# Transforming Particle Physics using the AI Toolbox

Tilman Plehn

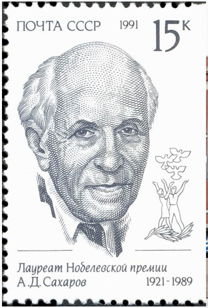
Universität Heidelberg

Baden-Württemberg Forschungstag 2024

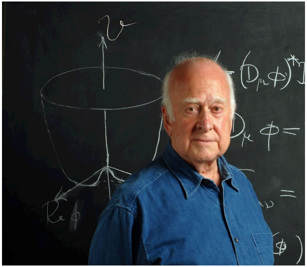
# AI and Modern particle physics

## Classic motivation

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







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

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- counting particles
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- looking for more discoveries

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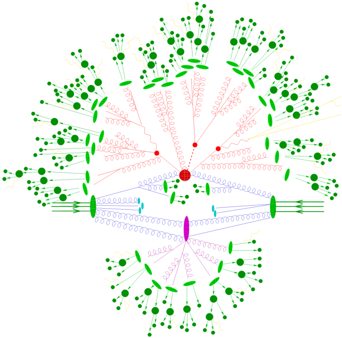

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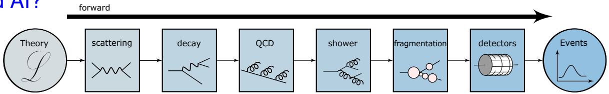
## Future analyses

- compare simulations and data
- understand LHC dataset completely
- determine underlying theory

$\to$ Data science and AI!



# Trust, Understand, Transform

# Internationale Spitzenforschung

## LHC collaborations

- ATLAS & CMS general purpose
  LHCb, ALICE, FASER... specialized
- international collaborations
  5000 scientists per experiment

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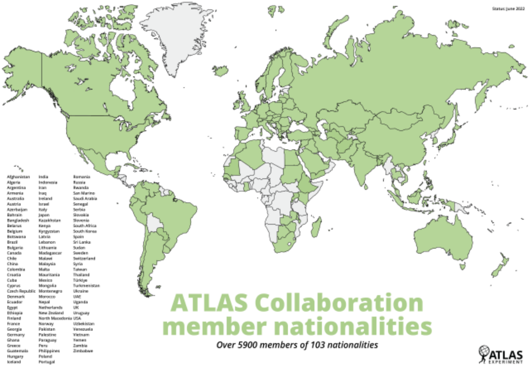

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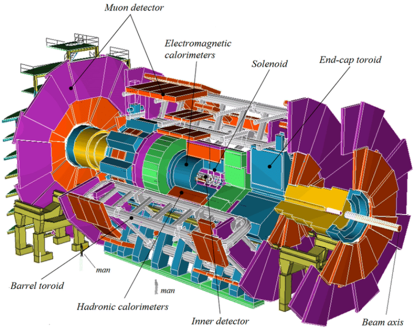
## LHC detectors

- measuring all outgoing particles
- seriously big and complex...



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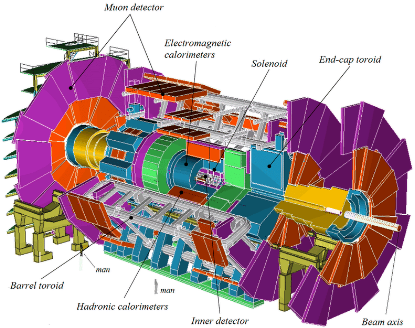
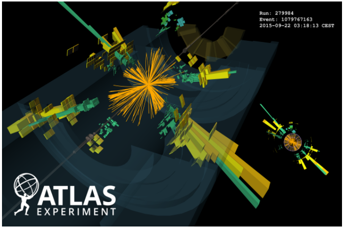



## LHC Event



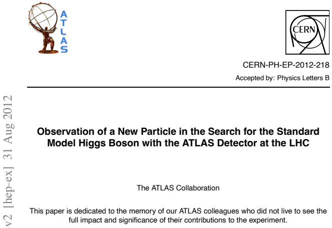

- colliding two protons at 40 MHz
- producing old and new particles
- most particles decaying
- measure energy, charge, etc
- electrons, muons easy
  quarks, gluons hard
- event: 100+ vectors $(E, \vec{p}, Q)$

