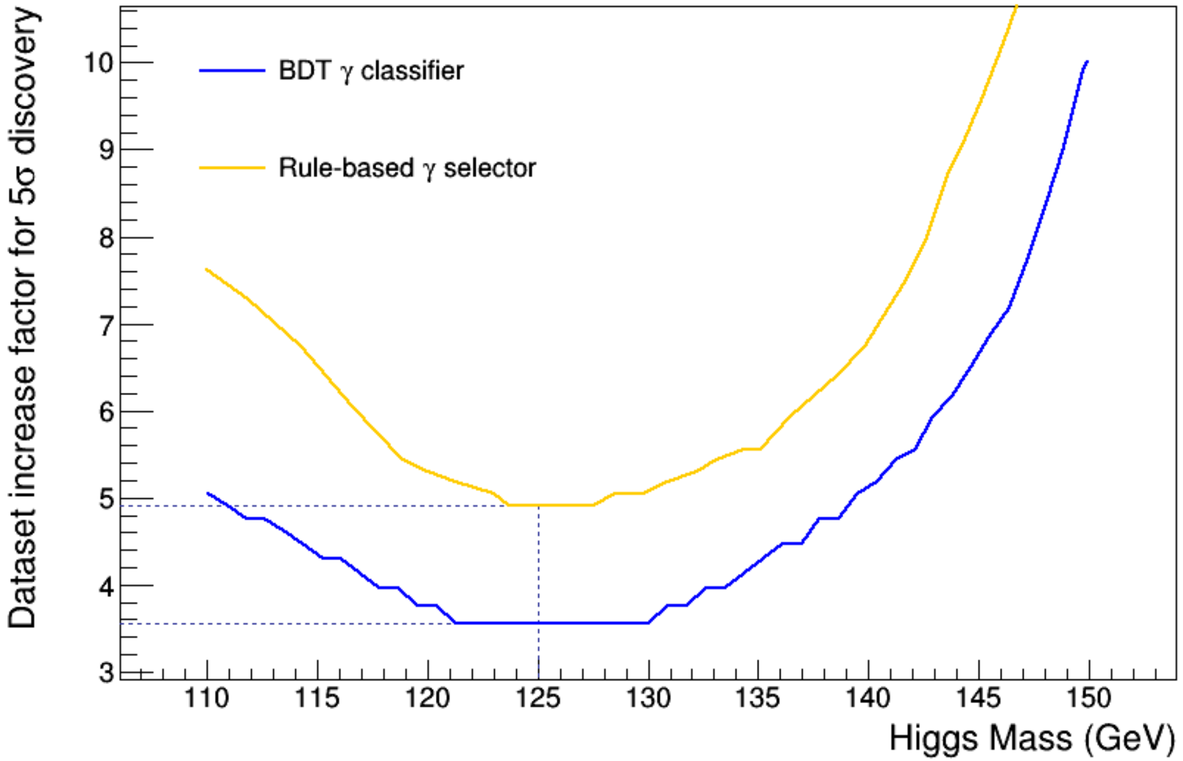


Centralised task (in online or offline reconstruction)
Analysis-specific task (by users on local computing infrastructures)

Example: ML for Higgs discovery

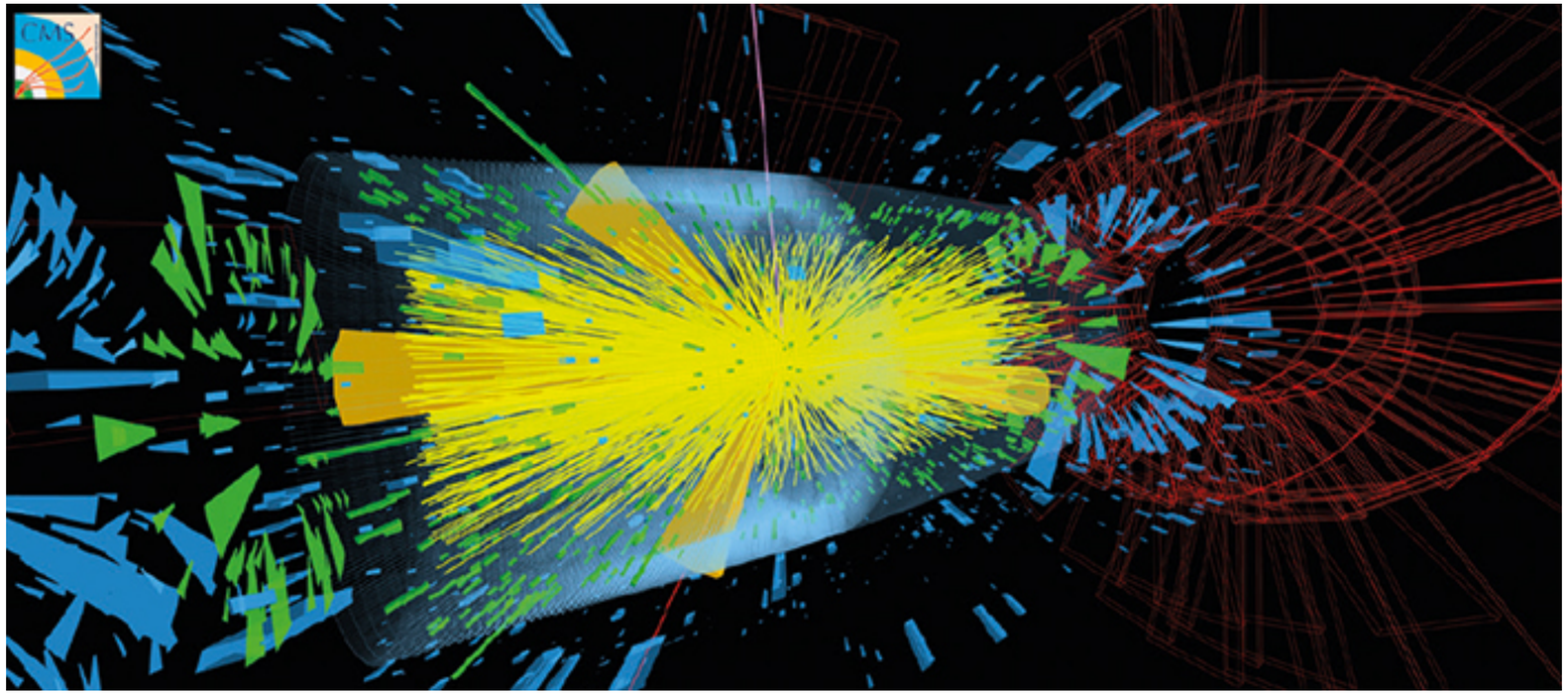
- *We were not supposed to discover the Higgs boson as early as 2012*
- *Given how the machine progressed, we expected discovery by end 2015 /mid 2016*
- *We made it earlier thanks (also) to Machine Learning*



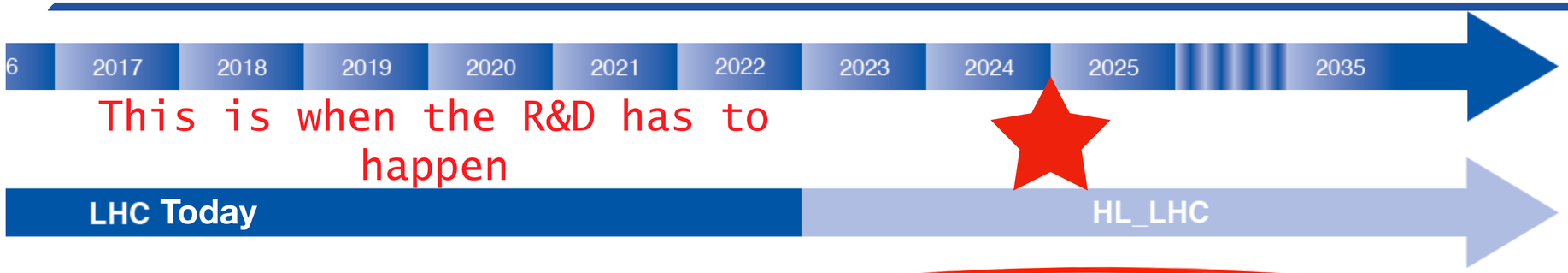


What is ahead of us

- *Deep Learning will be more and more central*
  - *Analysis-specific applications poses no problem in terms of latency/memory/etc*
- *Challenges ahead will force us (willing or not) to use DL in many centralised tasks*
  - *but we are still far from being ready to a systematic usage of DL in production*

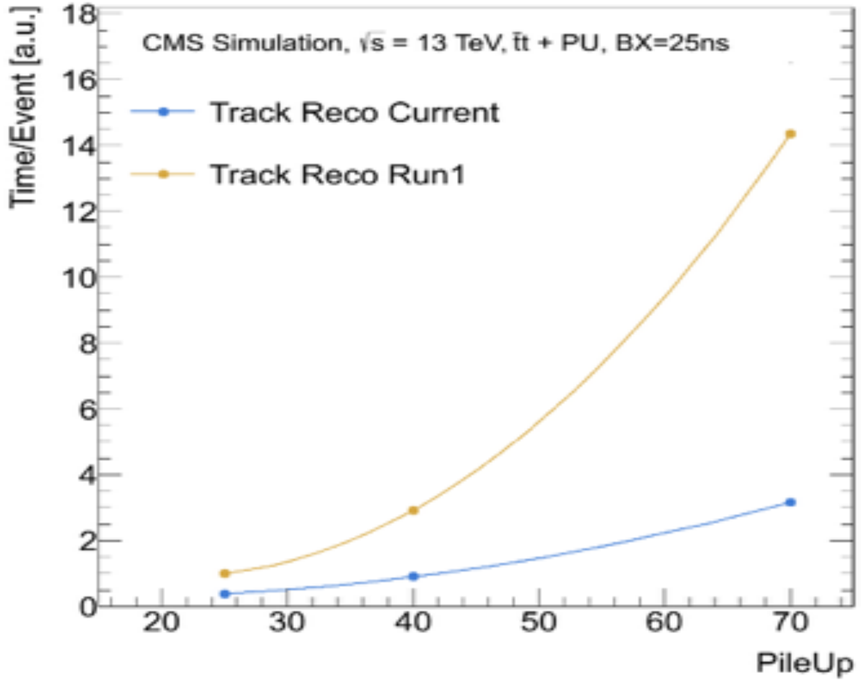


HL-LHC: elephant in the room



- ~40 collisions/event
- ~10 sec/event processing time
- (at best)Same computing resources as today

