Machine Learning for High-Energy Physics Reconstruction and Analysis

Sergei V. Gleyzer



University of Alabama

AI4EIC Workshop

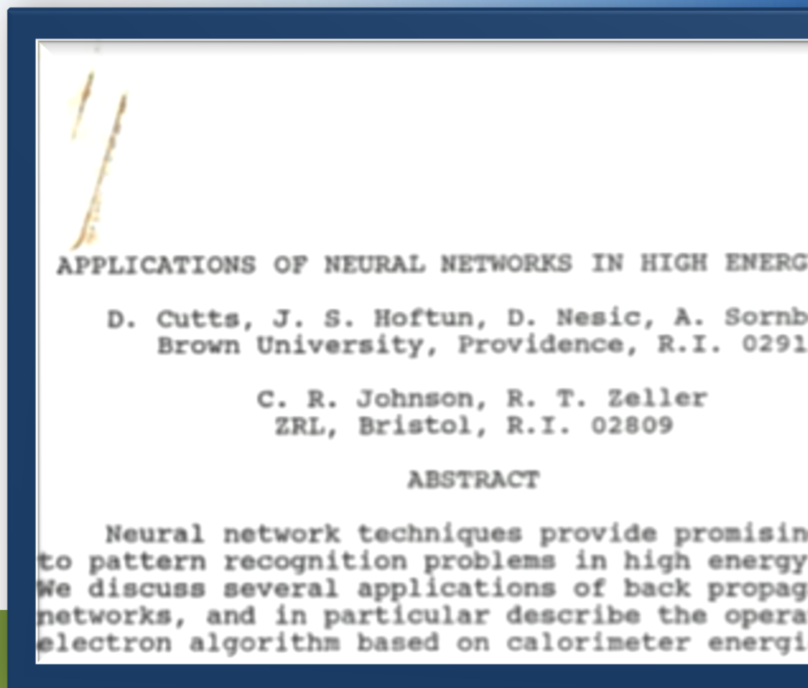
Sep. 8, 2021

Outline

- Introduction
- Machine Learning in High-Energy Physics Reconstruction and Analysis
  - LHC/HL-LHC Applications

Machine Learning in Particle Physics

History



DOE/ER/03130-52C
COO-3130TC-52
D0 Note 964

APPLICATIONS OF NEURAL NETWORKS IN HIGH ENERGY

D. Cutts, J. S. Hoftun, D. Nesic, A. Sornb
Brown University, Providence, R.I. 02912

C. R. Johnson, R. T. Zeller
ZRL, Bristol, R.I. 02809

ABSTRACT

Neural network techniques provide promising
to pattern recognition problems in high energy
We discuss several applications of back propaga
networks, and in particular describe the operation of an
electron algorithm based on calorimeter energies.

Machine Learning in HEP is as old as the web!

Large Hadron Collider

Modern scientific wonder:

Operating since 2010

Expected to run for the
next 15 years

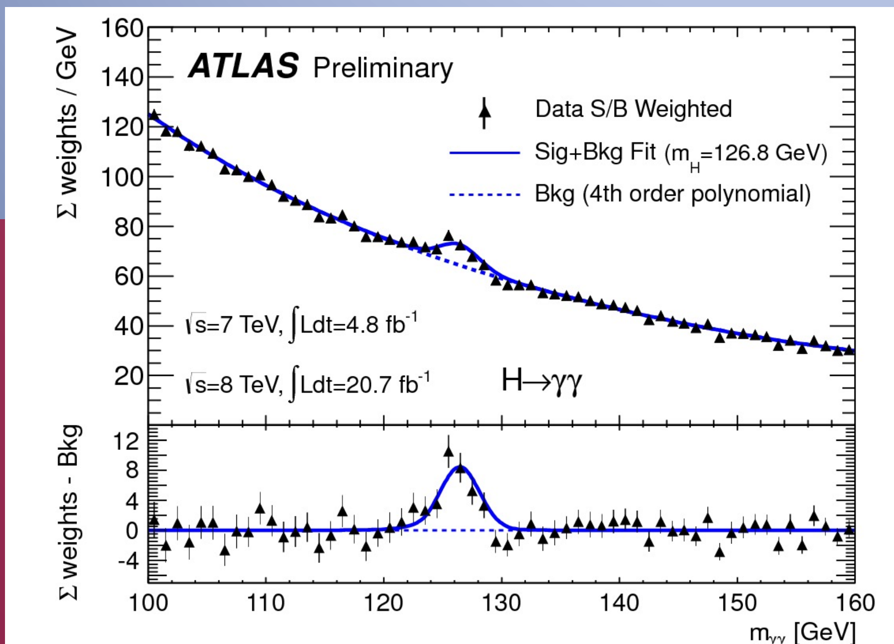
Amazing success of an international collaboration of thousands of scientists from across the world

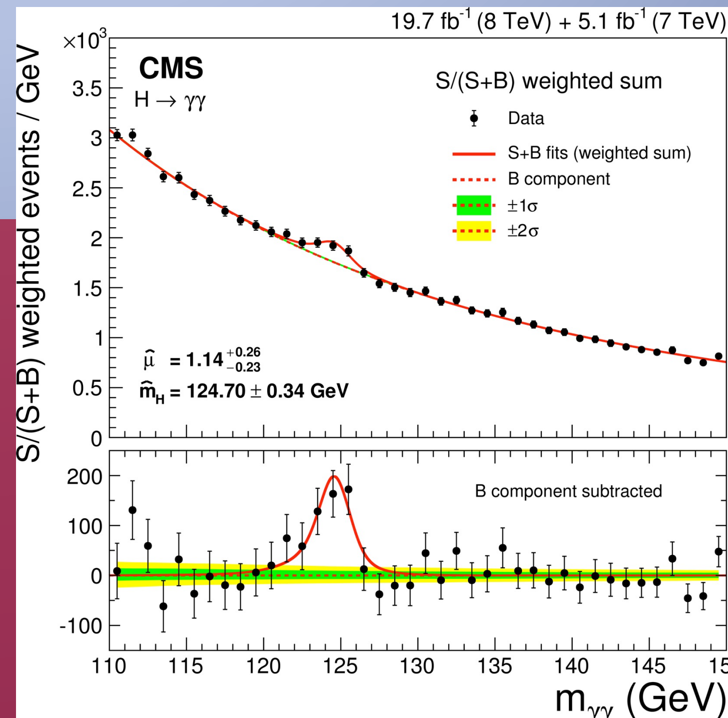
Higgs Discovery

July 4, 2012

Higgs Discovery

Higgs to di-photons





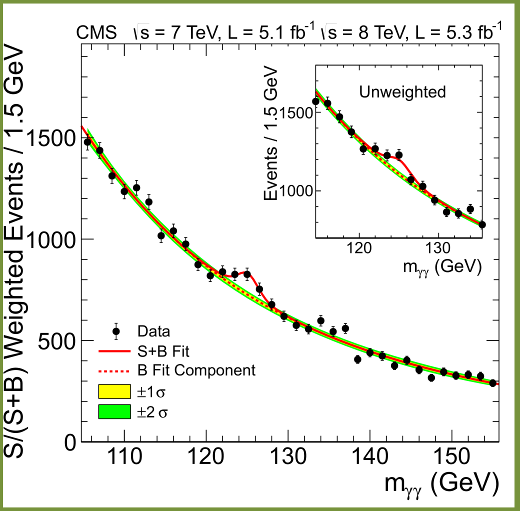
ATLAS

CMS

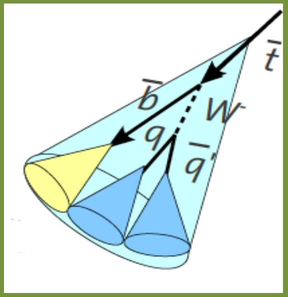
High-Energy Physics Today

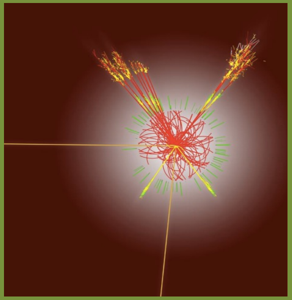
Machine learning at the forefront of what we do:

- Physics object **identification**
- Event type **classification**
- Fast event **generation**
- Object properties **regression**

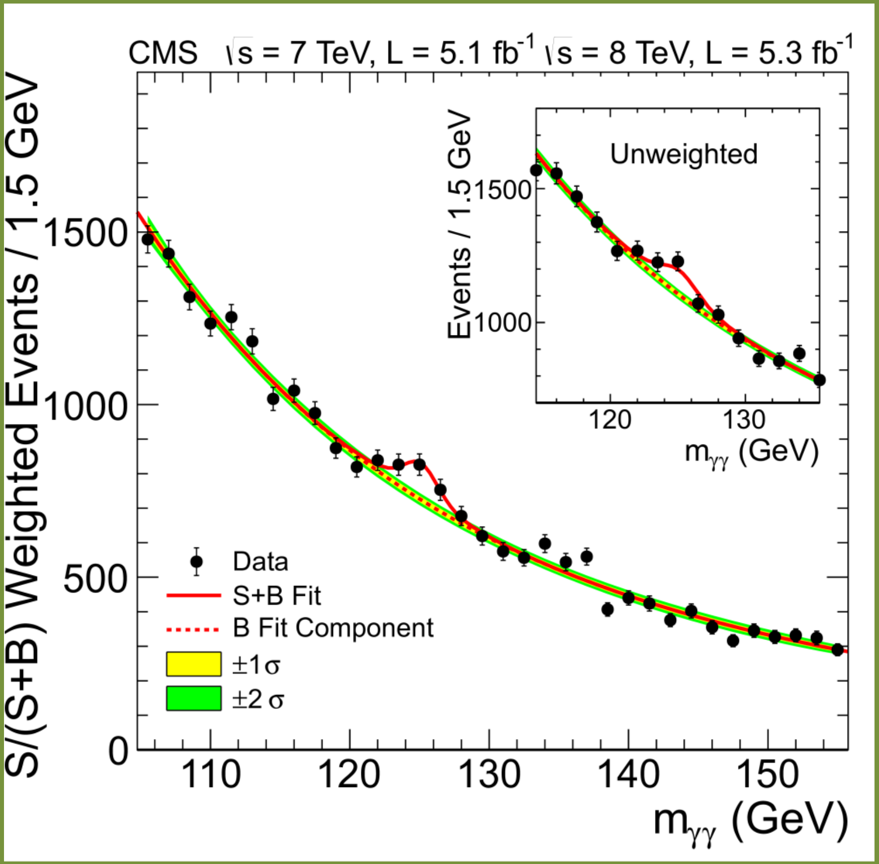


Expanding quickly

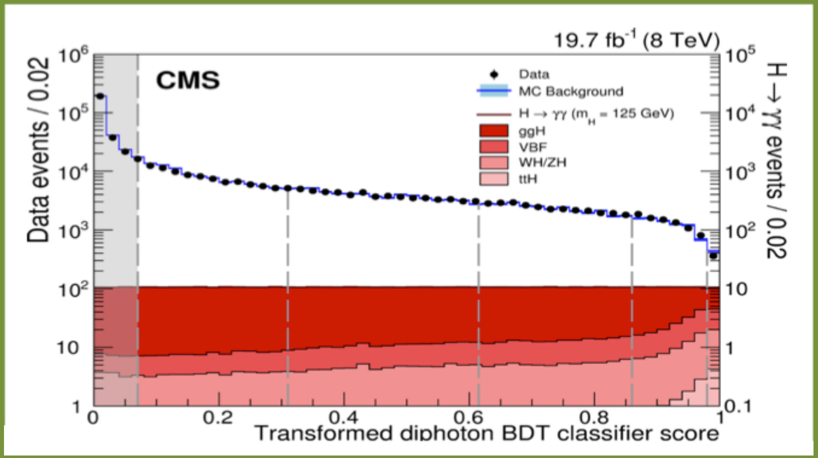




In Higgs Discovery

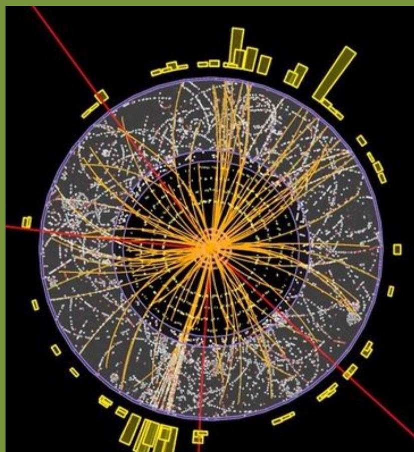


- Identification of particles
- Identification of interactions
- Energy regression
- Event selection

