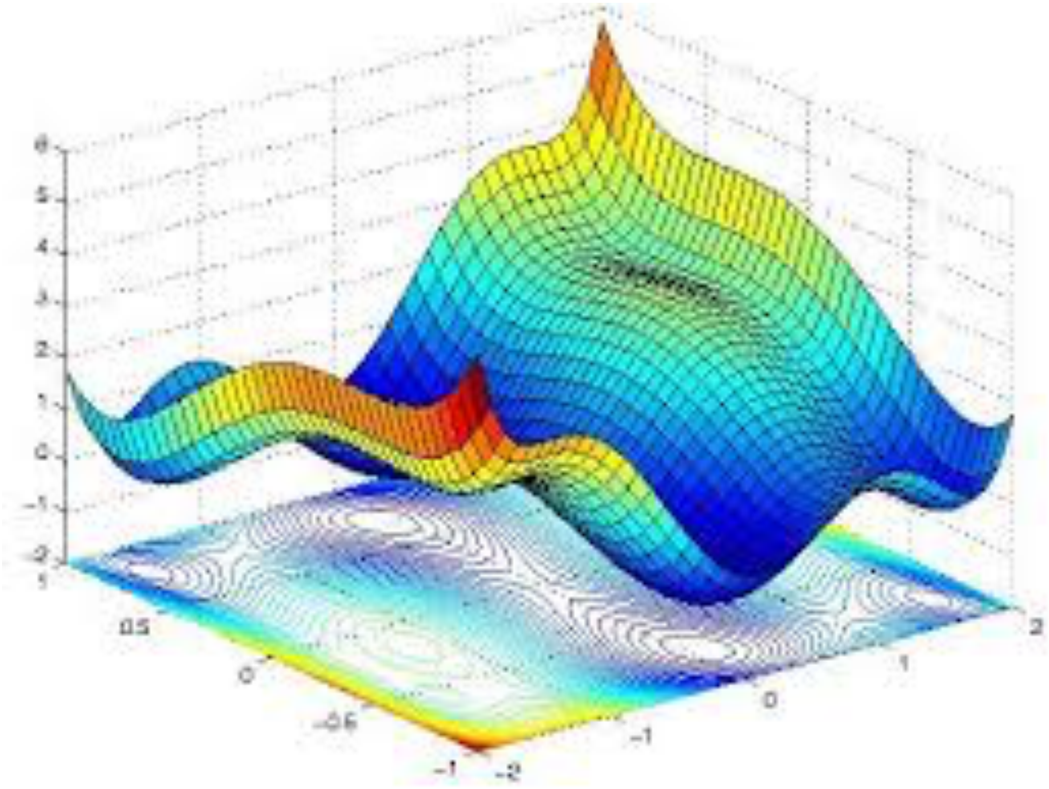
Machine Learning for future e^+e^- colliders

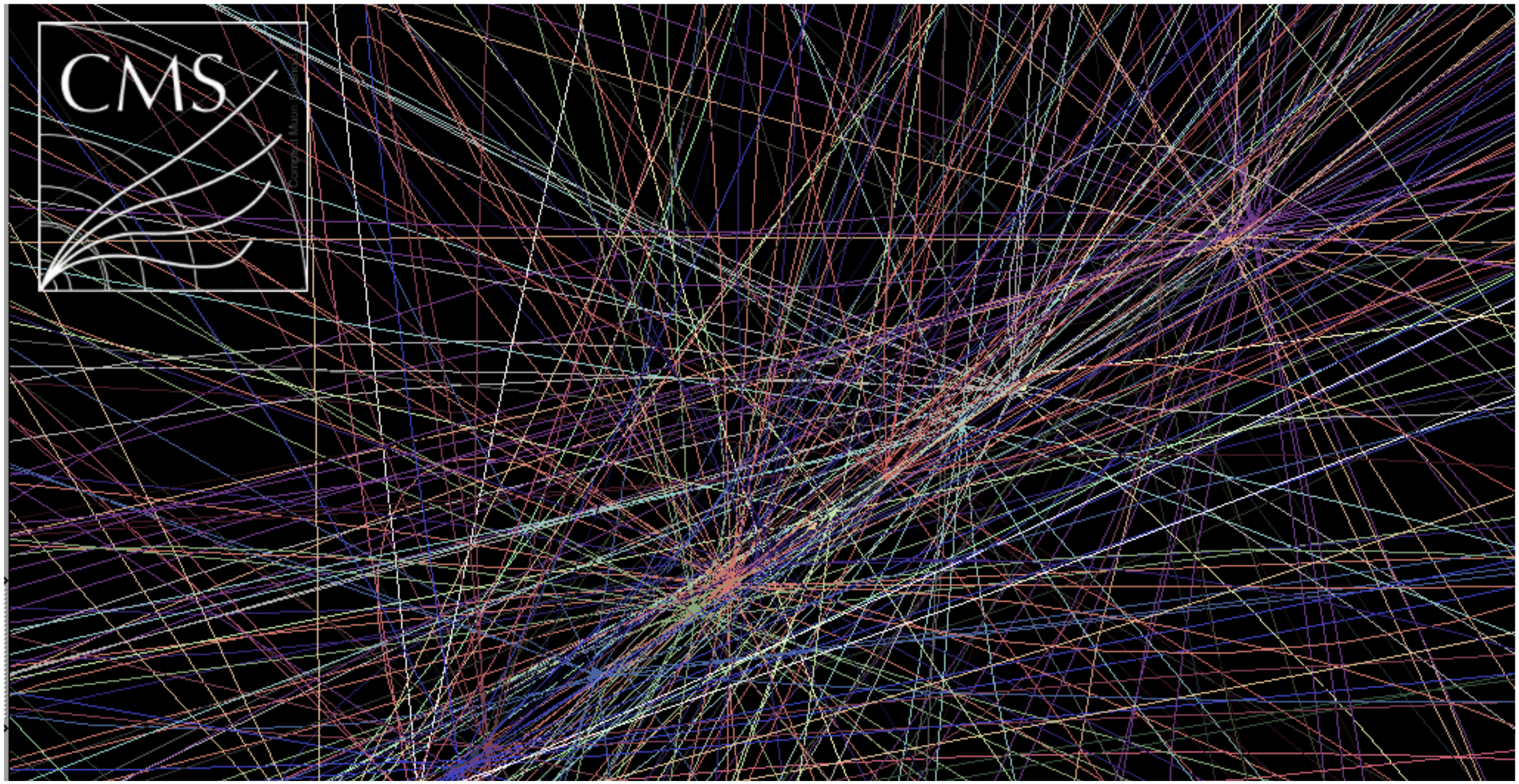
Maurizio Pierini

What is Machine Learning

- *Machine learning is a technique by which an algorithm in trained with example to accomplish a task*
  - *as opposed of being programmed to do so, by specified rules*
- *Deep Learning is the cutting-edge ML technology*
  - *based on "old-school" neural networks + augmented computational capabilities (e.g. GPUs) and "new" architectures (recurrent nets, convolutional nets, autoencoders, …)*
  - *the breakthrough is fast differentiability (back-propagation) allowing fast optimization*
  - *DL networks are good in learning non-linear functions: can be a fast shortcut to replace heavy processing tasks*



Training a Machine Learning algorithm consists in minimizing a complicated multi-dimensional function



Why ML for HEP?

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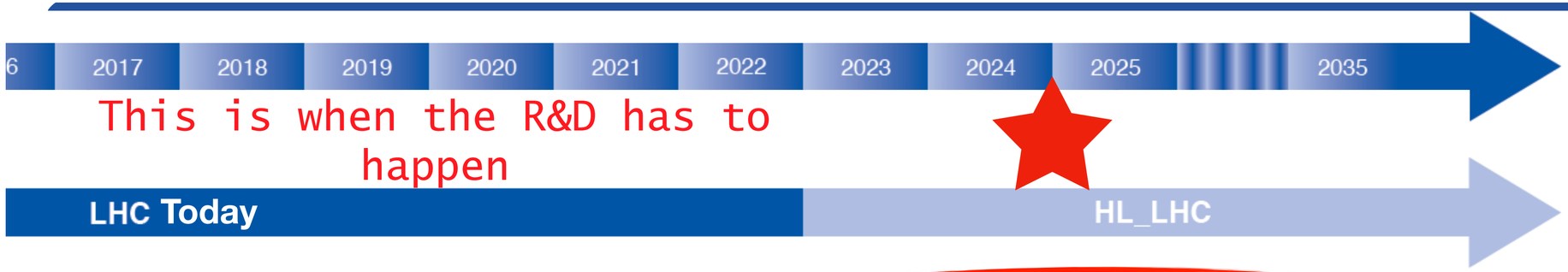
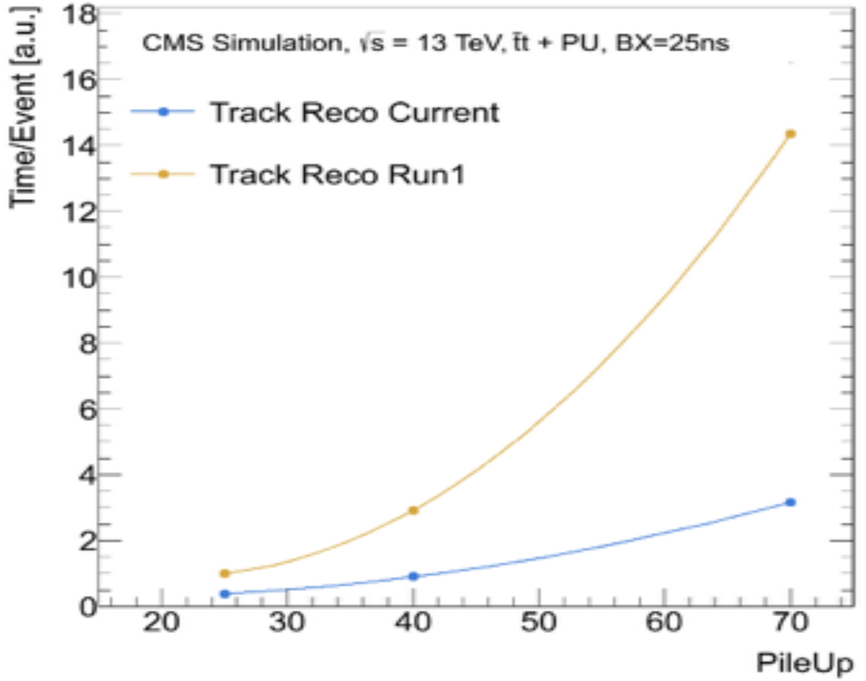
HL-LHC & ML as a must



- ~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

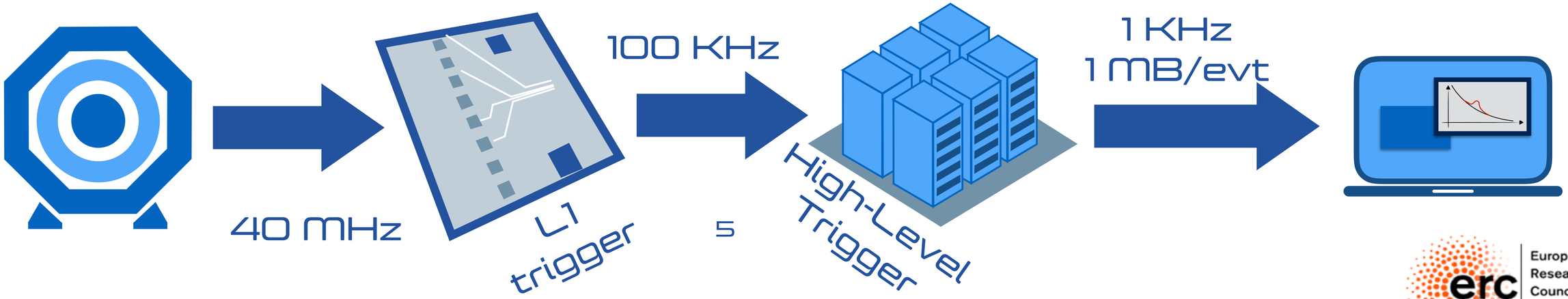


- *Flat budget vs. more needs = **current rule-based reconstruction algorithms will not be sustainable***
- ***Adopted solution:** more granular and complex detectors → more computing resources needed → more problems*
- ***Modern Machine Learning might be the way out***

(*)With nowadays software development

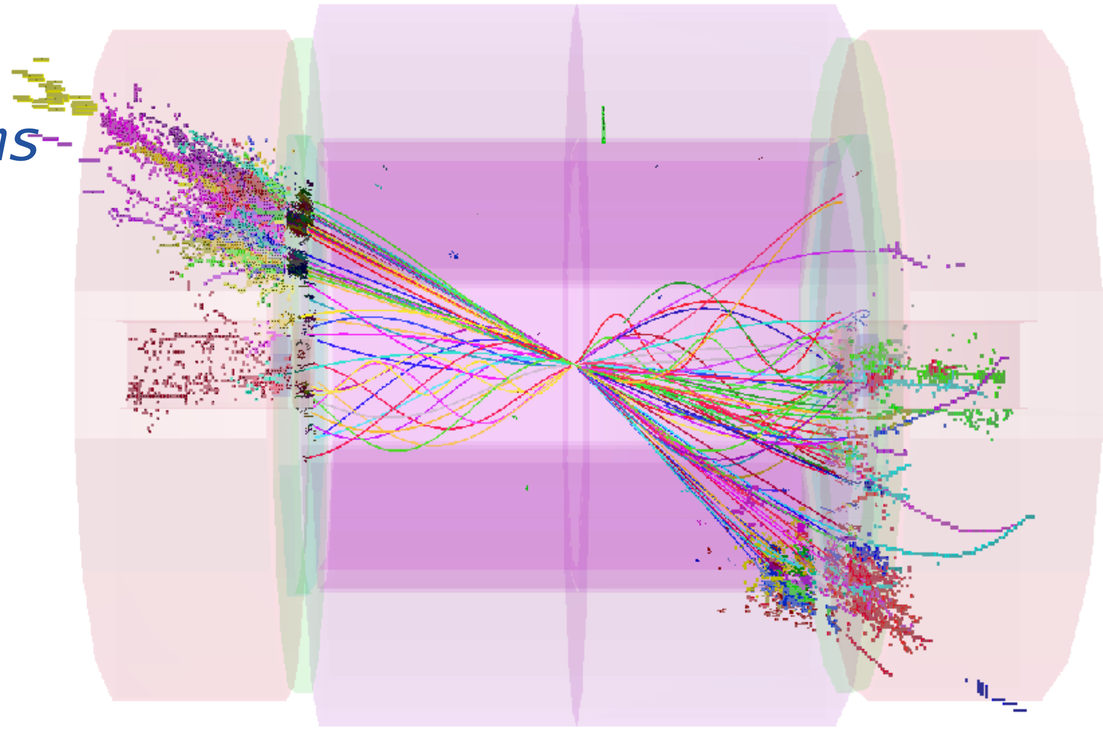
HL-LHC & ML as a must

- *Machine Learning can act as a short-cut to reduce CPU needs to accomplish computational tasks:*
  - *express the answer of a traditional algorithm as a function learned by examples*
- *ML deployment is happening at any level: L1, HLT, reconstruction, Monte Carlo generation & analysis*



Why ML for Future e^+e^-?