- ~200 collisions/event
- ~minute/event processing time(*)
- (at best)Same computing resources as today



- *Flat budget vs. more needs = **current rule-based reconstruction algorithms will not be sustainable***

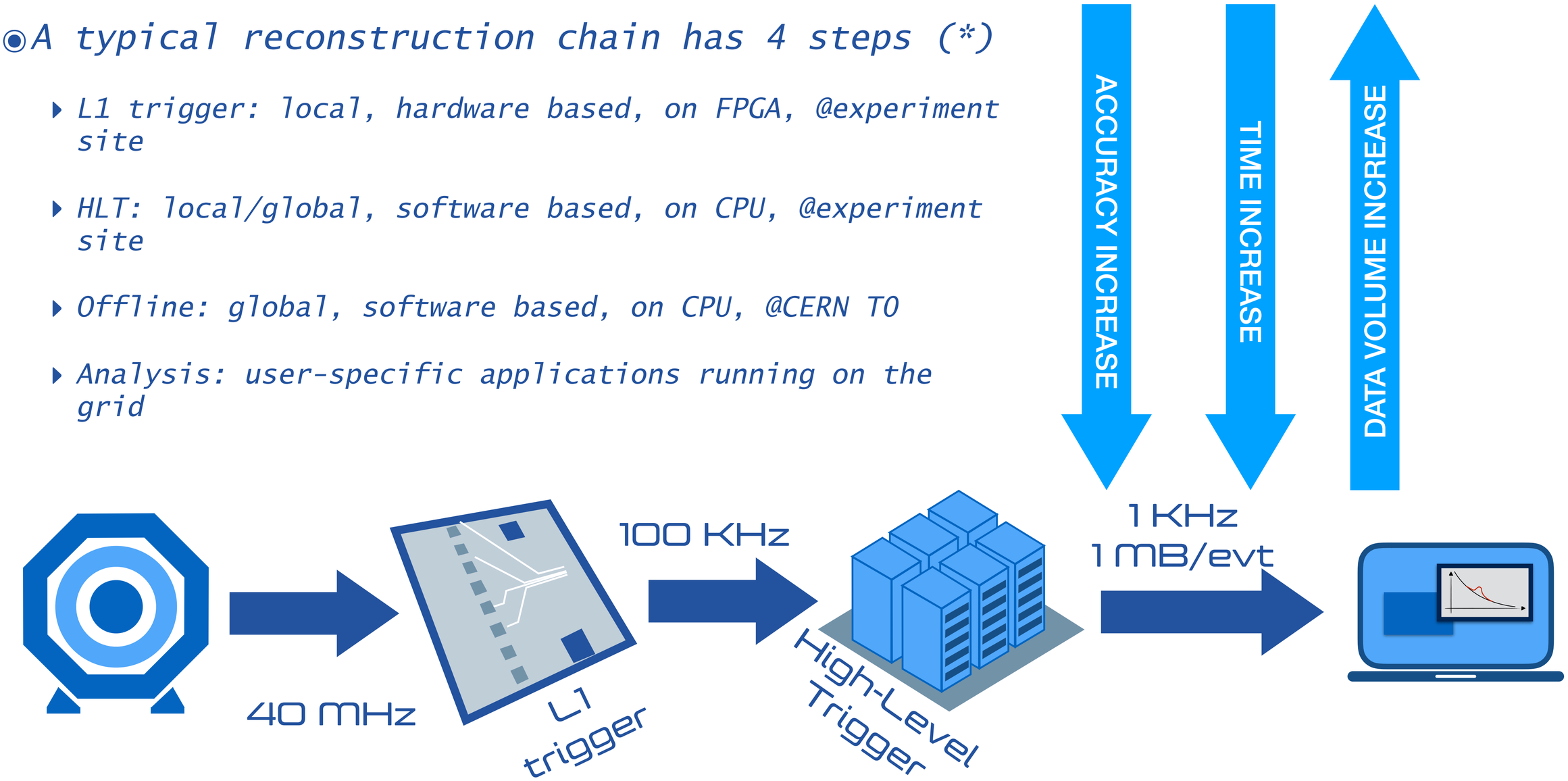
- ***Adopted solution:** more granular and complex detectors → more computing resources needed → more problems*

- ***Modern Machine Learning might be the way out***

(*)With nowadays software development

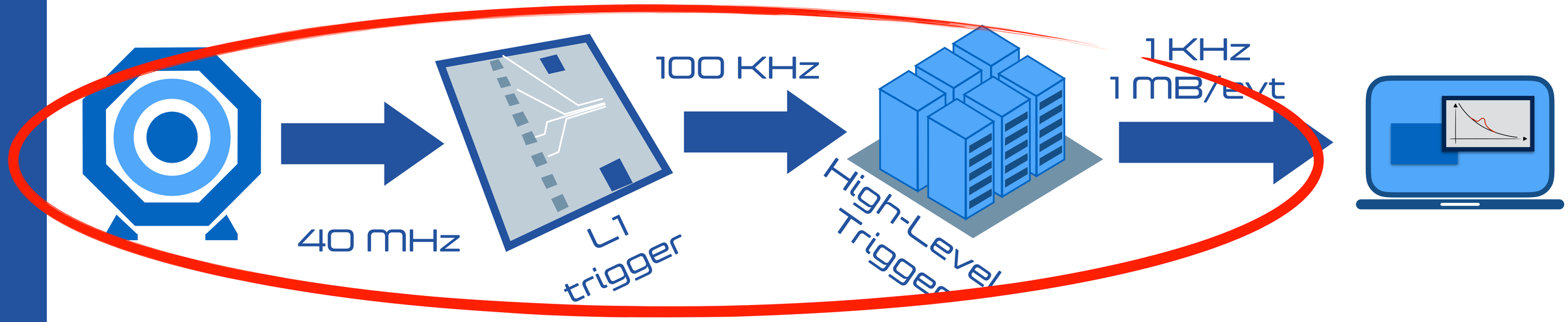
Three layers of reconstruction

- *A typical reconstruction chain has 4 steps (*)*
  - *L1 trigger: local, hardware based, on FPGA, @experiment site*
  - *HLT: local/global, software based, on CPU, @experiment site*
  - *Offline: global, software based, on CPU, @CERN T0*
  - *Analysis: user-specific applications running on the grid*



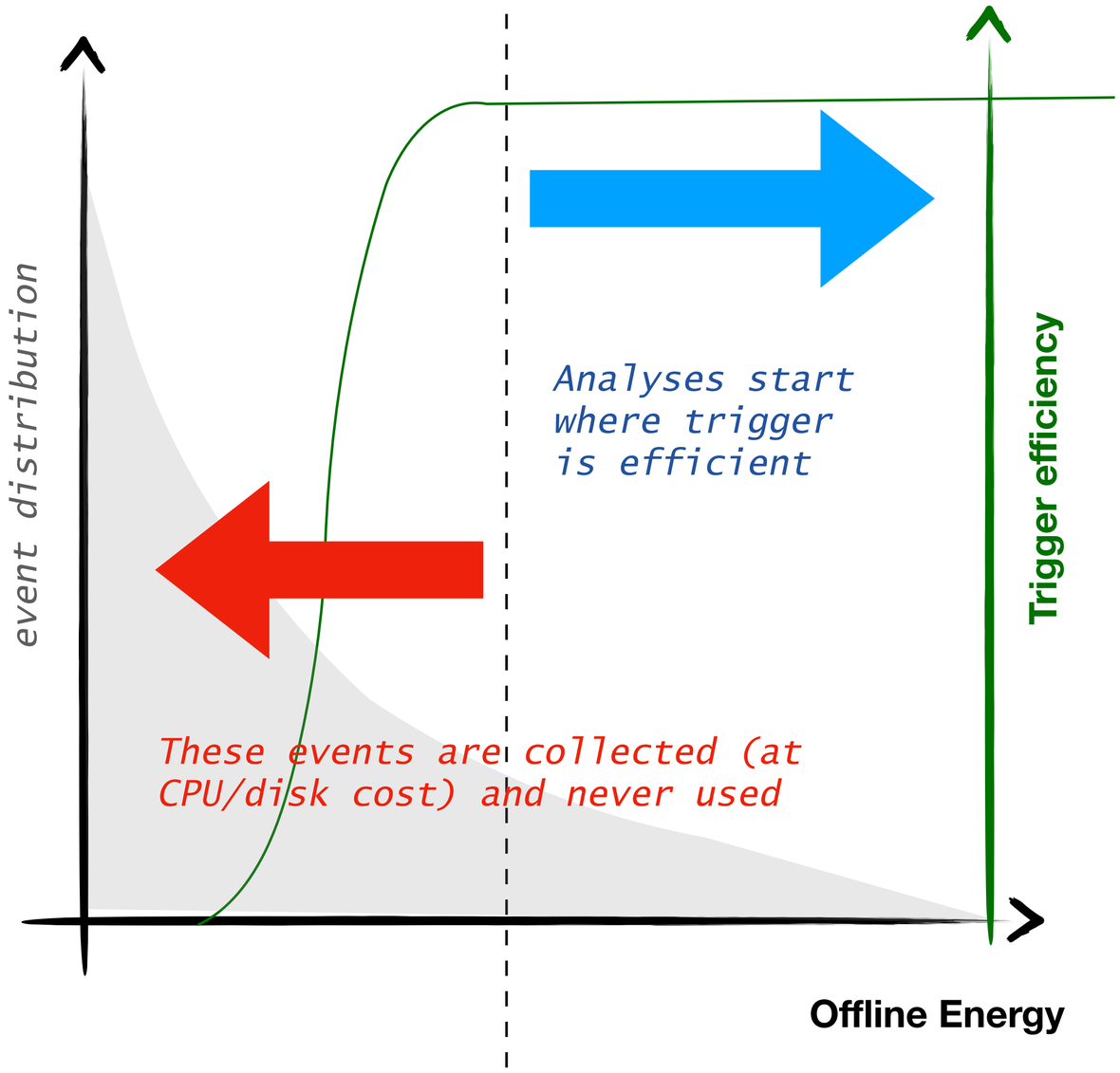
What DL could do for us

- *The solution to the HL-LHC problem: modern Machine Learning …*
  - *… to be faster*
  - *… to do better*
  - *… to do more*
- *And this is a NEED for what happens in between data taking and data analysis (trigger, reconstruction, simulation, …)*



