Artificial Intelligence at CERN

Jornadas de ICTEA 2024

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ICTEA

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If you are reading this as a web page: have fun! If you are reading this as a PDF: please visit

https://www.hep.uniovi.es/vischia/persistent/2024-05-07_ArtificialIntelligenceAtCERN_vischia.html

to get the version with working animations

We Try to Understand the Universe

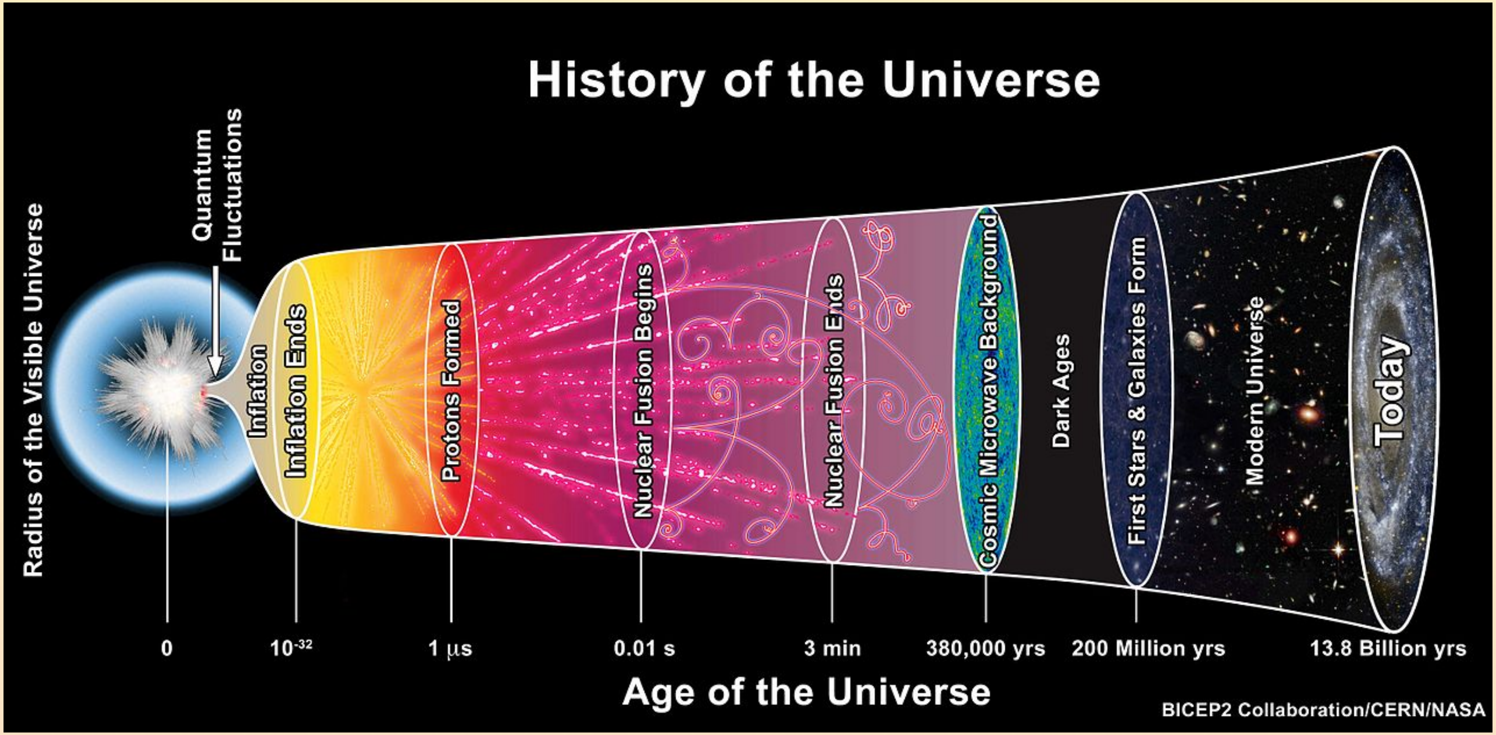

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Image from CERN

1954: CERN is founded

On 10 June 1955, CERN Director-General, Felix Bloch, laid the foundation stone on the Laboratory site, watched by Max Petitpierre, the President of the Swiss Confederation. (Image: CERN)

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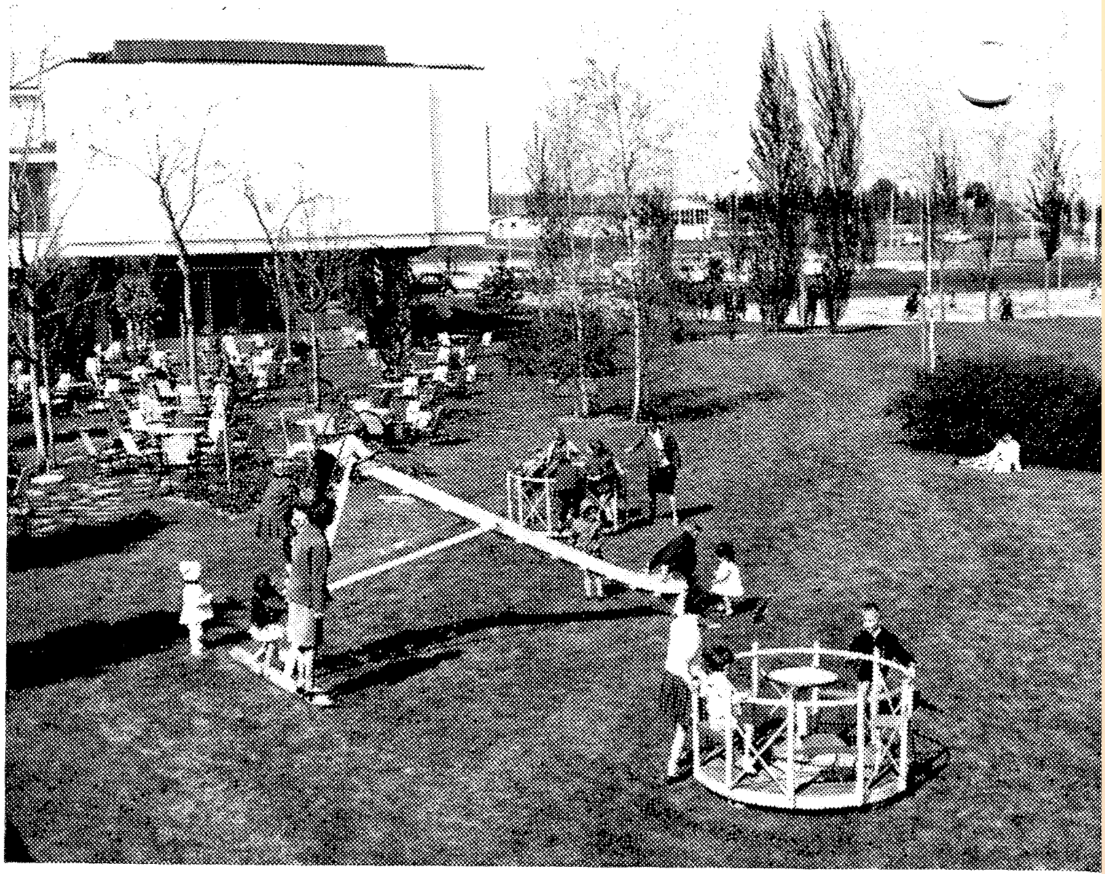
Image from the CERN archives

1964: CERN's nursery

CERN/PI 186.4.64



As well as firemen, cleaners and transport staff, teachers from the CERN nursery school and girl guides from the international troupe at Ferney-Voltaire helped to look after the children. The Geneva authorities kindly lent the playground equipment.

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Image from The CERN Courier

Our mission

Our mission is to:

- perform world-class research in fundamental physics.
- provide a unique range of particle accelerator facilities that enable research at the forefront of human knowledge, in an environmentally responsible and sustainable way.
- unite people from all over the world to push the frontiers of science and technology, for the benefit of all.
- train new generations of physicists, engineers and technicians, and engage all citizens in research and in the values of science.

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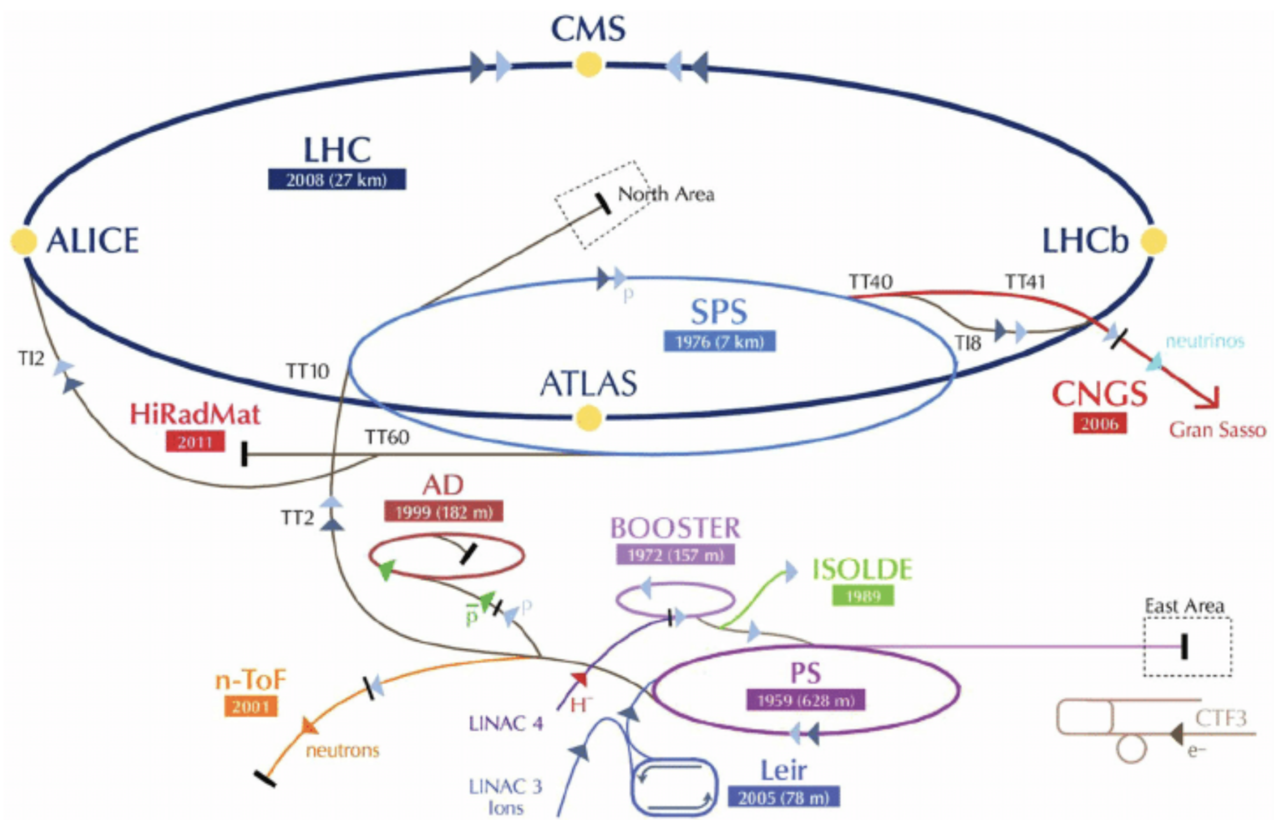
Image from the CERN website

A vocation for recycling



Existing CERN accelerator complex with Large Hadron Collider (LHC), Super Proton Synchrotron (SPS), Proton Synchrotron (PS), Antiproton Decelerator (AD), Low Energy Ion Ring (LEIR), Linear Accelerators (LINAC), CLIC Test Facility (CTF3), CERN to Gran Sasso (CNGS), Isotopes Separation on Line (ISOLDE), and neutrons Time of Flight (n-ToF).

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Image from 10.1103/PhysRevSTAB.16.054801

Discover!

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Image from the New York Times

Keep rediscovering!