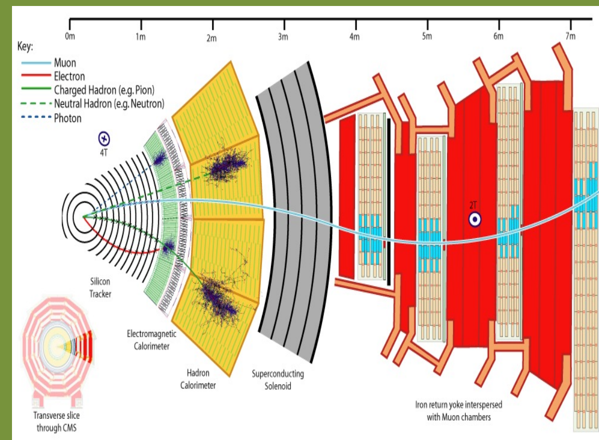


Improvement in analysis from all four areas

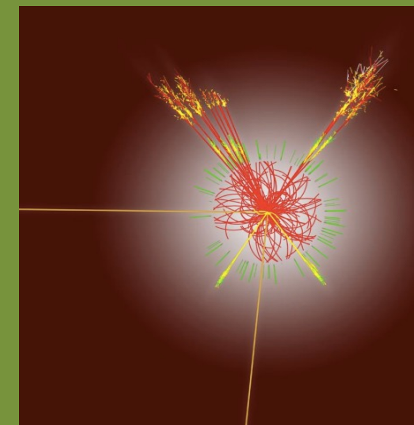
Relevant areas



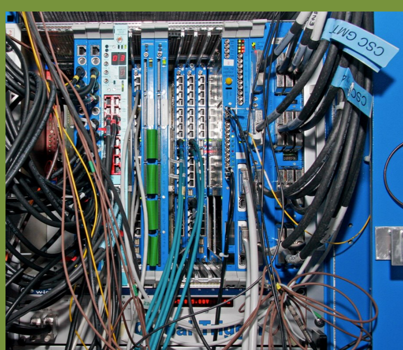
Tracking



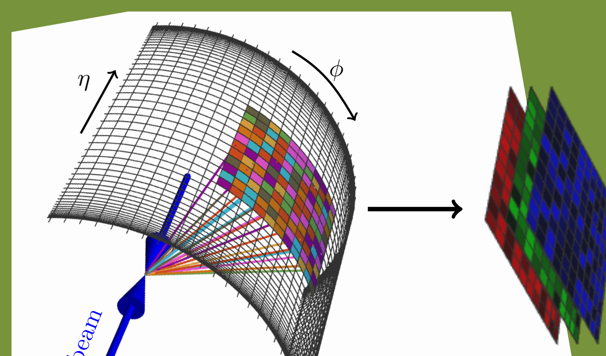
Object Identification



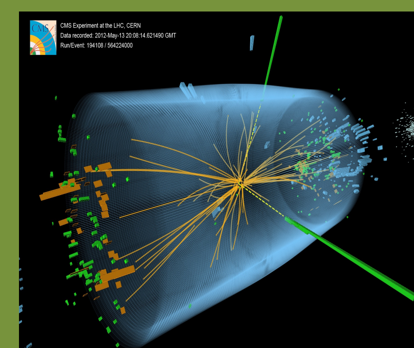
Fast Simulation



Trigger



Graph/Imaging Techniques



Event Level ID

First DNN paper in HEP

Searching for Exotic Particles in High-Energy Physics with Deep Learning

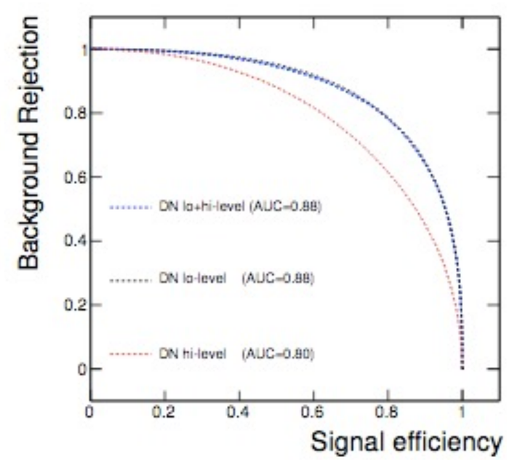
P. Baldi,[1] P. Sadowski,[1] and D. Whiteson[2]

[1]*Dept. of Computer Science, UC Irvine, Irvine, CA 92617**

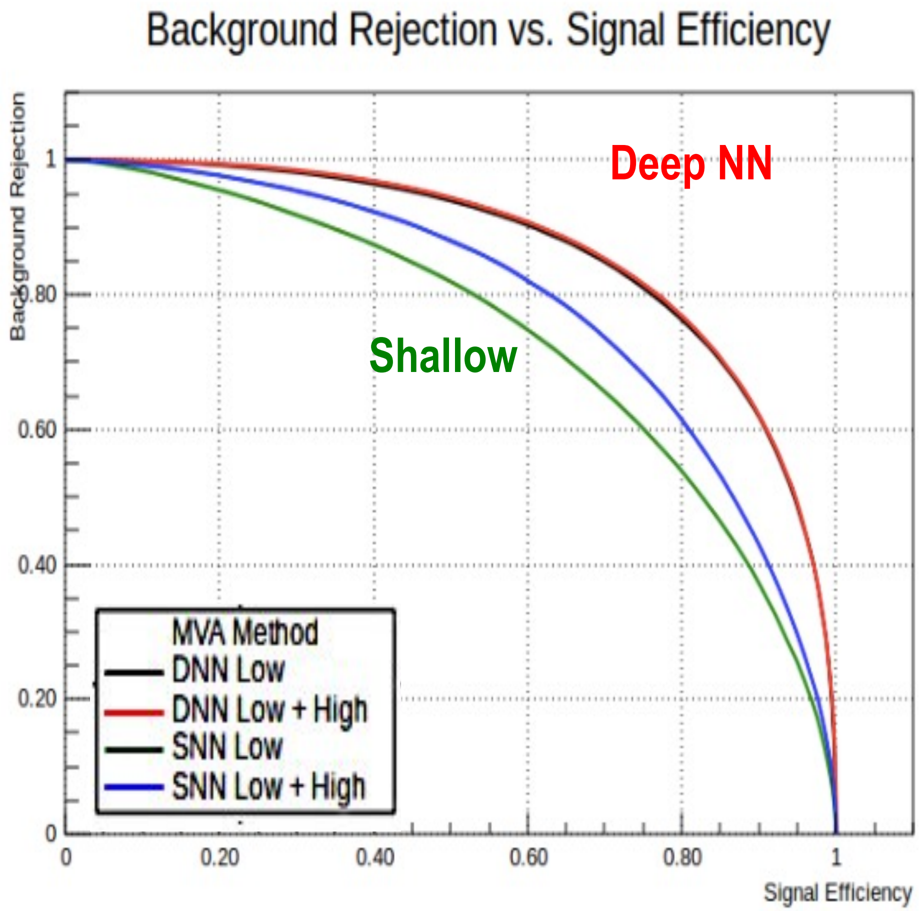
[2]*Dept. of Physics and Astronomy, UC Irvine, Irvine, CA 92617*†

Collisions at high-energy particle colliders are a traditionally fruitful source of exotic particle discoveries. Finding these rare particles requires solving difficult signal-versus-background classification problems, hence machine learning approaches are often used. Standard approaches have relied on 'shallow' machine learning models that have a limited capacity to learn complex non-linear functions of the inputs, and rely on a pain-staking search through manually constructed non-linear features. Progress on this problem has slowed, as a variety of techniques have shown equivalent performance. Recent advances in the field of deep learning make it possible to learn more complex functions and better discriminate between signal and background classes. Using benchmark datasets, we show that deep learning methods need no manually constructed inputs and yet improve the classification metric by as much as 8% over the best current approaches. This demonstrates that deep learning approaches can improve the power of collider searches for exotic particles.

Baldi, Sadowski, & Whiteson, 2014



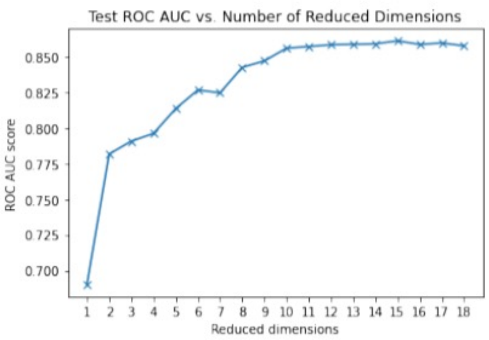
Feature Extraction



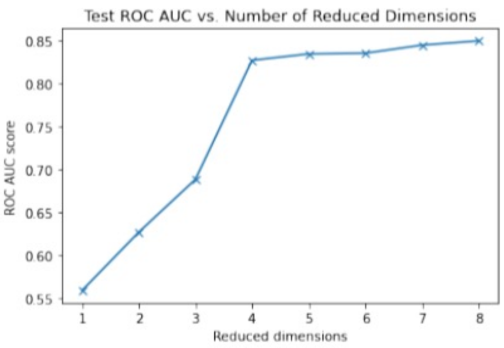
Feature Extraction

- $\not{E}_T{}^{Rel}$: $\not{E}_T$if $\Delta\phi \geq \pi/2$, $\not{E}_T\sin(\Delta\phi)$ if $\Delta\phi < \pi/2$, where $\Delta\phi$ is the minimum angle between $\not{E}_T$and a lepton
- Axial $\not{E}_T$, the missing transverse energy along the vector defined by the charged leptons
- Stransverse mass M_{T2}
- Razor quantities β, R, and M_R
- Super-razor quantities β_{R+1}, $\cos(\theta_{R+1})$, $\Delta\phi_R^\beta$, M_Δ^R, M_R^T, and $\sqrt{\hat{s}_R}$