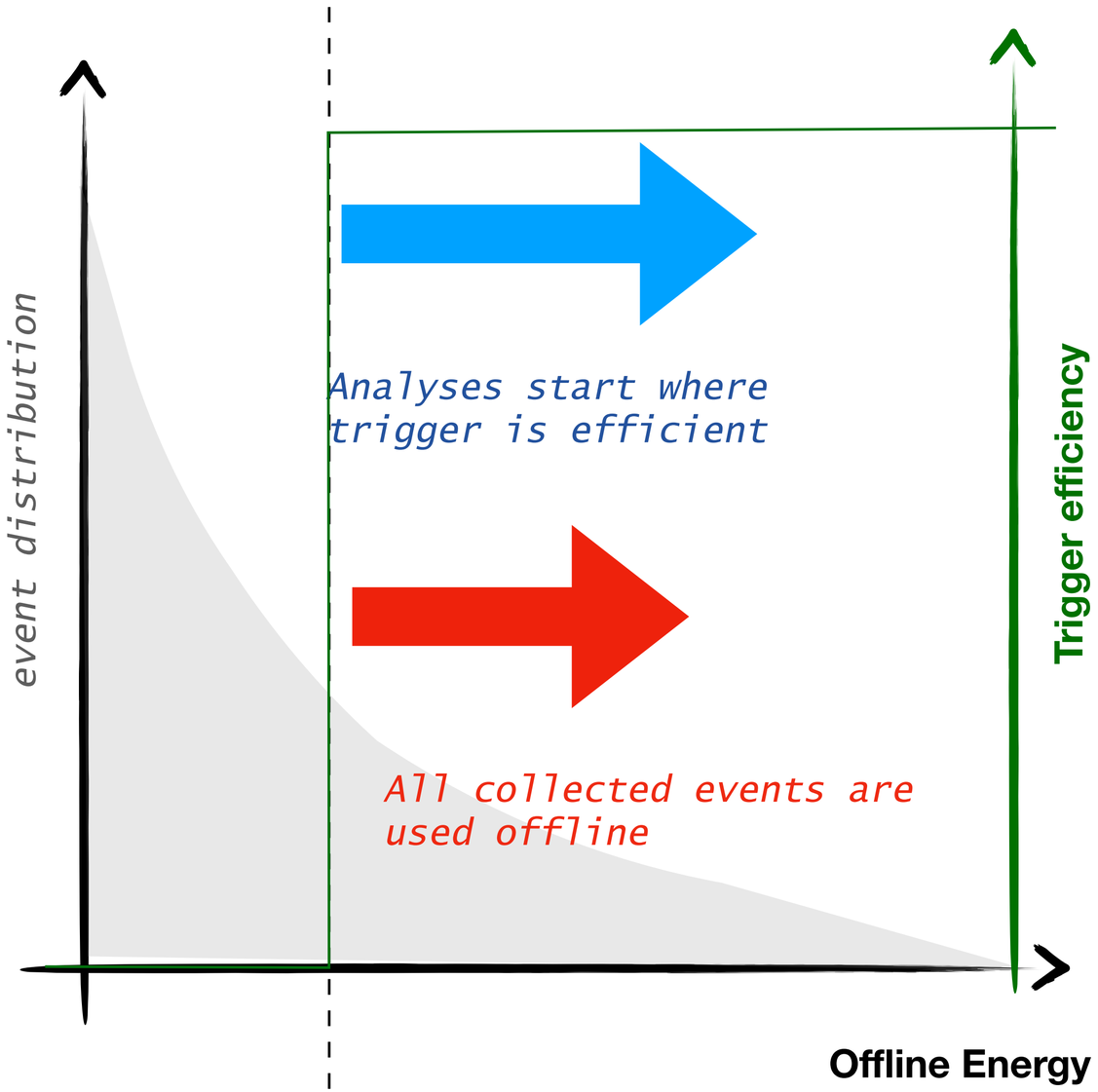
The Future that I dream of...

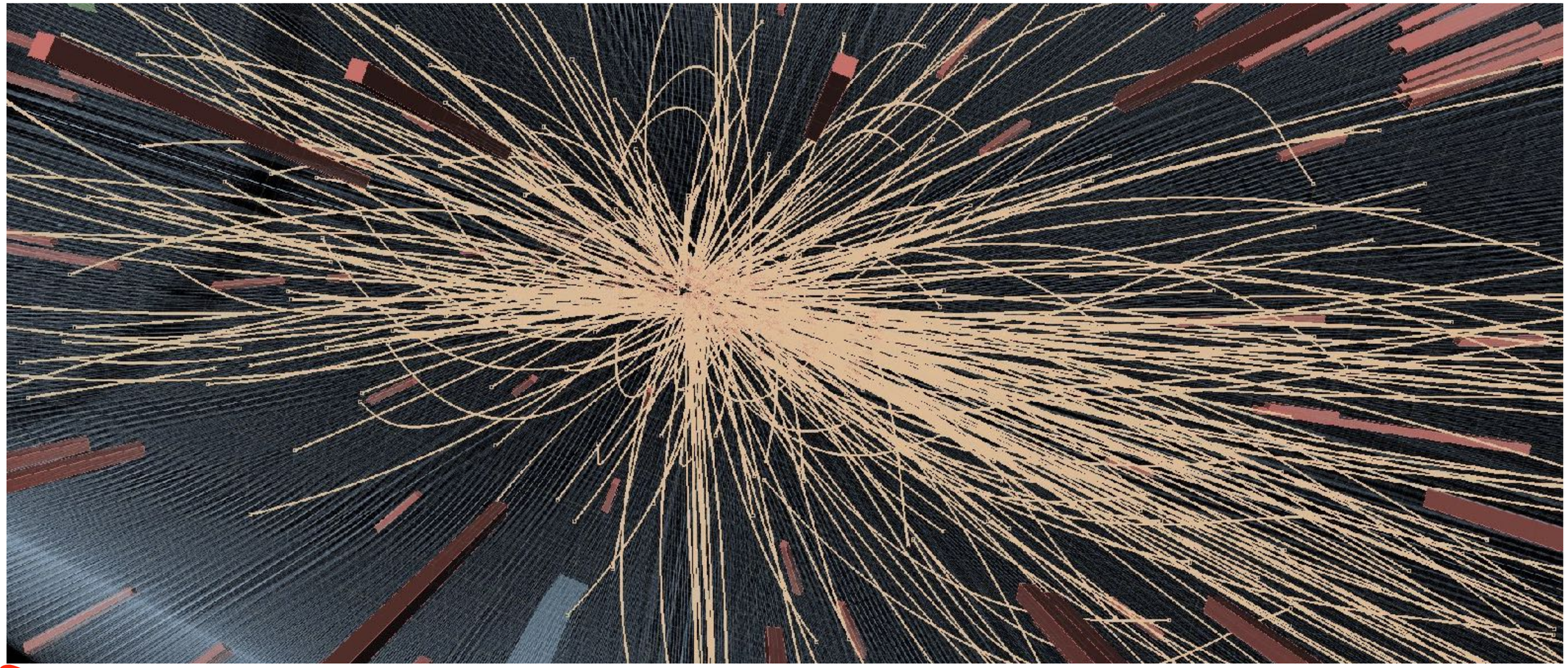
- Online vs offline reconstruction differences are limiting our discovery reach
  - Seen offline, the online selection is a not-flat response function
  - Forces us to work on tails of event distribution, reducing sensitivity to new physics
  - Not optimal use of resources



The Future that I dream of…

- ***Having the same reconstruction at L1/HLT/Offline*** *would help us to recover this lost sensitivity …*
- *… and to free resources that could be spent otherwise (e.g., looking for tricky new physics scenarios)*
- *This cannot be done exactly (offline code too slow)*
- *But it could be done "in average" (offline response modelled by ML algorithm)*