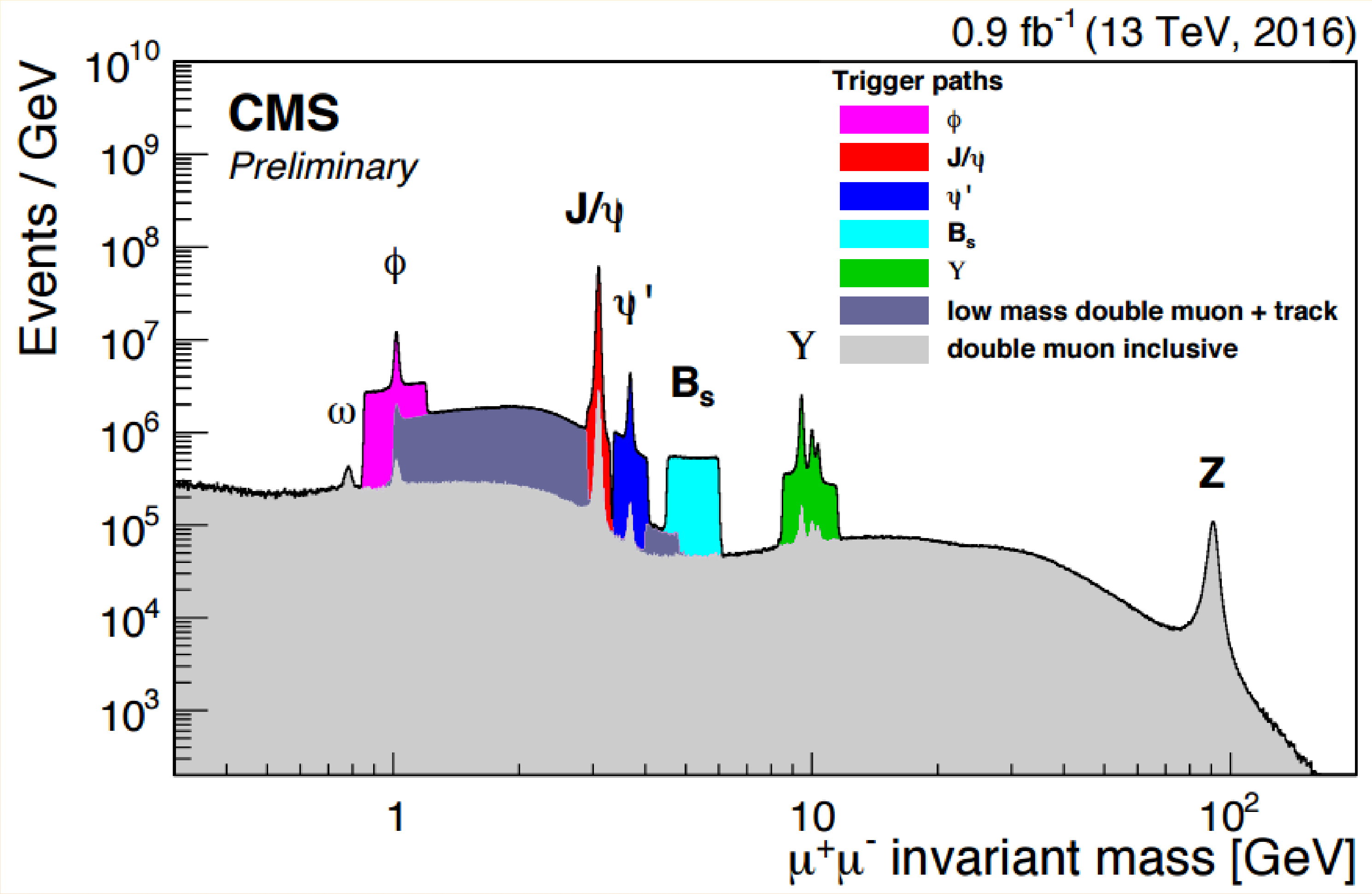

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Image from some CMS Analysis

Our latest Nature paper

(strong ICTEA contrib!)

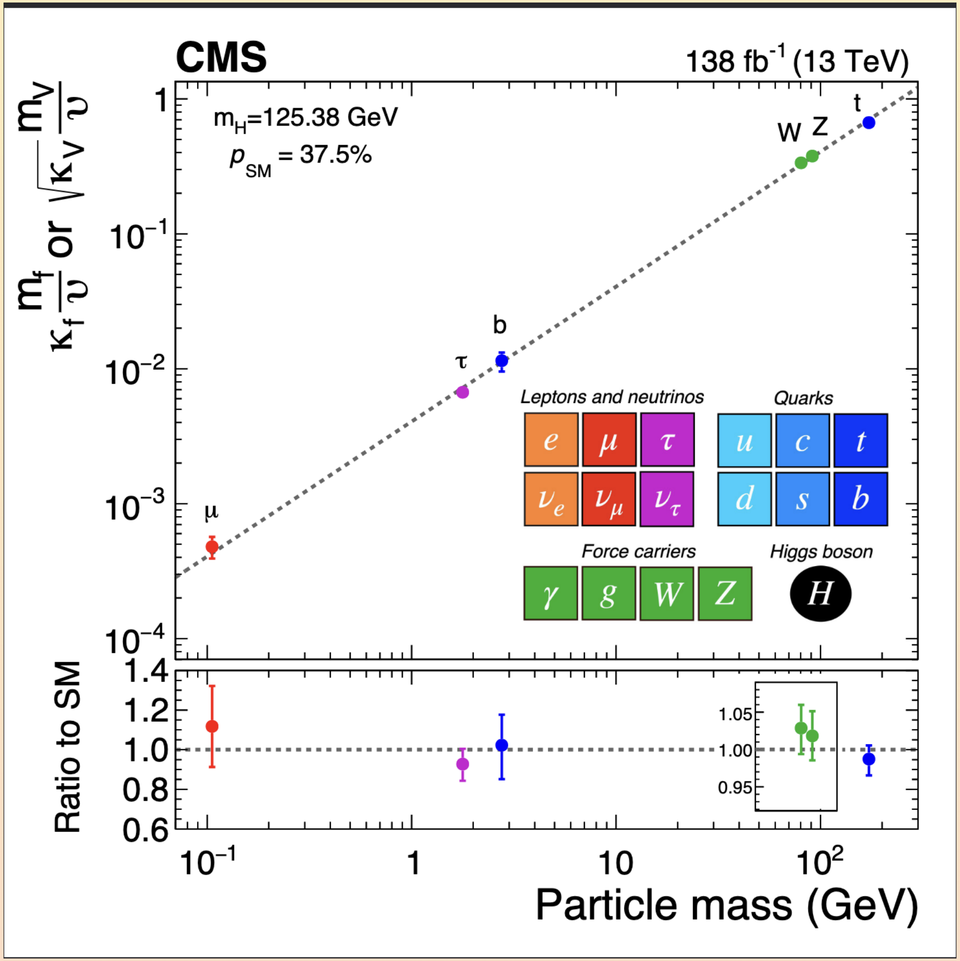

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Image from Nature 607 (2022) 60

AI, the eternal buzzword?

- Artificial Intelligence (AI)
- Machine Learning (ML)
- Statistical Learning

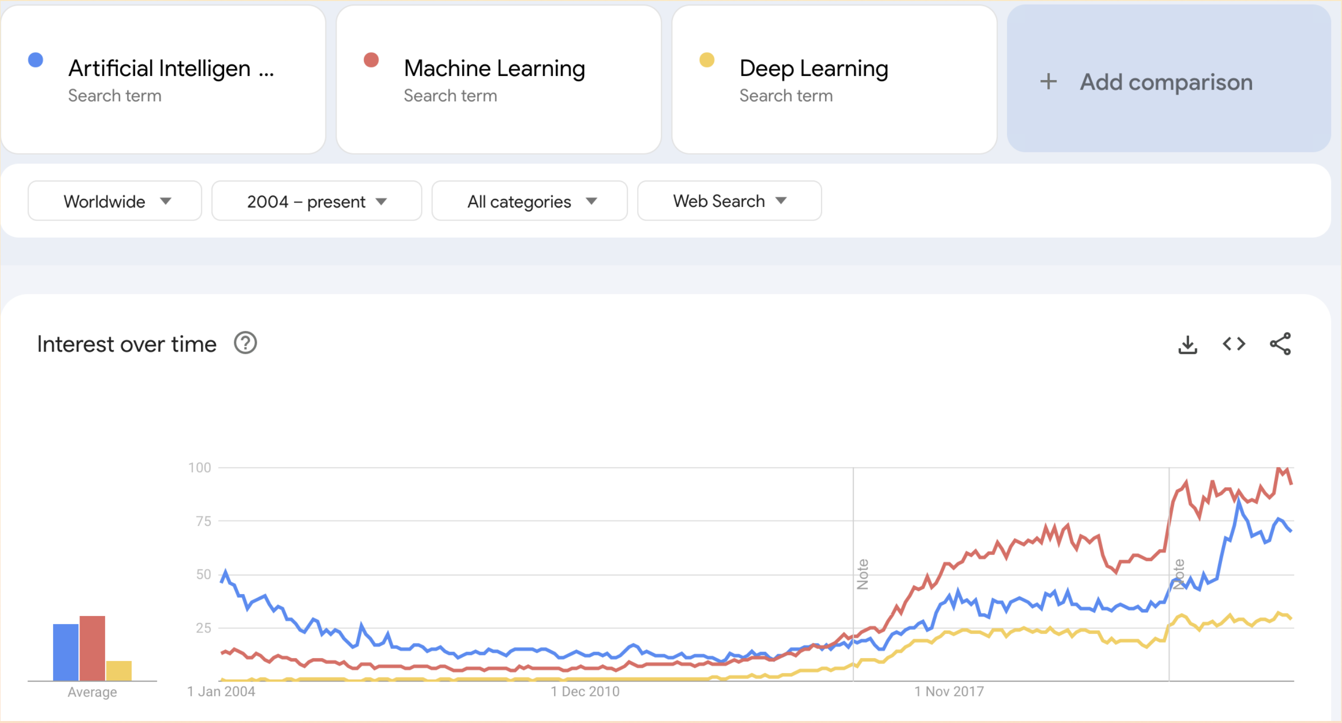

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Image produced by using Google Trends

AI, the eternal buzzword?

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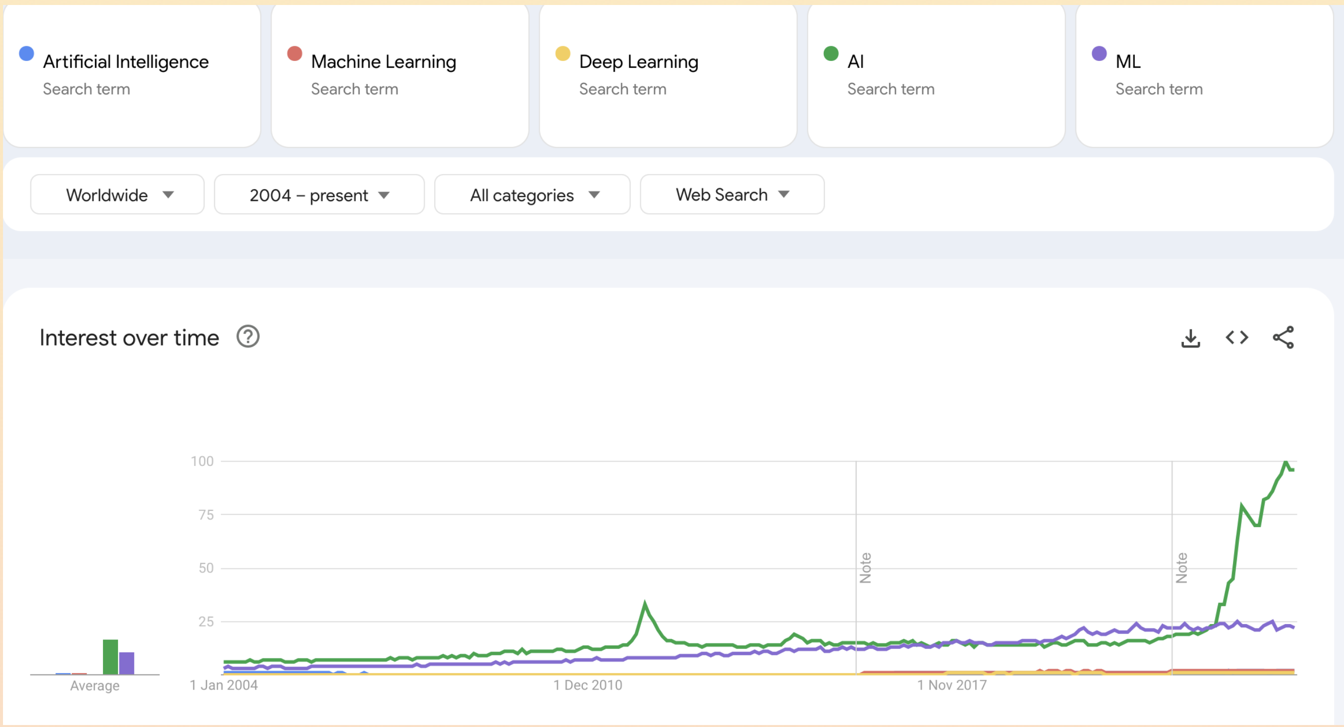

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Image produced by using Google Trends