- *A-priori, there is real need to go in this direction for e^+e^- colliders*
  - *traditional rule-based algorithms should scale up easily*
- *On the other hand, this is where HEP is going (pushed by LHC needs, but not only)*
- *Moreover, there might be a performance gain ~ for free with these techniques*
  - *See the successful story with neutrinos*



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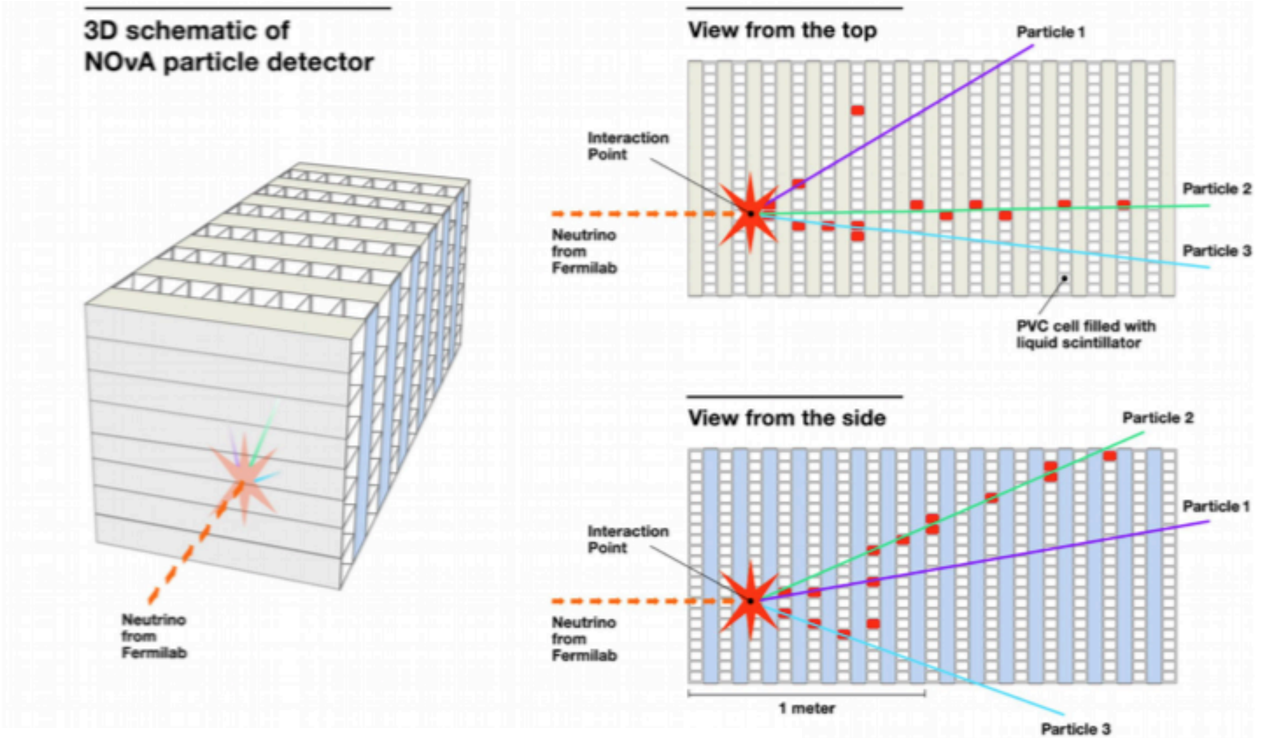
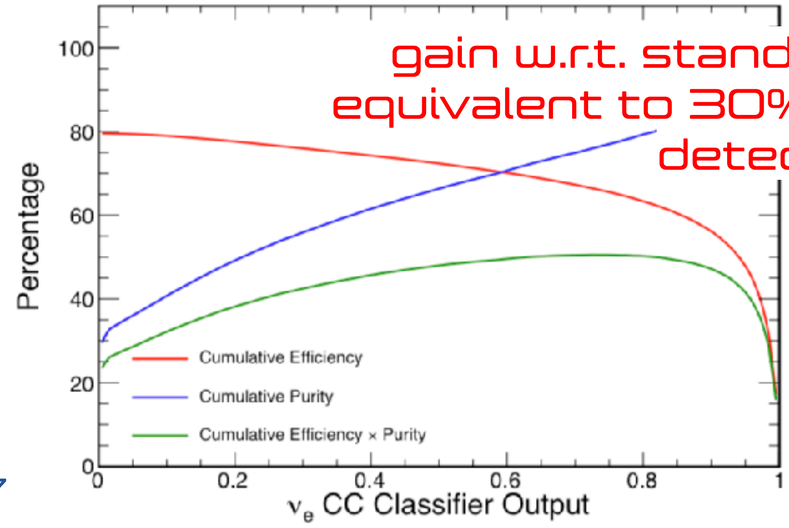
Example: PID for ν experiments

- *Many HEP detectors (particularly underground) more and more structured as regular arrays of sensors*
- *Modern computer-vision techniques work with images as arrays of pixel sensor (in 1D, 2D, and 3D)*
- *These techniques were applied by Nova on electron and muon ID*
- *Impressive gain over traditional techniques (comparable to +30% detector == $$$ saved)*





gain w.r.t. standard approach:
equivalent to 30% bigger mass of detector

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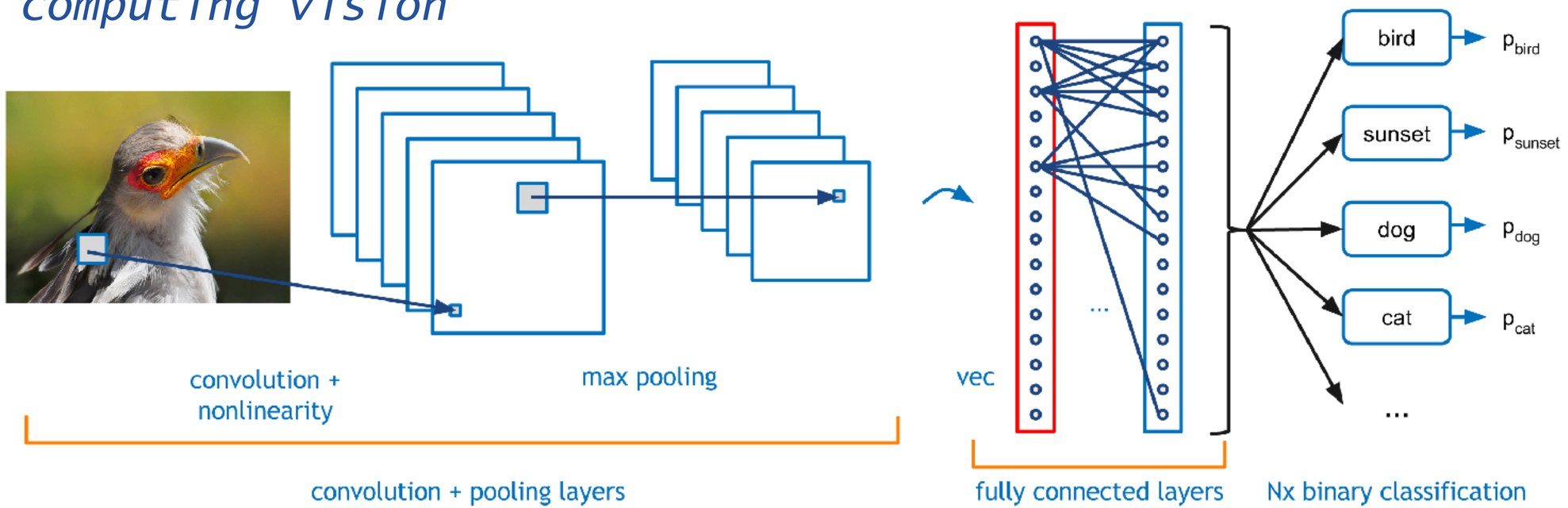
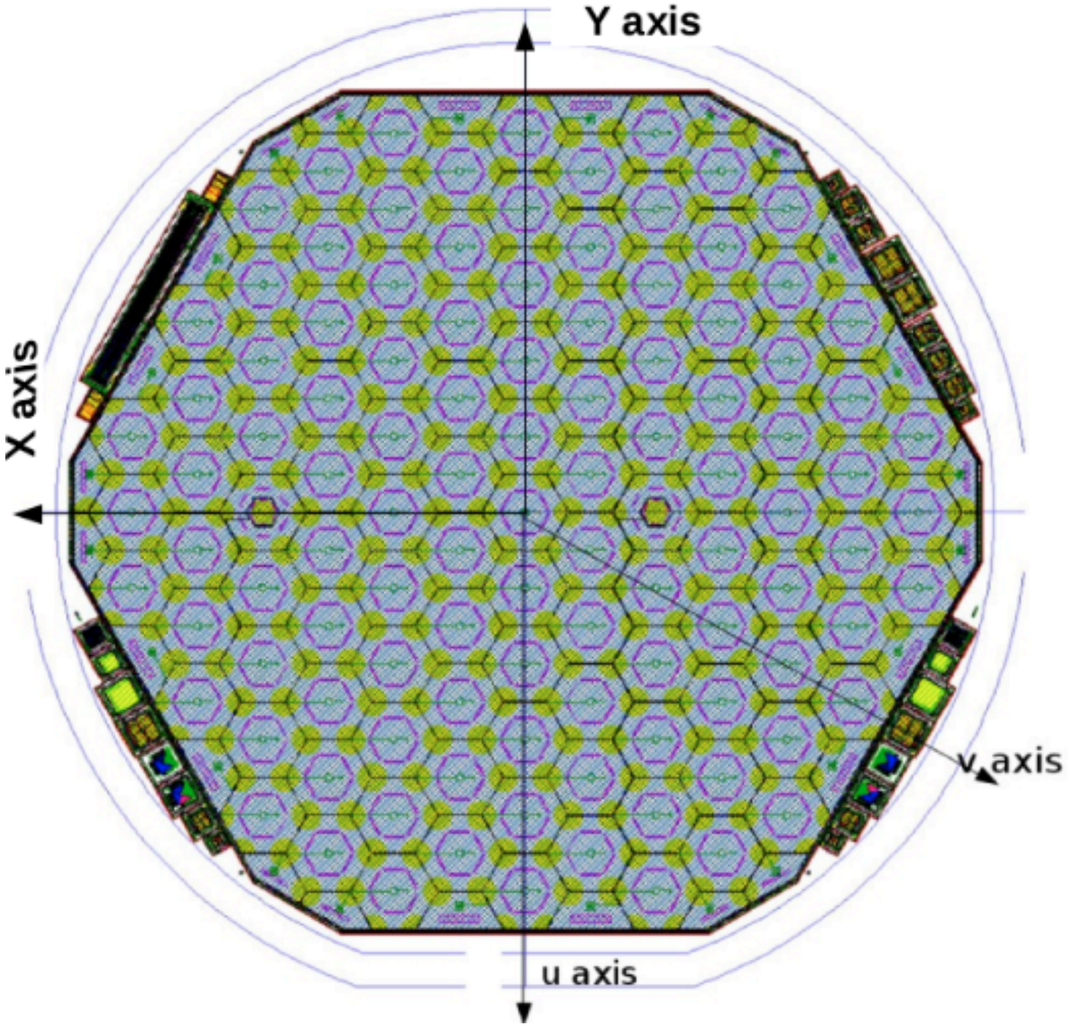
Which computing-vision technique?

- *The main breakthrough of Deep Leaning is the capability of processing directly raw data*
- *Special architectures read the raw information (e.g., images) and convert them into "smart variables" (high-level features) to accomplish the task*
- *Typical example: convolutional neural networks for image processing & computing vision*





Faster Particle Reconstruction With Computing Vision

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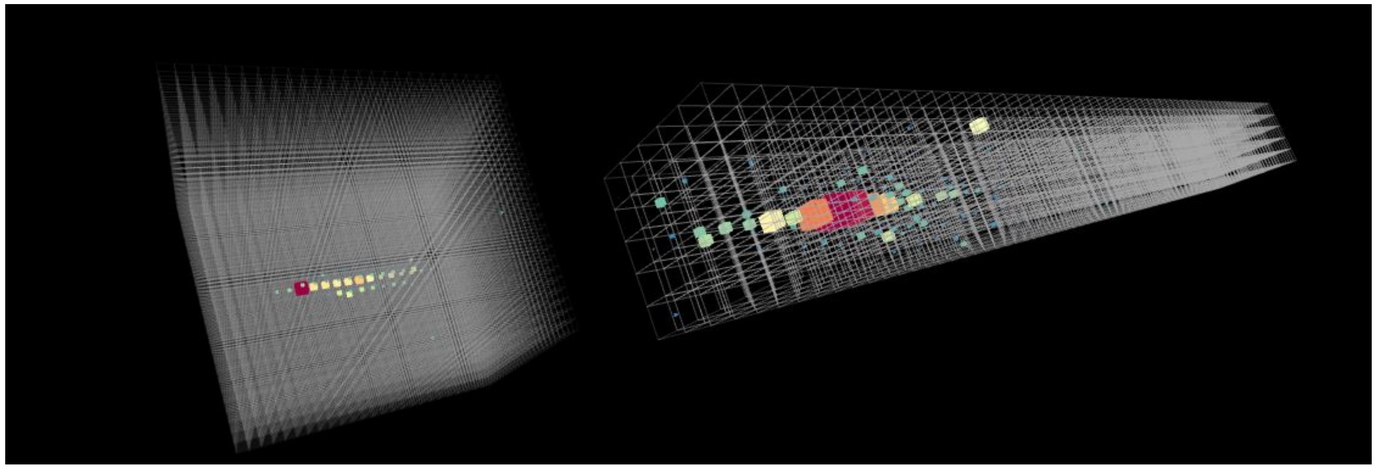
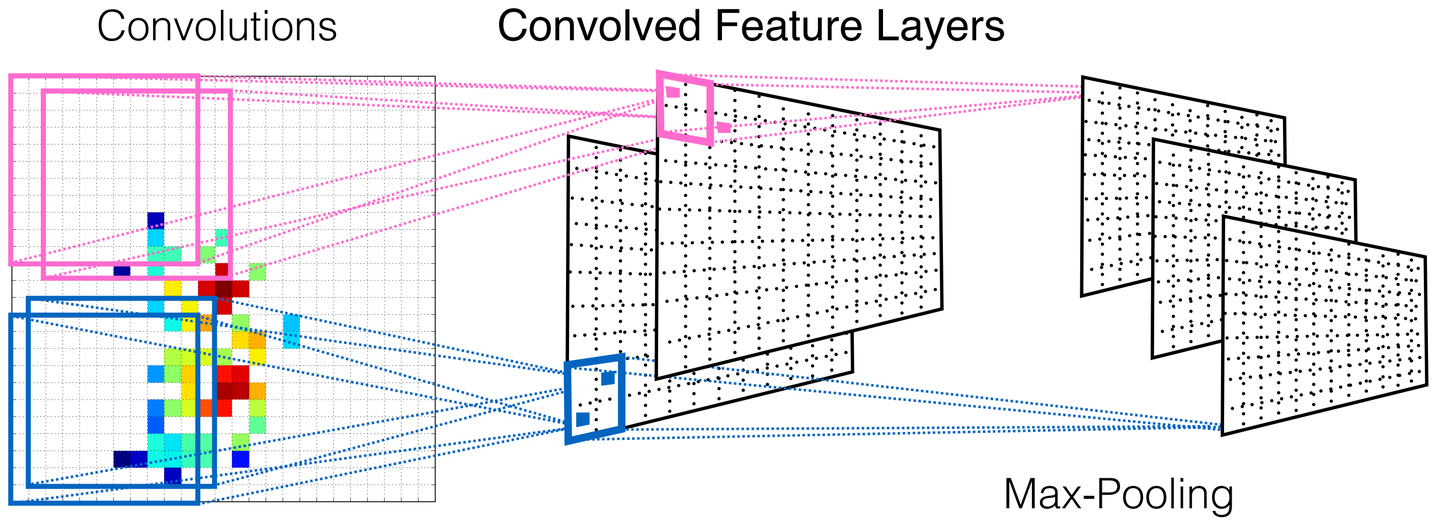
Particle reconstruction as image detection

- *Future detectors will be 3D arrays of sensors with regular geometry*
- *Ideal configuration to apply Convolutional Neural Network*
  - *speed up reconstruction at similar performances*
  - *and possibly improve performances*

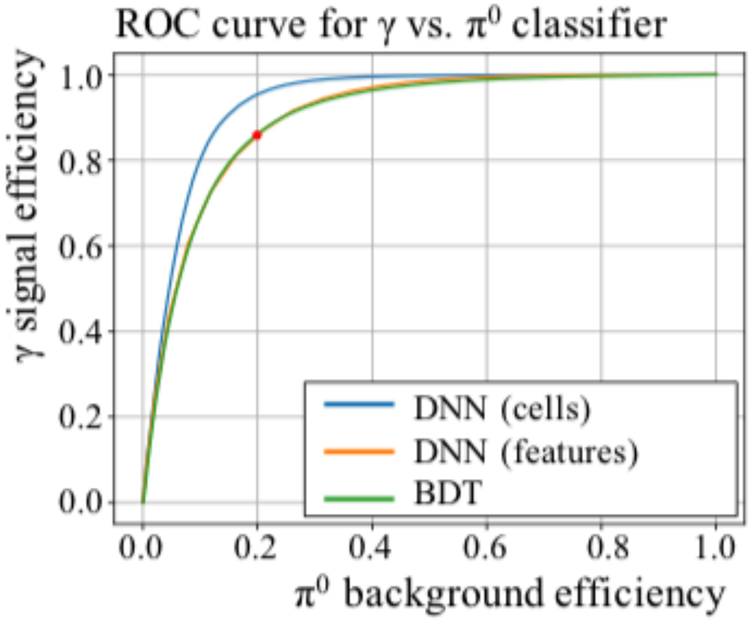
See contribution to NIPS workshop

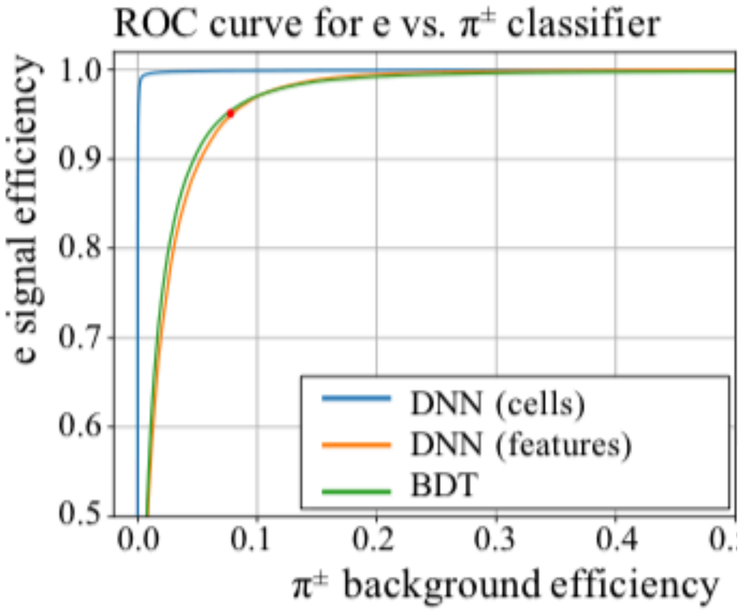




Proof of Principle: Particle ID

- *We tried particle ID on a sample of simulated events*
  - *one particle/event (e, γ, π^0, π)*
- *Different event representations*
  - *high-level features related to event shape (moments of X,Y, and Z projections, etc)*
  - *raw data (energy recorded in each cell)*
- *Pre-filtered pion events to select the nasty ones and make the problem harder*