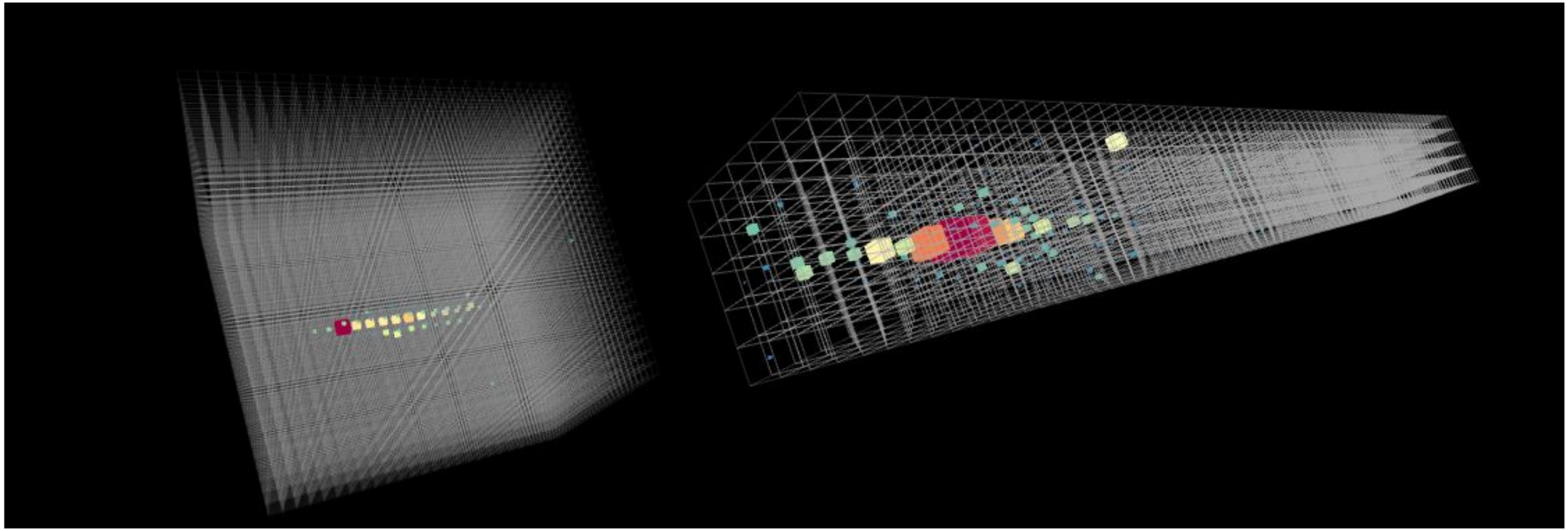


Deep ~~Machine~~ Learning to be faster

Particle reconstruction as image detection

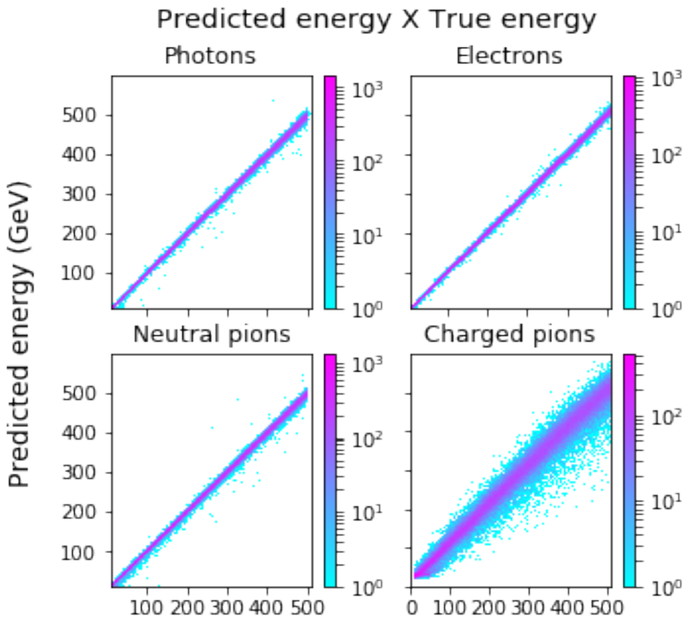
- *Future detectors will be 3D arrays of sensors with regular geometry*

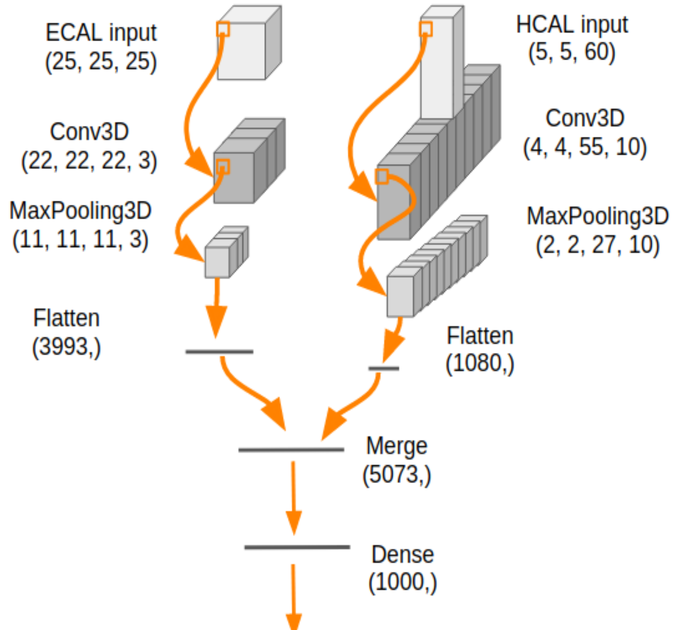
- *It would be ideal to quickly reconstruct particles directly from the image (which is what Deep Learning became famous for)*

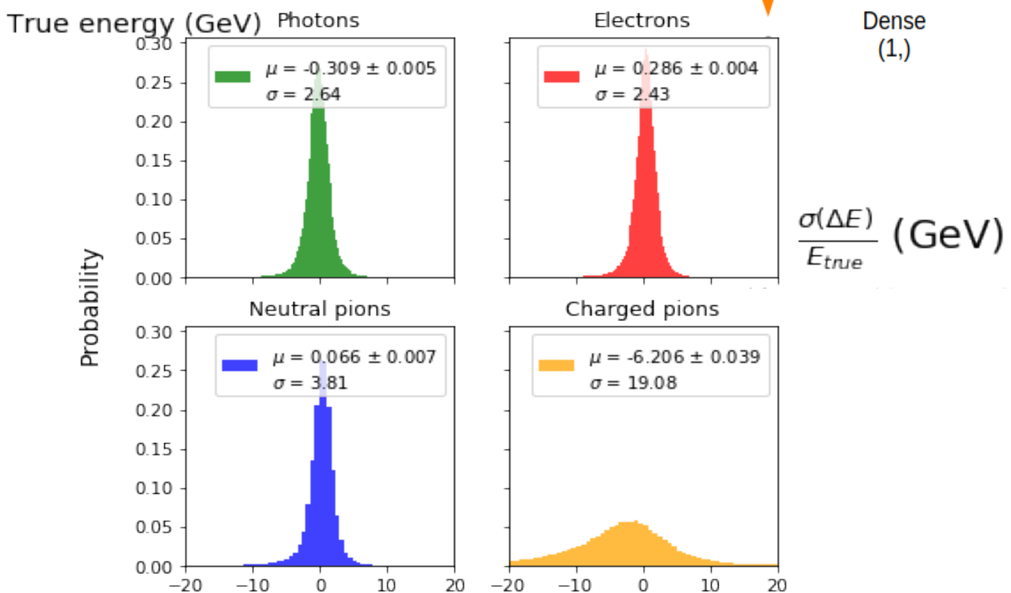


Proof of Principle: Energy Regression

- *3D Convolution NN can learn true energy of an incoming particle from the recorded hit pattern*
  - *Correctly reconstruct energy*
  - *ECAL performances better than HCAL (as expected)*
  - *π^0 resolution ~ $\sqrt{2}$ γ resolution (as expected)*
- *No high-level knowledge of physics and/or detector features*
  - *<u>used only RAW data as inputs</u>*
- In real life, this could be used offline, at HLT, and (maybe) even at L1





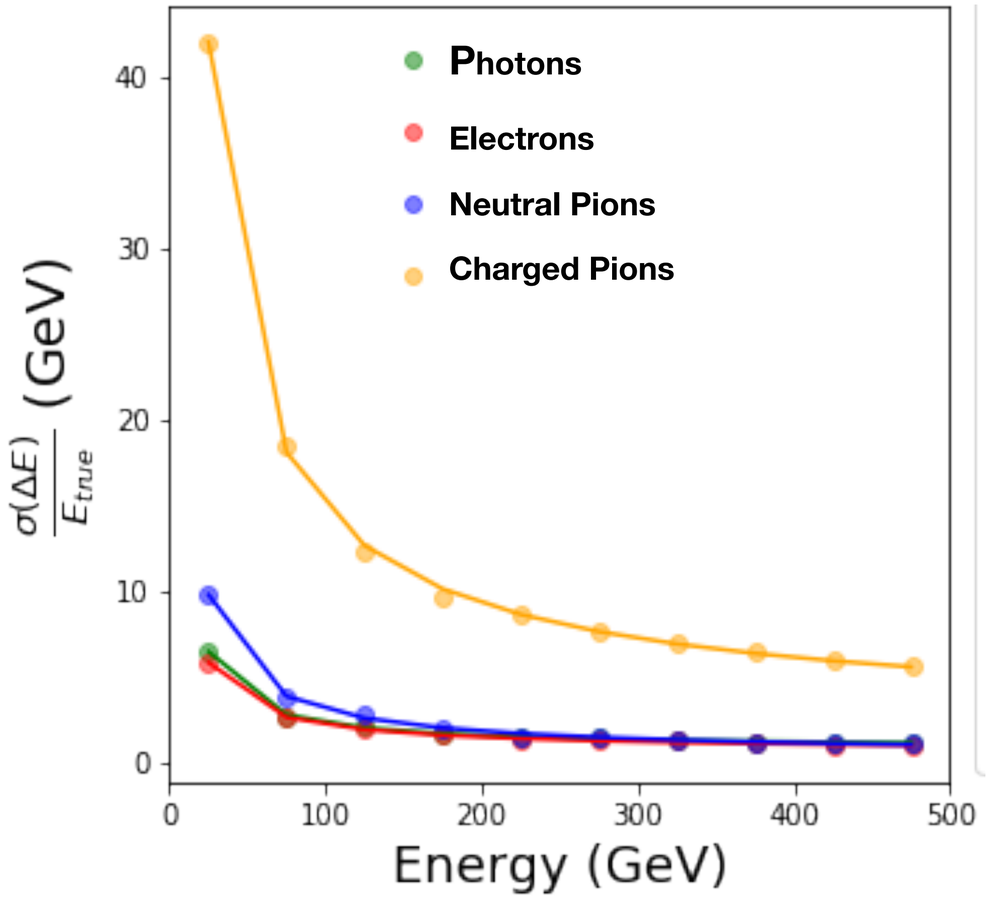


Work by K. Datta & V. Pacela, (2016/2017 Caltech Summer Students) and J.Mohapatra (OpenLab Summer student 2016)