What do we do

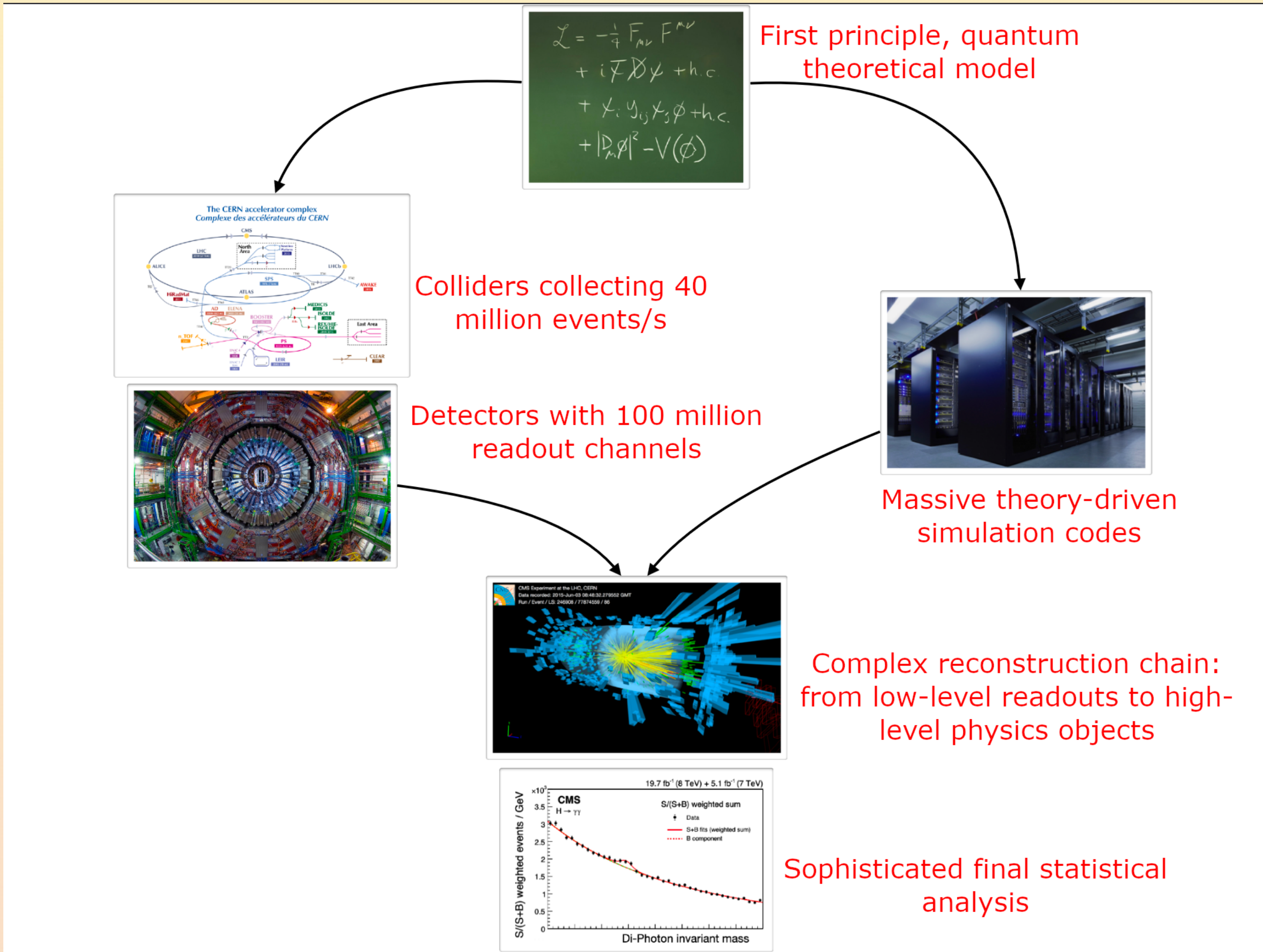

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Illustration reedited from original by Gregor Kasieczka

Where we can plug AI

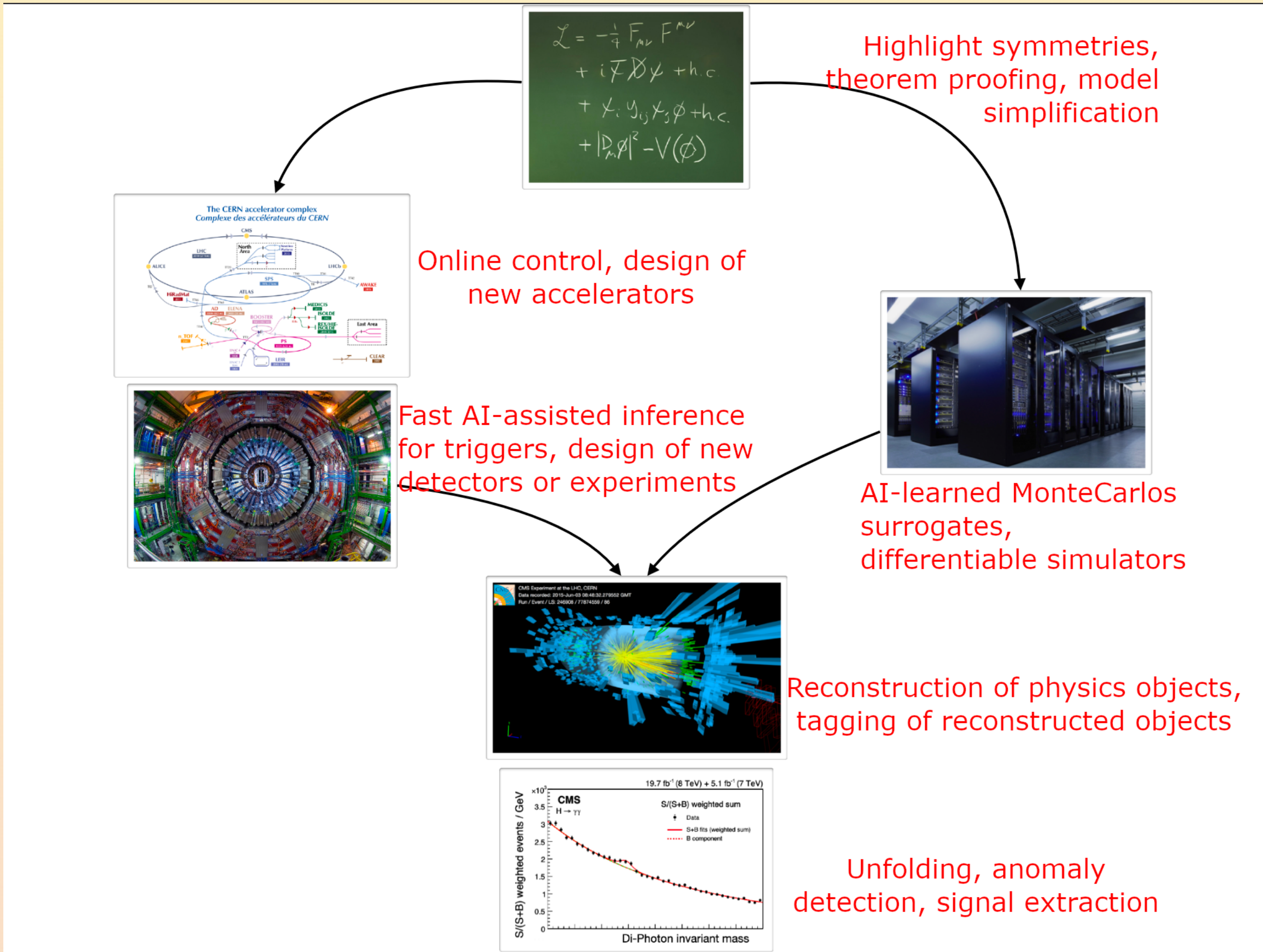

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Illustration reelaborated with some additions from original by Gregor Kasieczka

Where we can plug AI

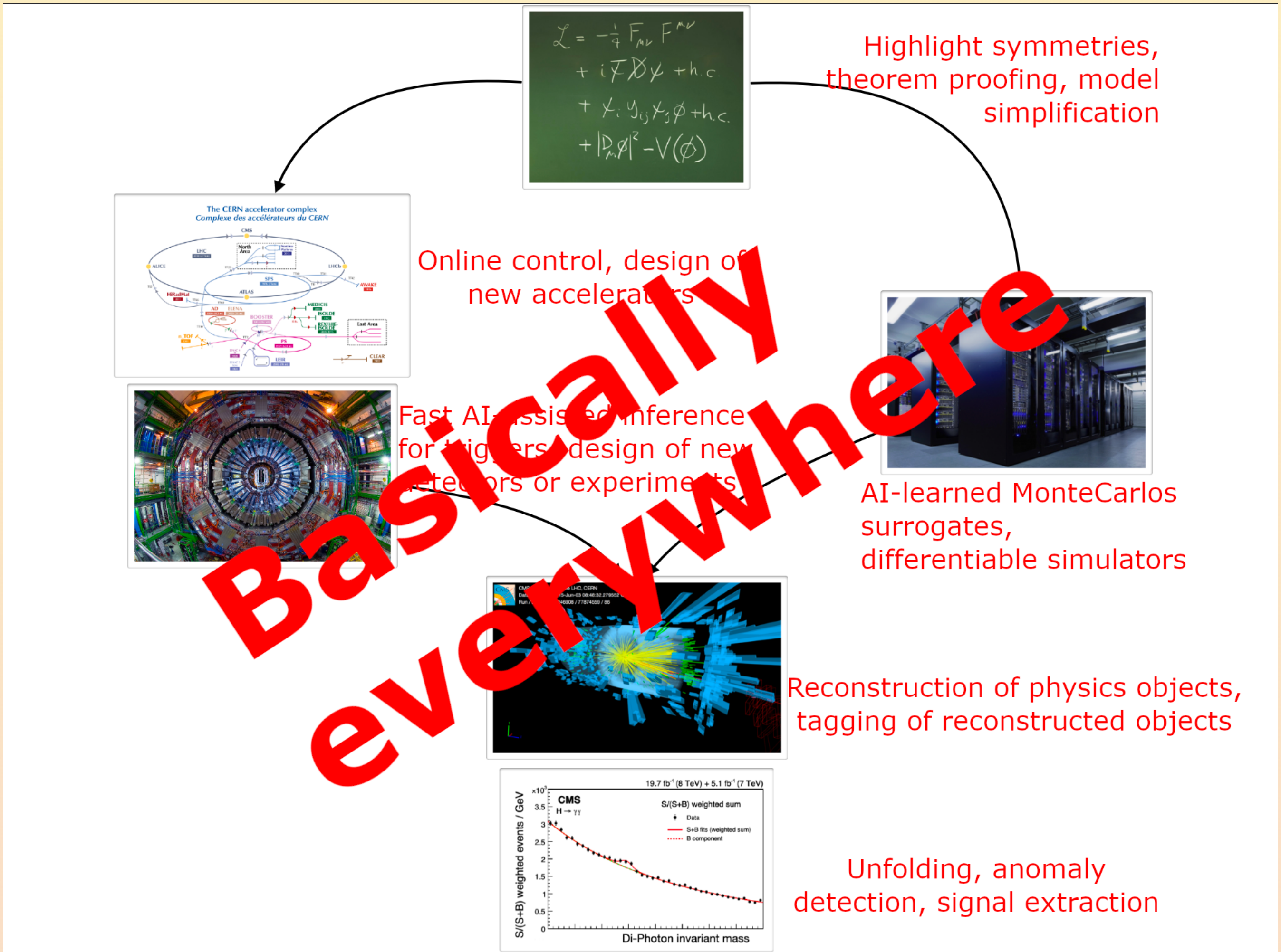

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Illustration reelaborated with some additions from original by Gregor Kasieczka

Most theory papers are symbolic

- AI-assisted theorem proofing

Lean [de Moura et al., 2015] Coq [Barras et al., 1997] Isabelle [Nipkow et al., 2002]

https://machine-learning-for-theorem-proving.github.io/ (NeurIPS 2023)

- LLMs to solve mathematical problems

Article | Open access | Published: 14 December 2023

Mathematical discoveries from program search with large language models

Bernardino Romera-Paredes, Mohammadamin Barekatain, Alexander Novikov, Matej Balog, M. Pawan

- Simplify polylogarithms (no classical algorithm available, LLMs 91% success!)

