AI in Fundamental Physics — Hype or Future?

Tilman Plehn

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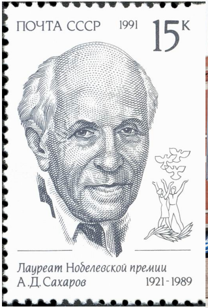
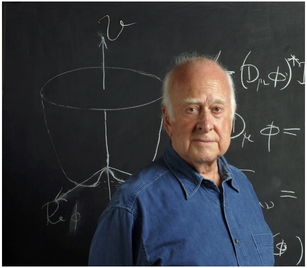
juFORUM 2025

AI for modern particle physics

Goals

- dark matter?
- matter vs antimatter?
- origin of Higgs boson?





Defining features

AI for modern particle physics

Goals

- dark matter?
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Defining features

- huge data set
- uncertainty control
- first-principle simulations

$\to$ Physics $\otimes$ AI?

Past

- counting particles
- theory-driven Higgs discovery
- testing more theories [my background]

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Virtual worlds

- start with Lagrangian/Hamiltonian
- calculate in quantum field theory
- simulate collisions

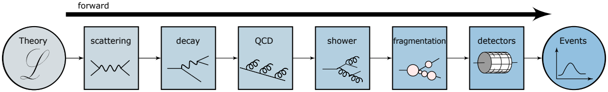
$\to$ Physics $\otimes$ AI?

Future

- simulate digital twins
- understand LHC dataset
- determine underlying theory

$\to$ Physics $\otimes$ AI?

[my background]



Large Hadron Collider at CERN

Community

- LHC: 2008-2040 [my stages]
- 5000+ scientists per experiment

→ International AI

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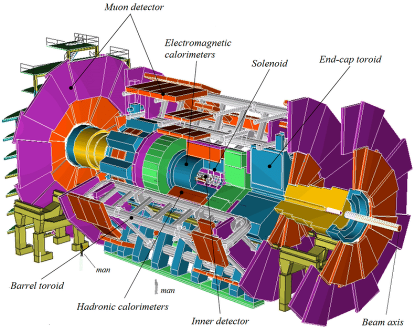
Detectors

- measure all produced particles
- multi-mode output



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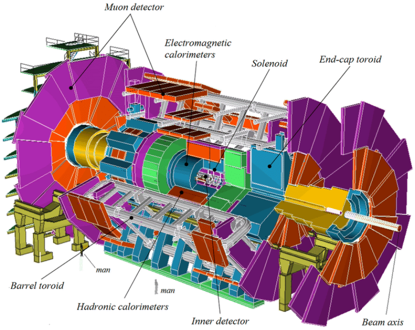
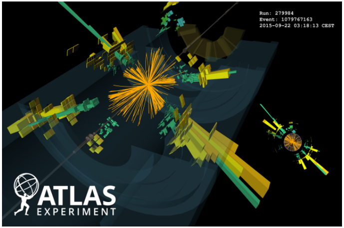


LHC Event



- colliding p-p at 40 MHz
- producing old and new particles
- most particles decaying
- measure energy, charge...
- electrons, muons easy
  quarks, gluons hard
- event: 100+ vectors $(E, \vec{p}, Q)$

→ ATLAS output 3 PB/s

Discoveries

LHC discoveries

- Higgs discovery, July 4, 2012
  Nobel Prize 2013

CERN-PH-EP-2012-218

Accepted by: Physics Letters B

v2 [hep-ex] 31 Aug 2012

Observation of a New Particle in the Search for the Standard Model Higgs Boson with the ATLAS Detector at the LHC

The ATLAS Collaboration

This paper is dedicated to the memory of our ATLAS colleagues who did not live to see the full impact and significance of their contributions to the experiment.

Discoveries

LHC discoveries

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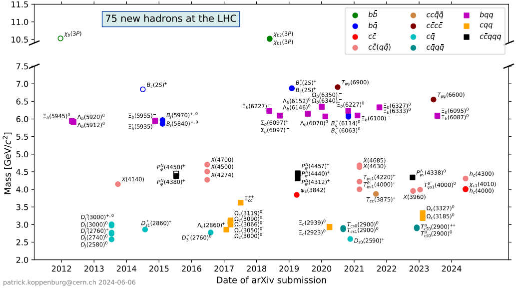
  Nobel Prize 2013
- since then: 75 more particles
- particles ↔ elementary particles?
  proton vs electron
  size, structure, constituents