Proof of Principle: Energy Regression

- *Competitive and meaningful results*
- *Processing time reduced by 10^3 wrt traditional approaches*

◉ In real life, this could be used while selecting events in real time ("trigger")



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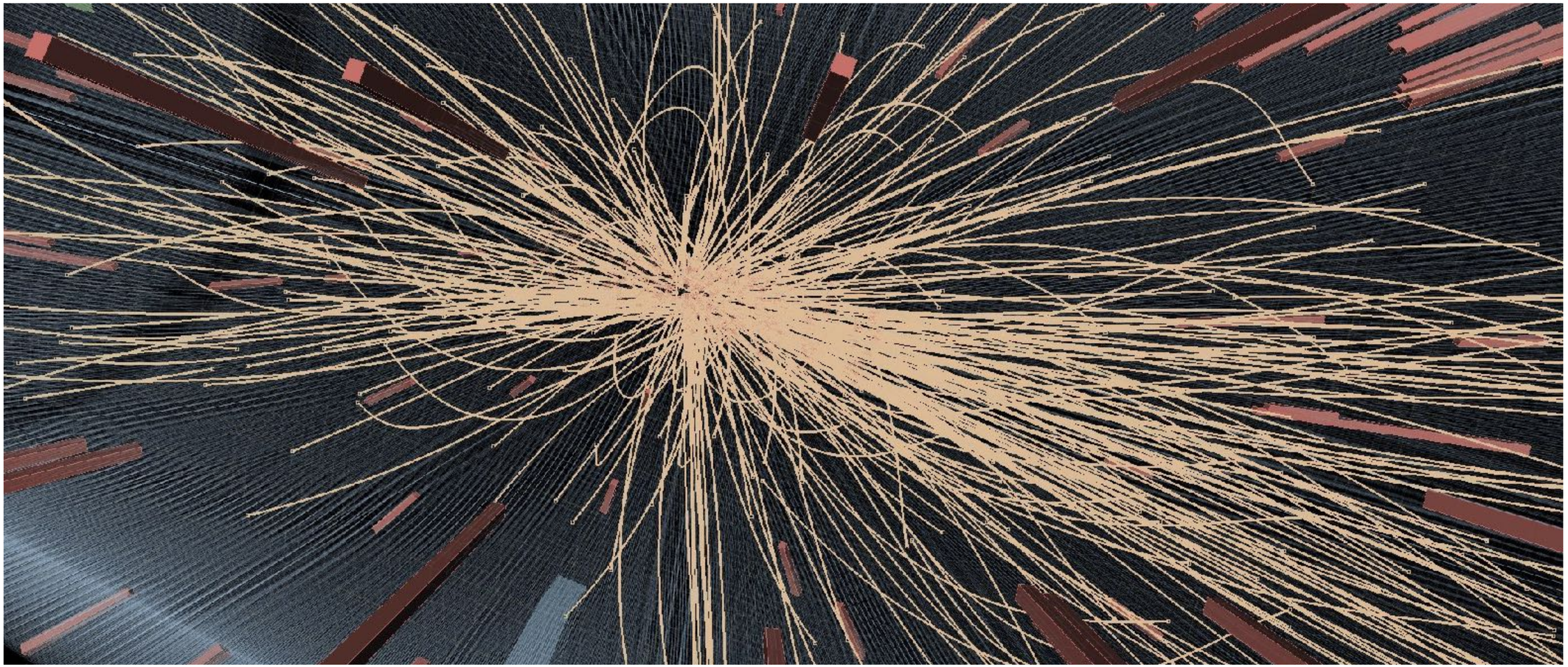


Deep Learning to do better

A change or roles

- *Deep Learning promises better jet tagging, particle identification, etc. than currently employed Machine Learning solutions (e.g., Boosted Decision Trees)*

- *Networks will engine variables. Our challenge will be helping the network to do this at best*

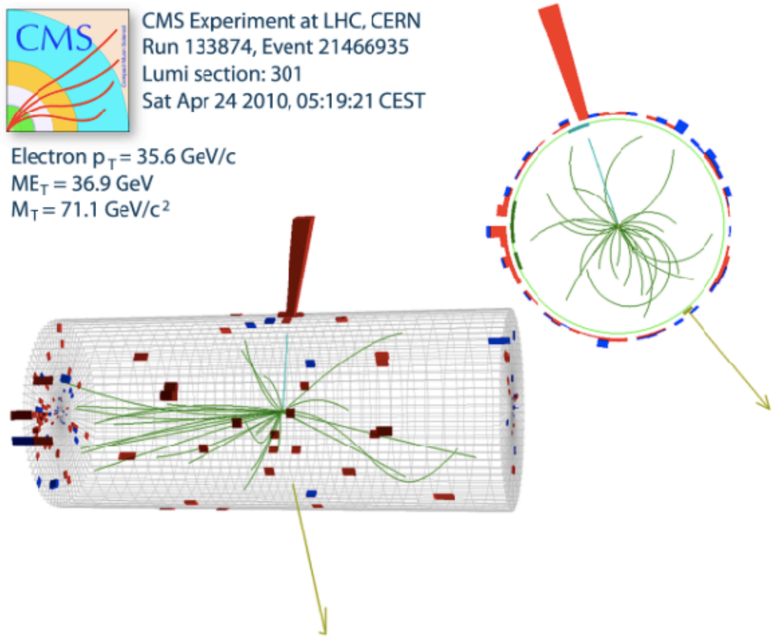
~~*a smart variables*~~

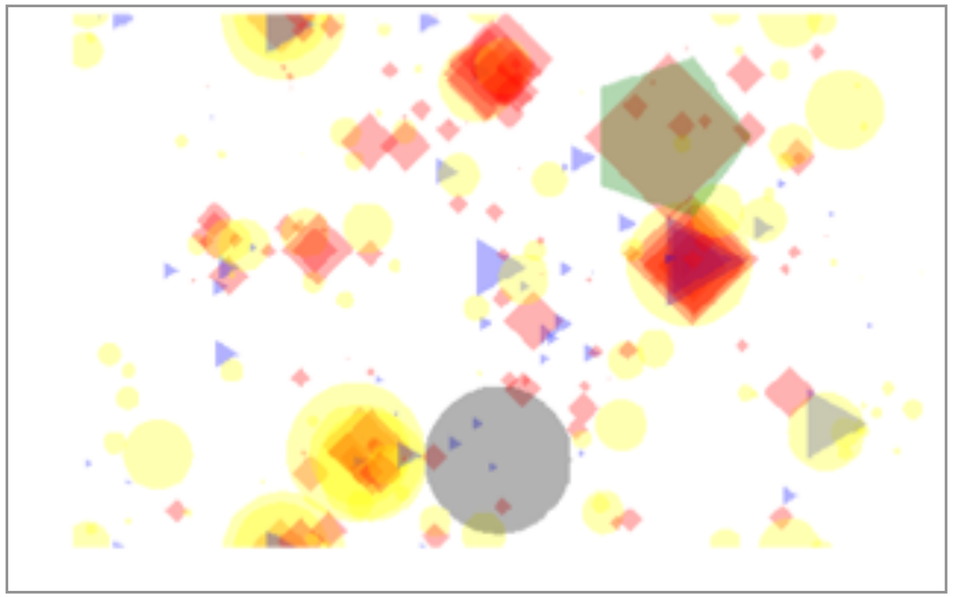
a smart event representation

Smart Event Representations

Event as an abstract image

- *Actual event images are sparse and irregular, mainly because of detector geometry*
- *Events abstracted to a regular image, turning physics quantities into image features (energy→ size, particle kind→colour,…)*
- *At this stage, Deep Learning (e.g., Conv. NN) could be used at best*