Dutch: naamsveranderingsdocumentenbriefgeheel

$$f(x) = 9\left(-\mathrm{Li}_3(x) - \mathrm{Li}_3\left(\frac{2ix}{-i+\sqrt{3}}\right) - \mathrm{Li}_3\left(-\frac{2ix}{i+\sqrt{3}}\right)\right) + 4\left(-\mathrm{Li}_3(x) + \mathrm{Li}_3\left(\frac{x}{x+1}\right) + \mathrm{Li}_3(x+1) - \mathrm{Li}_2(-x)\ln(x+1)\right) - 4\left(\mathrm{Li}_2(x+1)\ln(x+1) + \frac{1}{6}\ln^3(x+1) + \frac{1}{2}\ln(-x)\ln^2(x+1)\right)$$

translate

English: dossier

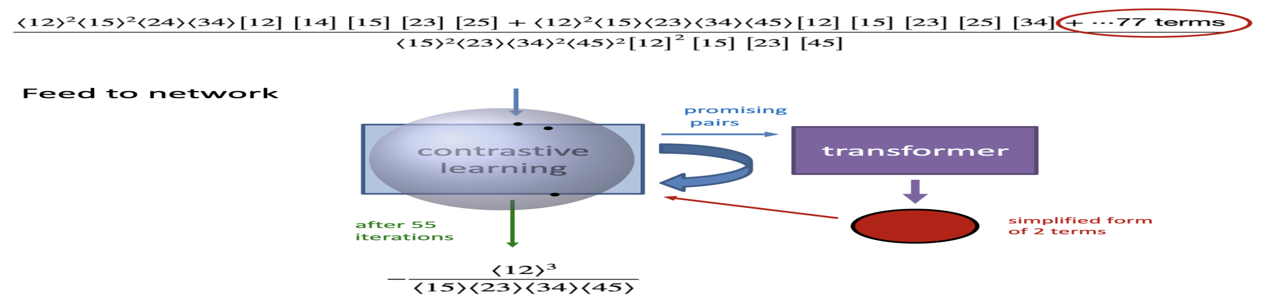
$$f(x) = -\mathrm{Li}_3(x^3) - \mathrm{Li}_3(x^2) + 4\zeta_3$$

—

Examples from Matthew Schwartz

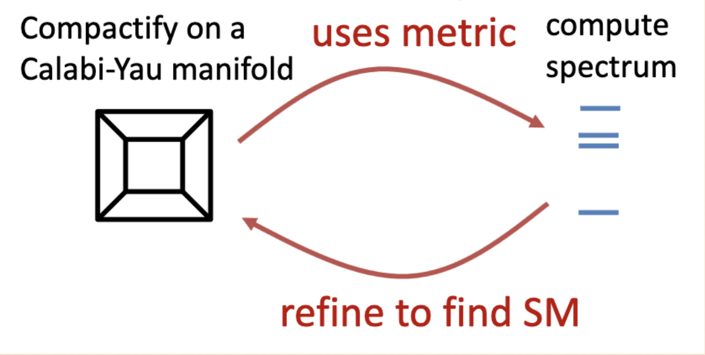
Most theory papers are symbolic

- 5-point MHV amplitude w/ Feynman diagrams: from 1990 tokens to 27 tokens



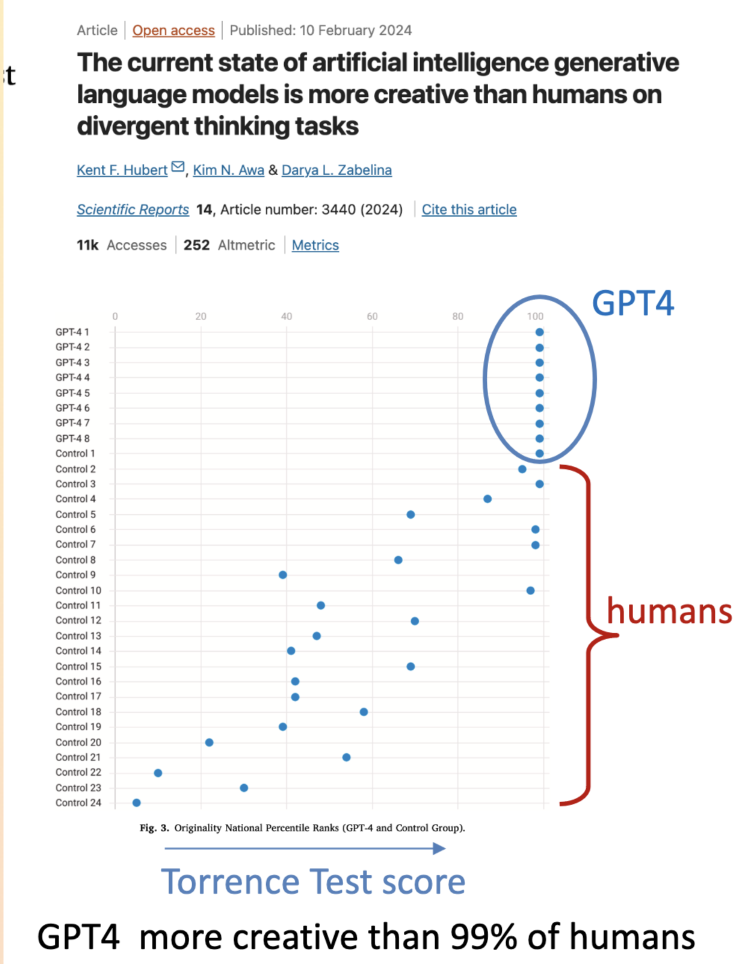
Solve string theory 😜

- Find nontrivial Calaby-Yau metrics (1910.08605)
- Look for fixed points of metric flows (2310.19870)
- Predict rank of gauge group (1707.00655, prediction later proven)



Beyond symbolic manipulation

- Can AI find interesting questions?
- Can AI models teach themselves to be good physicists using data?
- **If AI understands physics (can calculate everything) but we do not, do we consider it an acceptable "understanding"?**



Accelerate accelerators

- Daily operation and control have huge impact on resources and efficiency
  - Beam scheduling: changing supercycle requires 20-100 clicks (2-25min) about 60 times/day
  - 15% of the yearly cost of SPS fixed target cycle employed for "waste" cycles to mitigate hysteresis problems
- What if we could make them fully automatic (like e.g. Space telescopes)?

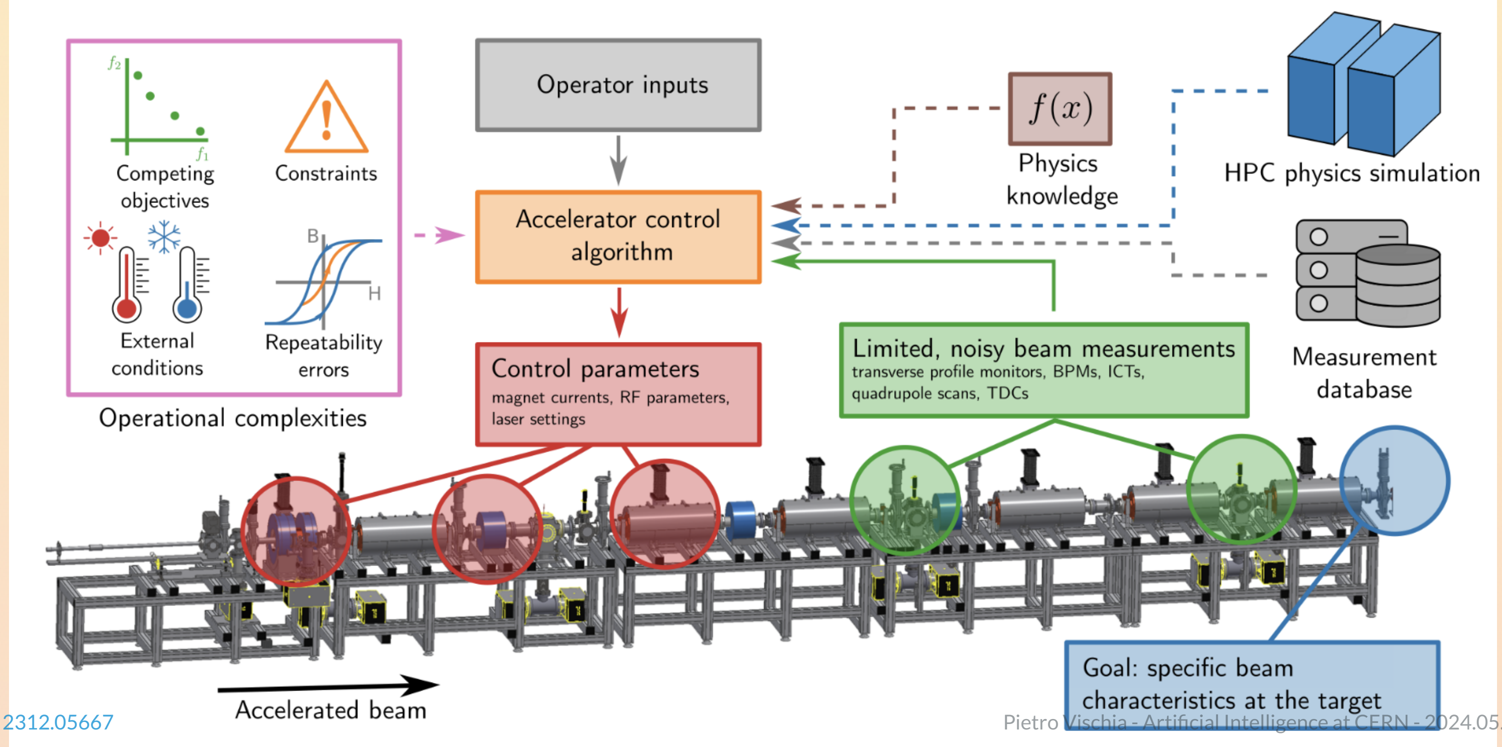


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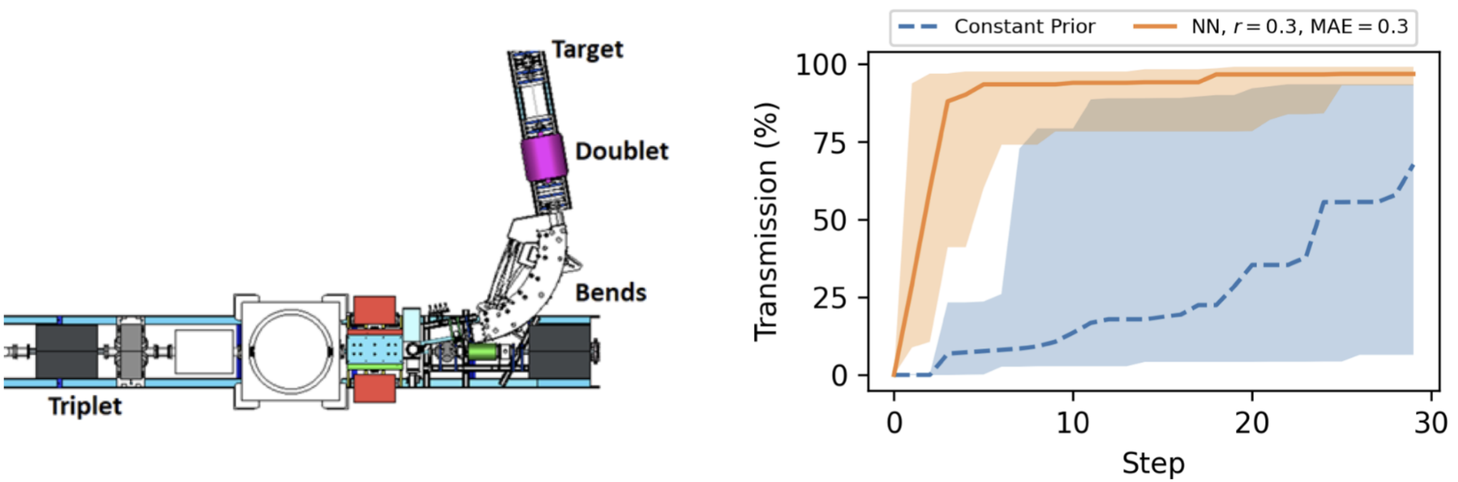
Image from 2312.05667

Accelerate accelerators

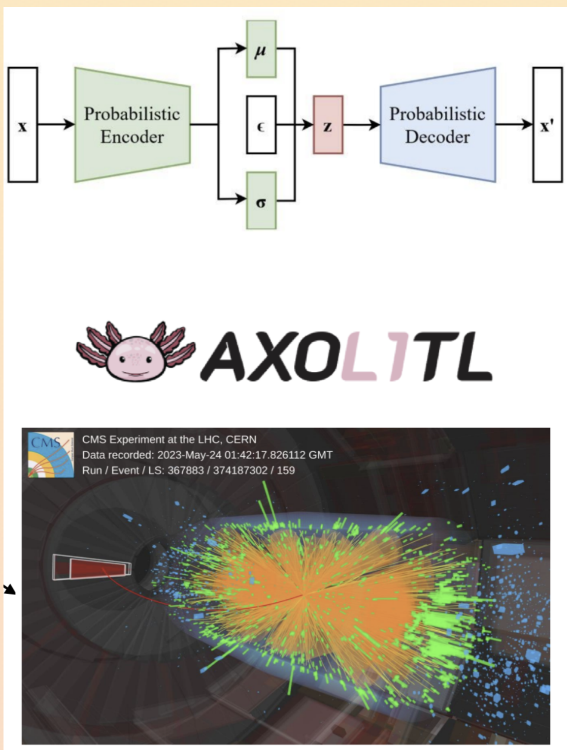
- Hierarchical, AI-controlled autonomous systems
- Optimize trasmission to target in a system with 5 DoF, using Bayesian Optimization