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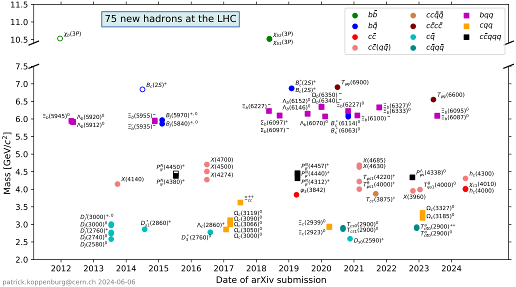
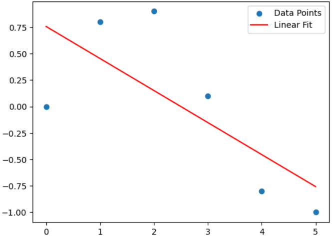


→ discoveries hiding in data
guarantee we do not miss anything in PB/s

→ Trustable AI

Neural networks



Fit

- approximate $f_\theta(x) = \theta_1 - \theta_2 x$
- no function, but very many θ
- data representation θ

Mappings

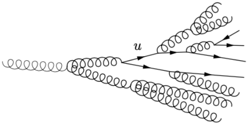
- regression $x \to f_\theta(x)$
- classification $x \to p_\theta(x) \in [0, 1]$
- generation $x \sim \mathcal{N} \to p_\theta(x)$
- conditional generation $x \sim \mathcal{N} \to p_\theta(x|y)$

LHC

- training on simulations
- x interpretable
- symmetries etc known
- uncertainties?

$\to$ Complexity vs data [LLMs]

AI-Jet physics



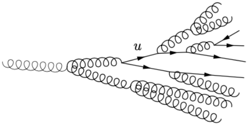
Particles as jets

- mostly $pp \to q\bar{q}, gg$
- splittings from quantum field theory
  observed as 'jets'
- jets as decay products

  67% $t \to jjj$ 60% $H \to jj$ 70% $Z \to jj$ 67% $W \to jj$ 60% $\tau \to j$ ...
- new particles in 'dark jets'

$\to$ LHC = precision jet physics

AI-Jet physics



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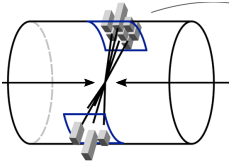
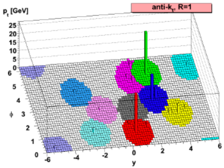


Understanding jets

- 50-200 constituents per jet
  tens of simultaneous scatterings

1. cluster algorithm: energy
2. classification algorithm: source



November revolution

Stanford, Nov 16, 2015

- interpret jet signature as image
- analyze using image networks

Jet-Images – Deep Learning Edition

Luke de Oliveira,[a] Michael Kagan,[b] Lester Mackey,[c] Benjamin Nachman,[b] and Ariel Schwartzman[b]

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Abstract: Building on the notion of a particle physics detector as a camera and the collimated streams of high energy particles, or jets, it measures as an image, we investigate the potential of machine learning techniques based on deep learning architectures to identify highly boosted W bosons. Modern deep learning algorithms trained on *jet images* can out-perform standard physically-motivated feature driven approaches to jet tagging. We develop techniques for visualizing how these features are learned by the network and what additional information is used to improve performance. This interplay between physically-motivated feature driven tools and supervised learning algorithms is general and can be used to significantly increase the sensitivity to discover new particles and new forces, and gain a deeper understanding of the physics within jets.

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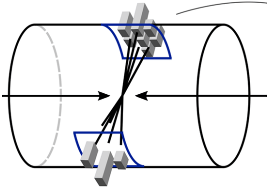
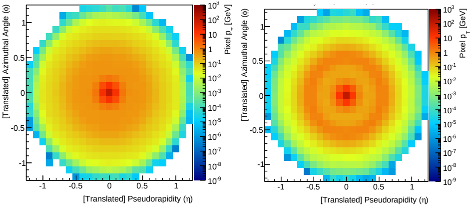
$\rightarrow$ Starting a revolution?





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→ Starting a revolution!

Towards old world

- Boston ... Heidelberg-Zürich January 2017
- physics advantages

  convincing application
  advanced benchmarking
  bring in Einstein

→ Performance AI [careers]

Deep-learning top taggers or the end of QCD?

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[c] *School of Physics and Astronomy, University of Glasgow, Glasgow G12 8QQ, Glasgow, United Kingdom*



Impact

Modern jet tagging

- 2017: What network architecture best?
- 2018: Image, text, physics architectures all work

SciPost Physics Submission

The Machine Learning Landscape of Top Taggers

G. Kasieczka (ed)[1], T. Plehn (ed)[2], A. Butter[2], K. Cranmer[3], D. Debnath[4], M. Fairbairn[5], W. Fedorko[6], C. Gay[6], L. Gouskos[7], P. T. Komiske[8], S. Leiss[1], A. Lister[6], S. Macaluso[3,4], E. M. Metodiev[8], L. Moore[9], B. Nachman,[10,11], K. Nordström[12,13], J. Pearkes[6], H. Qu[7], Y. Rath[14], M. Rieger[14], D. Shih[4], J. M. Thompson[2], and S. Varma[5]