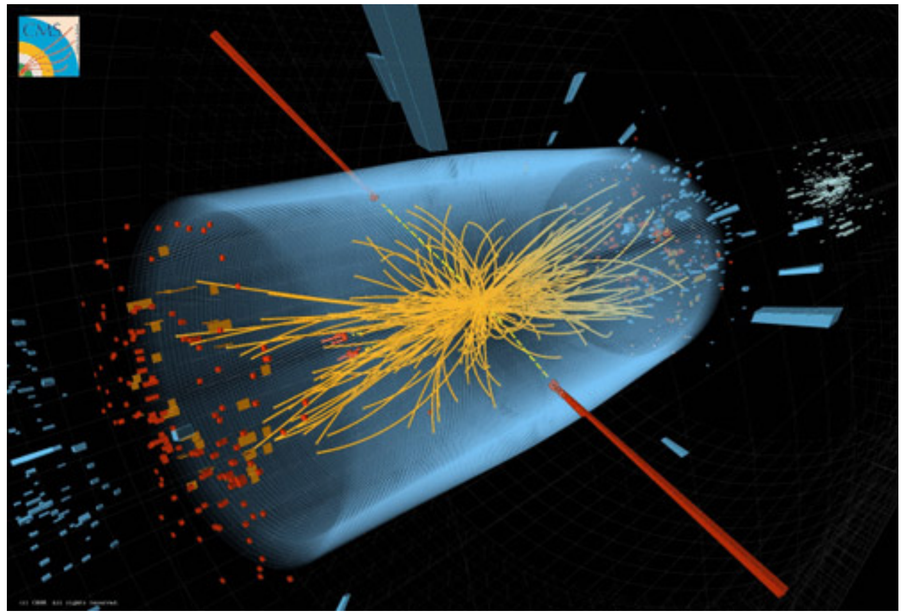


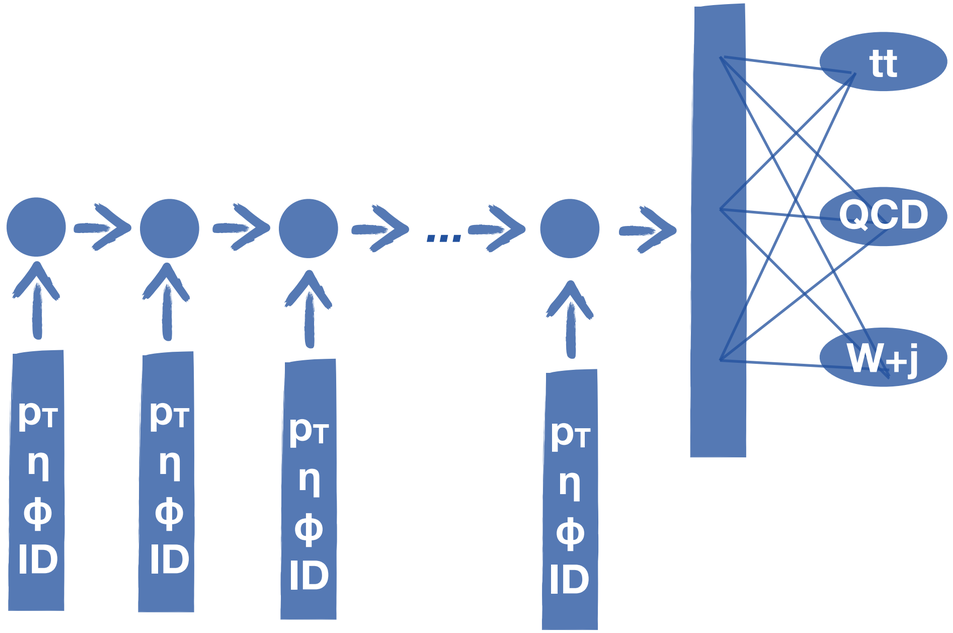


Smart Event Representations

Event as a sentence

- *Events are made of particles like sentences are made of words*
- *Physics is the grammar that dictates the order*
- *Use recursive neural networks to "understand" an event (like text-understanding applications)*

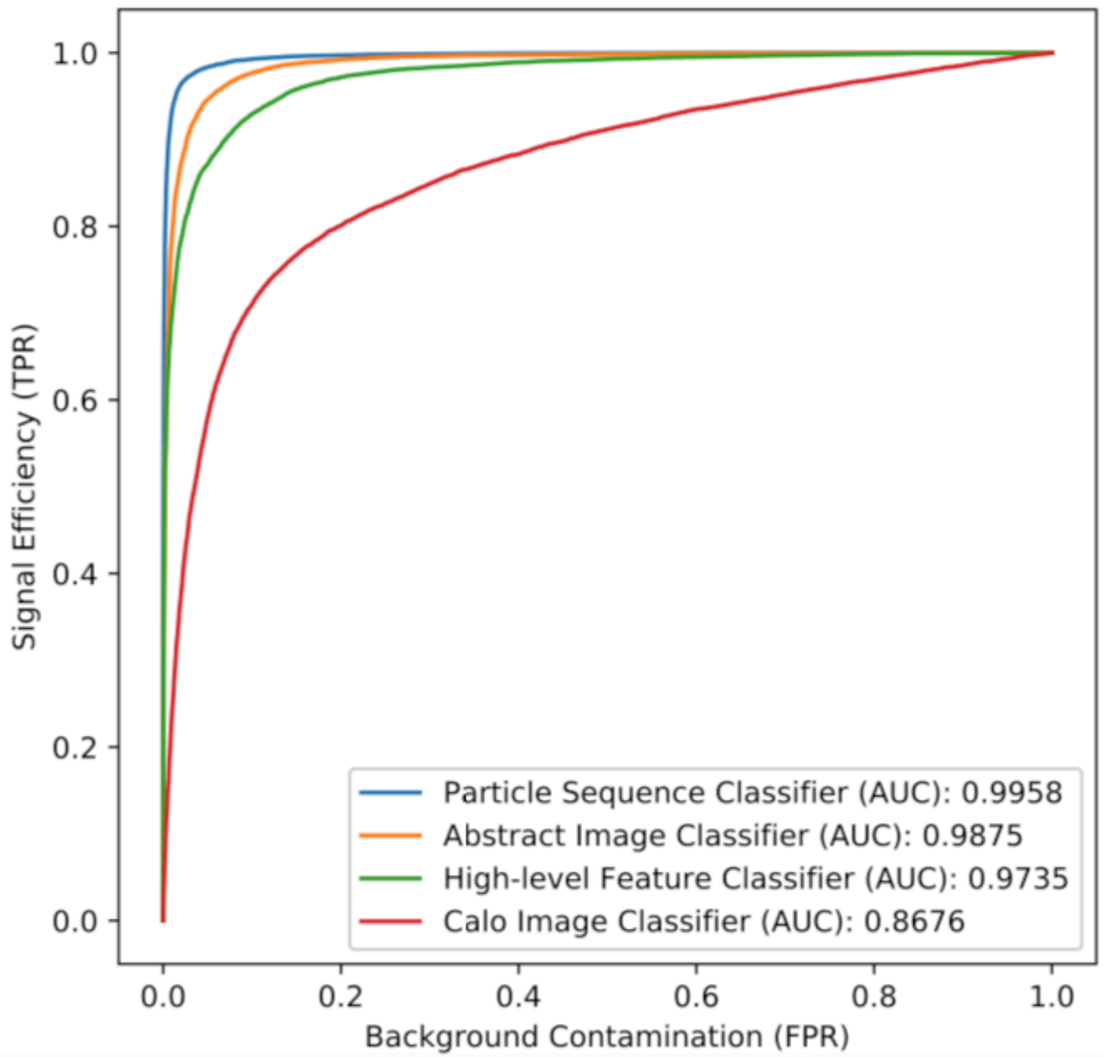




Work by D. Weitekamp, 2017 CERN OpenLab Summer Student

Proof of principle: trigger cleanup

- *tt events are a tiny fraction in single-lepton datasets*
- *This is because triggers are object- and not topology-based*
- *How does one quantify a topology?*
  - *the physicist represents the topology in a DL-compliant way*
  - *the neural networks "designs" the best classification criterion*



Work by D. Weitekamp, 2017 CERN OpenLab Summer Student

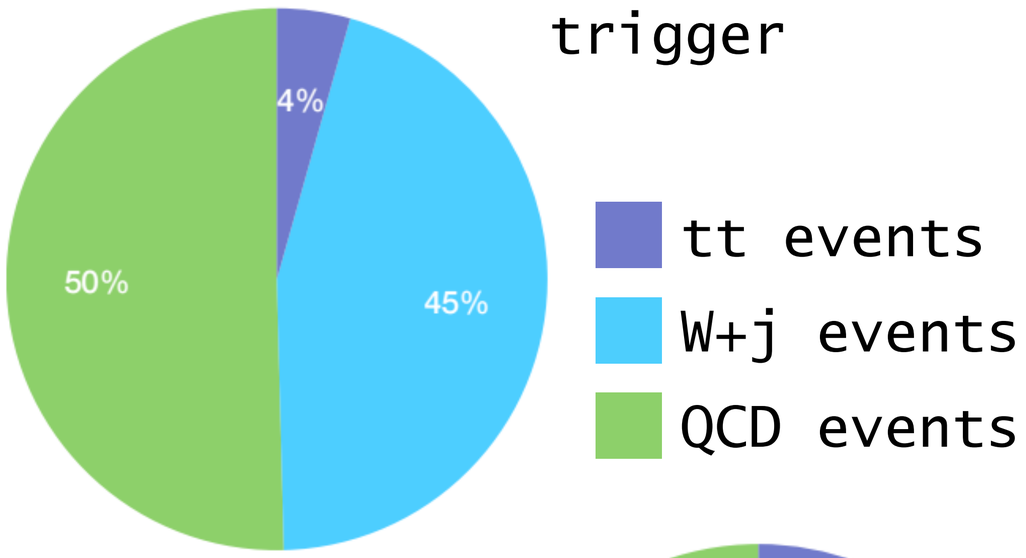
Proof of principle: trigger cleanup

- *Strong QCD/W+j background reaction for 99% efficiency on tt events*

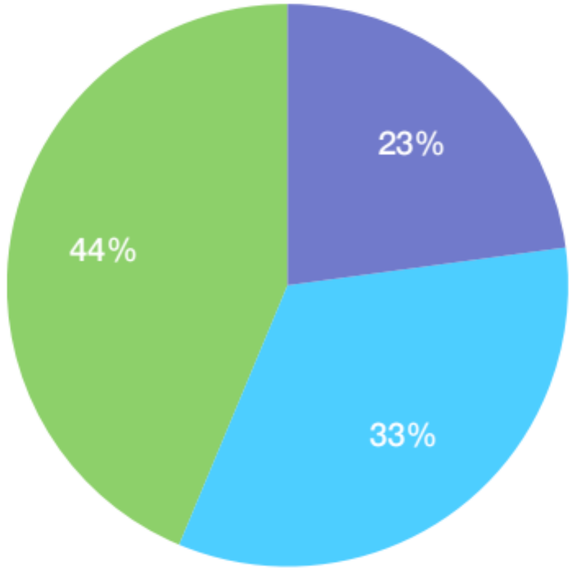
- *Such a filter at trigger level could save **x10 downstream resources***

Class	HL Trigger	99%	95%
QCD	255 Hz	22.4 Hz	3.57 Hz
W+Jets	230 Hz	20.1 Hz	2.73 Hz
ttbar	2 Hz	1.95 Hz	1.87 Hz
Total:	487 Hz	44.45 Hz	8.17 Hz