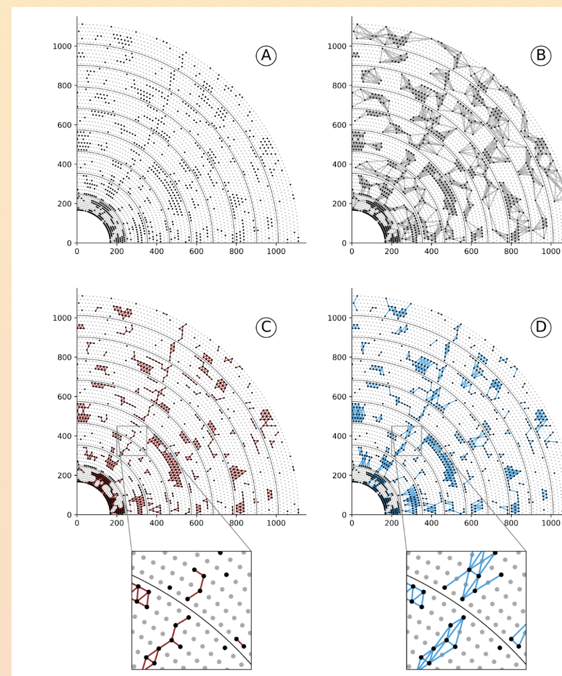


Courtesy T. Boltz et al, arXiv:2403.03225

Trigger

- See talks by A. Zabi and S. Folgueras
- Pack AI models into the L1 trigger $\longrightarrow$ improve selection criteria
  - At ICTEA!
- Can do e.g. anomaly detection, and online graph building

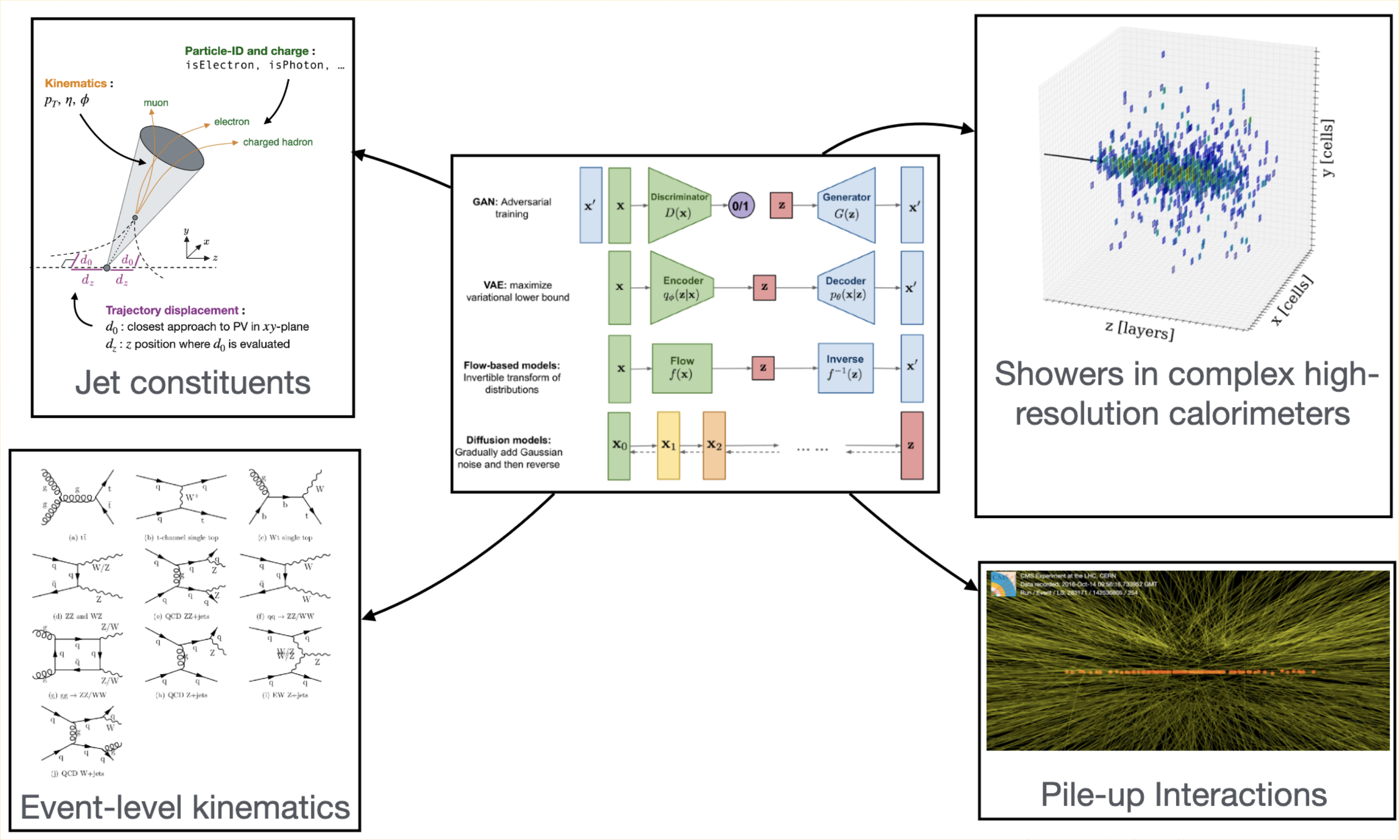




Neu et al 2307.07289

Simulations: the problem

- Monte Carlo simulations are very costly
- The more data we collect, the more simulated events we need

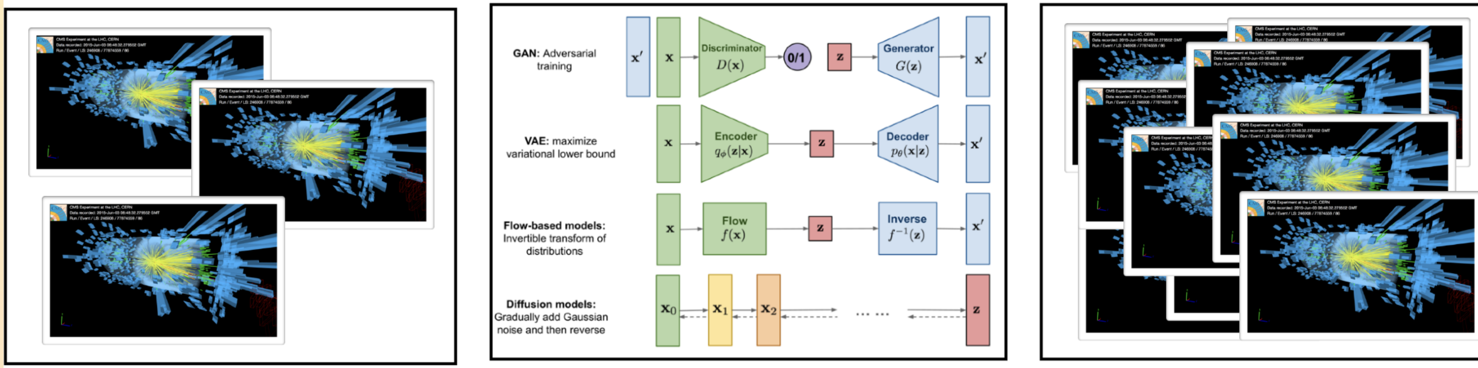


Simulation: two solutions

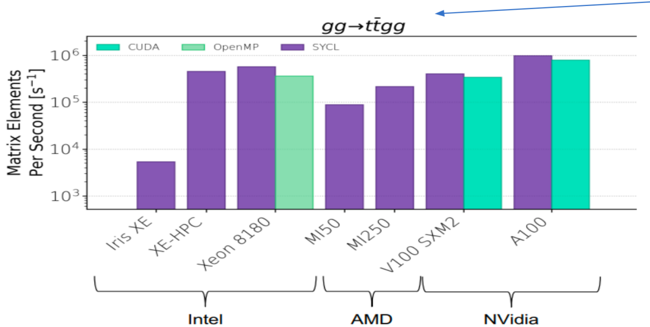
1. Use classical simulation or collider data as input

2. Train generative surrogate

3. Oversample



- Very recently, Madgraph5_aMC@NLO authors deployed a version of their code that can run on GPUs.
- This version significantly improves computation times (see this talk).



Talk by C. Vico Villalba

So our idea is: can we do this on hardware based accelerators?

- **FPGAs** are:
  - **Highly** parallelizable
  - In some cases not as fast as GPU.
  - But less power consuming.
  - Hardware based! really versatile.

See talk by P. Leguina.

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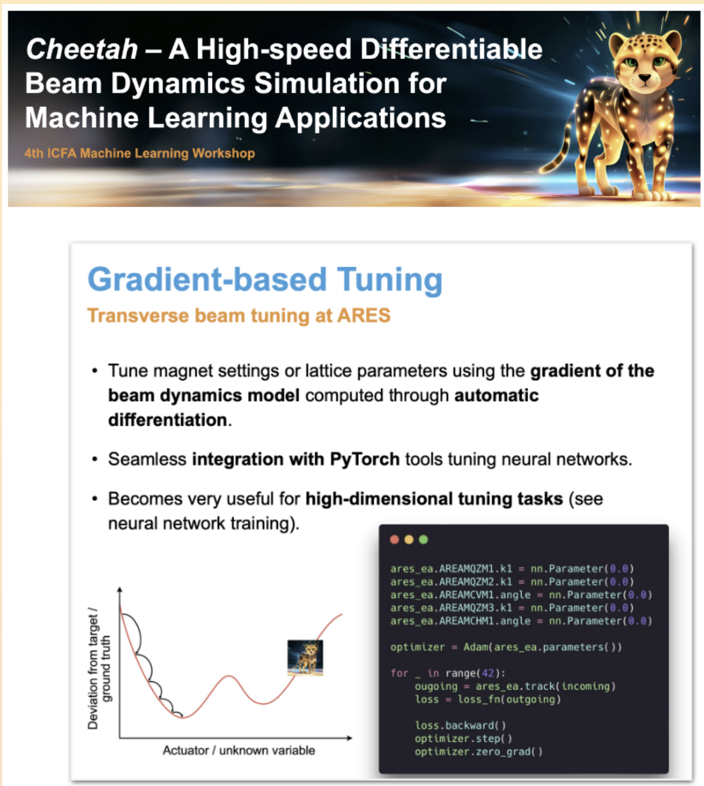
1705.02355, 2008.06545

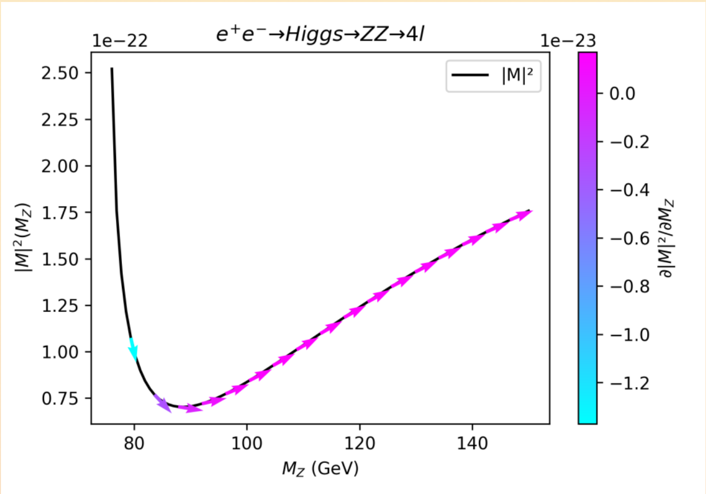
Simulation: long term solution

- Make everything differentiable, exploiting differentiable programming

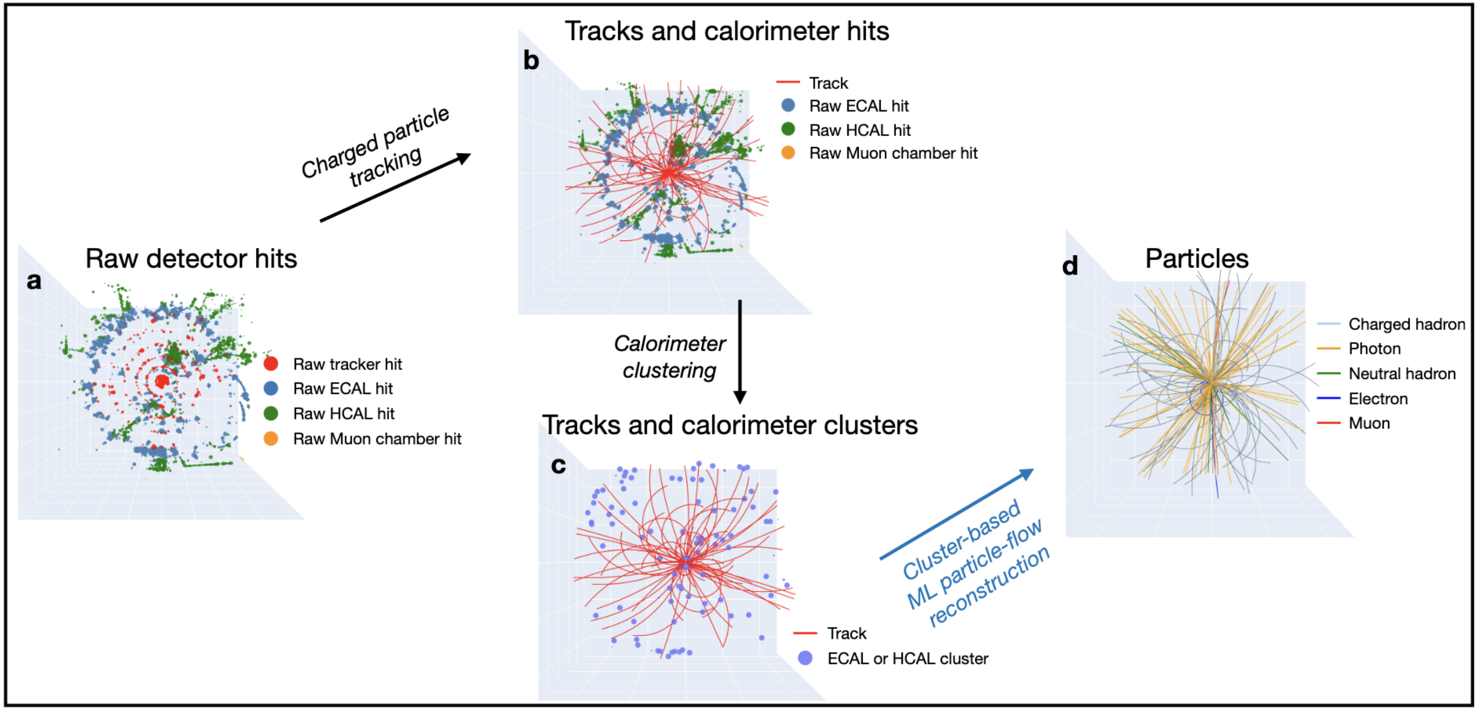
Cheetah



MadJax
(differentiable matrix element computation)



Reconstruction...