SUSY high-level features



(a) ROC all variables

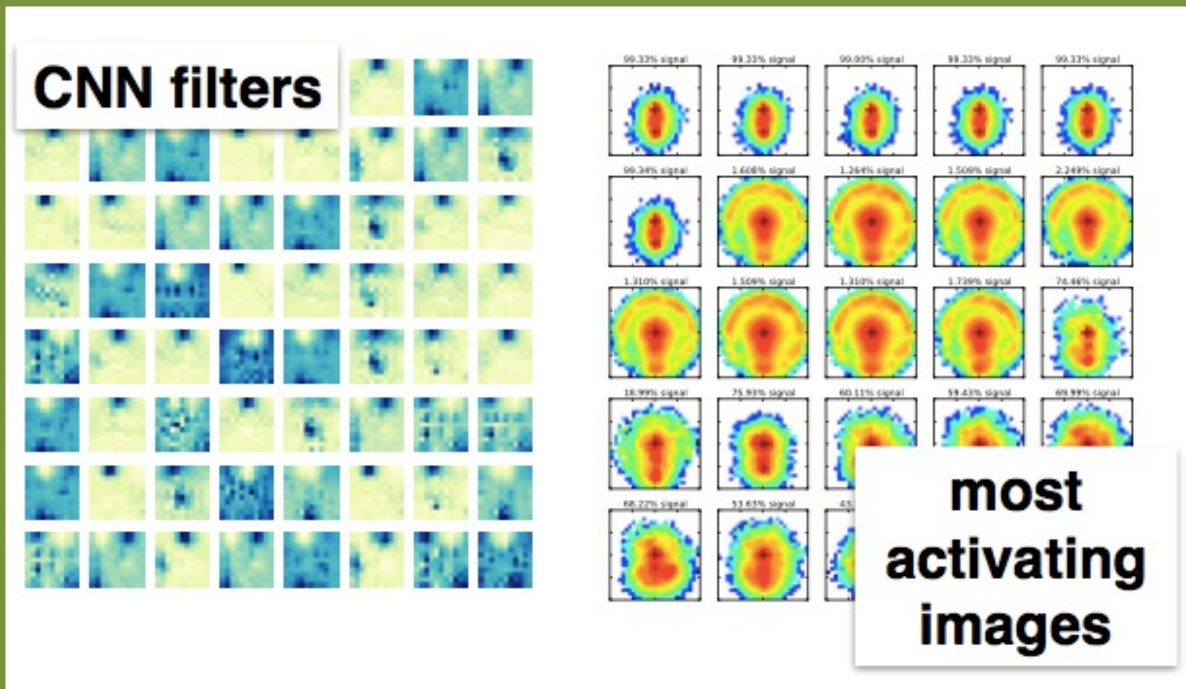


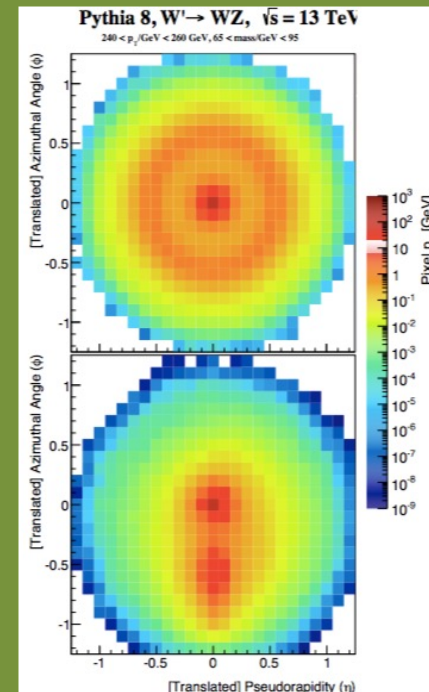
(a) ROC low level only

SUSY Classification

Jet Images

With convolutional neural networks



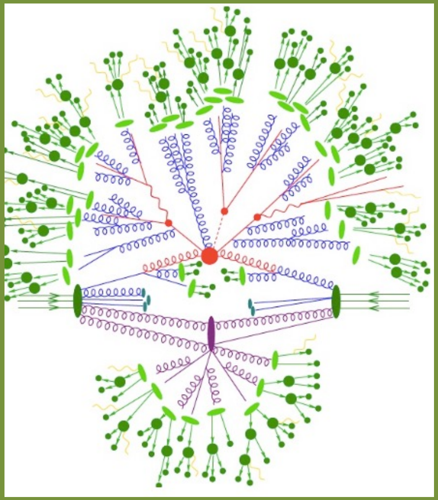


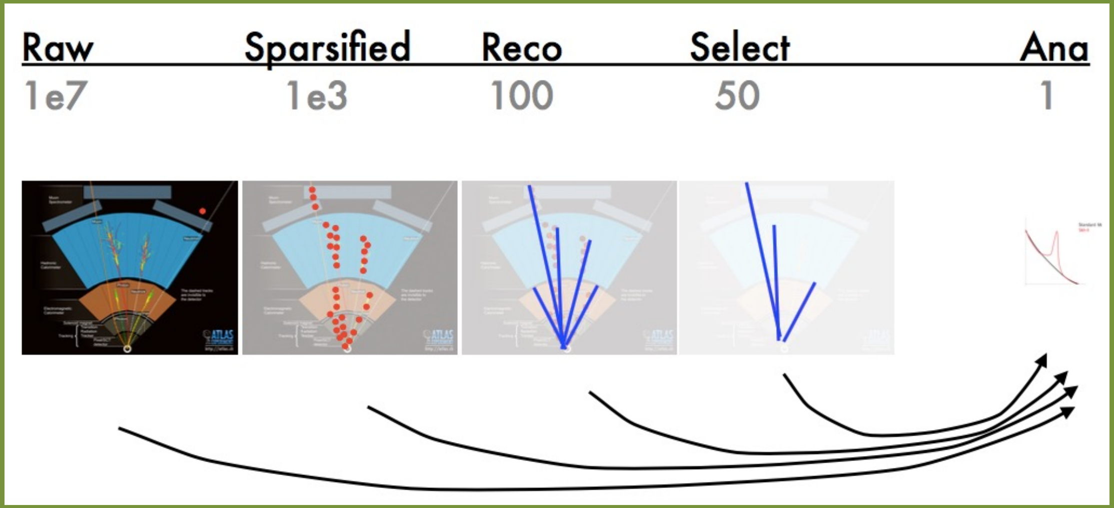
Oliveira et al., JHEP 07 (2016) 069

Key Question

Can we fully exploit the detectors?