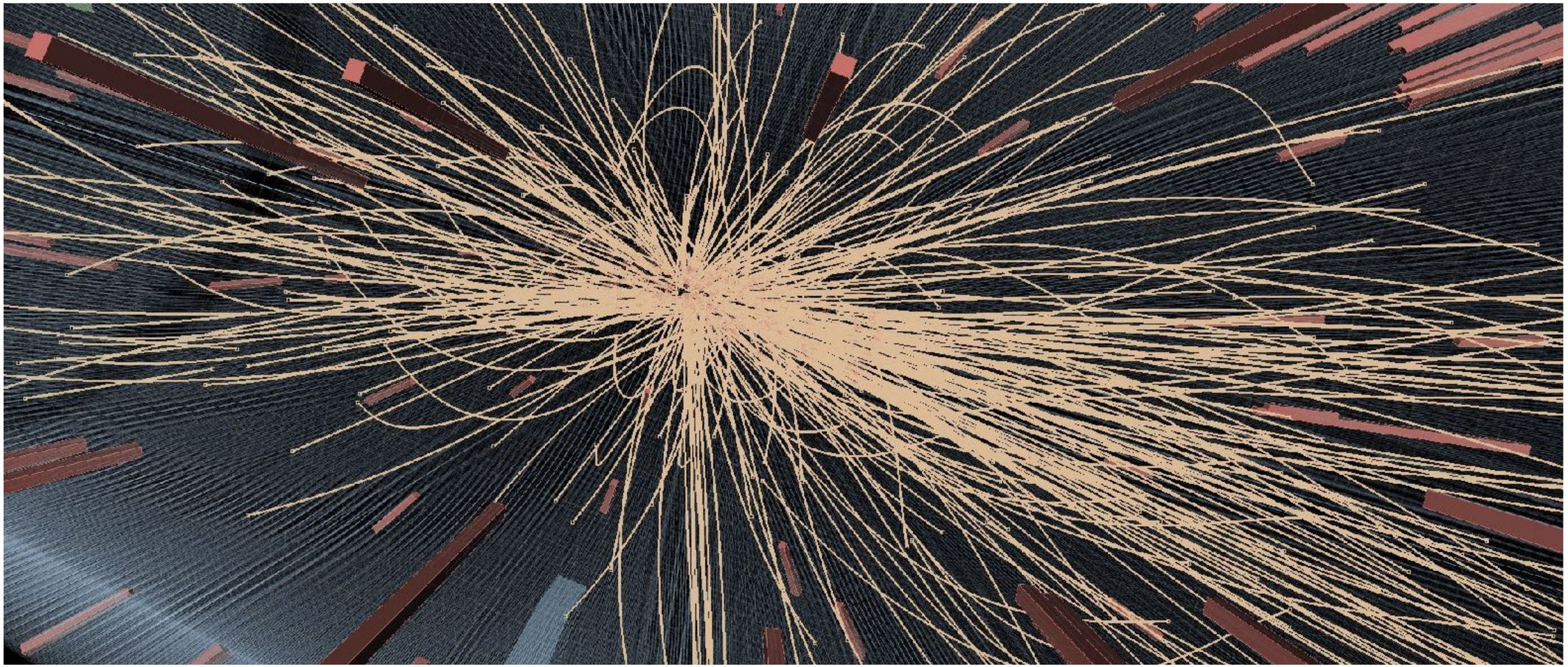
Sample composition after traditional trigger



Sample composition after LSTM selection



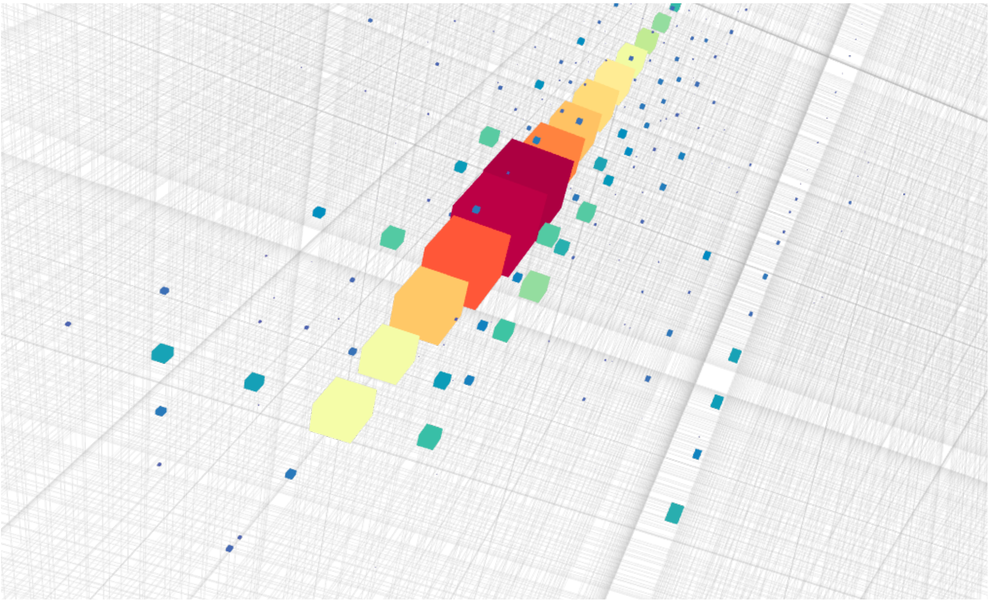
Work by D. Weitekamp, 2017 CERN OpenLab Summer Student

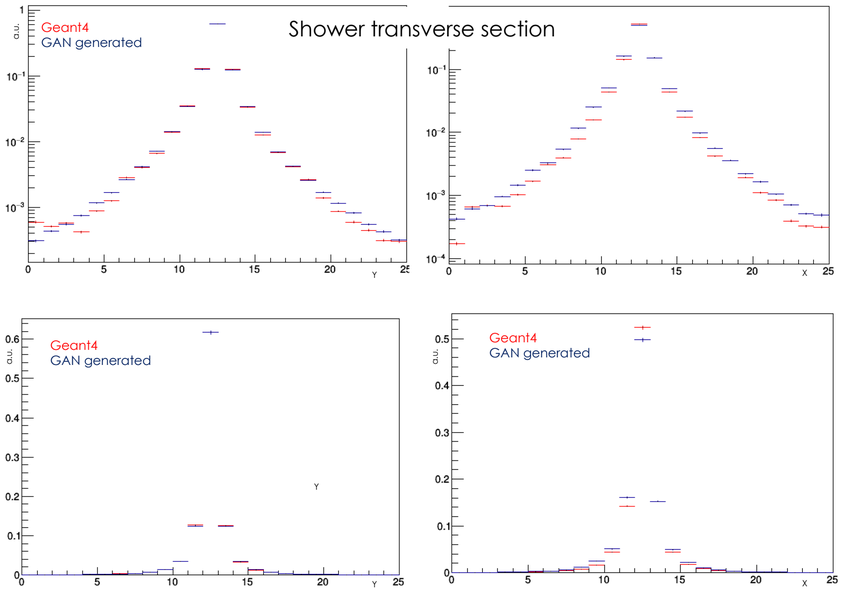


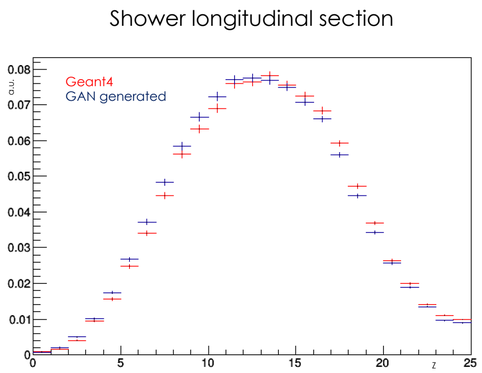
Deep Learning to do more: generation

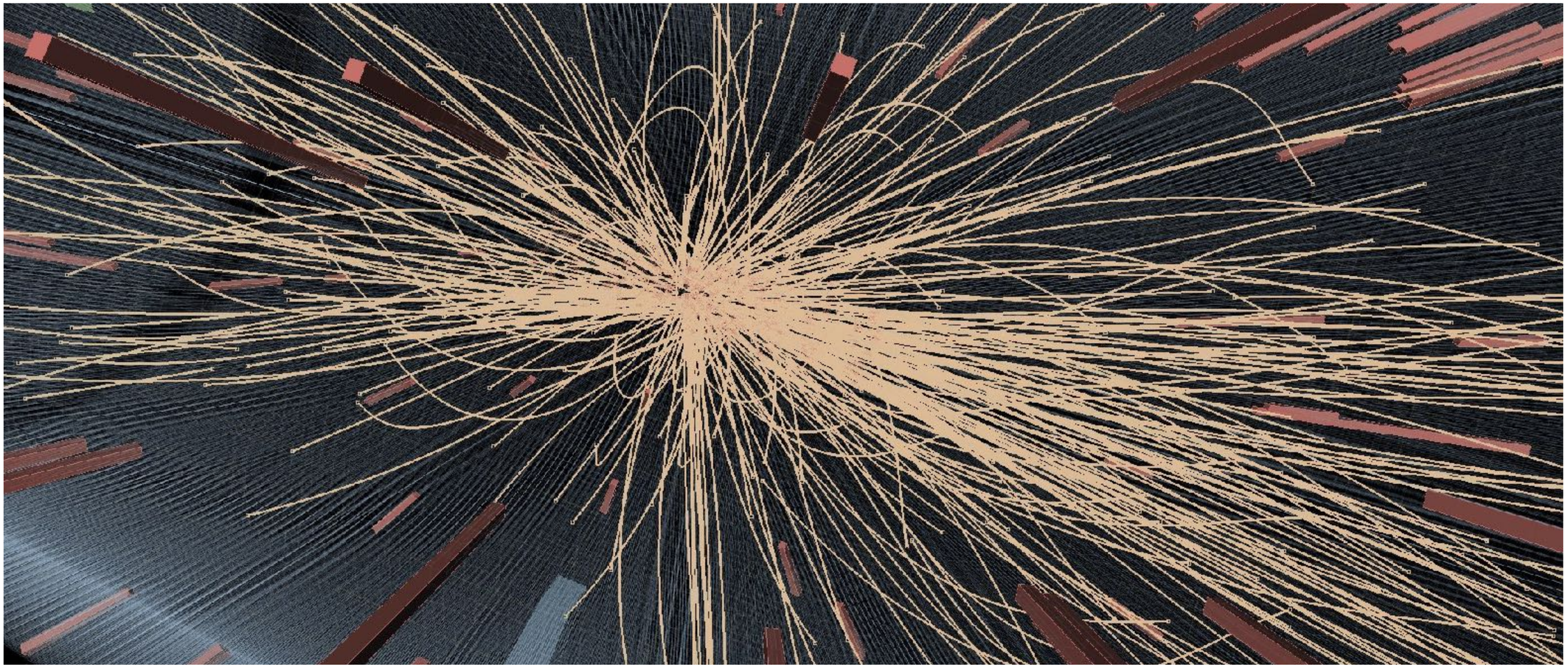
Generative Adversarial Networks

- With x10 more data being stored during HL-LHC, we will need > x10 more Monte Carlo to do precision physics
- This will not be possible with current generation techniques
- Generative models might provide a way out of this dead end
- **<u>See Sofia's talk for full story</u>**