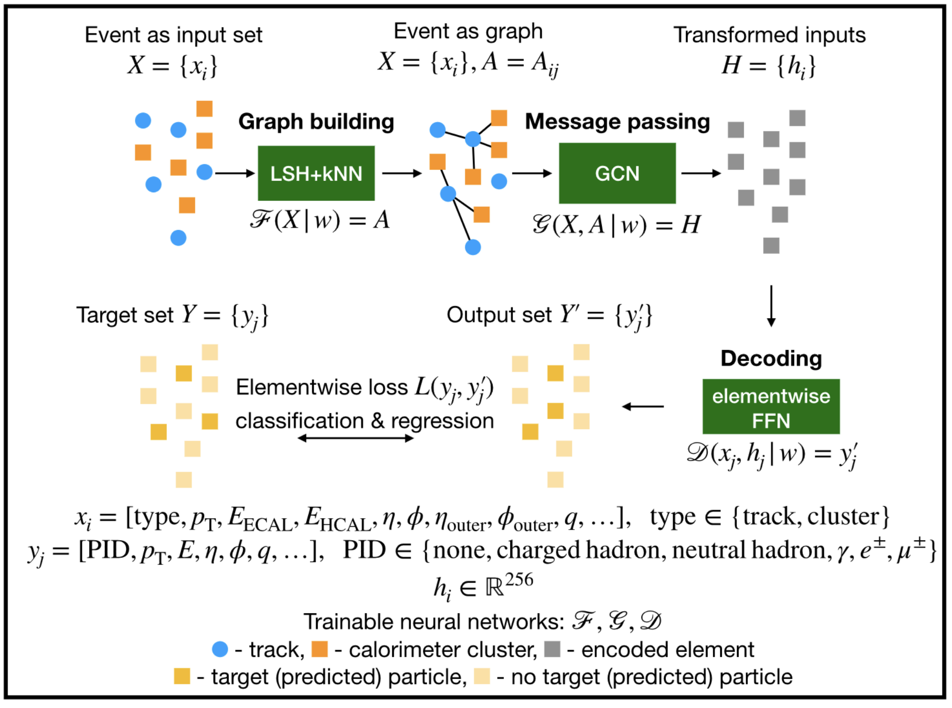


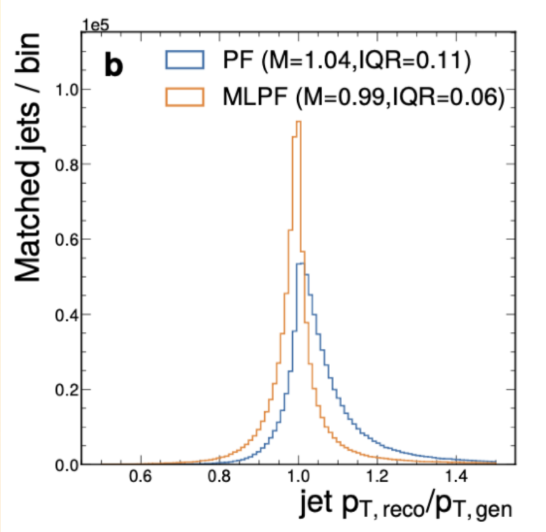
Reconstruction maps low-level detector read-outs

to physical particles

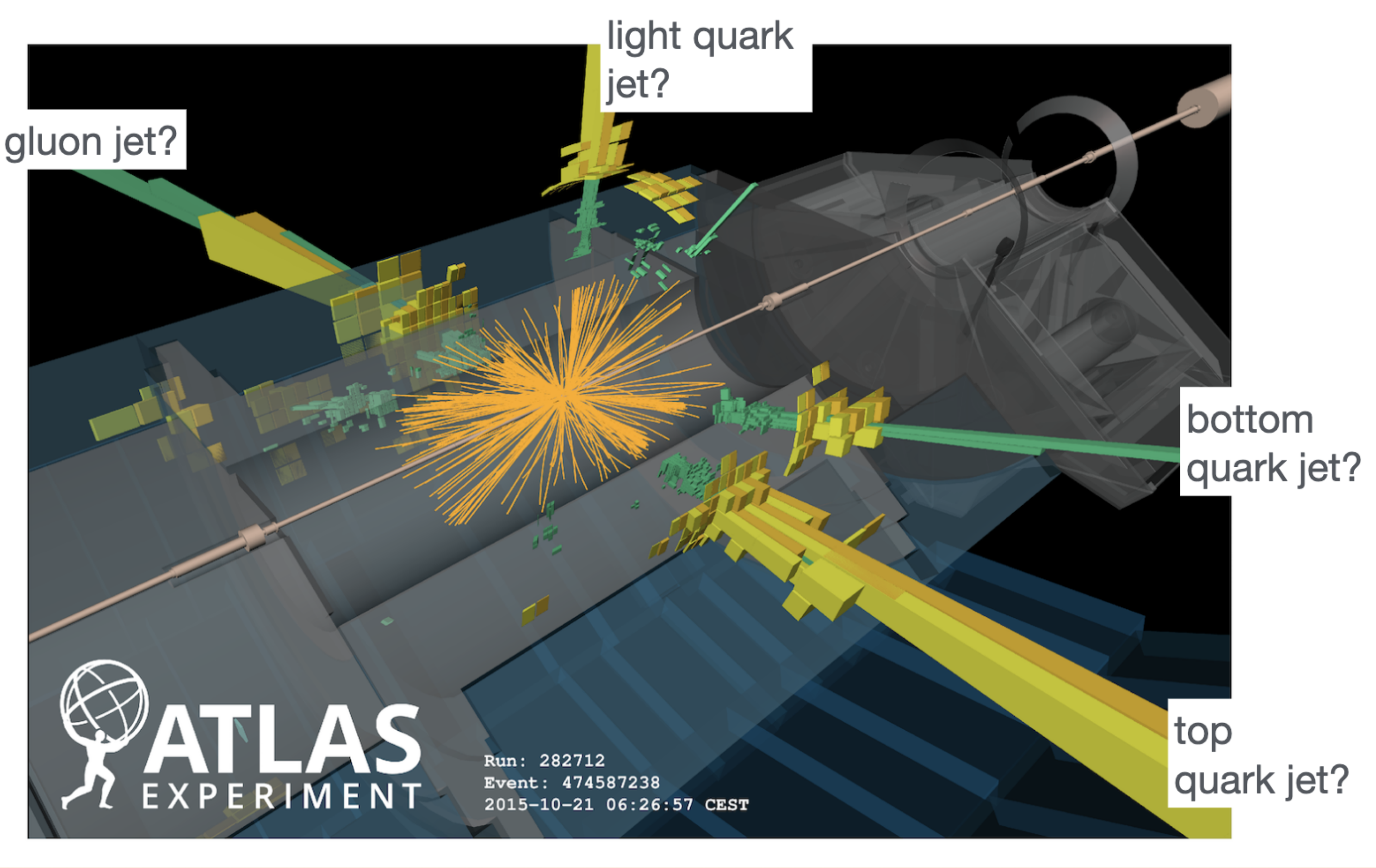
(Which in-turn are the basis of higher-level interpretation)

...with AI


Event as input set $X = \{x_i\}$
Event as graph $X = \{x_i\}, A = A_{ij}$
Transformed inputs $H = \{h_i\}$
Graph building
LSH+kNN
$\mathcal{F}(X|w) = A$
Message passing
GCN
$\mathcal{G}(X, A|w) = H$
Target set $Y = \{y_j\}$
Output set $Y' = \{y'_j\}$
Decoding
elementwise FFN
$\mathcal{D}(x_j, h_j|w) = y'_j$
Elementwise loss $L(y_j, y'_j)$
classification & regression
$x_i = [\text{type}, p_T, E_{ECAL}, E_{HCAL}, \eta, \phi, \eta_{outer}, \phi_{outer}, q, \ldots], \quad \text{type} \in \{\text{track, cluster}\}$
$y_j = [\text{PID}, p_T, E, \eta, \phi, q, \ldots], \quad \text{PID} \in \{\text{none, charged hadron, neutral hadron}, \gamma, e^\pm, \mu^\pm\}$
$h_i \in \mathbb{R}^{256}$
Trainable neural networks: $\mathcal{F}, \mathcal{G}, \mathcal{D}$
- track, - calorimeter cluster, - encoded element
- target (predicted) particle, - no target (predicted) particle


b
PF (M=1.04,IQR=0.11)
MLPF (M=0.99,IQR=0.06)
1e5
Matched jets / bin
jet $p_{T,reco}/p_{T,gen}$
0.0
0.2
0.4
0.6
0.8
1.0
0.6
0.8
1.0
1.2
1.4

Identification...



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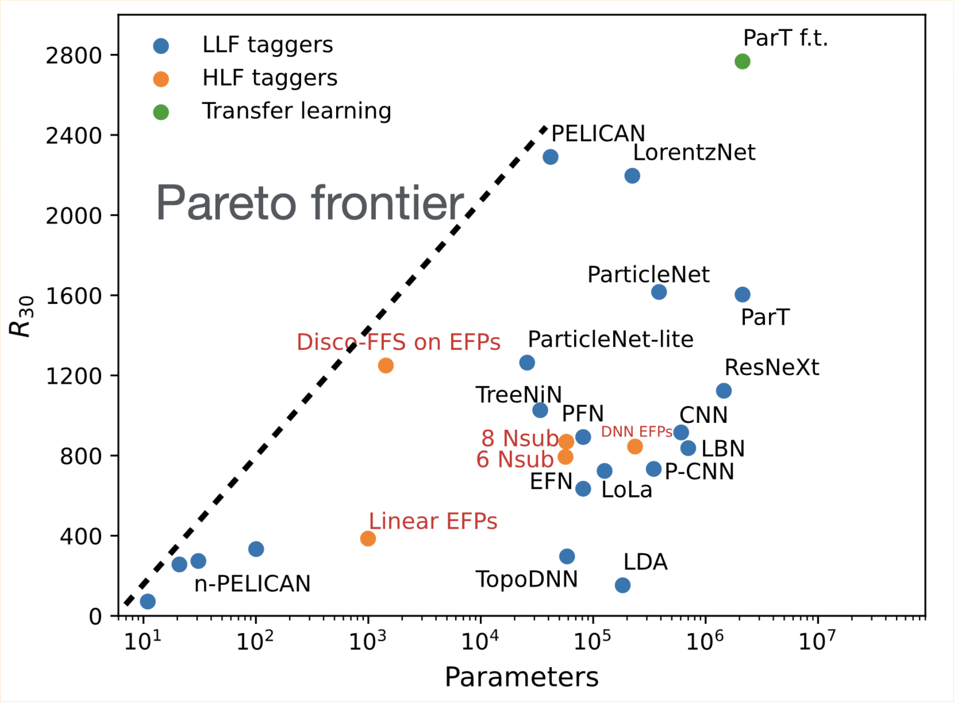
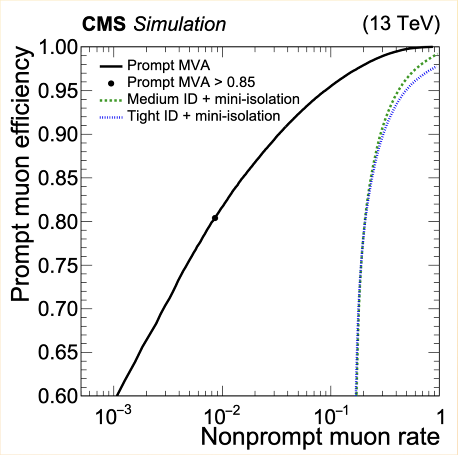
From Gregor Kasieczka's talk at EuCaifCon24

...with AI

Vast landscape of taggers



CMS Muon ID: made in ICTEA!