low-level data + modern deep learning

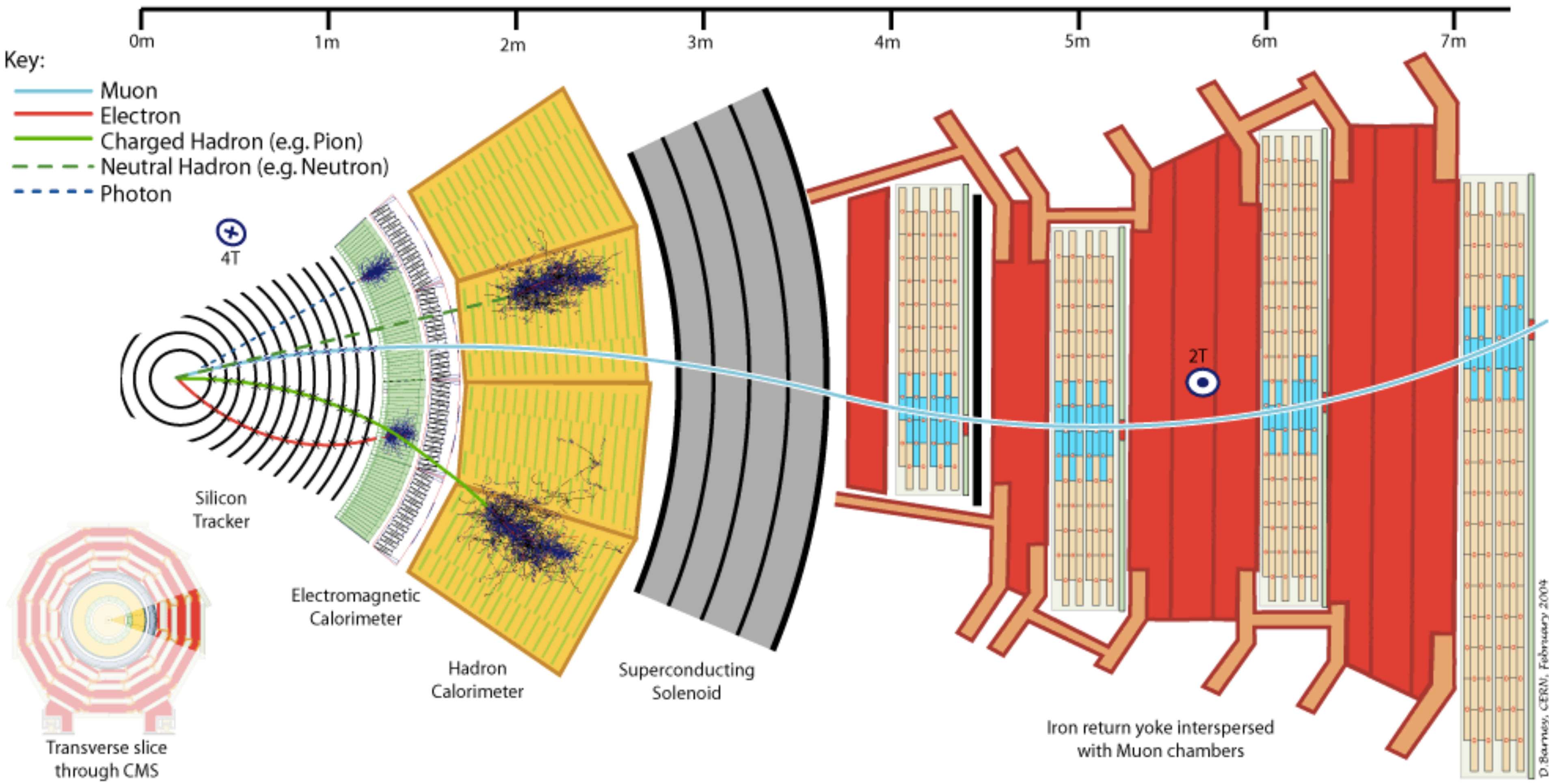




Andrews et al *2018, 2020*

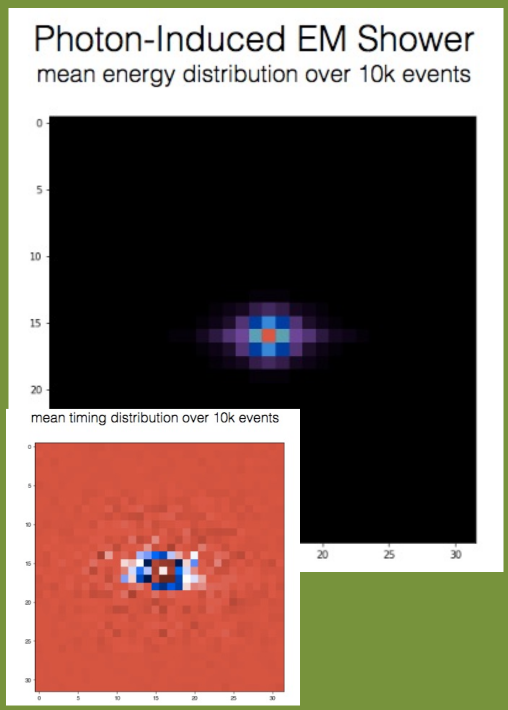
End-end learning

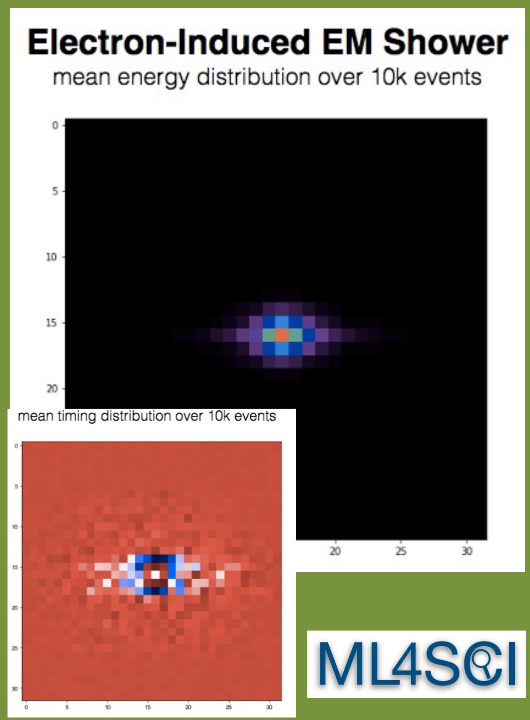
CMS Detector and Particle ID

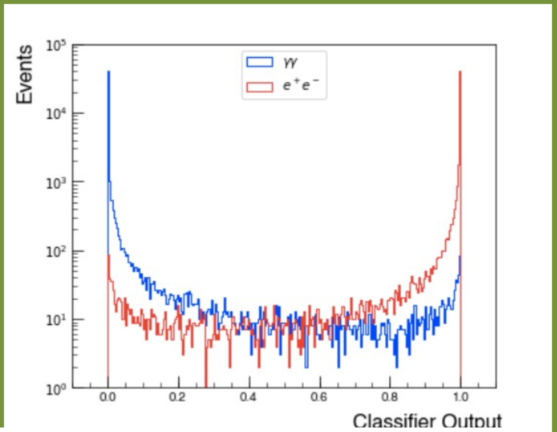


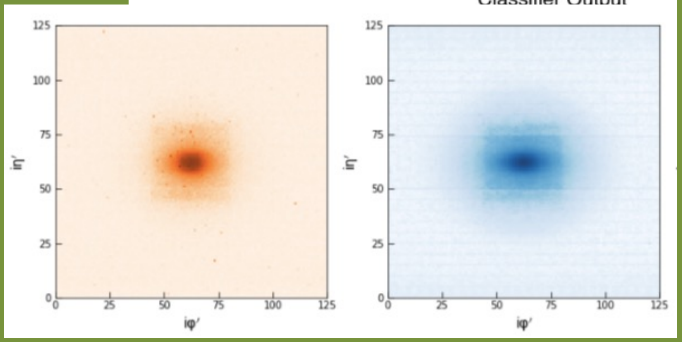
End-to-End Learning

By-passing traditional reconstruction with deep neural networks







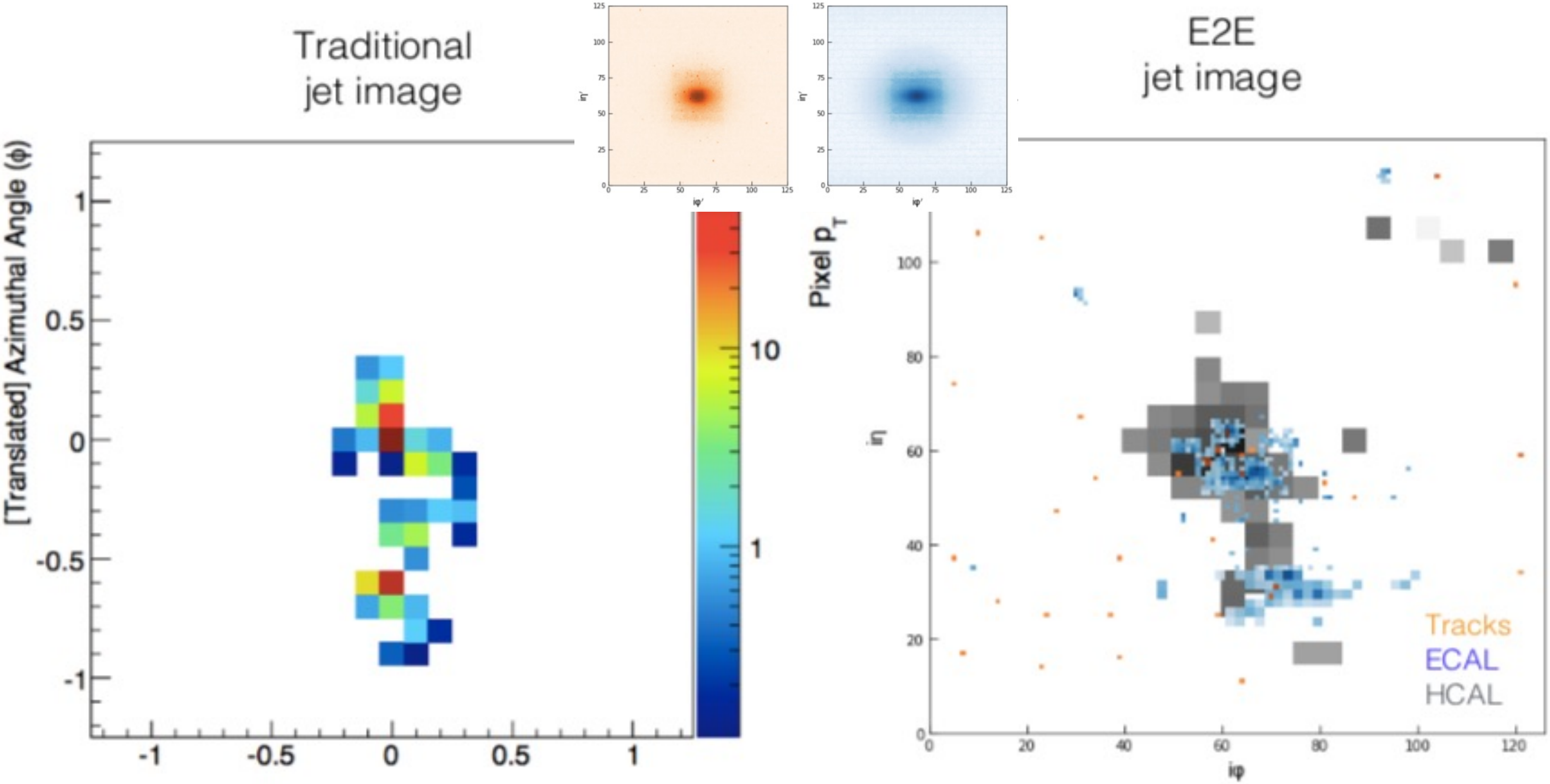


arXiv:1807.11916

arXiv:1907.08276

ML4SCI

End-to-End Jets



Andrews et al. 2020

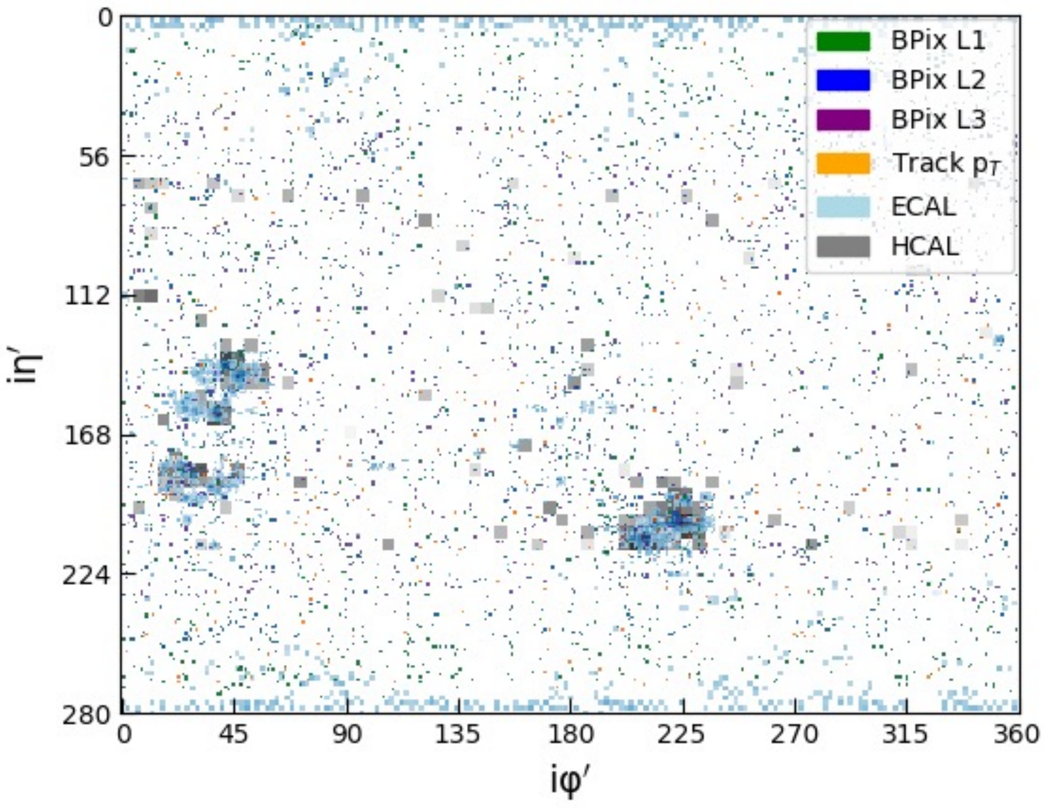
Jet ID | quark vs gluon

	ROC AUC
E2E image, ECAL+HCAL+Tracks	**0.8077 ± 0.0003***
RecNN, ascending-p_T	0.8017 ± 0.0003*
RecNN, descending-p_T	0.802
RecNN, anti-k_T	0.801
RecNN, Cambridge/Aachen	0.801
RecNN, no rotation/reclustering	0.800
RecNN, k_T	0.800
RecNN, k_T-colinear10-max	0.799
RecNN, random	0.797
Traditional Jet Images	0.721

- **RecNN Results, Jet ID**
  - Use 4-momenta derived from CMS Particle Flow
  - Perform boost/rotation, then reclustering with different algos
  - **E2E jet images perform well**