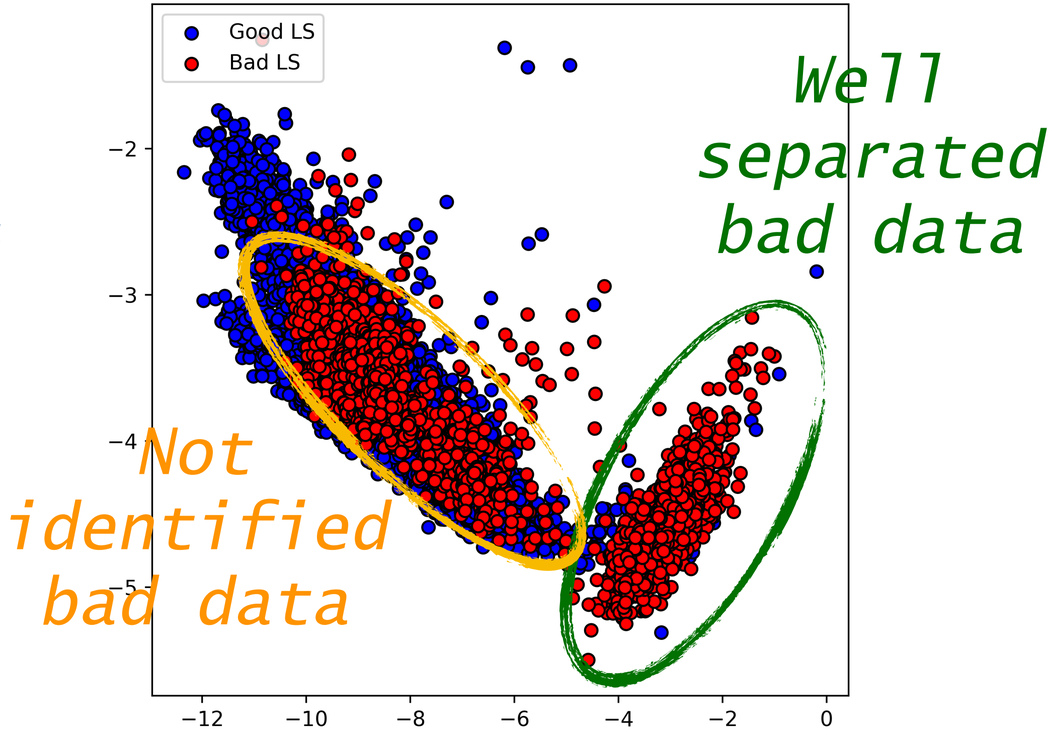




Deep Learning to do more: going unsupervised

Looking for Detector anomalies

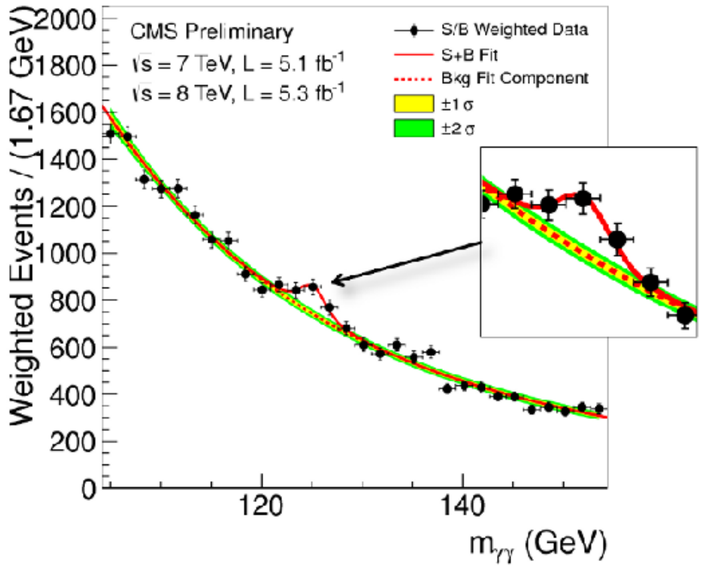
- *Look for a detector failure/bad data w/o having to specify the failure*
- *Example: look for anomaly in muon detection/reconstruction*
- *Input: array of muon kinematic features (p_T, η, φ, Vertex information, charge)*
- *use auto encoder to project the information into a latent space optimized to separate signal from background*
- *Direction is promising,* ***but more work is needed***
- ***See Virginia's talks for the big picture***

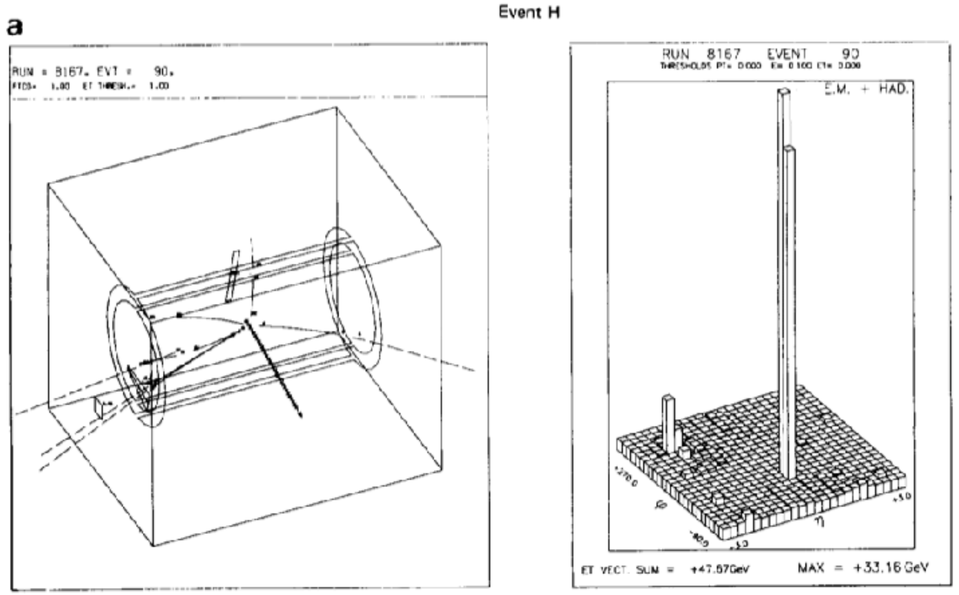


Work by C. Fernandez Madrazo, 2017 CERN Summer Student

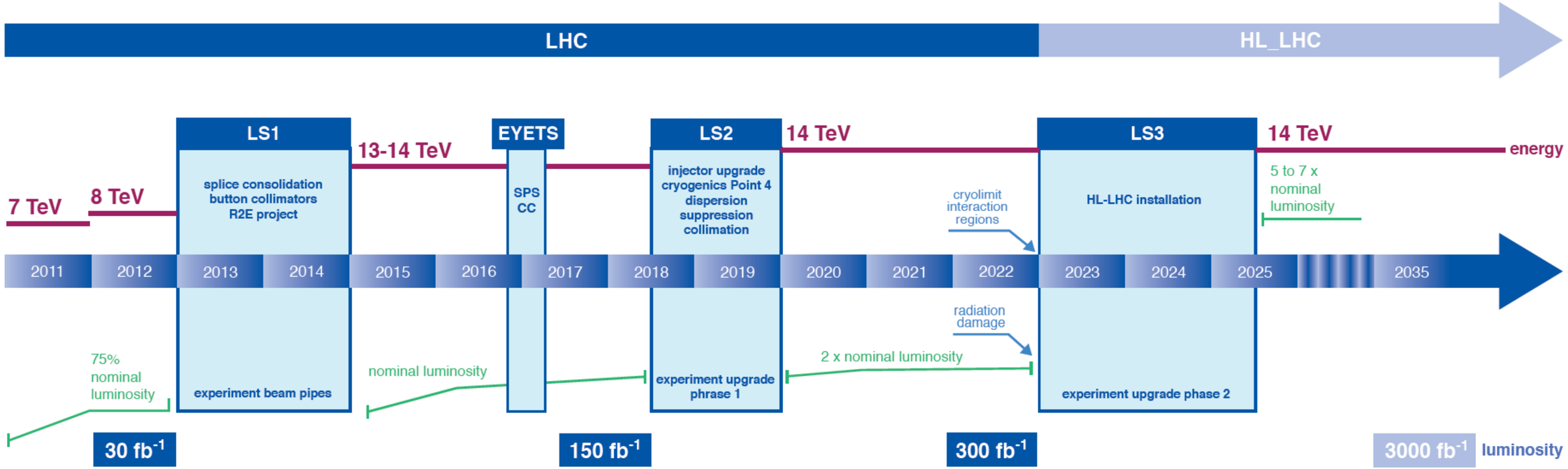
What could we do with this?

- *We could get some help looking for new physics*
  - *Humans run classic searches: look for what you expect*
  - *Machines do Data Mining: keep eyes open for what we don't expect*





A roadmap towards HL-LHC



- *We need to be ready by **2025** (High-Luminosity LHC)*
- *LHC Run 3 (2020-2022) is the ultimate demonstration opportunity*
  - *produce proof-of-principle studies on simulations and open datasets*
  - *bring ML expertise at CERN and in the experiments*
  - *within experiments, develop/test/deploy ML solutions to solve technical tasks*