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6 Department of Physics and Astronomy, The University of British Columbia, Canada
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8 Center for Theoretical Physics, MIT, Cambridge, USA
9 CP3, Université Catholique de Louvain, Louvain-la-Neuve, Belgium
10 Physics Division, Lawrence Berkeley National Laboratory, Berkeley, USA
11 Simons Inst. for the Theory of Computing, University of California, Berkeley, USA
12 National Institute for Subatomic Physics (NIKHEF), Amsterdam, Netherlands
13 LPTHE, CNRS & Sorbonne Université, Paris, France
14 III. Physics Institute A, RWTH Aachen University, Germany

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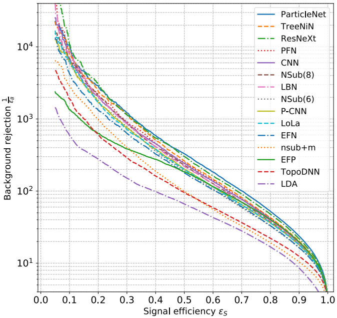
April 12, 2019

Abstract

Based on the established task of identifying boosted, hadronically decaying top quarks, we compare a wide range of modern machine learning approaches. We find that they are extremely powerful and great fun.



Impact

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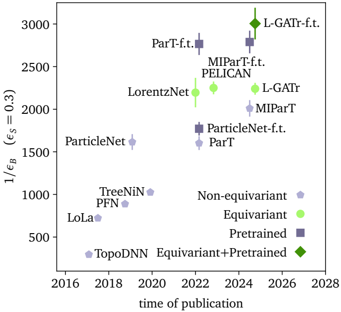
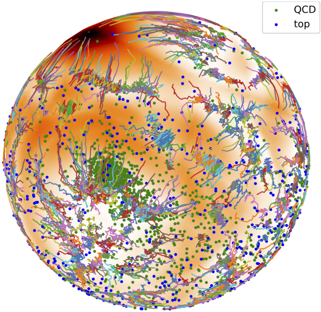
- 2017: What network architecture best?
- 2018: Image, text, physics architectures all work
- 2024: ML-classification standard [10x moment]

$\rightarrow$ Understandable AI





Detector calibration

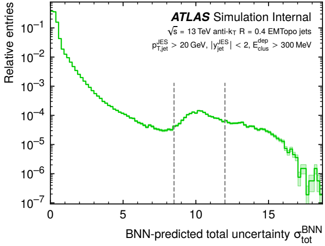
Energy correction with uncertainties

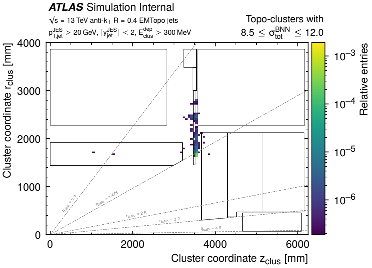
- learned calibration

$$\mathcal{R}_\theta(x) \pm \Delta\mathcal{R}_\theta(x) \approx \frac{E^{\text{obs}}(x)}{E^{\text{dep}}(x)}$$

- systematics: noise in data
  network expressivity
  data representation ...

$\rightarrow$ Pro-bono AI





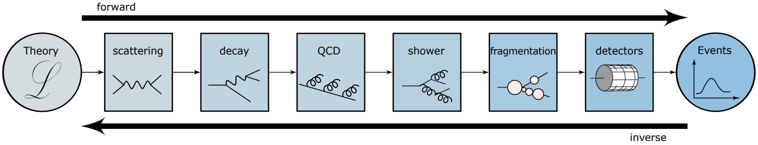
Generative AI

Forward and inverse simulations

- conditional probabilities from joint probabilities

$$\begin{tikzcd}
p_\text{sim}(x_\text{part}) \arrow[r, leftrightarrow, "\text{inference}"] \arrow[d, "p(x_\text{reco}|x_\text{part})"'] & p_\text{unfold}(x_\text{part}) \\
p_\text{sim}(x_\text{reco}) \arrow[r, leftrightarrow, "\text{inference}"] & p_\text{data}(x_\text{reco}) \arrow[u, "p(x_\text{part}|x_\text{reco})"']
\end{tikzcd}$$

- forward: collisions, fragmentation, detector,...
- inverse: unfolding, de-convolution, inference,...



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- forward: collisions, fragmentation, detector,...
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Techniques [images and text]

- generative adversarial networks [2019]
- normalizing flow [2020]
- diffusion [2023]
- diffusion with attention [2023]
- autoregressive transformer [2023/2024]
- equivariant diffusion generator [2024]

→ Fast-moving AI

Outlook

AI in particle physics

- trustable AI crucial for quantitative science
- performance AI to convince users
- understandable AI for deep problems
- transformative AI generating excitement and progress [ML4Jets]