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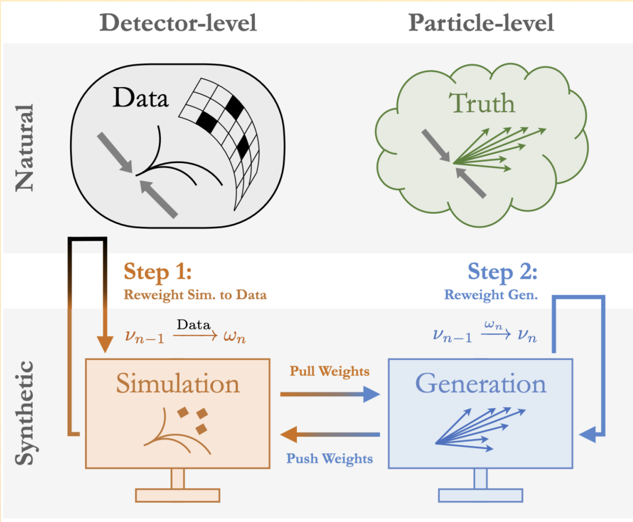
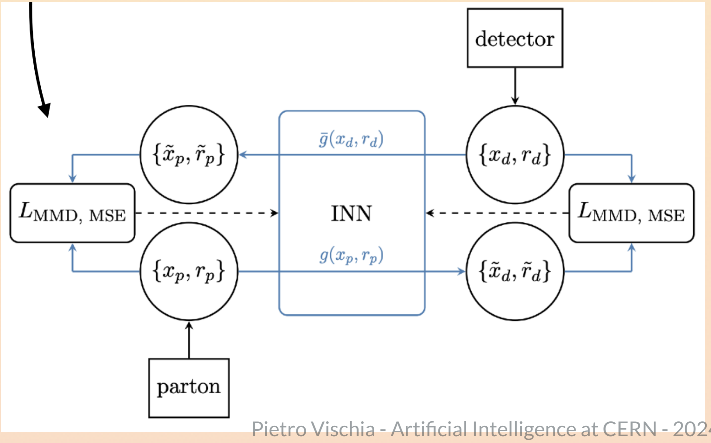
From Gregor Kasieczka's talk at EuCaifCon24, and from 10.1088/1748-0221/19/02/P02031

Inference: unfolding

- Use classifiers to learn appropriate weights



- Morph distributions one into the other using diffusion models



Inference: anomaly detection

Gaussian processes)

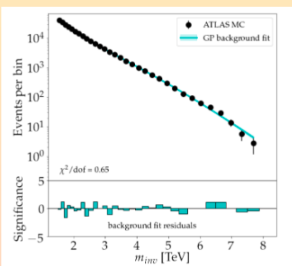
- Multivariate gaussian associated to a set of random variables ($N_{dim} = N_{random\ variables}$)
  - *Kernel* as a similarity measure between bin centers (counts) and a *averaging function*

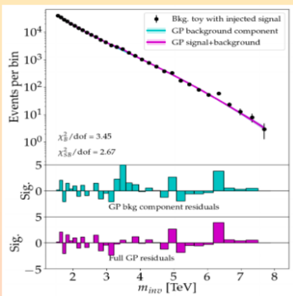
$$\mu(x) = 0\,, \quad (9)$$

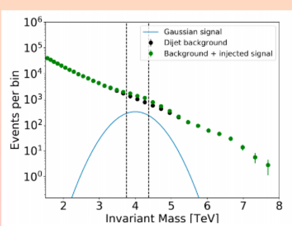
$$\Sigma_B(x,x') = A\ \exp\left(\frac{d-(x+x')}{2a}\right)\sqrt{\frac{2l(x)l(x')}{l(x)^2+l(x')^2}}\ \exp\left(\frac{-(x-x')^2}{l(x)^2+l(x')^2}\right), \quad (10)$$

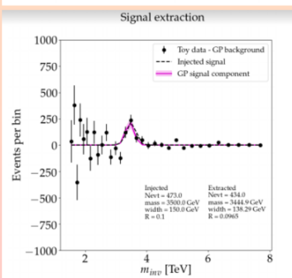
$$\Sigma_S(x,x') = C\ \exp\left(-\frac{1}{2}(x-x')^2/k^2\right)\exp\left(-\frac{1}{2}\left((x-m)^2+(x'-m)^2\right)/t^2\right), \quad (11)$$

-
  - Signal is not parameterized
  - Hyperparameters fixed by the B-only fit
- S: residual of B-subtraction







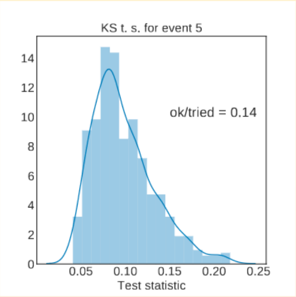


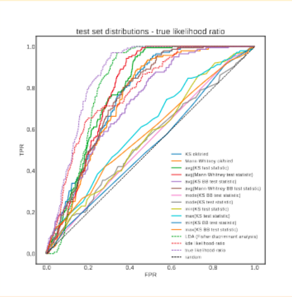
AMVA4NewPhysics deliverable 2.5 public report

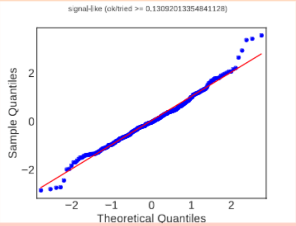
Inverse Bagging

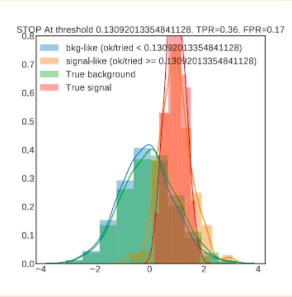
- Data: mixture model with small S
- Classification based on sample properties
  - Compare bootstrapped samples with reference (pure B)
  - Use Metodiev theorem to translate inference into signal fraction
- Validate with LR y LDA
  - Promising results

At ICTEA!



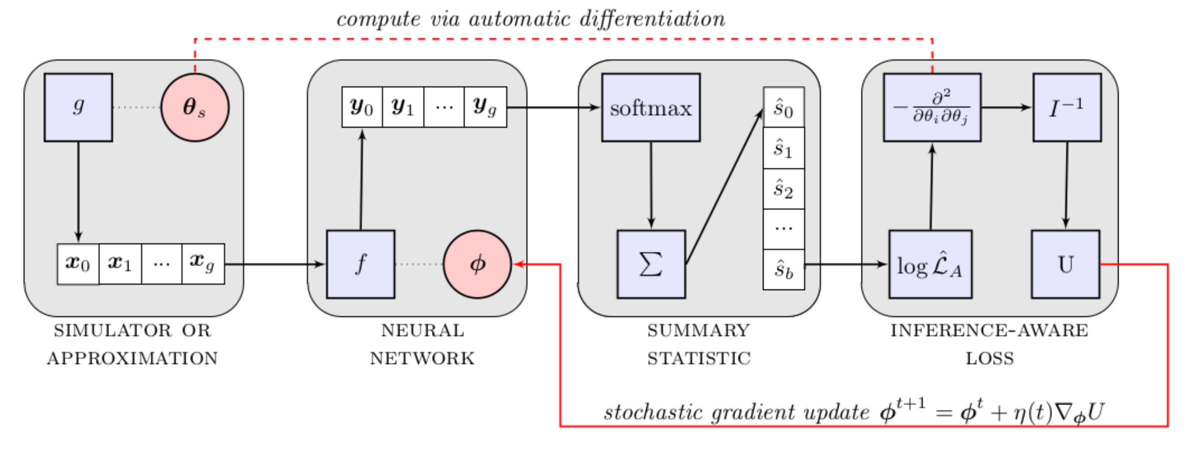


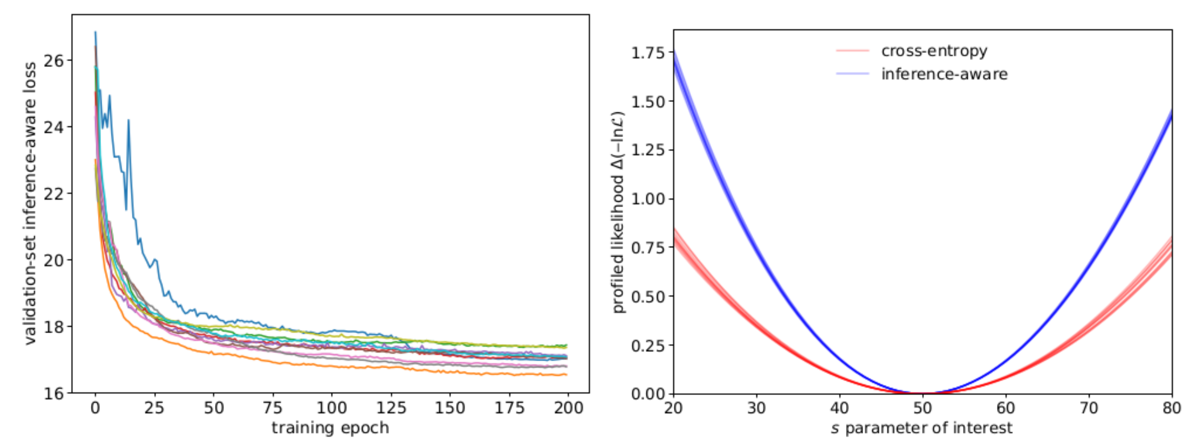




Vischia-Dorigo arXiv:1611.08256, doi:10.1051/epjconf/201713711009, and P. Vischia's talk at EMS2019

Go to INFERNO: syst-aware inference opt.





(a) inference-aware training loss

(b) profile-likelihood comparison

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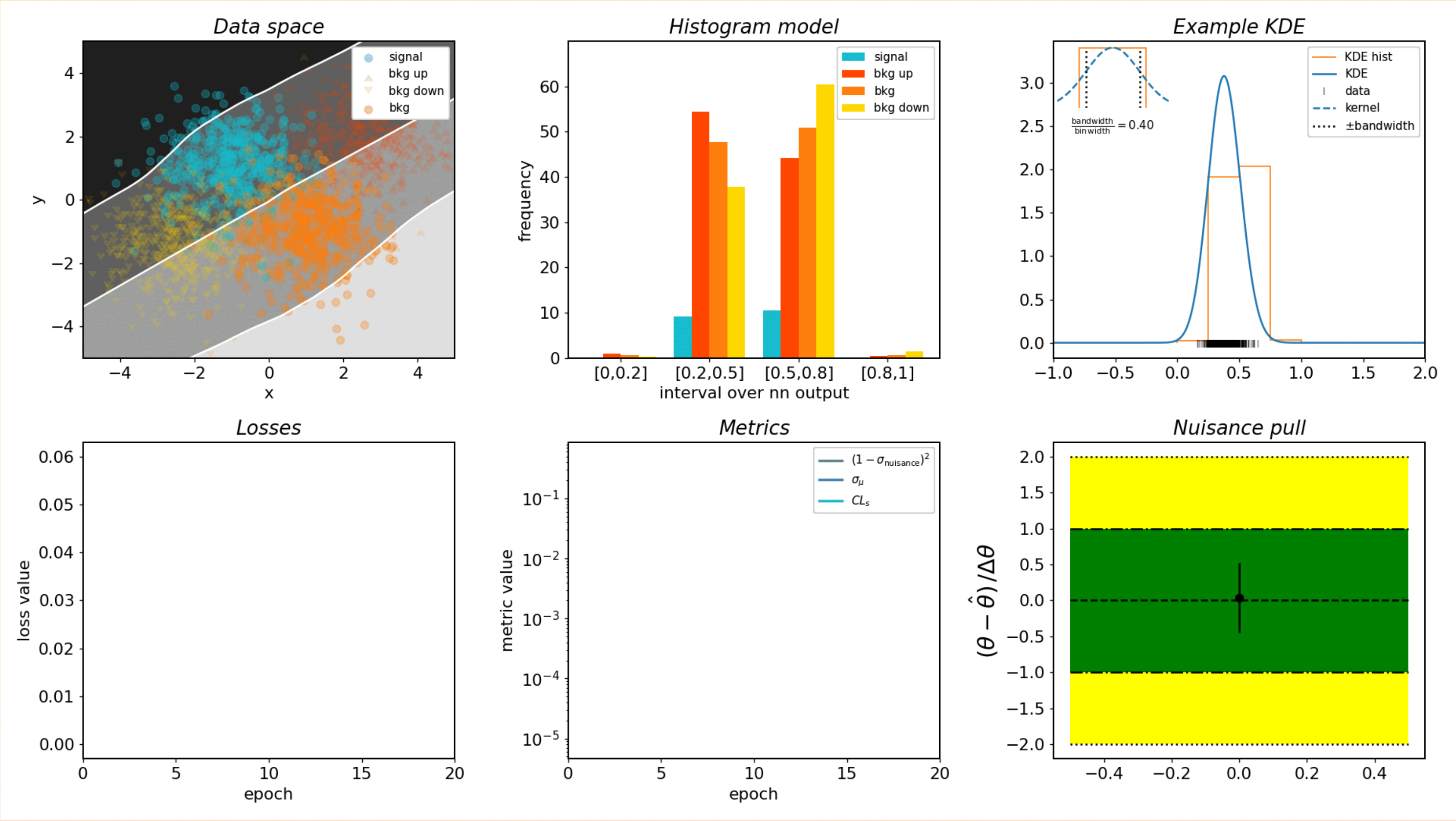
Figures from 10.1016/j.cpc.2019.06.007