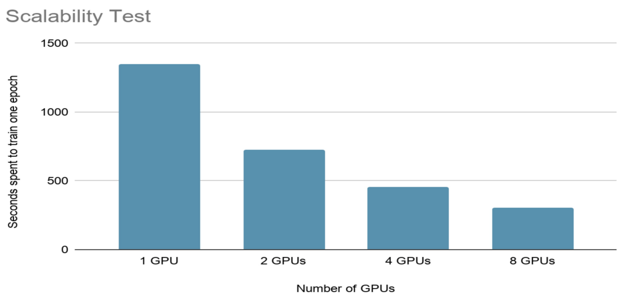
Andrews et al. 2020

End-to-End Top ID



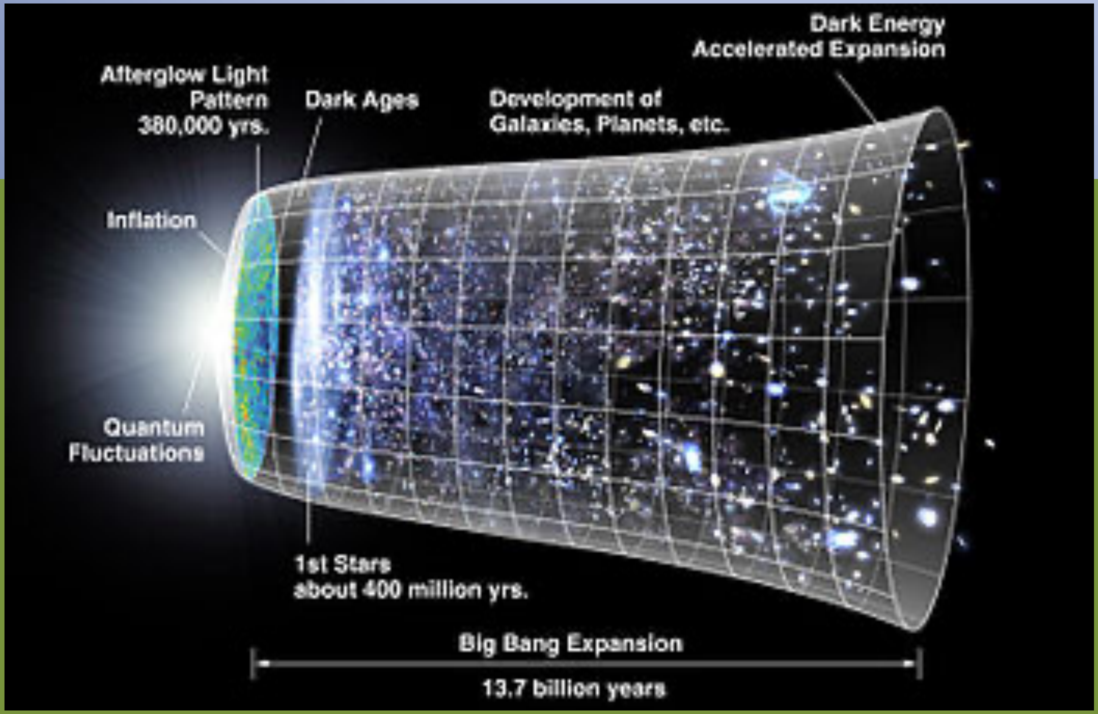
Block	Layer Type	Extra Parameters
Input Node	Conv 2D	filter size 7, stride 2, 16 channels
	Global Pool 2D	2×2 pool size
Resblock 1	Conv 2D	filter size 3, stride 1, 16 channels
	Conv 2D	filter size 3, stride 1, 16 channels
Resblock 2	Conv 2D	filter size 3, stride 2, 32 channels
	Conv 2D	filter size 3, stride 1, 32 channels
Resblock 3	Conv 2D	filter size 3, stride 1, 32 channels
	Conv 2D	filter size 3, stride 1, 32 channels
Output Node	Max Pooling 2D	global pool size
	Dense	size 32×2
	Activation	Sigmoid

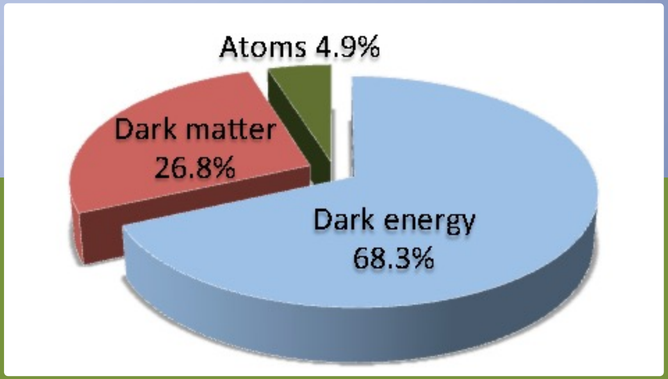
Layer Combinations	ROC-AUC
BPIX1–3	0.947±0.002
BPIX1–3 + Track p_T	0.965±0.002
BPIX1–3 + ECAL + HCAL (no reconstructed variables)	0.975±0.002
BPIX1–3 + Track p_T + $d0$ + dZ	0.977±0.002
BPIX1–3 + Track p_T + $d0$ + dZ + ECAL + HCAL (full image)	0.9824±0.0013

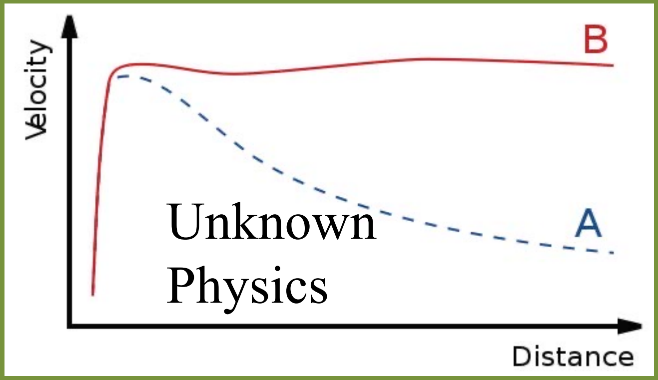


Andrews et al. (2021)

Upcoming Challenges



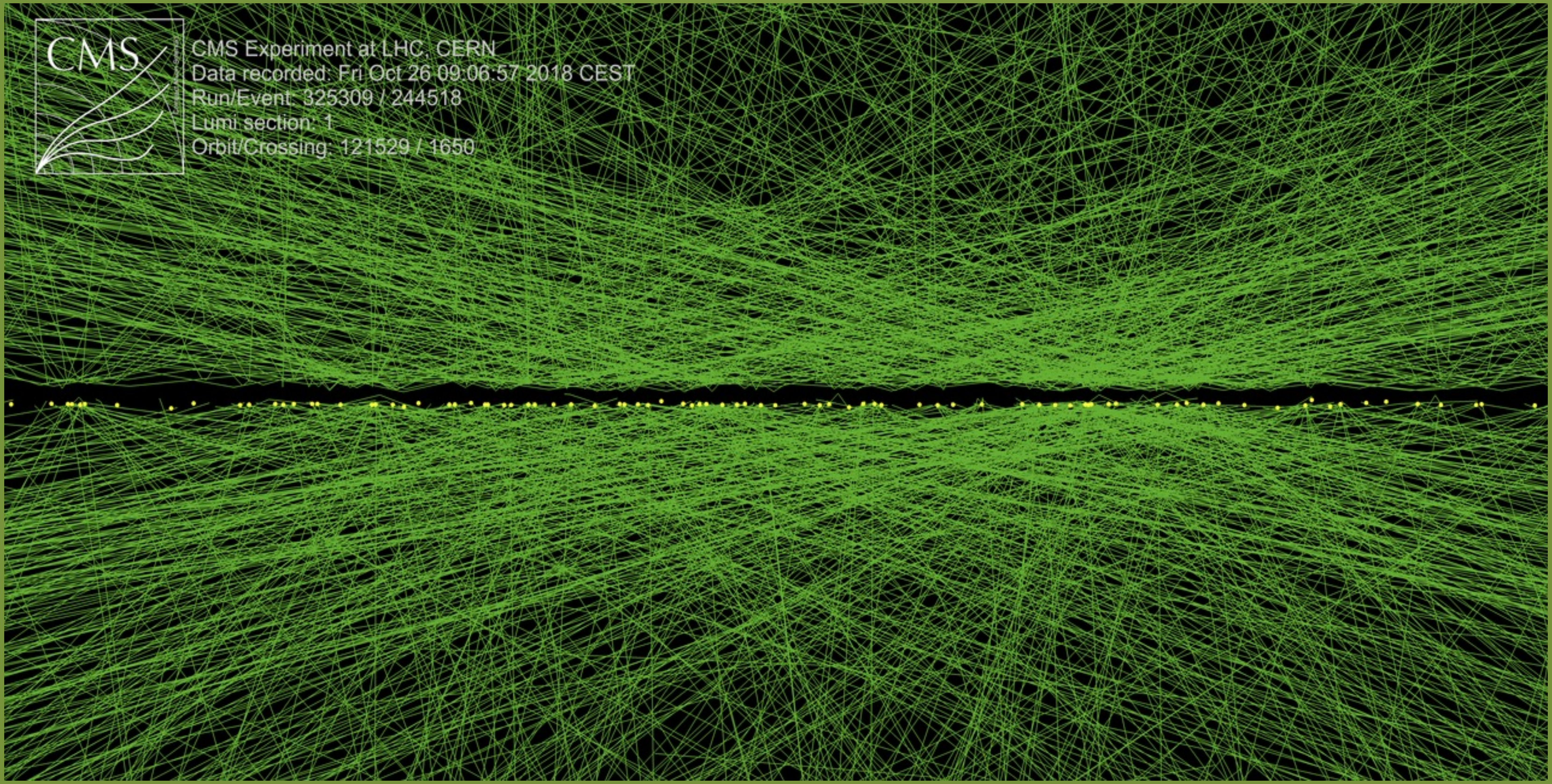




Data size:

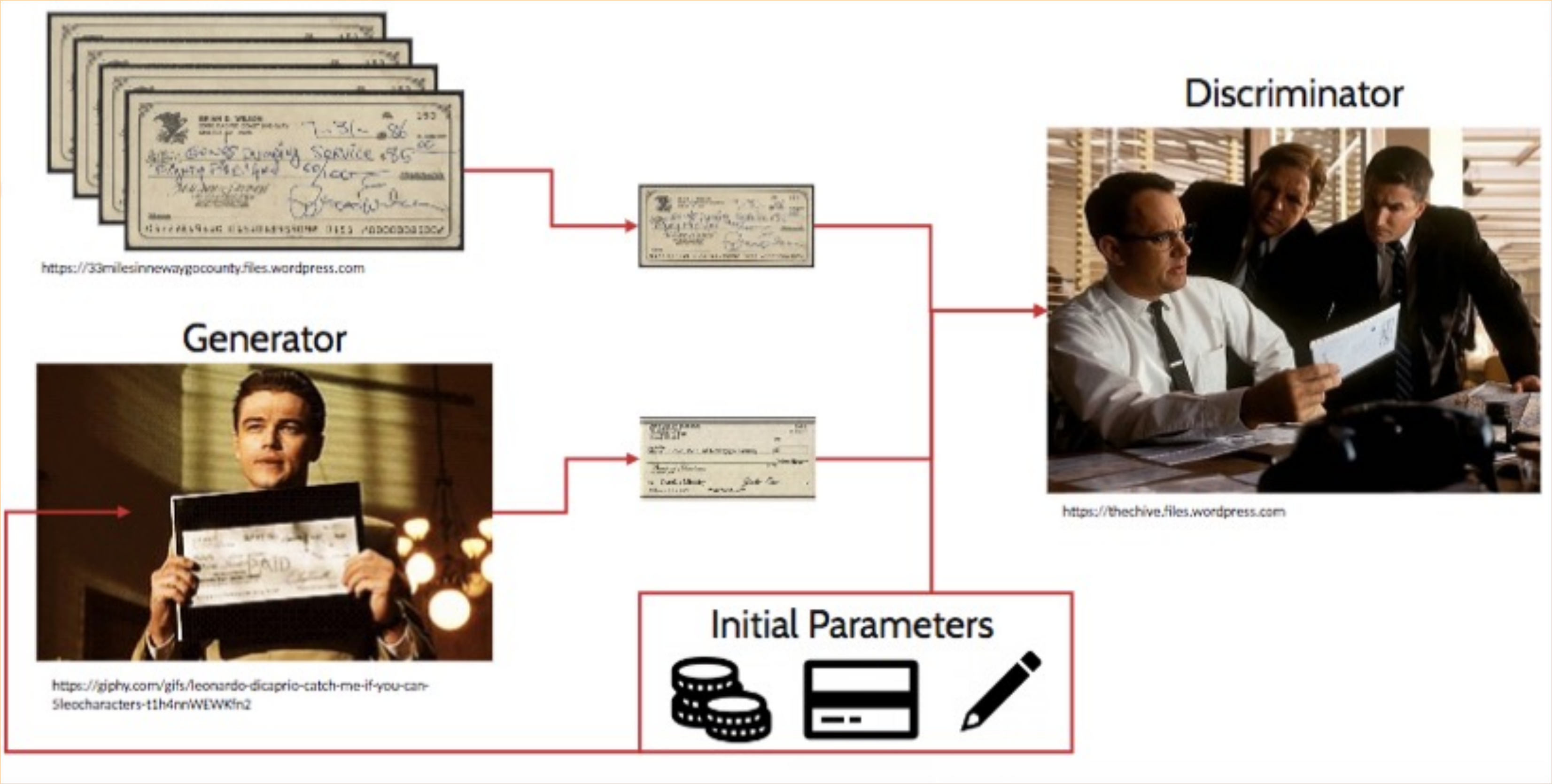
– LHC **15,000,000 Tb** 2010 - 2035
– Resources not up as fast as data volumes