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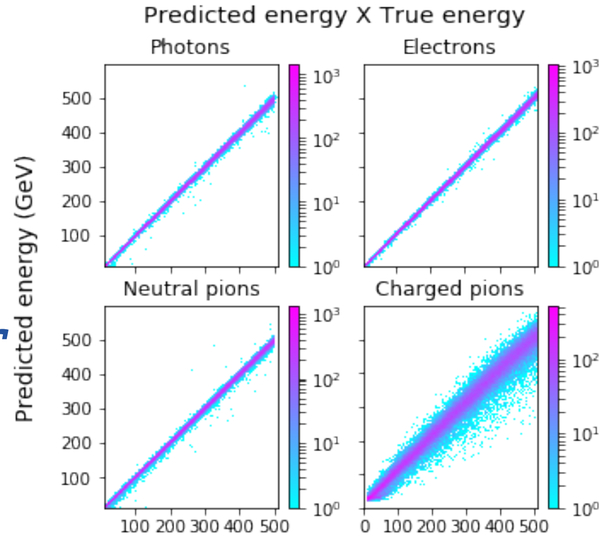
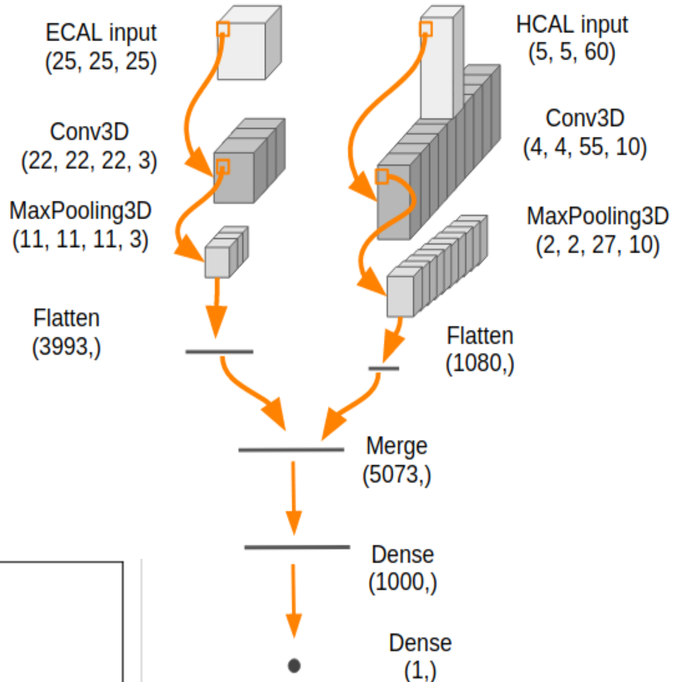
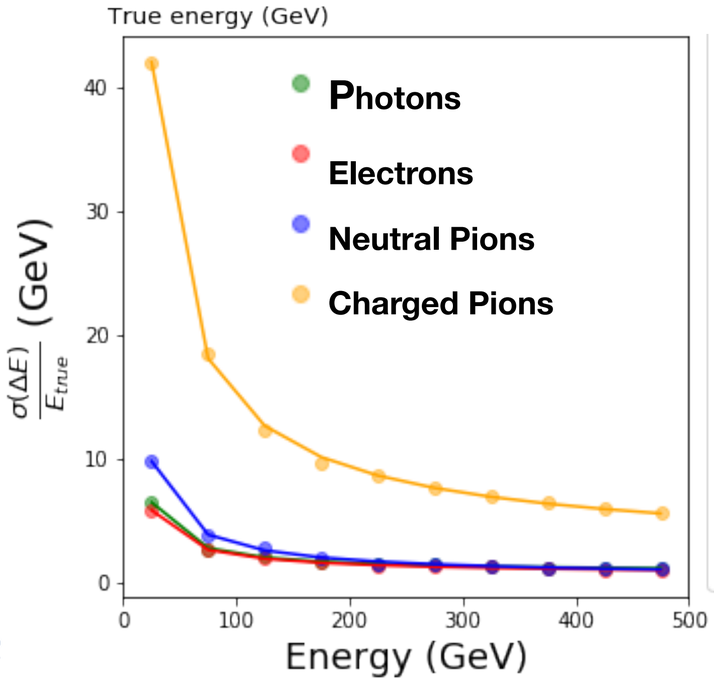
Proof of Principle: Energy Regression

- *Correctly reconstruct energy*
- *ECAL performances better than HCAL (as expected)*
- *π^0 resolution ~ $\sqrt{2}$ γ resolution (as expected)*
- *used only RAW data as inputs*
- *Processing time reduced by <msec*







$\frac{\sigma(\Delta E)}{E_{true}}$ (GeV)

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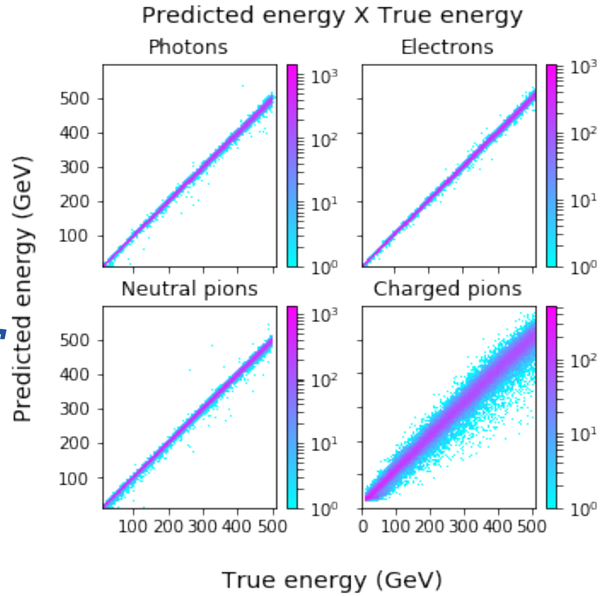

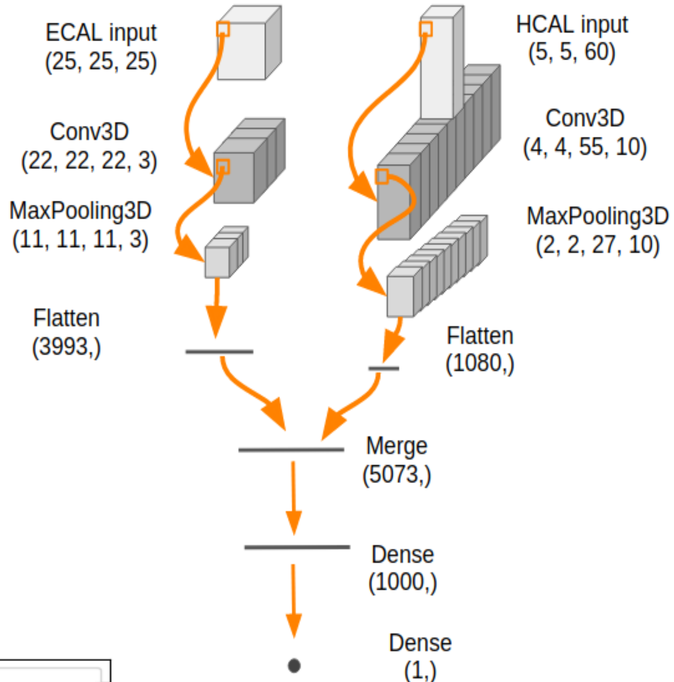

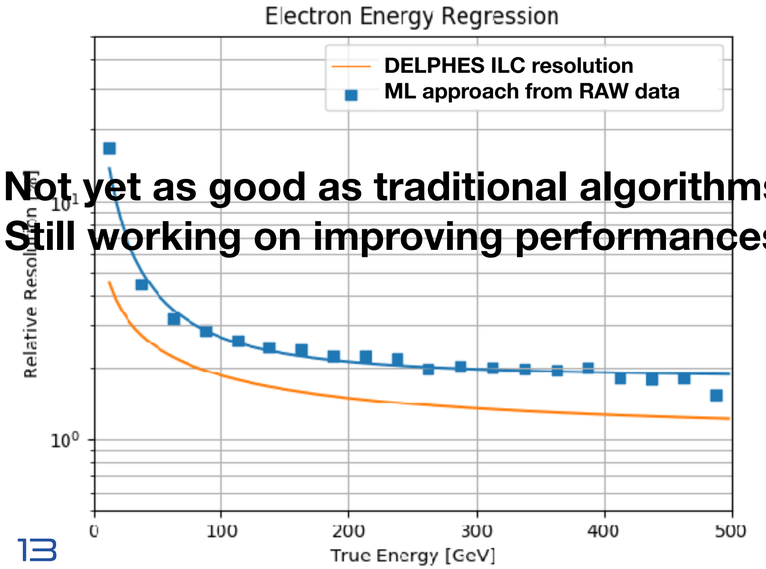

Not yet as good as traditional algorithms
Still working on improving performances

$\frac{\sigma(\Delta E)}{E_{true}}$ (GeV)

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Generating large datasets with small resources

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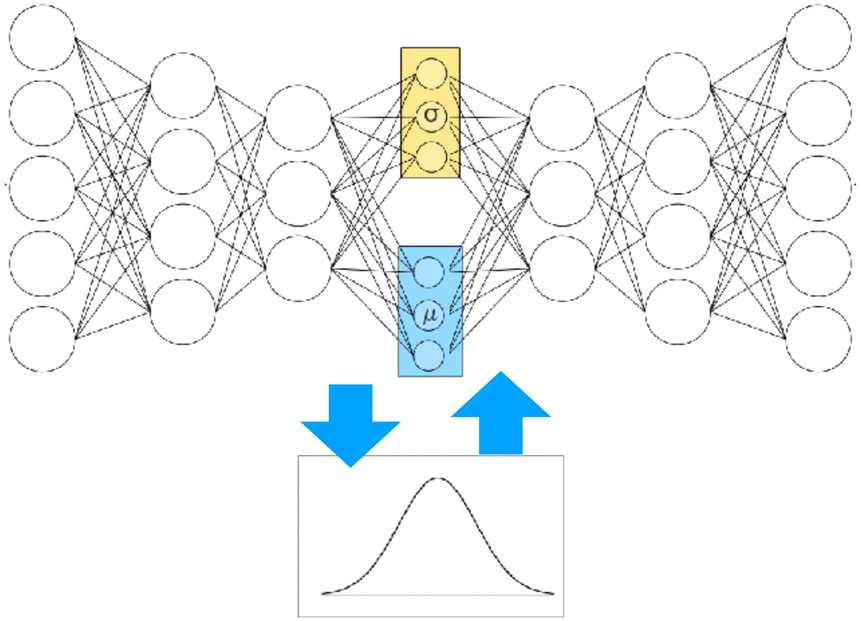
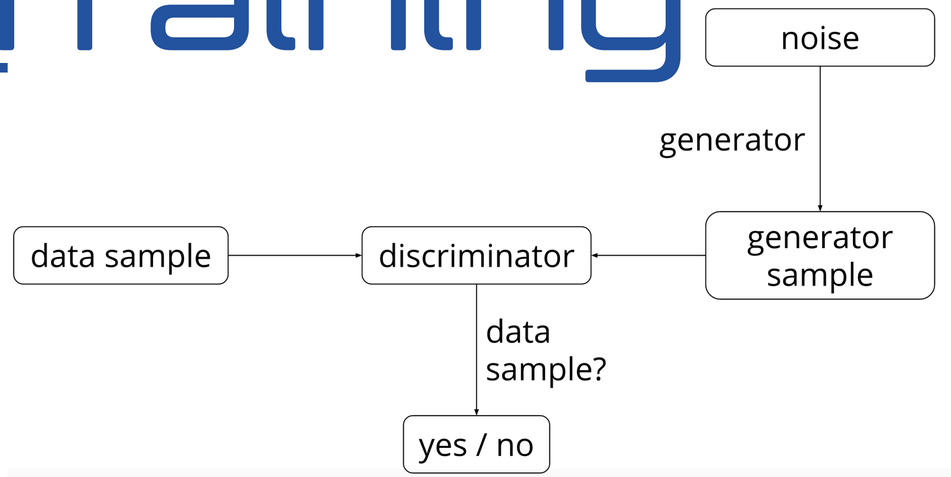
Generative Models

- Neural Networks can be trained to generate events similar to those they are trained on



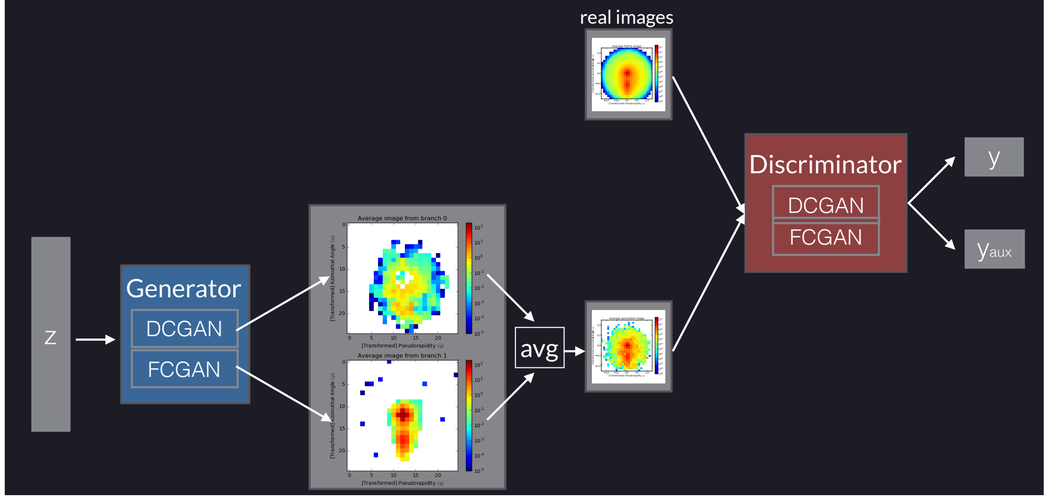
- Two main approaches these days
  - Variational Autoencoder: train the encoder, sample from the latent distribution & decode the sampled point
  - Generative Adversarial networks: train a generator by fooling a classifier

Adversarial Training



- *Two networks trained simultaneously*
  - *Generator: from noise to an event (e.g. image)*
  - *Discriminator: distinguish real events from those created by generator*
- *Loss function given by discriminator*
- *Parameter space = SUM of weights of the two networks*

- DCGAN — convolutional layers in both *G* and *D*
- FCGAN — fully-connected layers in both *G* and *D*
- HYBRIDGAN — a combination of the two:

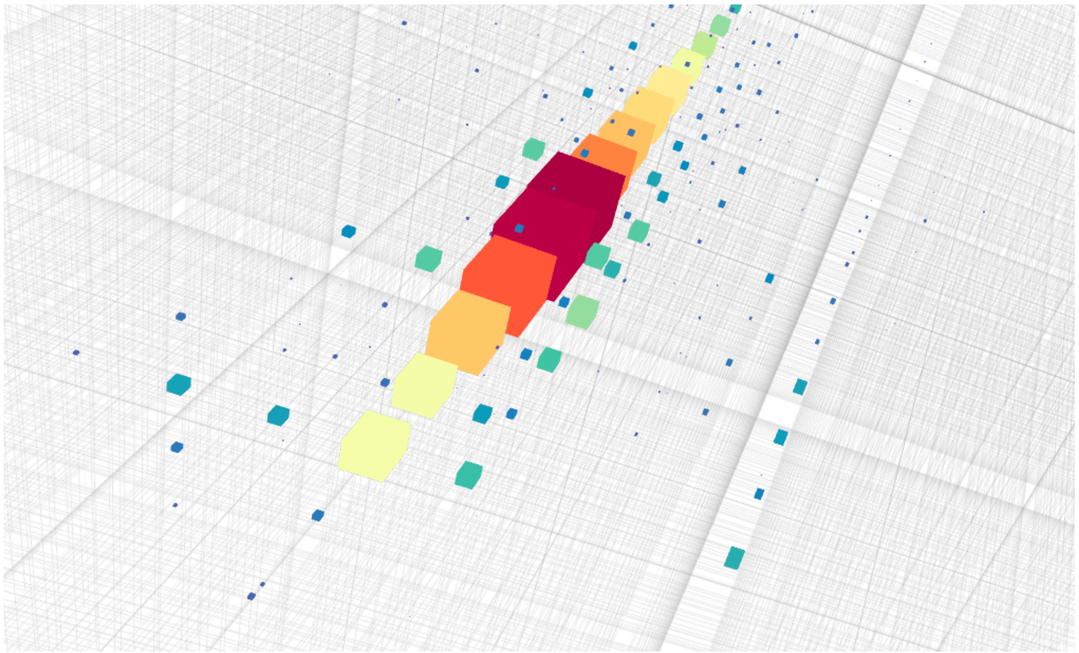


arXiv:1701.05927

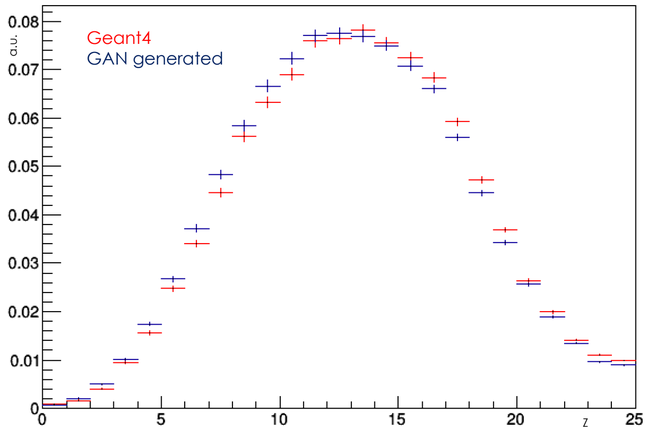
Particle shower generation

See contribution to NIPS workshop

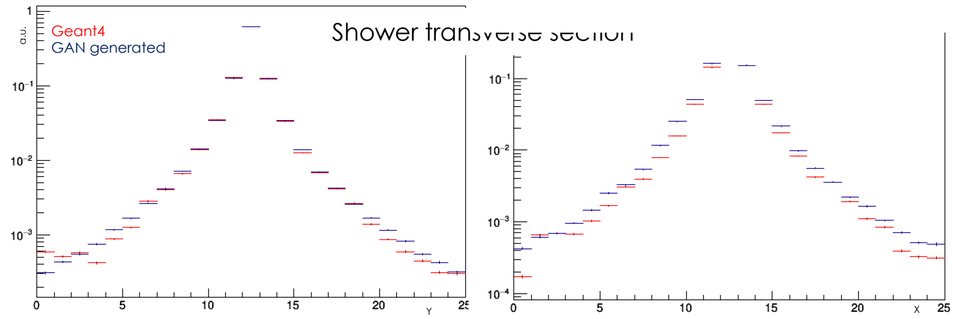
- Start from random noise
- Works very well with images
  - Applied to electron showers in digital calorimeters as a replacement of GEANT

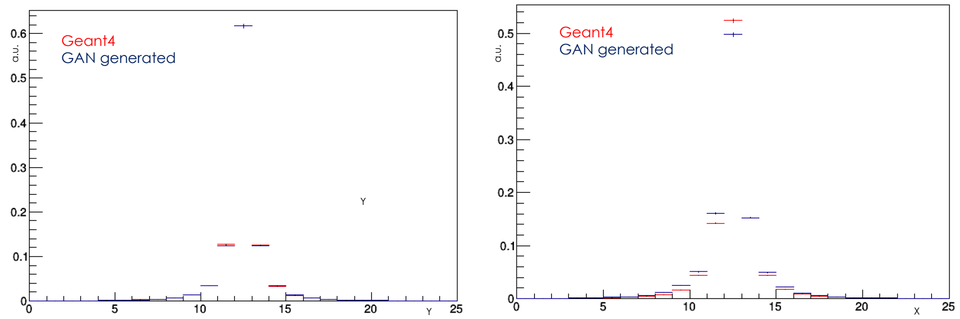


Shower longitudinal section



Shower transverse section





see also de Olivera, Paganini, and Nachman
https://arxiv.org/abs/1712.10321

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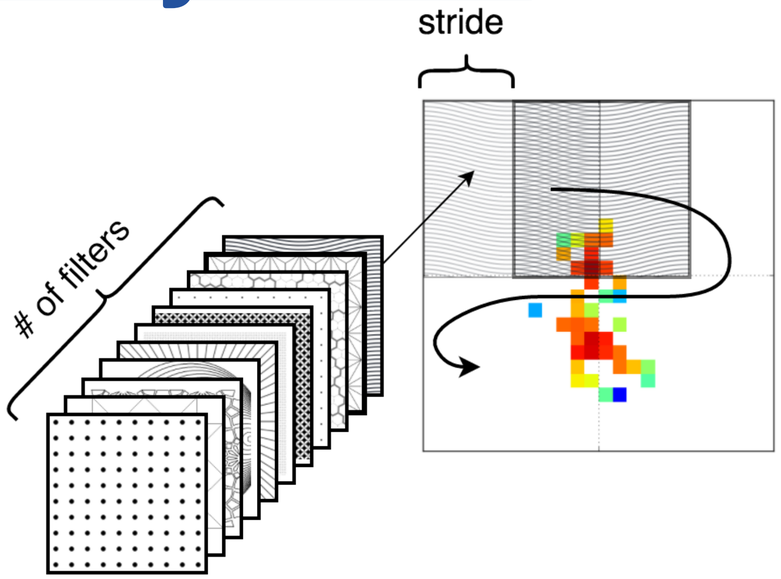
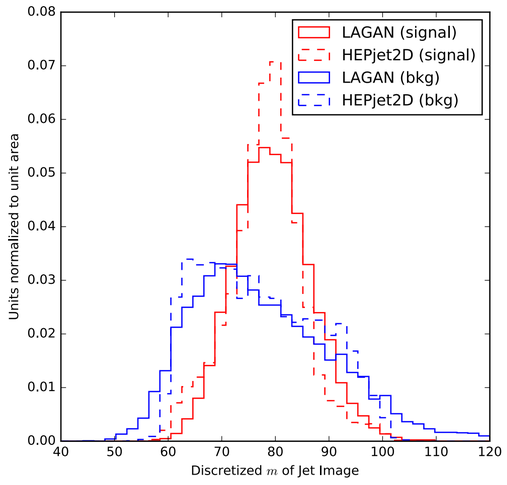
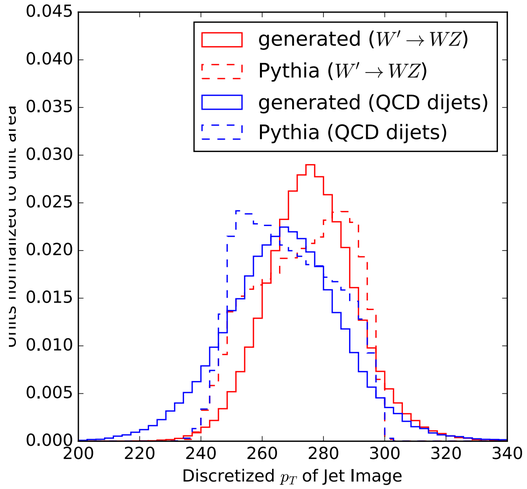
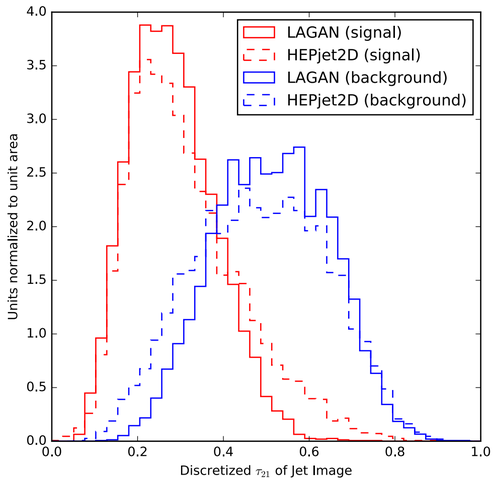
Generating full jets

- Start from random noise
- Works very well with images
  - Applied to electron showers in digital calorimeters as a replacement of GEANT









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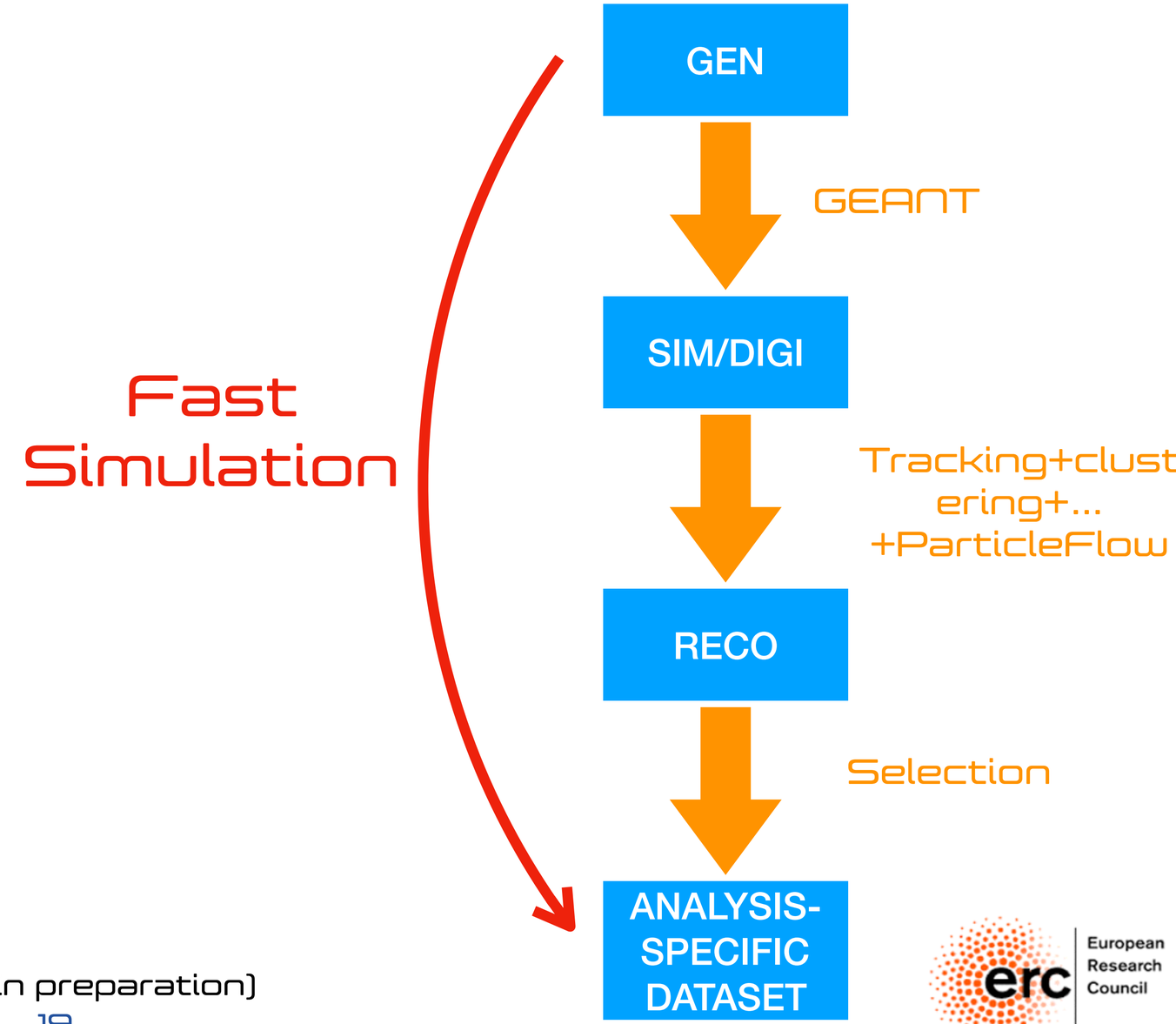
https://arxiv.org/pdf/1701.05927.pdf

Figure 6: The distributions of image mass $m(I)$, transverse momentum $p_{\mathrm{T}}(I)$, and n-subjettiness $\tau_{21}(I)$. See the text for definitions.

Analysis-specific dataset generation

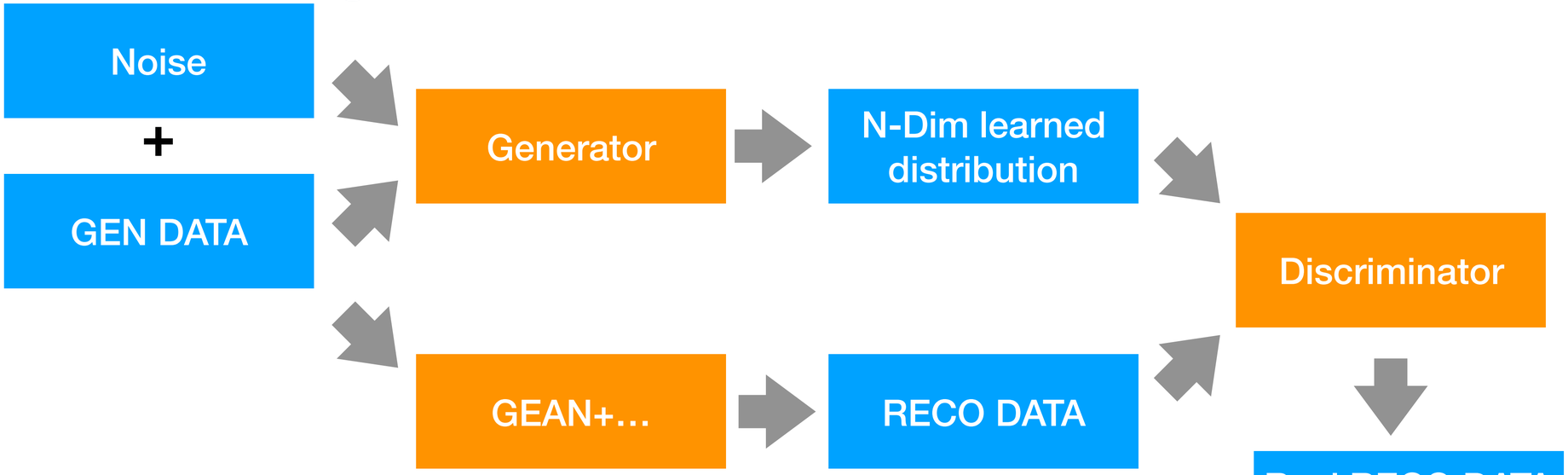
- In view of large statistics needs, one can use generative models as statistics augmentation tools
- For instance, could generate expert-feature quantities used in an analysis (muon four-momenta, jet momenta, etc.)
- Like sampling from histogram with two main advantages
  - no need to bin
  - generalizes to multi-dimensional problems



with K. Dutta, N. Amin, B. Hashemi and D. Olivito (in preparation)

An example

- *Dimuon events at LHC*
- *Typical analysis would use a few handful of quantities (muon momenta, isolation, jet pTs, etc)*
- *Can learn the N-dim distribution of these quantities with GAN setup*
- *Can use the generator network as a fastsim tool*