Measurement-aware analysis opt.

neos



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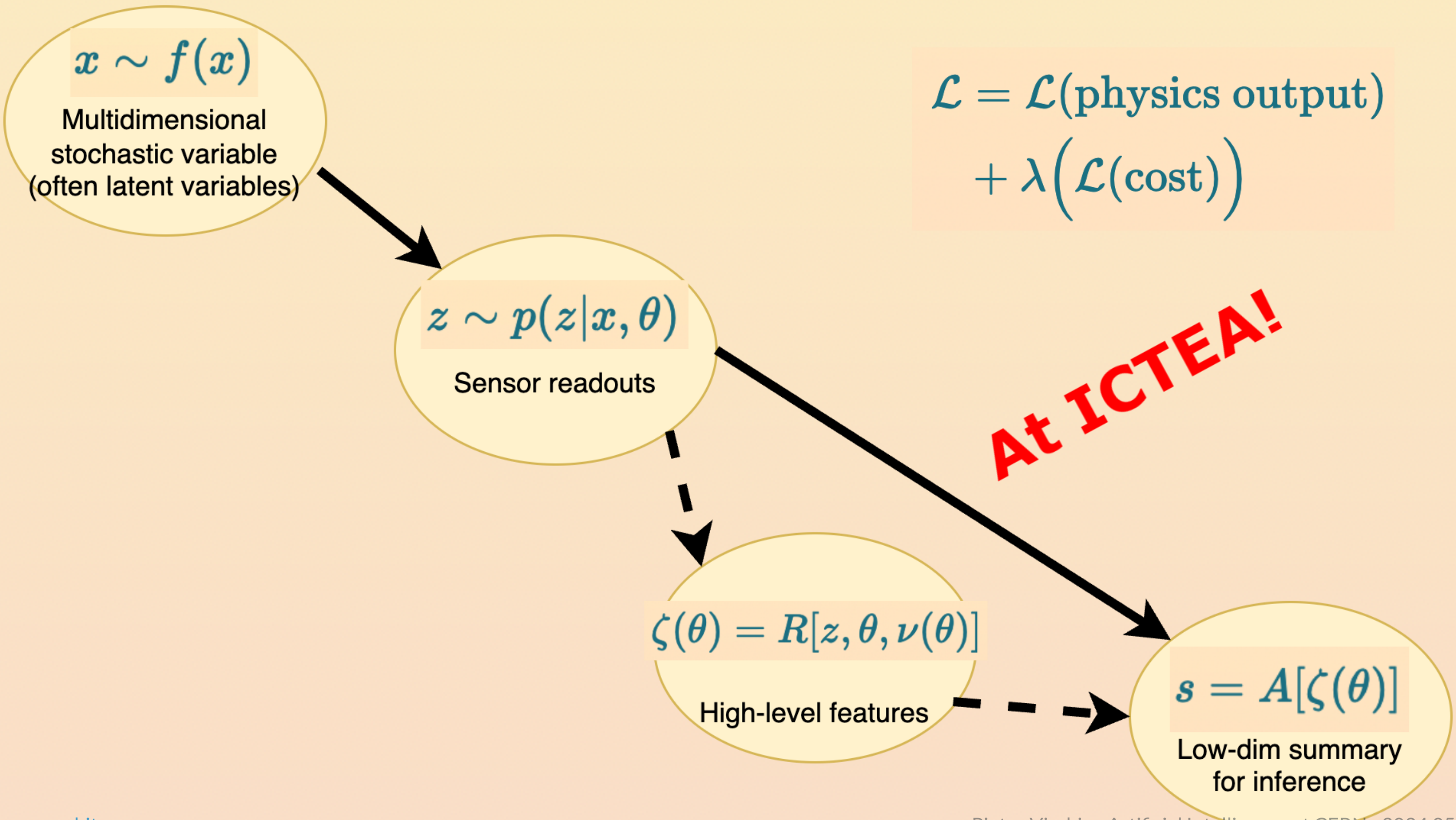
Animation from 2203.05570

Measurement-aware detector opt.!

- Joint optimization of design parameters w.r.t. inference made with data
- MODE White Paper, 10.1016/j.revip.2023.100085 (2203.13818), 117-pages document, physicists + computer scientists



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Formulas from our white paper

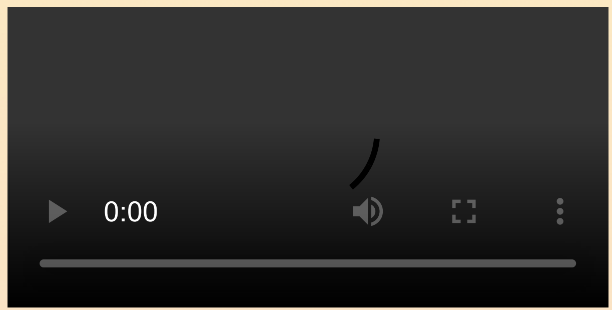
Prototype for muon tomography

TomOpt: Differential optimisation for task- and constraint-aware design of particle detectors in the context of muon tomography

Giles C. Strong, Maxime Lagrange, Aitor Orio, Anna Bordignon, Florian Bury, Tommaso Dorigo, Andrea Giammanco, Mariam Heikal, Jan Kieseler, Max Lamparth, Pablo Martínez Ruíz del Árbol, Federico Nardi, Pietro Vischia, Haitham Zaraket

At ICTEA!

We describe a software package, TomOpt, developed to optimise the geometrical layout and specifications of detectors designed for tomography by scattering of cosmic-ray muons. The software exploits differentiable programming for the modeling of muon interactions with detectors and scanned volumes, the inference of volume properties, and the optimisation cycle performing the loss minimisation. In doing so, we provide the first demonstration of end-to-end-differentiable and inference-aware optimisation of particle physics instruments. We study the performance of the software on a relevant benchmark scenarios and discuss its potential applications.



CERN AI structures

- CERN Interexperimental Machine Learning Working Group, https://iml.web.cern.ch

The IML working group holds regular meetings open to all interested parties and maintains a discussion forum to facilitate the exchange of information among the LHC experiments in machine learning. The IML working group also fosters connections with other HEP experiments and the ML community at large.

CMS AI structures

- Shared coordination area between Physics and Offline&Computing
- Informs the collaboration, promotes new techniques, review AI-based analyses
- Real impact on steering AI applications in a 5000k members collaboration

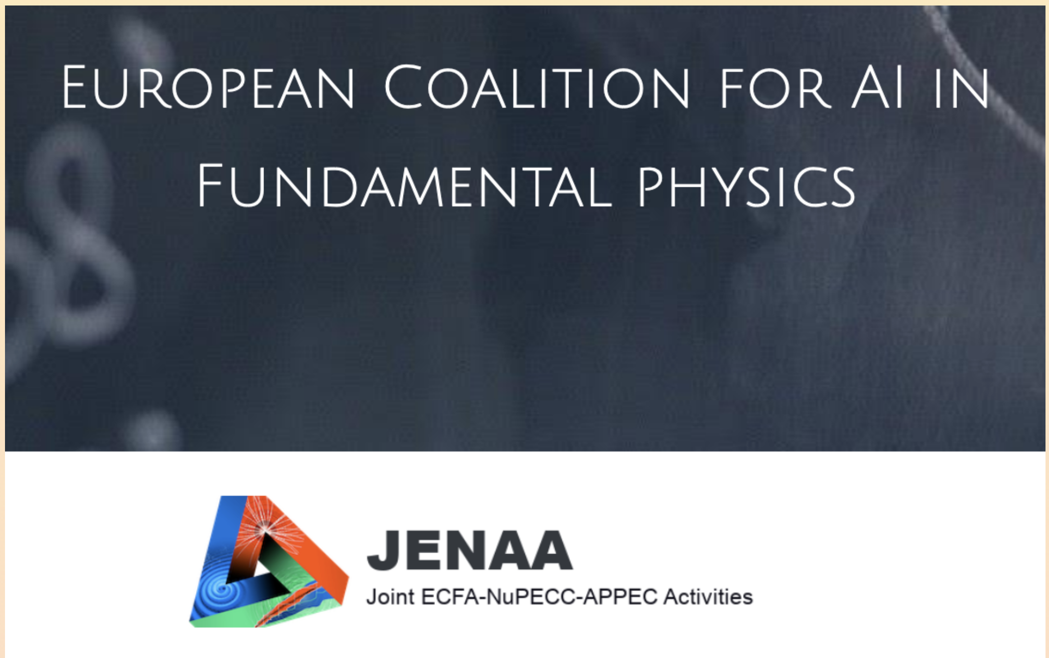
ML Group Coordinator: Pietro Vischia

ICTEA (2024-2026)

- CMS member since 2009
- Ph.D. in 2016 from Instituto Superior Técnico (Lisboa)
  - Bachelor and Master's: Università degli Studi di Padova
- "Ramón y Cajal" Senior Researcher at Universidad de Oviedo and ICTEA since 01/2023
  - Postdoc: UCLouvain (BE, 2018-2022), Universidad de Oviedo (ES, 2016-2018)
  - Predoc: research fellow at LIP Lisboa (PT, 2011-2016)
- Analysis highlights: top mass and xsec, charged Higgs, WZ, ttH multilepton
- Roles in CMS
  - CERN **IML coordinator** for CMS (2020-2024)
  - **Statistics Committee** member (2015-ongoing)
  - **HiggsWW** L3 (2021-2023), LHC EWK multiboson WG convener (2018-2020)
  - **Combine contact** (SMP and TOP), Computing coordinator and PT Grid T2 admin (2013-2016), **ARC chair** (3x) and member (13x), **CCLE** (6x), MC contact (HIG-Exo, HIG, HWW), CMSDAS facilitator (3x), **Trigger shifter** (online and offline)
- ML in several papers and preprints (various CMS analyses, anomaly detection, design of experiments, neuroscience), badly edited the photo to the right with ML
- Other: PI of NeuroMODE (neuromorphic computing for design of experiments and trigger applications), steering board of MODE (Machine-learning Optimized Design of Experiments), steering group of EUCAIF (European Coalition for AI in Fundamental physics). Past: partner node PI of AMVA4NewPhysics (Advanced MultiVAriate Analyses for New Physics)
- Regular courses and lectures on ML; book on Stat and ML near completion (or at least this is what I told the editor :D)

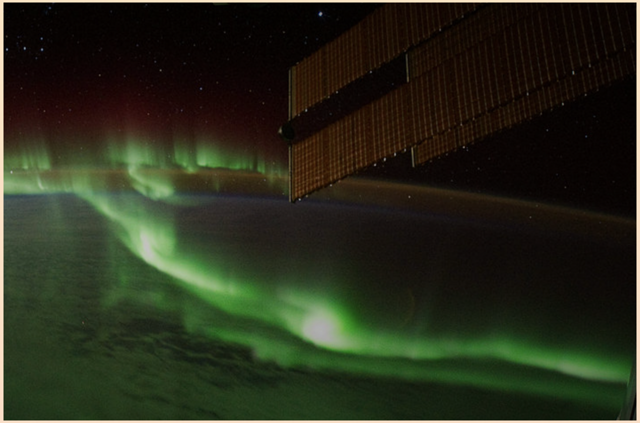
European AI structures

- European initiative for advancing the use of Artificial Intelligence (AI) in Fundamental Physics"
  - ICTEA (PV) in the Steering Board!



Fundamental $\rightarrow$ Applied

- Industries (e.g. in Asturias) can profit from AI developed at CERN!
  - **Just contact us!**
- Many industrial applications of CERN AI technology
  - X/γ detectors (Xrays, PET)
  - Hadron therapy and proton CT
  - Vacuum technology
  - Cryogenics
  - Art
  - WWW
  - MRI
  - GPS
  - Satellites
  - Solar panels
  - Airport security scanners
  - Space watch (avoid asteroids)



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Images from CERN

We have been doing "AI"-assisting since thousands of years

Be prepared for the next thousand!

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Tabula Rogeriana by Al Idrisi (1154) 1929 reproduction