Pile-Up Collisions

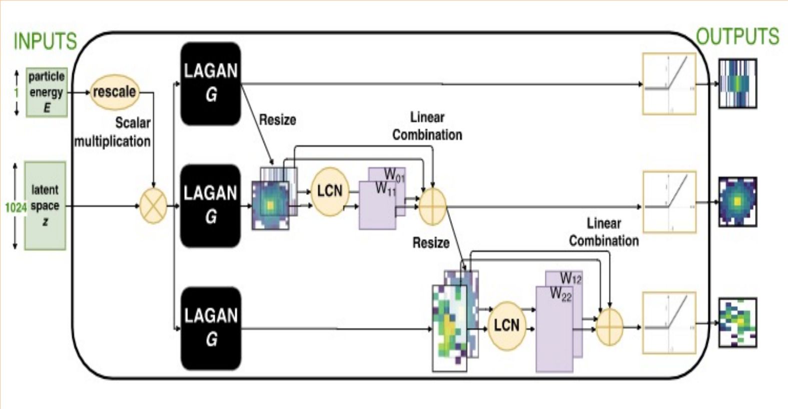


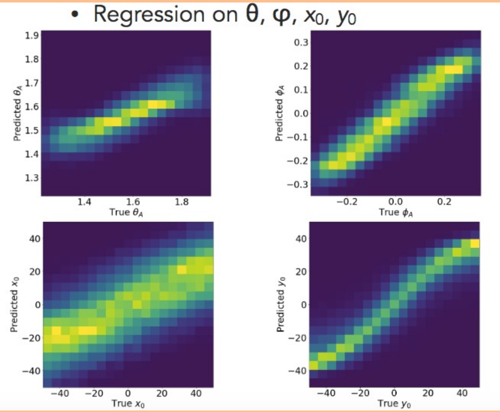
Going Beyond Classification

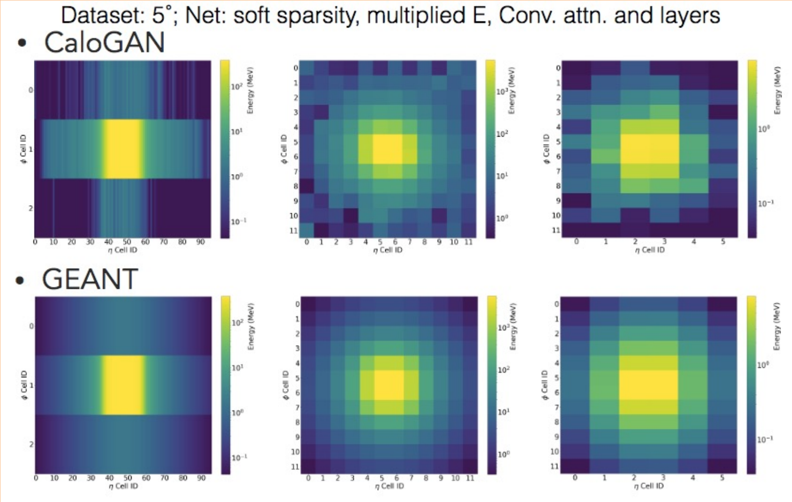
Generative Models

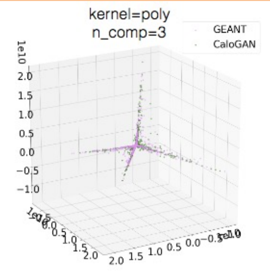


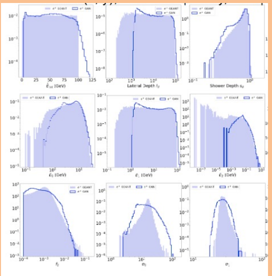
Simulation GANs





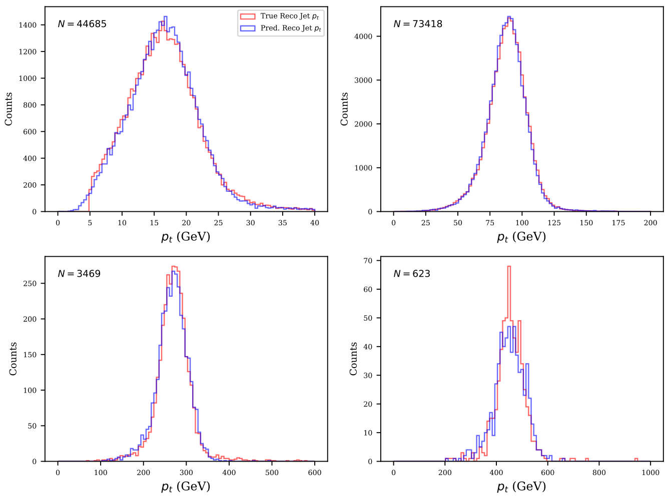


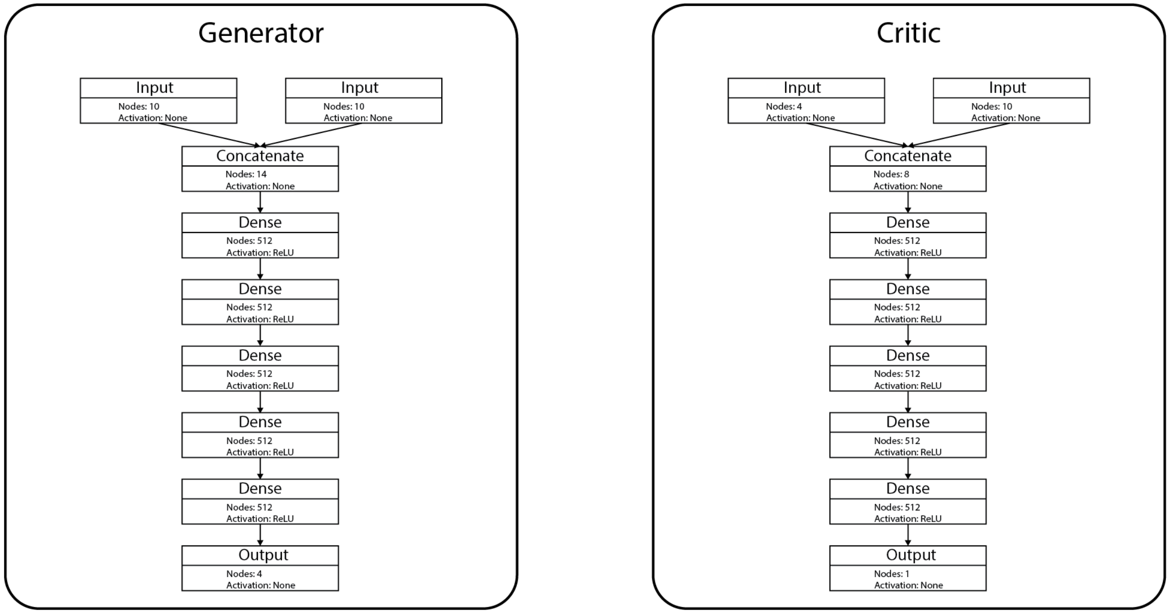


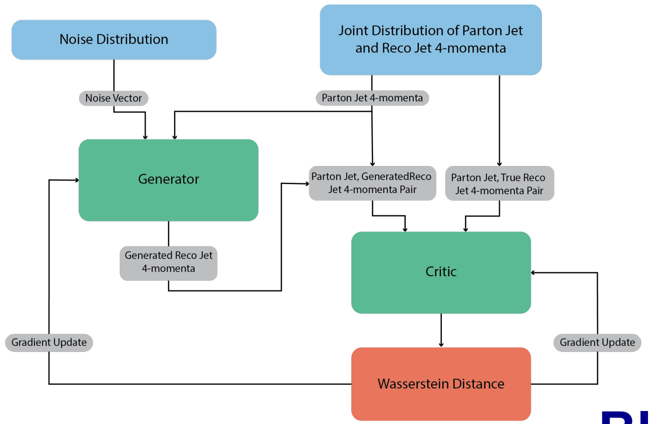


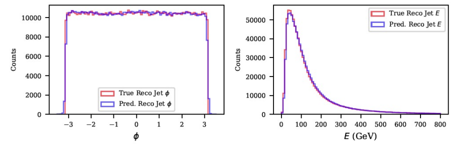
Paganini et al. (2017)

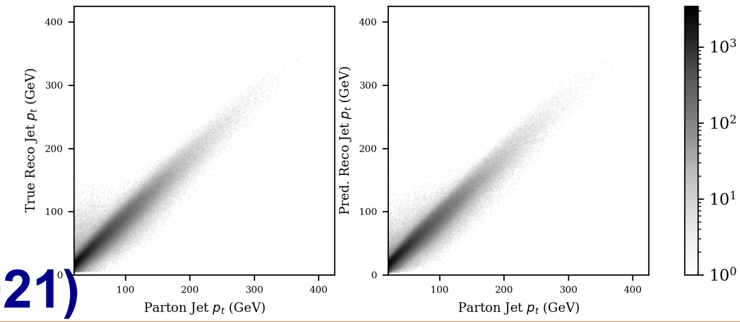
CWGANs





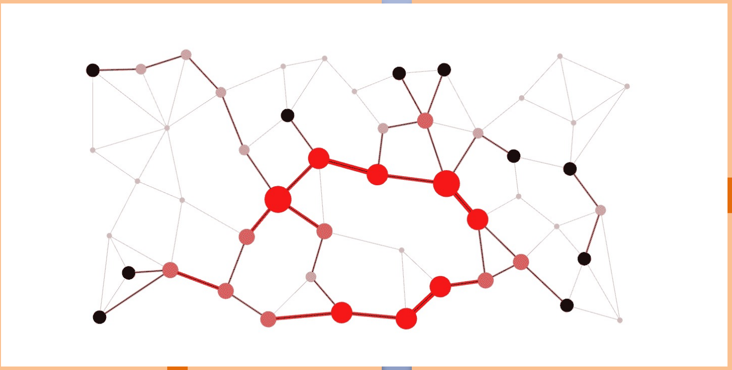






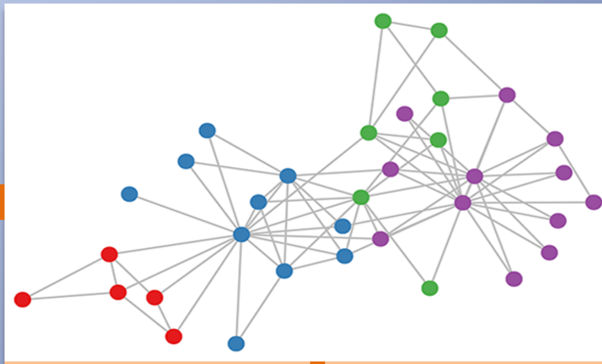
Blue et al. vCHEP (2021)