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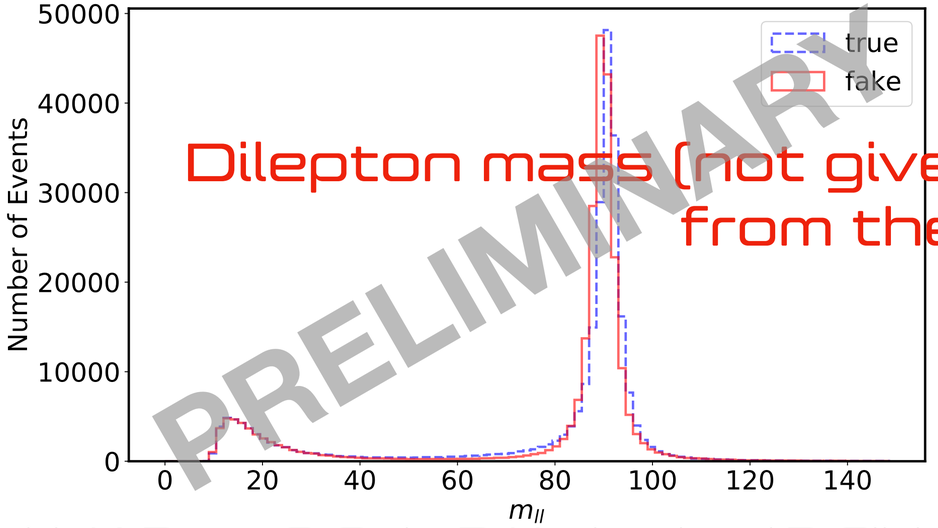

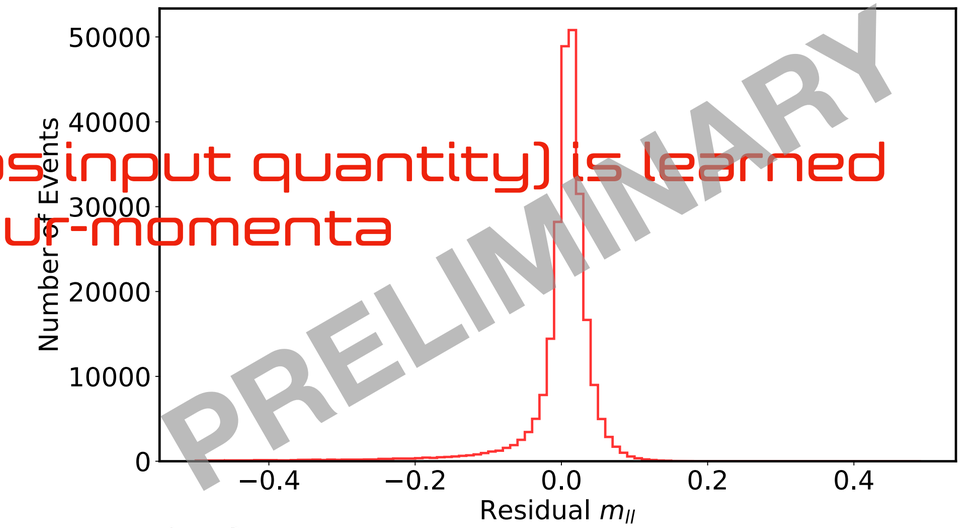

Dilepton mass (not given as input quantity) is learned from the four-momenta

with K. Dutta, N. Amin, B. Hashemi and D. Olivito (in preparation)

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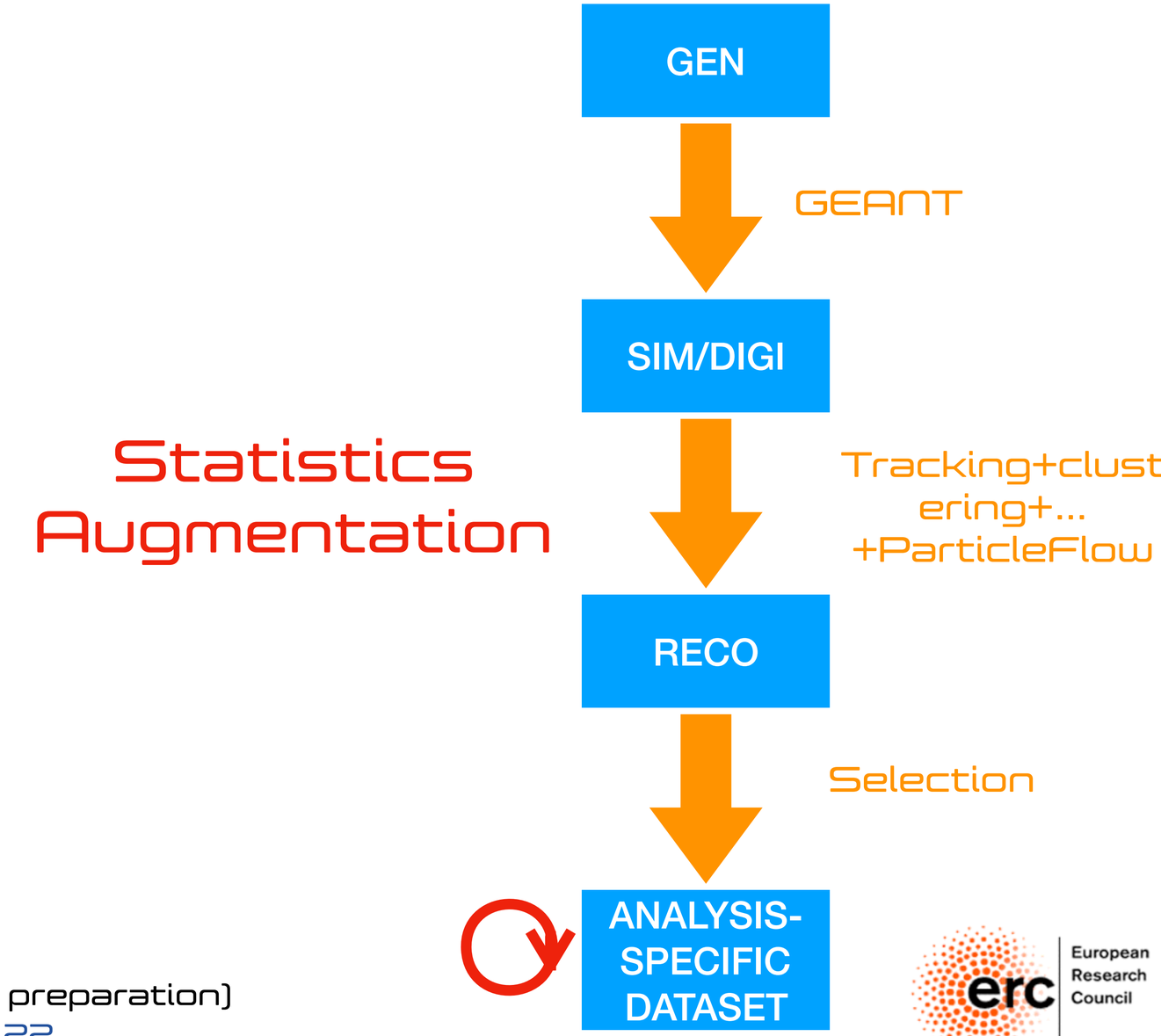

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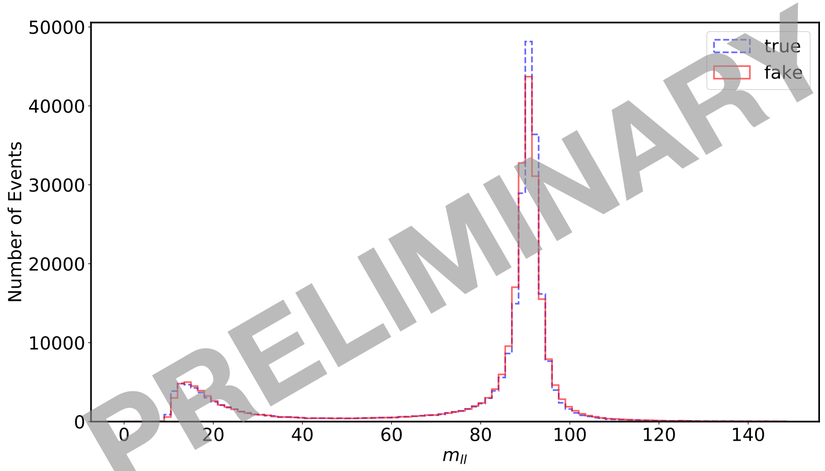
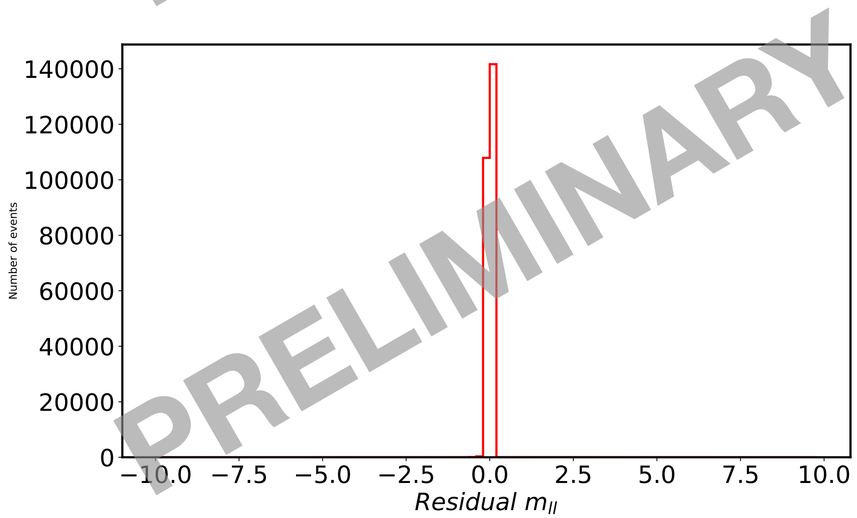
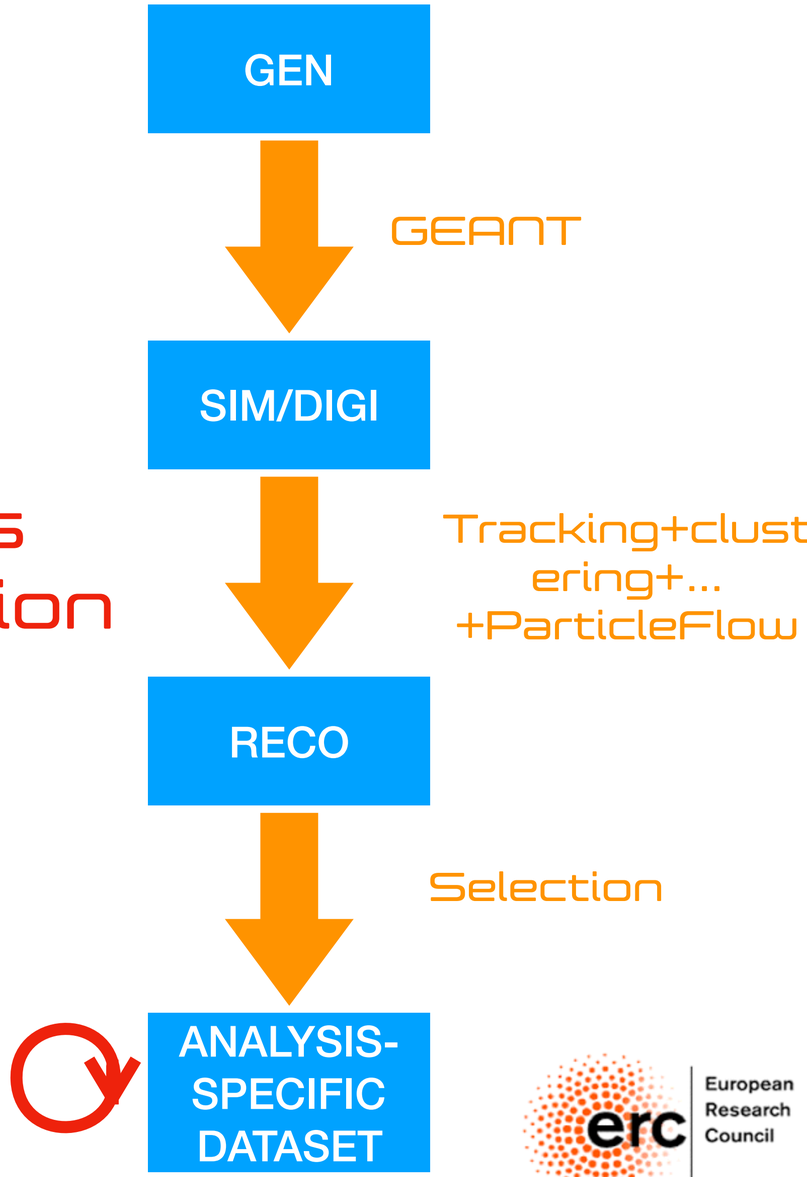
Analysis-specific dataset generation





Statistics Augmentation

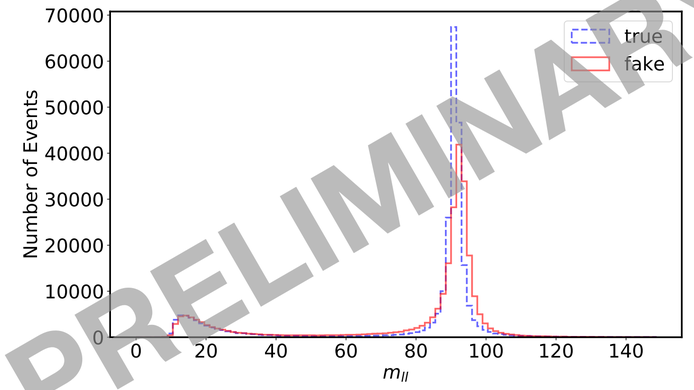


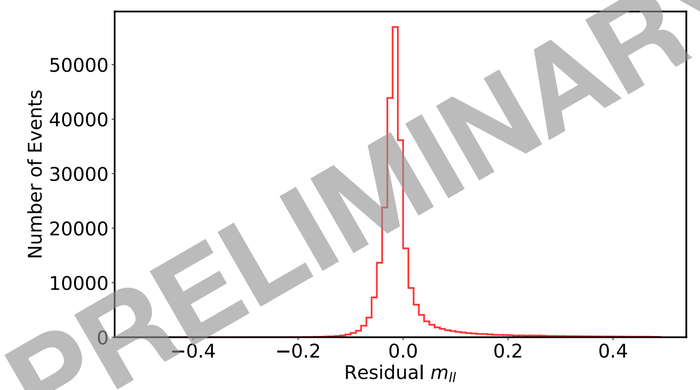
with K. Dutta, N. Amin, B. Hashemi and D. Olivito (in preparation)

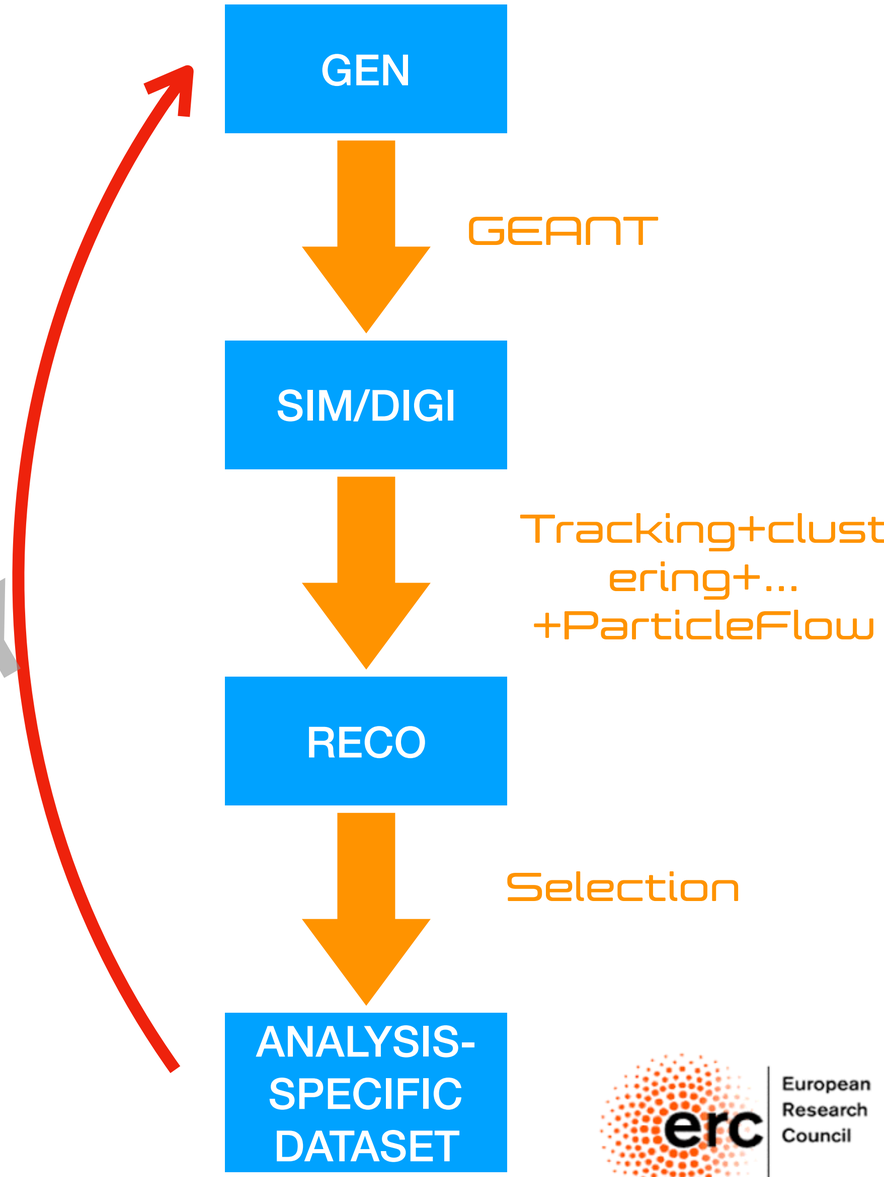
Analysis-specific unfolding

- One could invert the process and learn to predict the GEN features from the RECO ones
- Formally the same procedure
- Invert the role of the target and the input datasets