$\rightarrow$ ATLAS output 3 PB/s

# Discovering (elementary) particles

## 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.

# Discovering (elementary) particles

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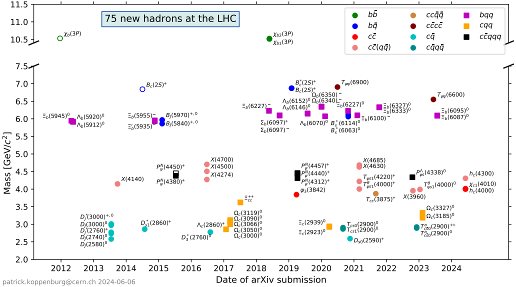
- 75 more discovered particles
- particles ↔ elementary particles?
  like proton vs electron
  no size, structure, constituents



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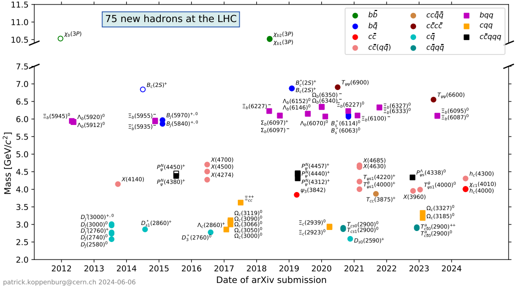
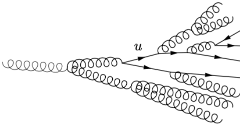



→ discoveries hiding in LHC data
guarantee we do not miss anything in PB/s

→ Trustworthy AI

# AI-Jet physics




## Partons as jets

- most interactions just $q\bar{q}, gg \to q\bar{q}, gg$
- quarks/gluon visible as jets
  splittings described by QCD
  hadronization and hadron decays in 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 physics as 'dark jets'

$\to$ Everywhere in LHC physics

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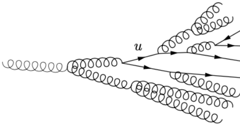


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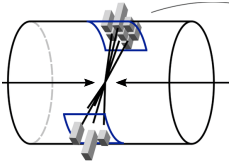
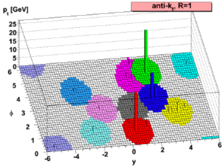


## Dealing with jets

- 50-200 constituents per jet
  40 simultaneous scatterings
- jet algorithms returning energy and momentum
- sub-jet physics new at LHC

$\to$ Crucial for precision hadron collider



# November revolution

## Stanford, Nov 16, 2015

- interpret jet signal as image
- analyze using image networks [CNNs]

**Jet-Images – Deep Learning Edition**

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

[a] *Institute for Computational and Mathematical Engineering, Stanford University, Stanford, CA 94305, USA*
[b] *SLAC National Accelerator Laboratory, Stanford University, 2575 Sand Hill Rd, Menlo Park, CA 94025, U.S.A.*
[a] *Department of Statistics, Stanford University, Stanford, CA 94305, USA*
*E-mail:* lukedeo@stanford.edu, mkagan@cern.ch, lmackey@stanford.edu, bnachman@cern.ch, sch@slac.stanford.edu

v1 [hep-ph] 16 Nov 2015

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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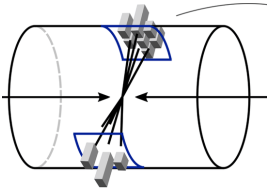
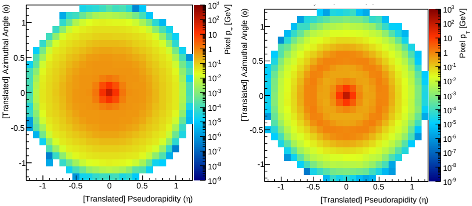
$\to$ Starting a revolution?





# November revolution

## Stanford, Nov 16, 2015

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→ Starting a revolution!