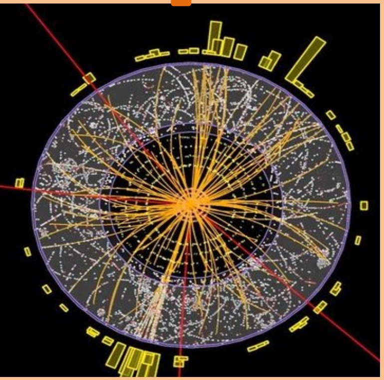
Graph Neural Networks



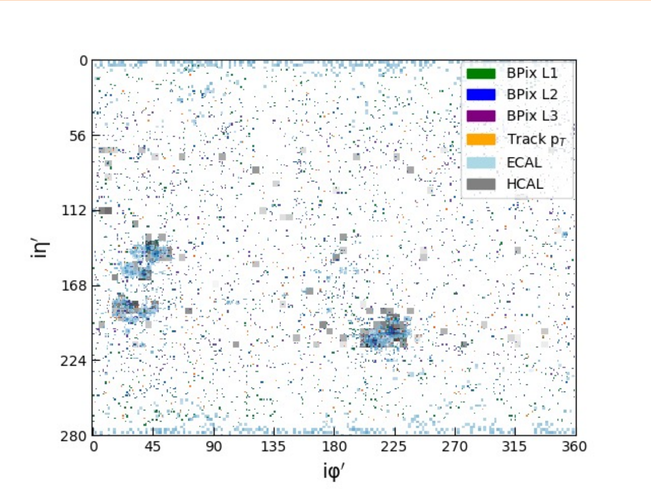
Applied to

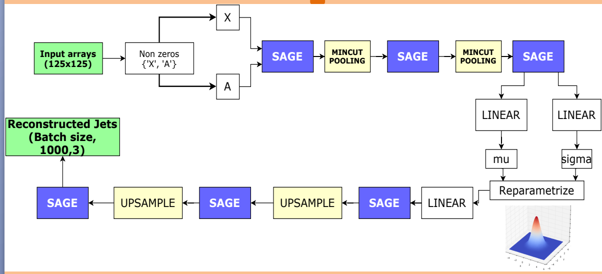
Reconstruction





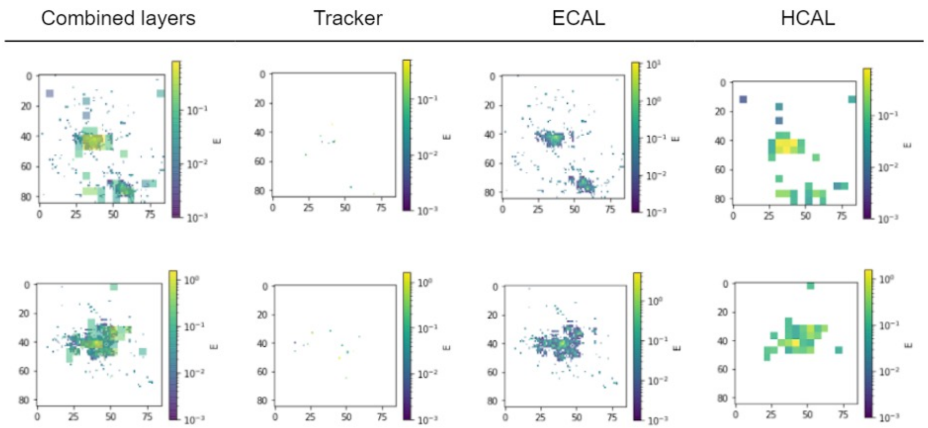
Trigger

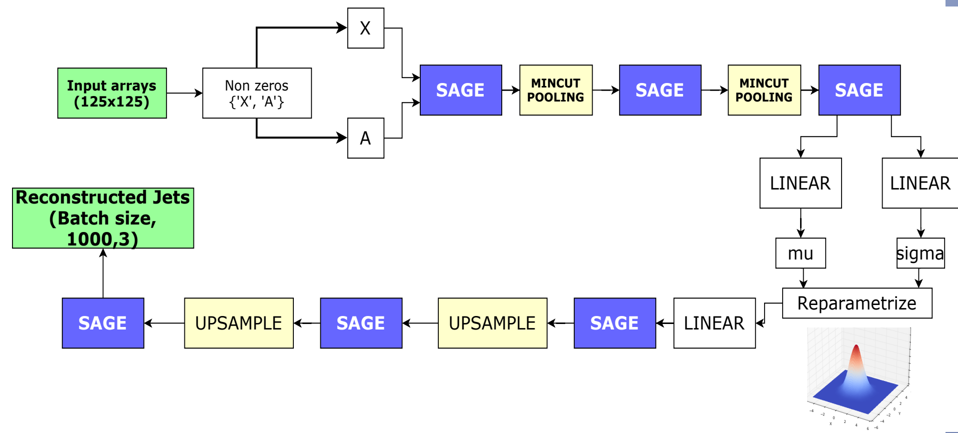


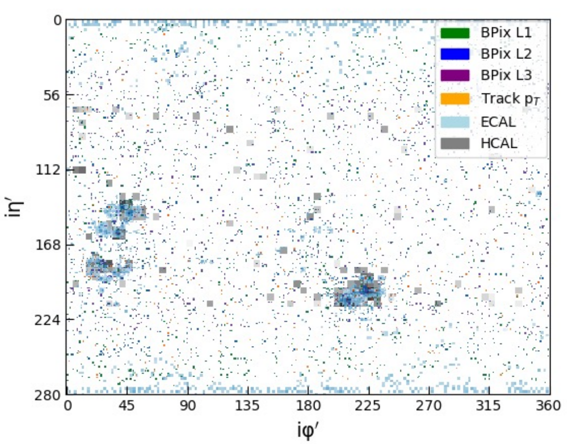


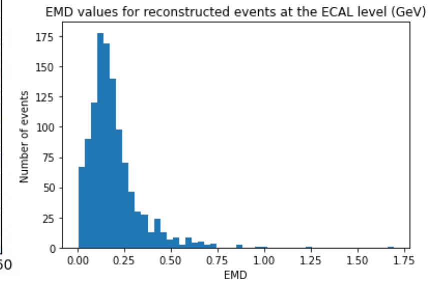
Simulation

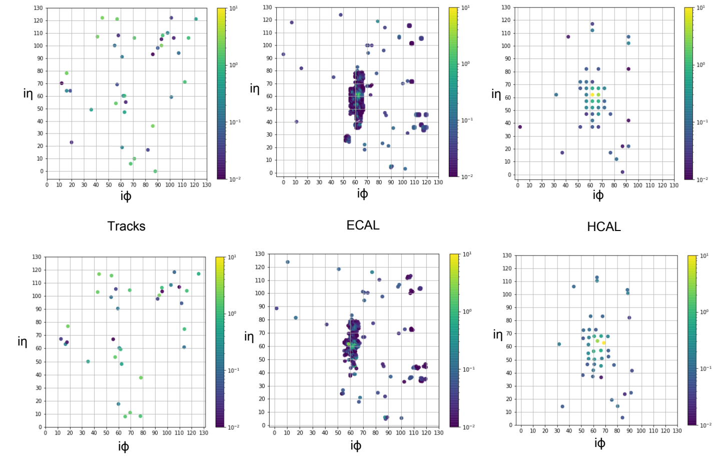
GNNs for Simulation





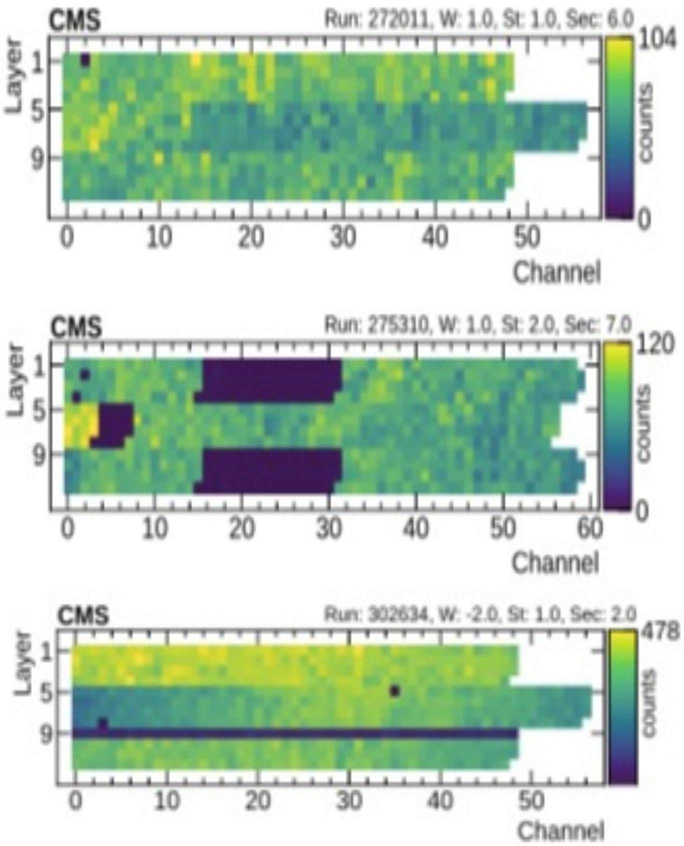


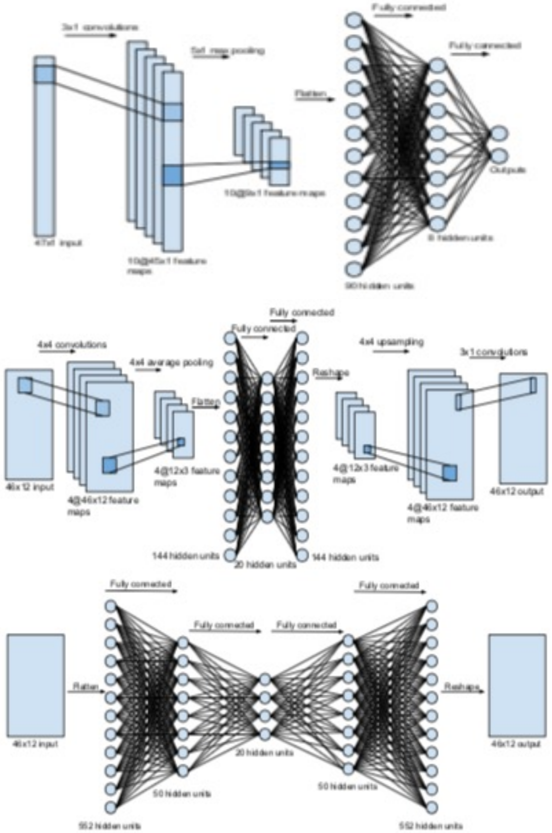


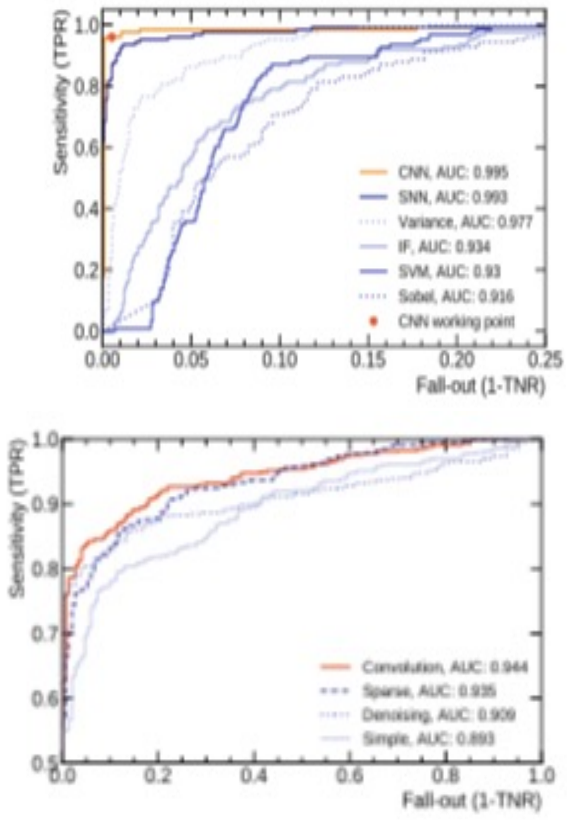


Hariri et al., 2104.01725

Anomaly Detection (DQM)