Unfolding







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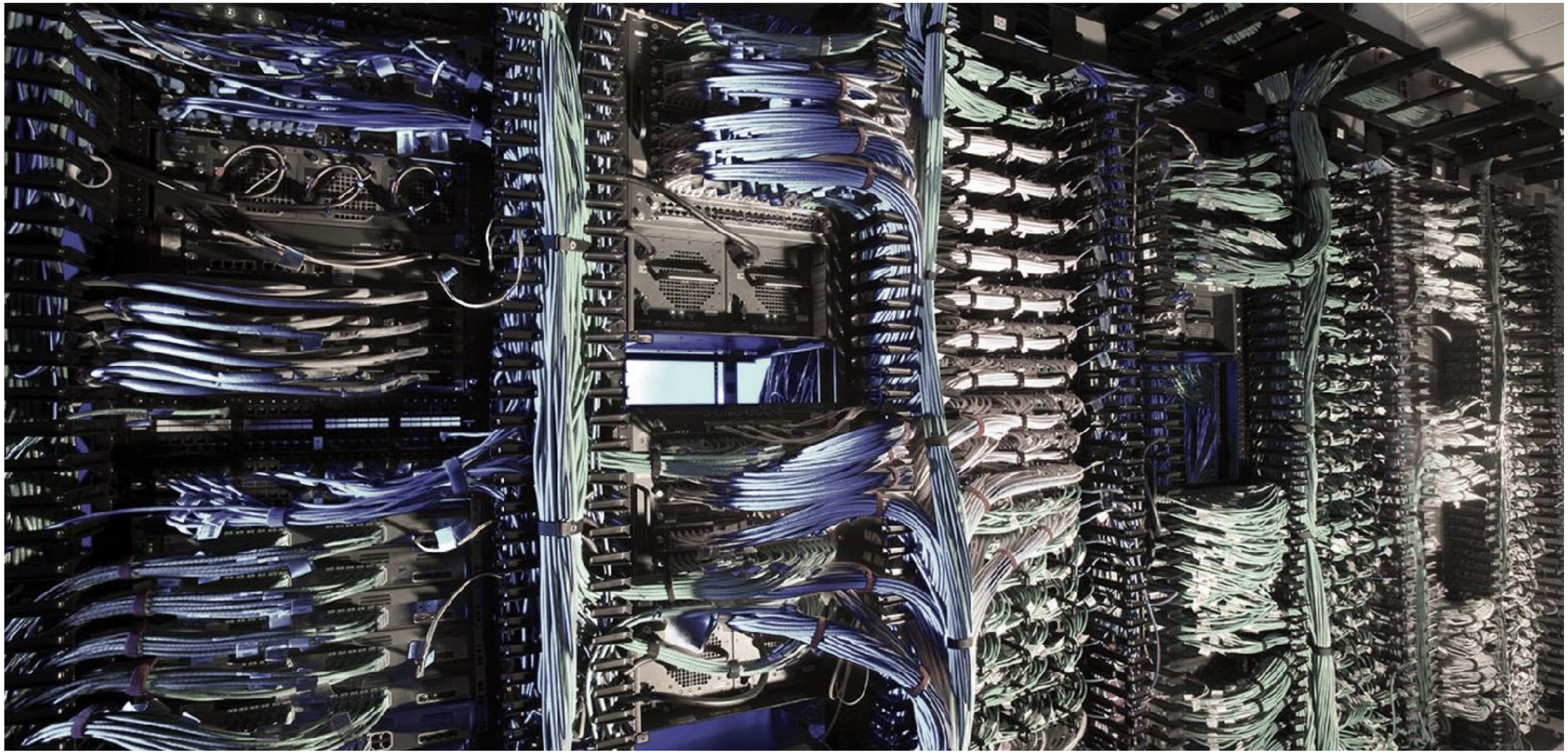

Machine Learning for trigger systems

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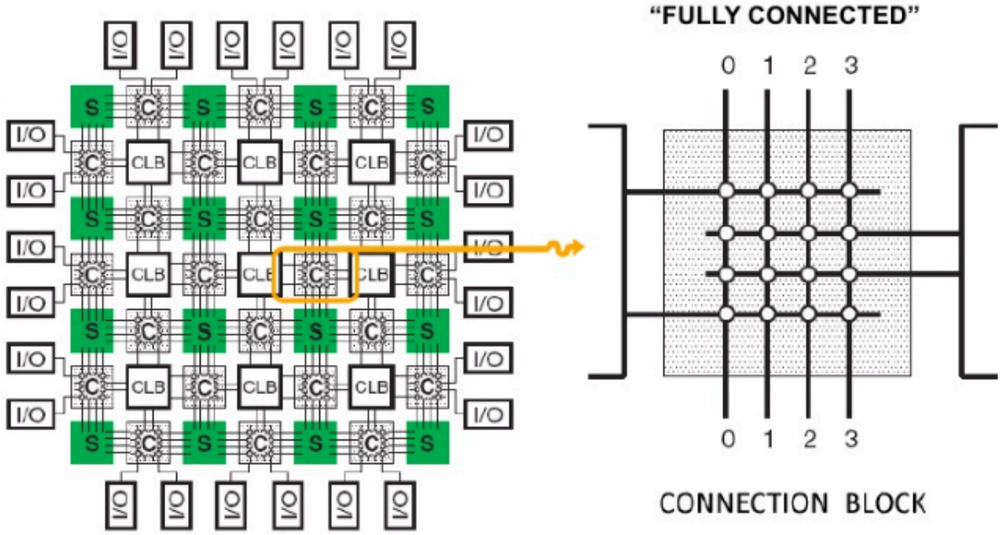
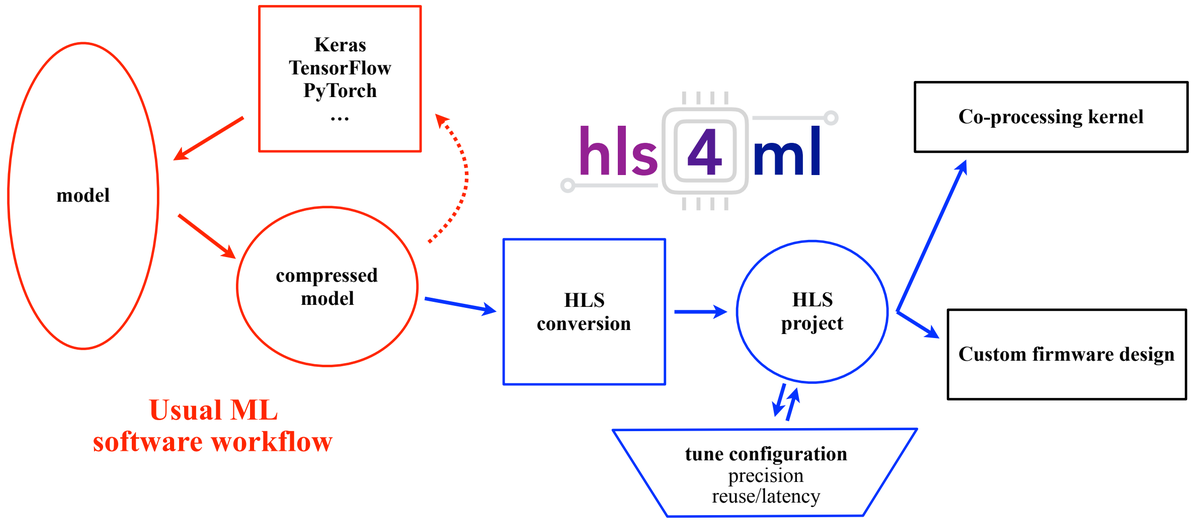
The frontier: bring DL to L1

- *The L1 trigger is a complicated environment*
  - *decision to be taken in ~10 µsec*
  - *only access to local portions of the detector*
  - *processing on Xilinx FPGA, with limited memory resources*
- *Some ML already running @L1*
  - *CMS has BDT-based regressions coded as look-up tables*
- *Working to facilitate DL solutions @L1 with dedicated library*

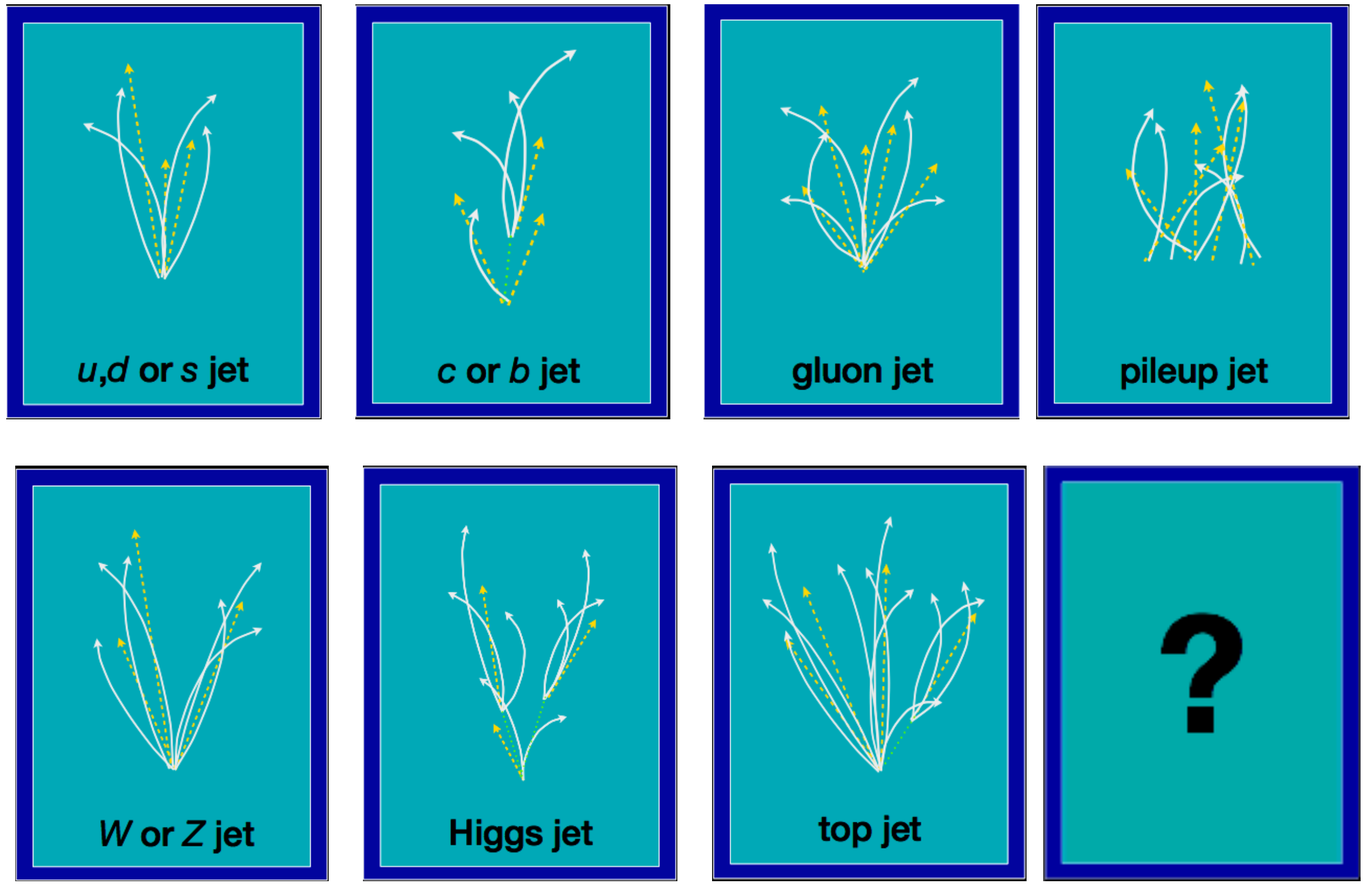


HLS4ML: CERN/FNAL/MIT collaboration



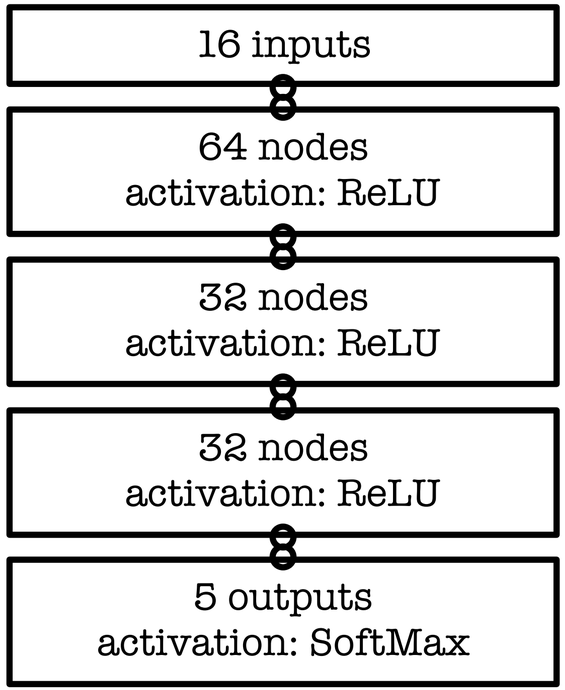
The use case: jet tagging

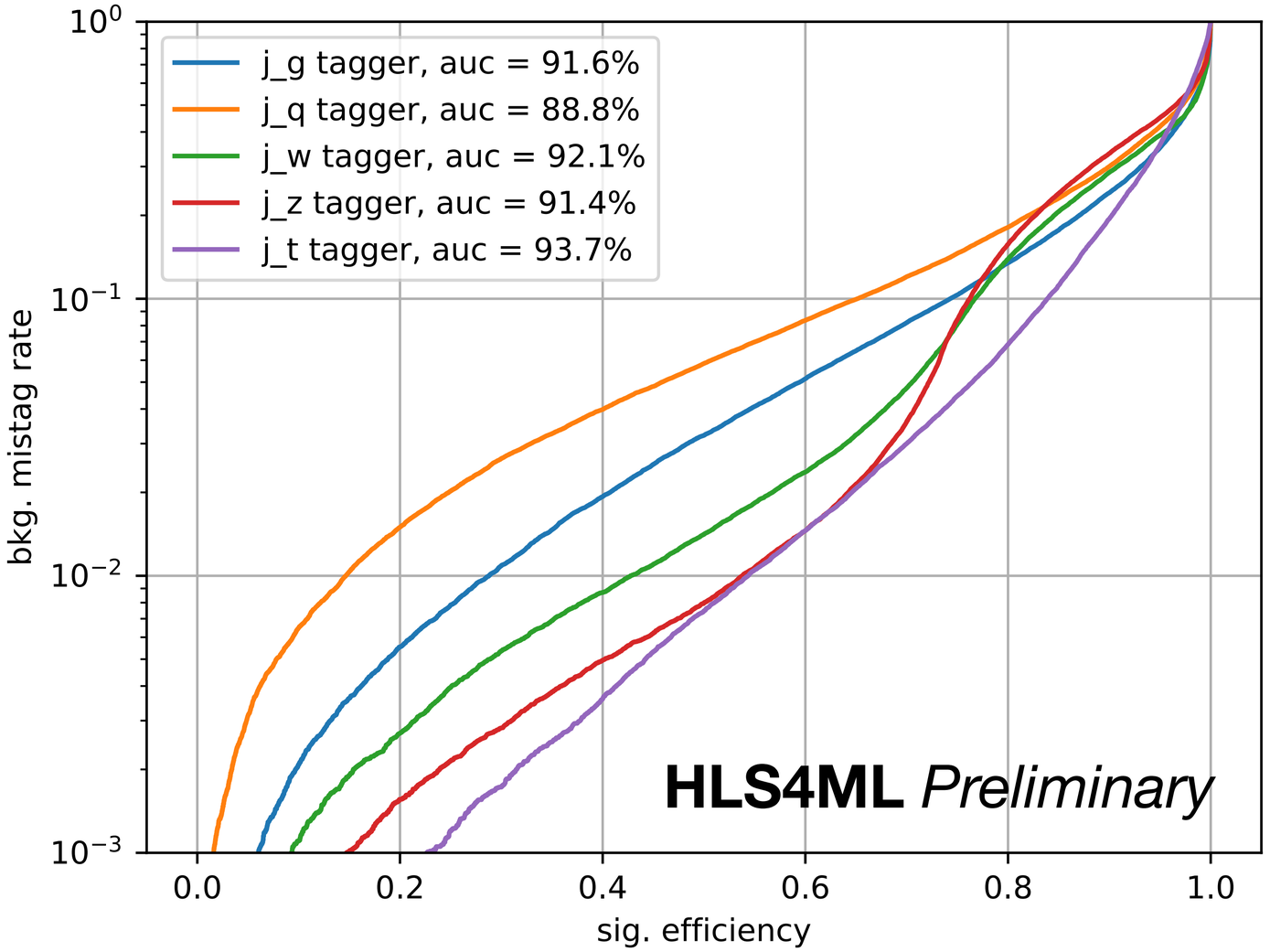
- *An LHC collision produces many kinds of jets*
- *Usually, jet tagging is resources demanding and happens late in the game*
- *We took this as a use case for a NN to be deployed @L1*