## Starting slowly

- MIT/Harvard December 2016
  Heidelberg January 2017
- looking for convincing application
- comparison with standard methods
- using special relativity

→ First working analysis tool

# Hello World of LHC-AI

## History of 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]

**1** Institut für Experimentalphysik, Universität Hamburg, Germany
**2** Institut für Theoretische Physik, Universität Heidelberg, Germany
**3** Center for Cosmology and Particle Physics and Center for Data Science, NYU, USA
**4** NHECT, Dept. of Physics and Astronomy, Rutgers, The State University of NJ, USA
**5** Theoretical Particle Physics and Cosmology, King's College London, United Kingdom
**6** Department of Physics and Astronomy, The University of British Columbia, Canada
**7** Department of Physics, University of California, Santa Barbara, USA
**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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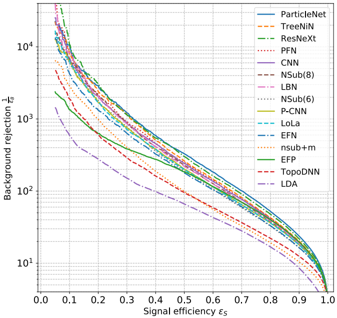
April 12, 2019

### 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.**



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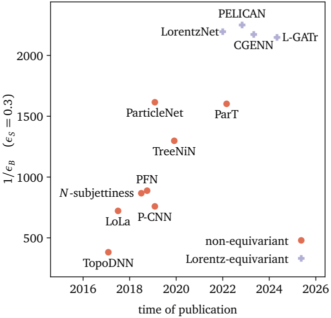
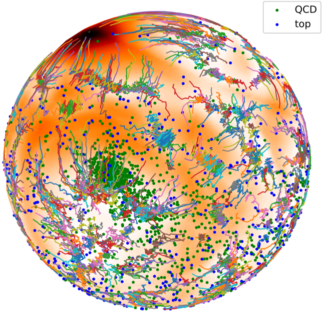
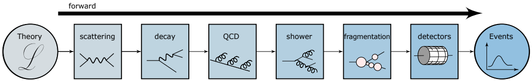
- 2018: Image, text, physics architectures all work
- 2024: ML-classification standard
- known and learned structures the future

$\rightarrow$ Understandable AI



# Generative AI




## First-principle simulations

- start with particles
  and their interactions
- compute scattering amplitudes
  include decays
  add extra jets
- apply parton shower
  create and decay hadrons
- simulate detector

$\rightarrow$ Modular precision simulations

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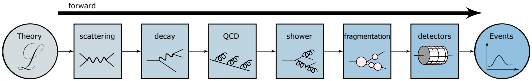


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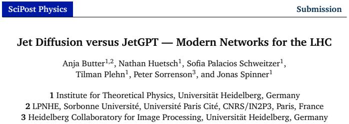
- generative adversarial networks [2019]
- normalizing flow [2020]
- diffusion [2023]
- diffusion with attention [2023]
- autoregressive transformer [2023/2024]


SciPost Physics Submission

**Jet Diffusion versus JetGPT — Modern Networks for the LHC**

Anja Butter[1,2], Nathan Huetsch[1], Sofia Palacios Schweitzer[1],
Tilman Plehn[1], Peter Sorrenson[3], and Jonas Spinner[1]

**1** Institute for Theoretical Physics, Universität Heidelberg, Germany
**2** LPNHE, Sorbonne Université, Université Paris Cité, CNRS/IN2P3, Paris, France
**3** Heidelberg Collaboratory for Image Processing, Universität Heidelberg, Germany

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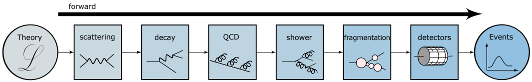


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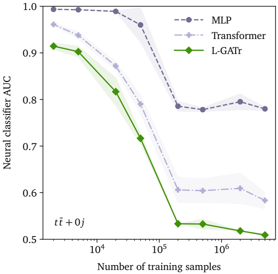
- equivariant diffusion generator [2024]

$\to$ Work vs glamour...