A jet multiclass classifier

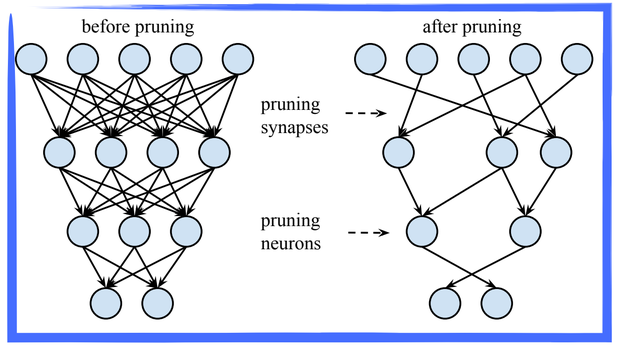
- *Simple DNN based on high-level features (jet masses, multiplicities, energy correlation functions)*

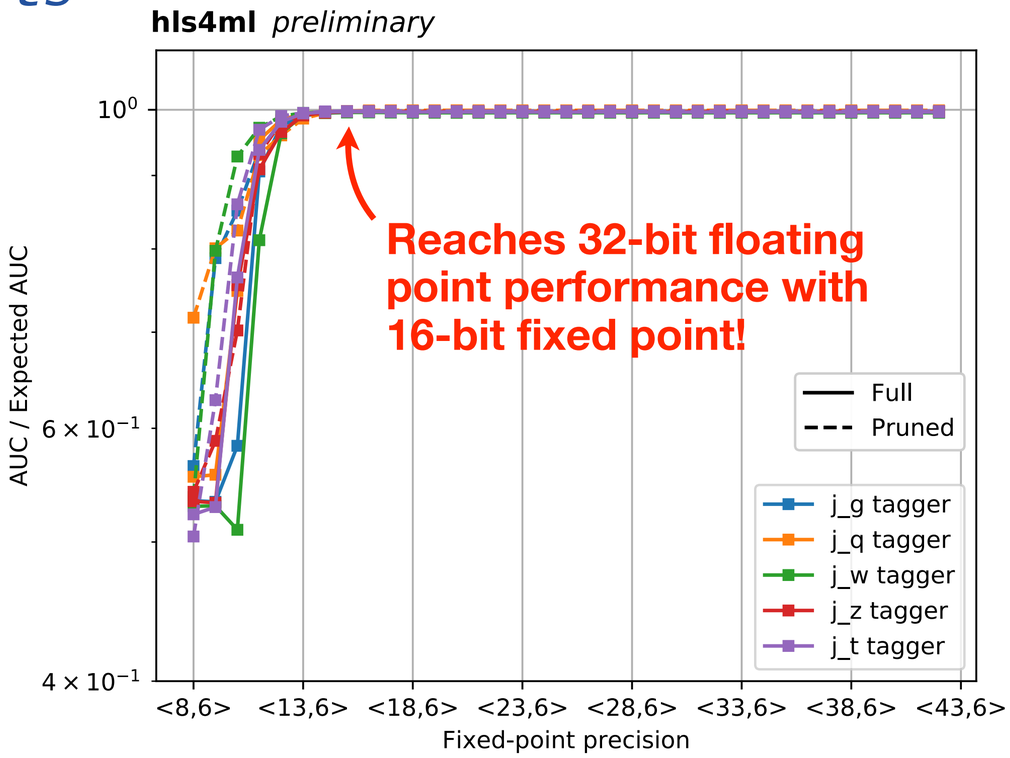


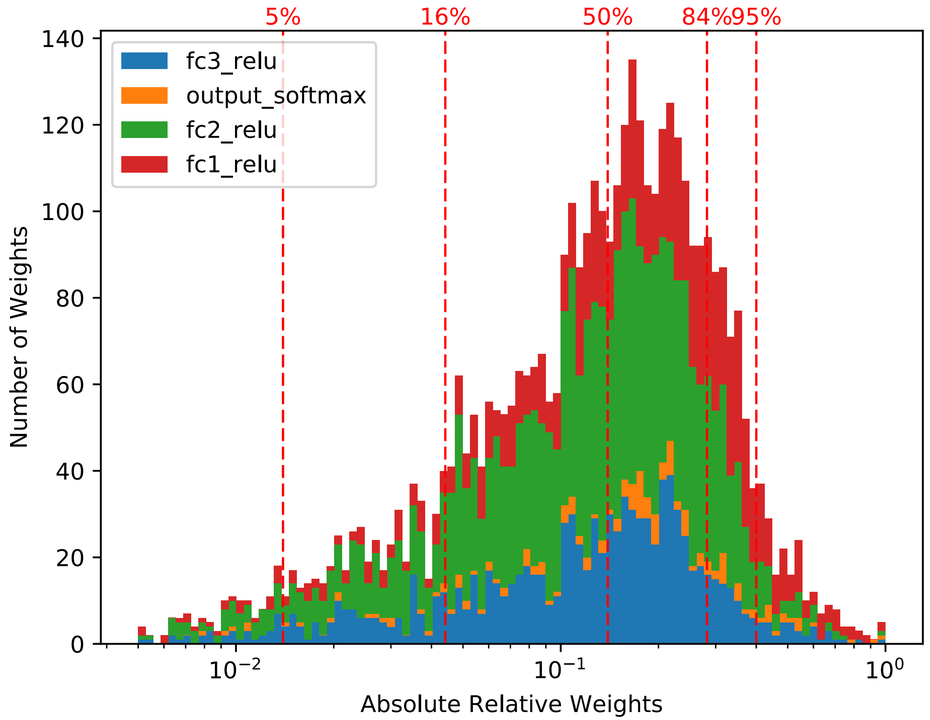


Online deployment: pruning

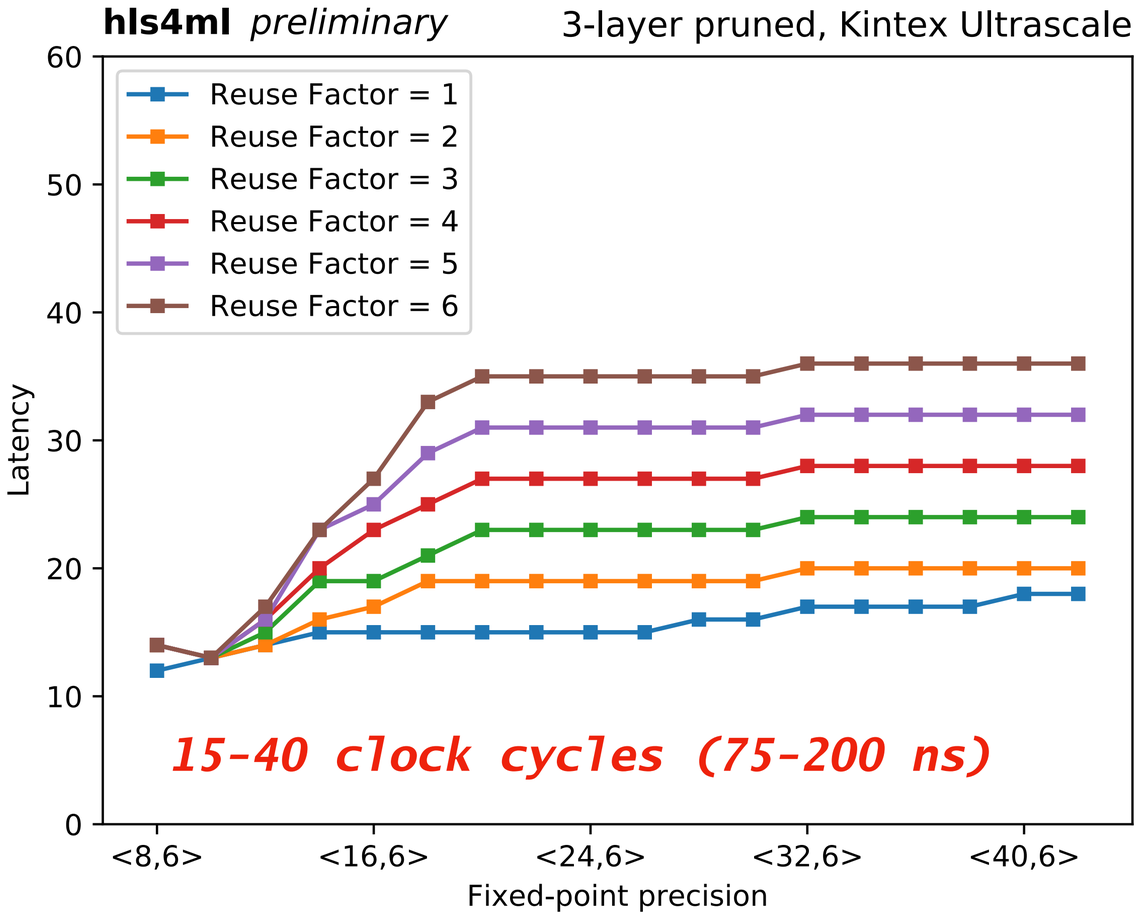
- *Reduced needed resources:*
  - *pruning: removes nodes and connections preserving performances*
  - *quantization: limit numerical precisions saving bits*

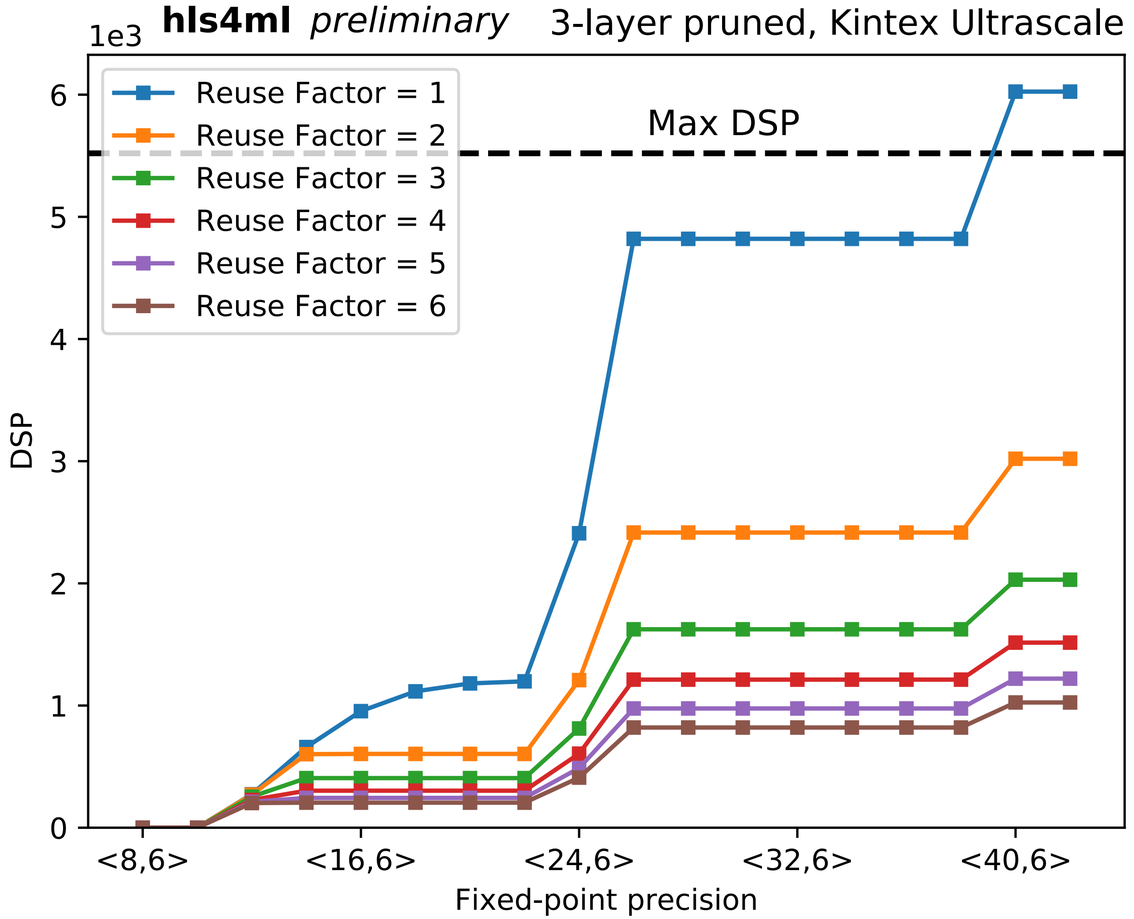






Performances





NB: FPGA emulator over-estimates resource needs by a factor 2-4 (tested our emulation vs actual deployment)

Conclusions

- *Modern Machine Learning is becoming a crucial ingredient to HEP, mainly due to the challenges of High-Luminosity LHC*
- *The clean e^+e^- environment might not necessarily call for advanced ML applications. Nevertheless*
  - *A clear advantage was prove in similar situations (neutrinos)*
  - *This is where the field is going. Why not profiting?*
- *Applications span across many typical HEP workflows*
  - *PID, energy measurement, simulation, DAQ/Trigger*
- *Work started, and a long way to go to meet very-high precision requirements of an intense e^+e^- collider*

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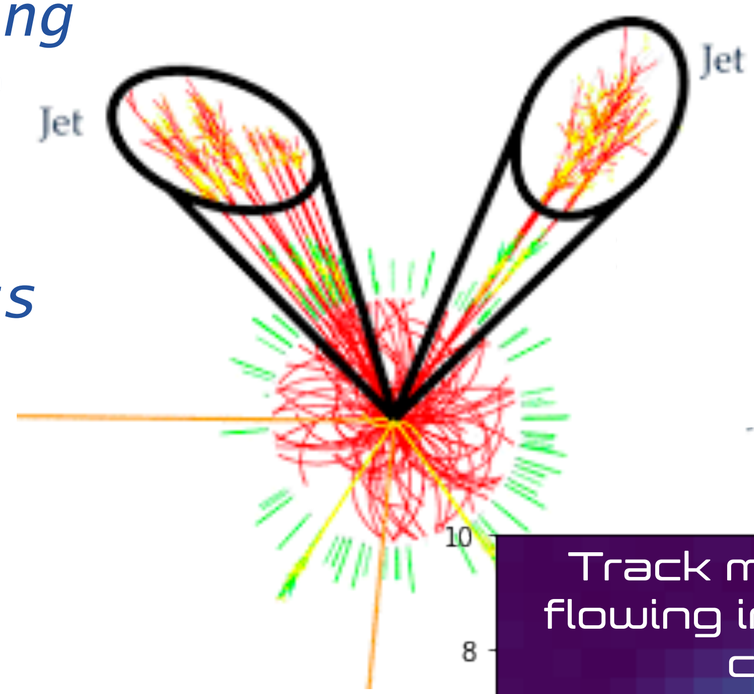
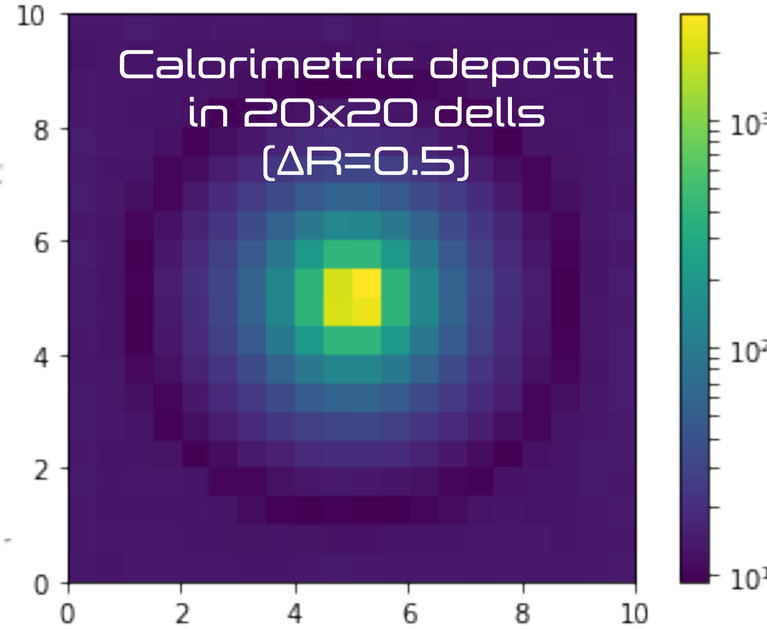
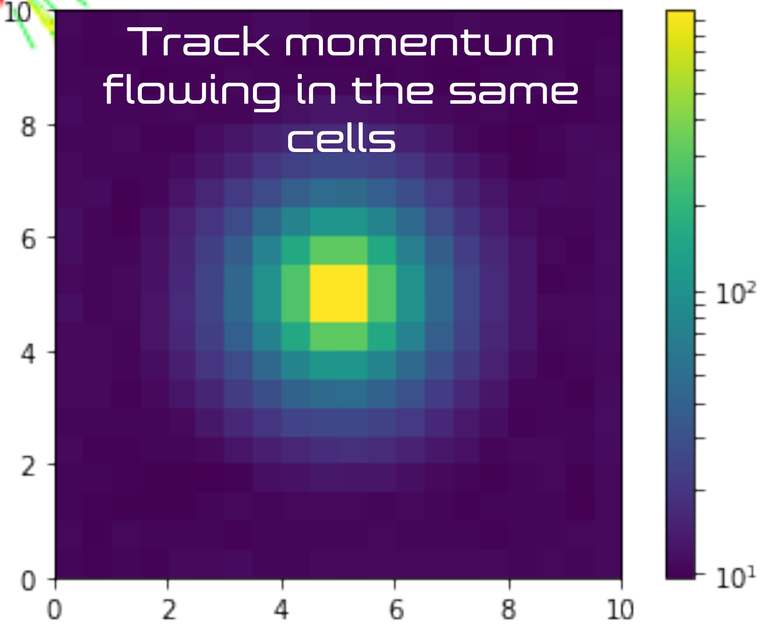
Backup

Faster/better Jet Reco

- *Offline, reconstructed from full particles using Particle Flow (accurate but slow)*
- *At L1, low-level objects are used*
  - *map of energy deposit on calorimeter*
  - *(in the future) local tracking (maybe pixel only)*
- ***ML could make jet reco at trigger faster & better***







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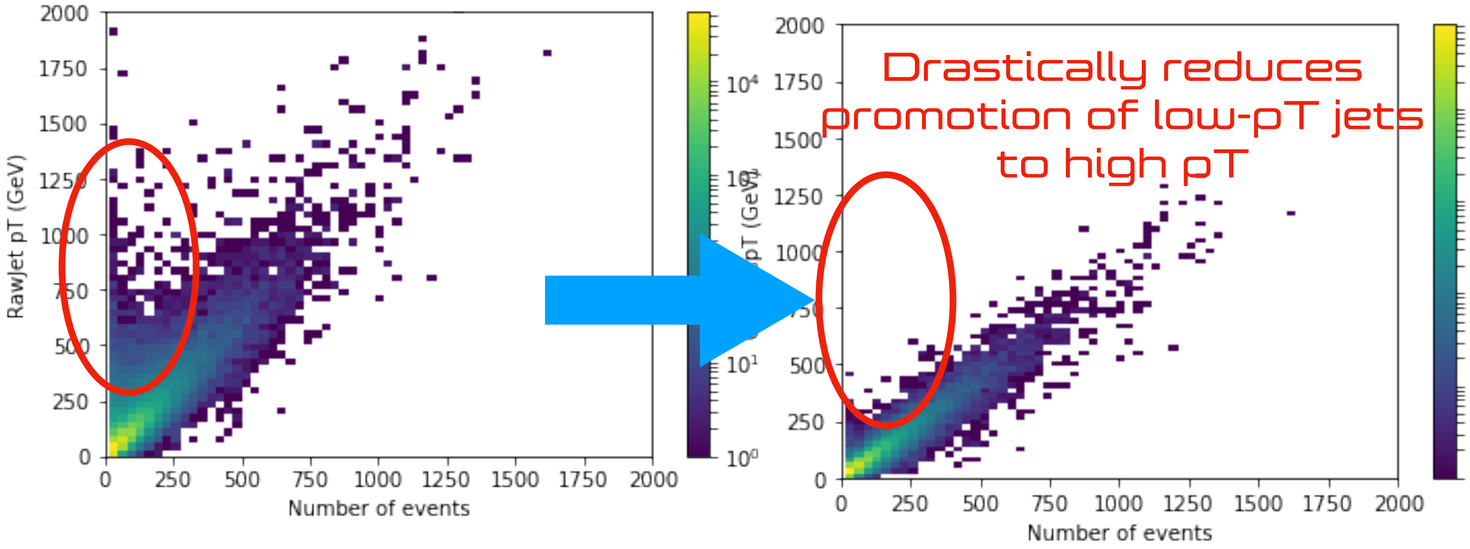
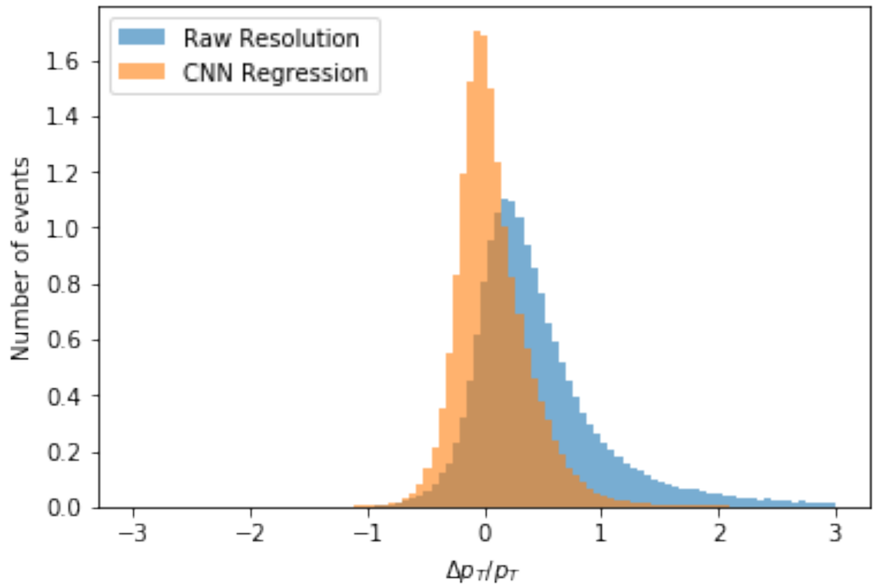
Faster/better Jet Reco

- *With a simple network, substantial improvement observed (could be pushed further, optimizing the network architecture)*
- *Consequences downstream:*
  - *better select the 100000 events to write /sec*
  - *With better input, HLT could work even better*
  - *We could recover lost territory/gain new territory and extend our search capability*

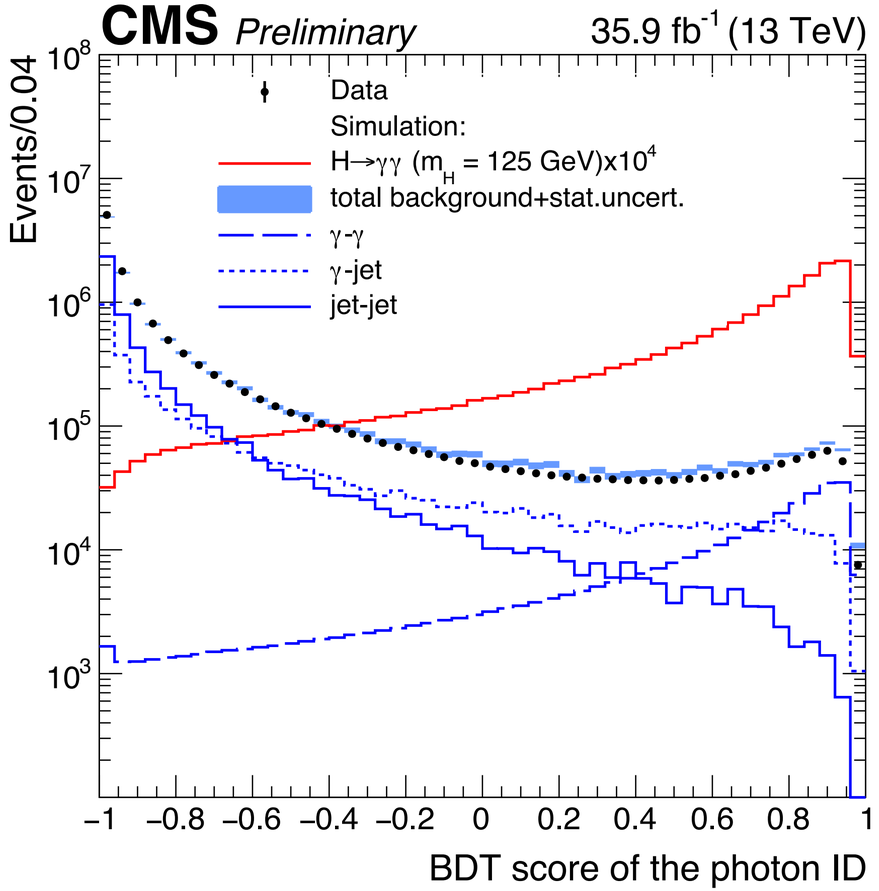




RAW resolution: 125%
CNN resolution: 36%

What we do with ML today

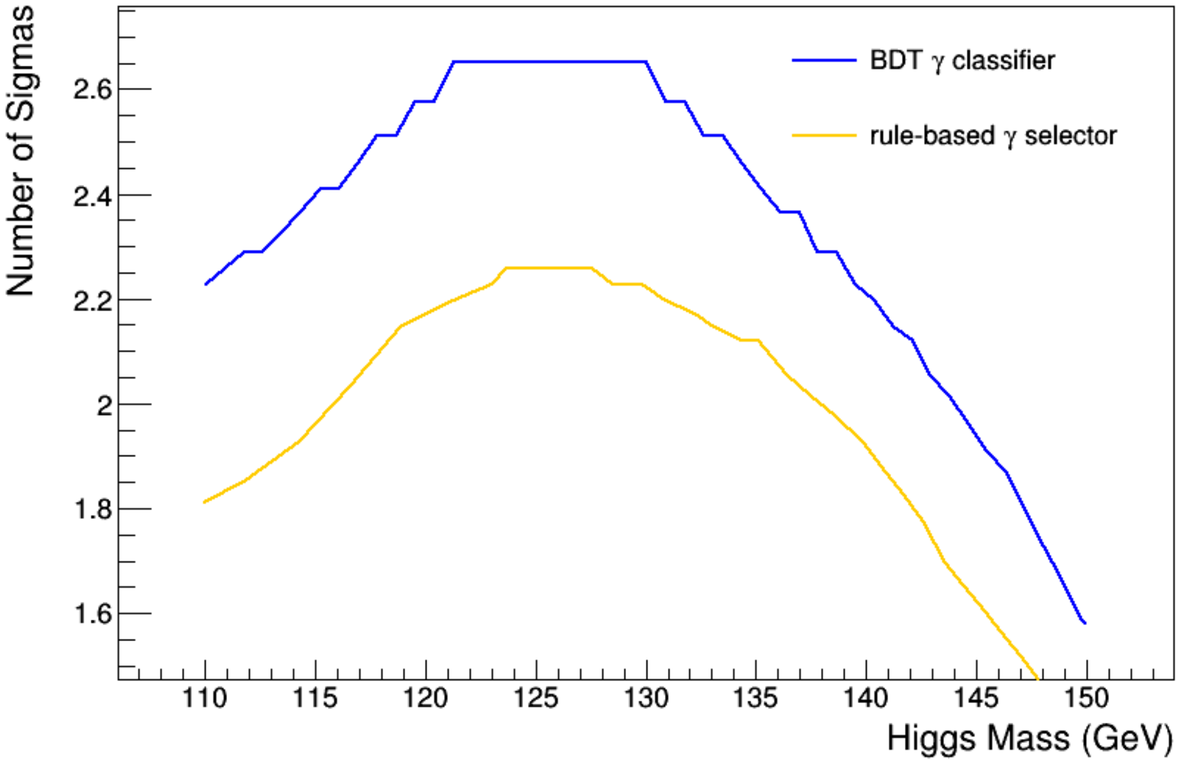
- *Classification:*
  - *identify a particle & reject fakes*
  - *identify signal events & reject background*
- *Regression:*
  - *Measure energy of a particle*
- *We typically use BDTs for these task*
  - *moved to Deep Learning for analysis-specific tasks*
  - *same will happen for centralised tasks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

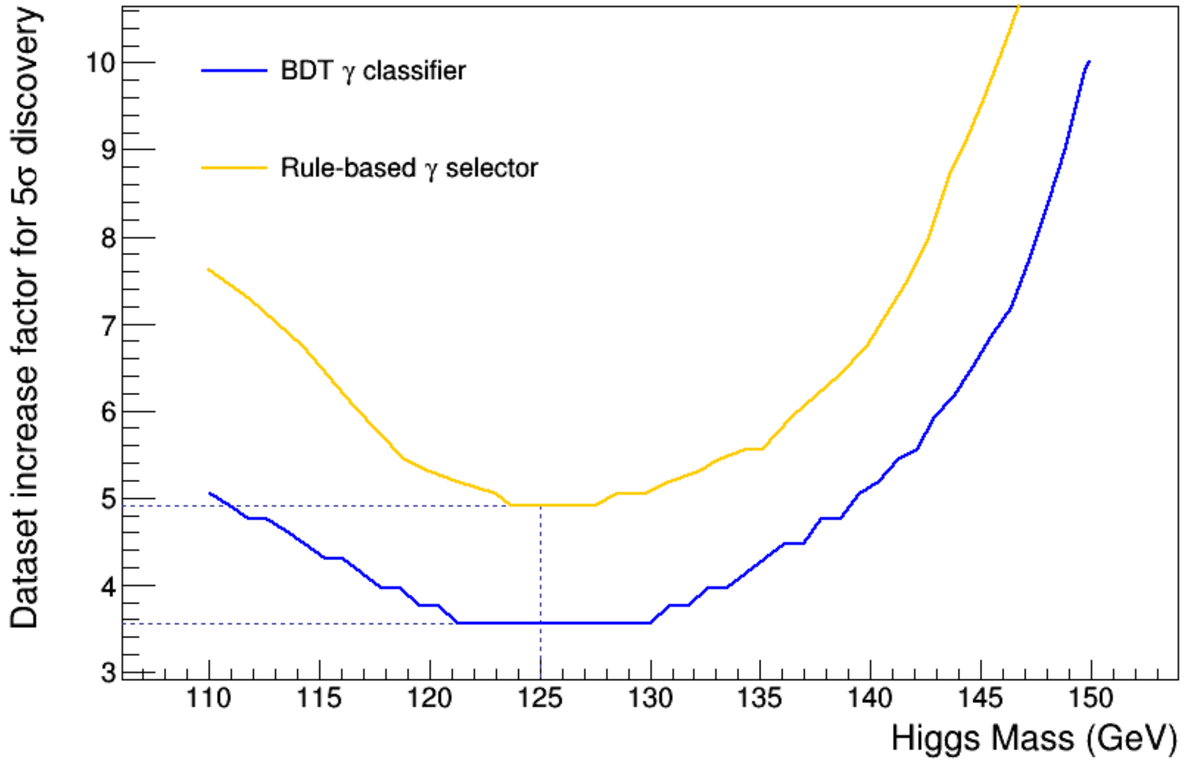


Centralised task (in online or offline reconstruction)
Analysis-specific task (by users on local computing infrastructures)

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*





HL4ML: FPGA details

Xilinx Vivado 2017.2

Results are slightly different in other versions of Vivado

e.g. 2016.4 optimization is less performant for Xilinx ultrascale FPGAs

Clock frequency: 200 MHz

Latency results can vary (~10%) with different clock choices

FPGA: Xilinx Kintex Ultrascale (XCKU115-FLVB2104)

Results are slightly different in other FPGAs

e.g. Virtex-7 FPGAs are slightly differently optimized

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