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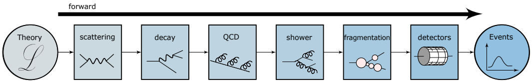


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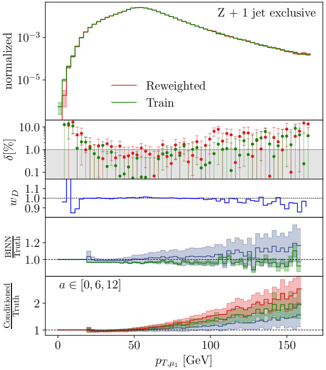
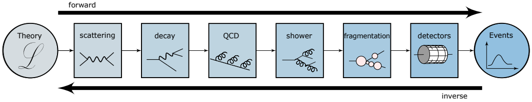
→ And then we add error bars



# Inverse simulation




## Number of analyses

- backgrounds known
- too many potential signals

$\rightarrow$ Backwards-simulate detector once

## Optimal analyses

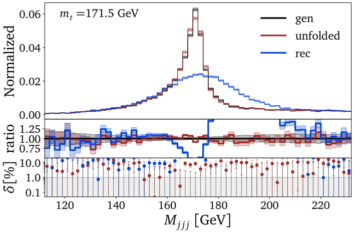
- make use of continuous progress
- allow for analyses to be updated

$\rightarrow$ Backwards-simulate detector and save data

## Public data

- common lore:
  LHC data too complicated for amateurs
- in truth:
  scattering simulations easy

$\rightarrow$ Backwards-simulate to hard scattering



# Outlook

## AI in particle physics

- thank you to the BW-Foundation for fundings us!
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- trustable AI crucial for quantitative science
- understandable AI for established problems
- transformative AI generating excitement
- if you think society is tough, try 10000 university physicists...

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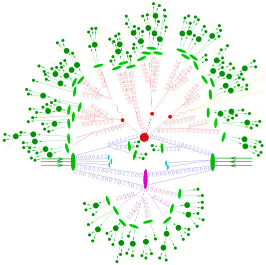
→ instead of a conclusion...



→

**JUNE:**
**open-source individual-based epidemiology simulation**

Joseph Bullock[1,2,*], Carolina Cuesta-Lazaro[1,3,*], Arnau Quera-Bofarull[1,3,*], Miguel Icaza-Lizaola[1,3,**], Aidan Sedgewick[1,4,**], Henry Truong[1,2,**], Aoife Curran[1,3], Edward Elliott[1,3], Tristan Caulfield[7], Kevin Fong[8,9], Ian Vernon[1,6], Julian Williams[5], Richard Bower[1,3], and Frank Krauss[1,2,+]

[1]Institute for Data Science, Durham University, Durham DH1 3LE, UK
[2]Institute for Particle Physics Phenomenology, Durham University, Durham DH1 3LE, UK
[3]Institute for Computational Cosmology, Durham University, Durham DH1 3LE, UK
[4]Centre for Extragalactic Astronomy, Durham University, Durham DH1 3LE, UK
[5]Institute for Hazard, Risk & Resilience, Durham University, Durham DH1 3LE, UK
[6]Department of Mathematical Sciences, Durham University, Durham DH1 3LE, UK
[7]Department of Computer Science, University College of London, London WC1E 6BT, UK
[8]Department of Science, Technology, Engineering and Public Policy, University College London, London WC1E 6BT, UK
[9]Department of Anaesthesia, University College London Hospital, London NW1 2BU, UK
[*]Equal contribution
[**]Equal contribution
[+]Corresponding author: frank.krauss@durham.ac.uk

**Abstract:** We introduce JUNE, an open-source framework for the detailed simulation of epidemics on the basis of social interactions in a virtual population constructed from geographically granular census data, reflecting age, sex, ethnicity, and socio-economic indicators. Interactions between individuals are modelled in groups of various sizes and properties, such as households, schools and workplaces, and other social activities using social mixing matrices. JUNE provides a suite of flexible parameterisations that describe infectious diseases, how they are transmitted and affect contaminated individuals. In this paper we apply JUNE to the specific case of modelling the spread of COVID-19 in England. We discuss the quality of initial model outputs which reproduce reported hospital admission and mortality statistics at national and regional levels as well as by age strata.