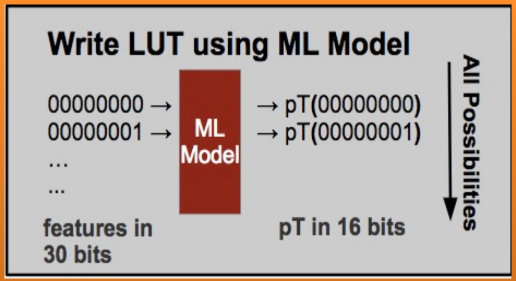


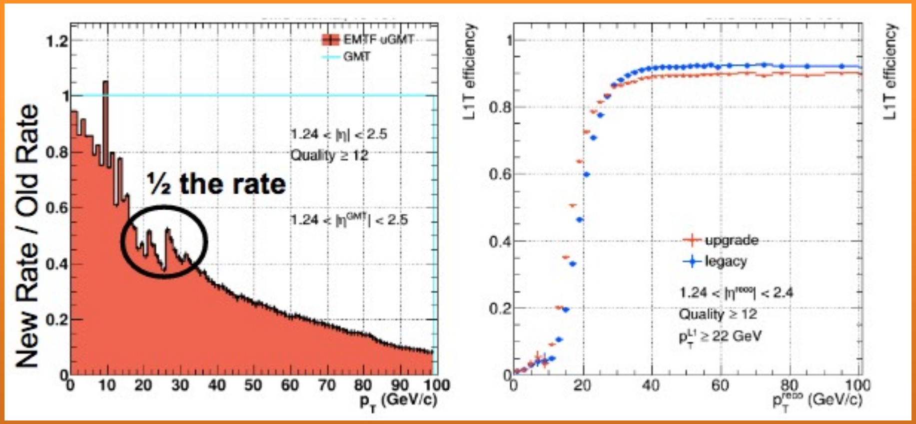


A. Pol et al. (2018)

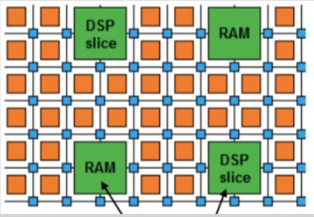
Machine Learning Trigger

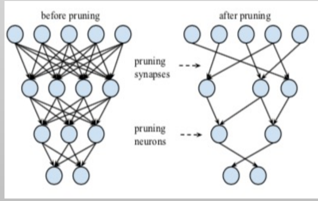
ML at Level-1 Trigger

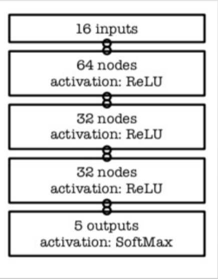


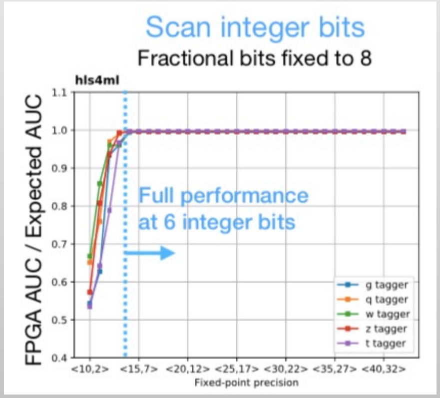


FPGAs and Deep Learning

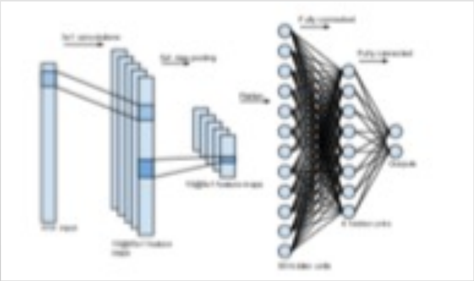






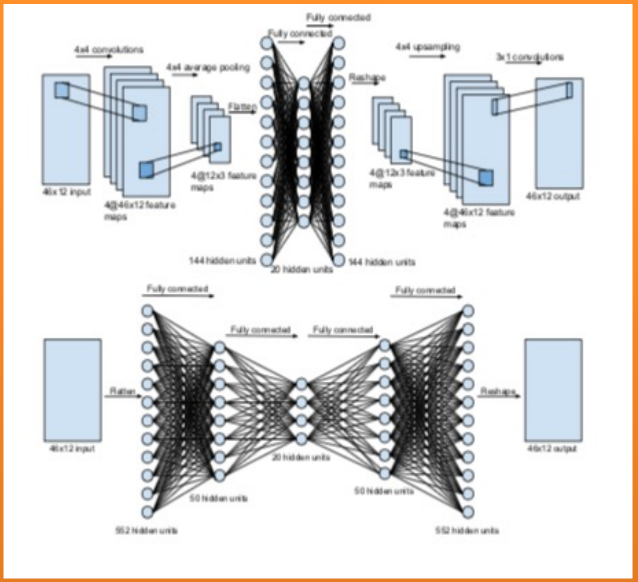


Auto-Encoders

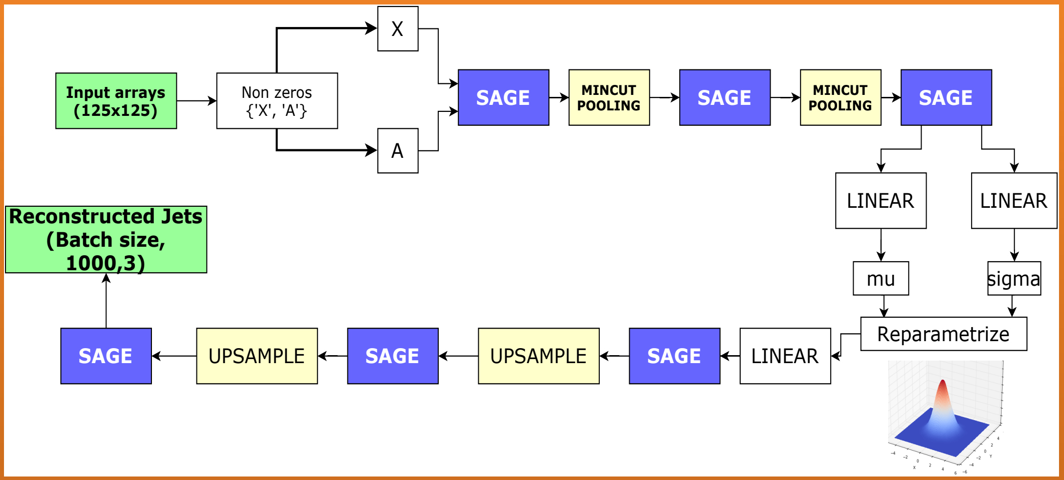


Search for New Physics

Train on Standard Model processes
New physics as an anomaly



Auto-encoder



Key Ideas for HL-LHC

Deep Combination of Spatio-Temporal Data

Graph and End-End Representation Learning

Tensor decomposition (towards trigger)

Compositionality, causal modeling (inference)

Unsupervised learning and physics

Open Questions

How to quantify uncertainty

First principles models

Model interpretability

What features are learned

Machine Learning in High Energy Physics Community White Paper

May 8, 2019

Abstract: Machine learning has been applied to several problems in particle physics research, beginning with applications to high-level physics analysis in the 1990s and 2000s, followed by an explosion of applications in particle and event identification and reconstruction in the 2010s. In this document we discuss promising future research and development areas for machine learning in particle physics. We detail a roadmap for their implementation, software and hardware resource requirements, collaborative initiatives with the data science community, academia and industry, and training the particle physics community in data science. The main objective of the document is to connect and motivate these areas of research and development with the physics drivers of the High-Luminosity Large Hadron Collider and future neutrino experiments and identify the resource needs for their implementation. Additionally we identify areas where collaboration with external communities will be of great benefit.

Editors: Sergei Gleyzer[30], Paul Seyfert[13], Steven Schramm[32]

Contributors: Kim Albertsson[1], Piero Altoe[2], Dustin Anderson[3], John Anderson[4], Michael Andrews[5], Juan Pedro Araque Espinosa[6], Adam Aurisano[7], Laurent Basara[8], Adrian Bevan[9], Wahid Bhimji[10], Daniele Bonacorsi[11], Bjorn Burkle[12], Paolo Calafiura[10], Mario Campanelli[9], Louis Capps[2], Federico Carminati[13], Stefano Carrazza[13], Yi-Fan Chen[4], Taylor Childers[14], Yann Coadou[15], Elias Coniavitis[16], Kyle Cranmer[17], Claire David[18], Douglas Davis[19], Andrea De Simone[20], Javier Duarte[21], Martin Erdmann[22], Jonas Eschle[23], Amir Farbin[24], Matthew Feickert[25], Nuno Filipe Castro[6], Conor Fitzpatrick[26], Michele Floris[13], Alessandra Forti[27], Jordi Garra-Tico[28], Jochen Gemmler[29], Maria Girone[13], Paul Glaysher[18], Sergei Gleyzer[30], Vladimir Vava Gligorov[31], Tobias Golling[32], Jonas Graw[2], Lindsey Gray[21], Dick Greenwood[33], Thomas Hacker[34], John Harvey[13], Benedikt Hegner[13], Lukas Heinrich[17], Ulrich Heintz[12], Ben Hooberman[35], Johannes Junggeburth[36], Michael Kagan[37],

AAAS2021 Session on Artificial Intelligence for Physics: Experimental and Theoretical Perspectives

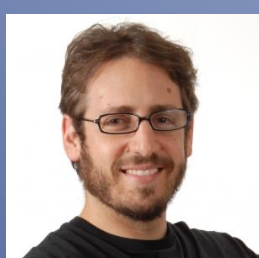
Tuesday 9 Feb 2021, 08:30 → 16:00 US/Central

Meenakshi Narain (Brown University (US)), Sergei Gleyzer (University of Alabama (US))

Description This session focuses on the latest breakthroughs and ideas from artificial intelligence which are transforming the field of particle physics, providing attendees the audience with both theoretical and experimental perspectives on the ongoing transformation. Topics to be discussed include the influence of artificial intelligence on event and particle reconstruction in particle detectors; theoretical model building and optimization, large scale simulations and theoretical predictions, physics-inspired machine learning algorithms and realtime AI for detection of exotic physics signals.

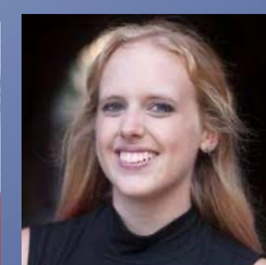
https://aaas.confex.com/aaas/2021/meetingapp.cgi/Session/27471

The session consists of prerecorded videos by speakers and respondents on specific topics followed by a live moderated panel discussion. Session participants include: Prof. Sergei Gleyzer (Alabama), Prof. Meenakshi Narain (Brown), Prof. Jesse Thaler (MIT), Prof. Daniel Whiteson (UCI), Prof. Harrison Prosper (FSU), Prof. Risi Kondor (UChicago/Flatiron), Prof. Rose Yu (UCSD), Prof. Taritree Wongjirad(Tufts) and Dr. Savannah Thais (Princeton).







https://indico.cern.ch/event/1031957/

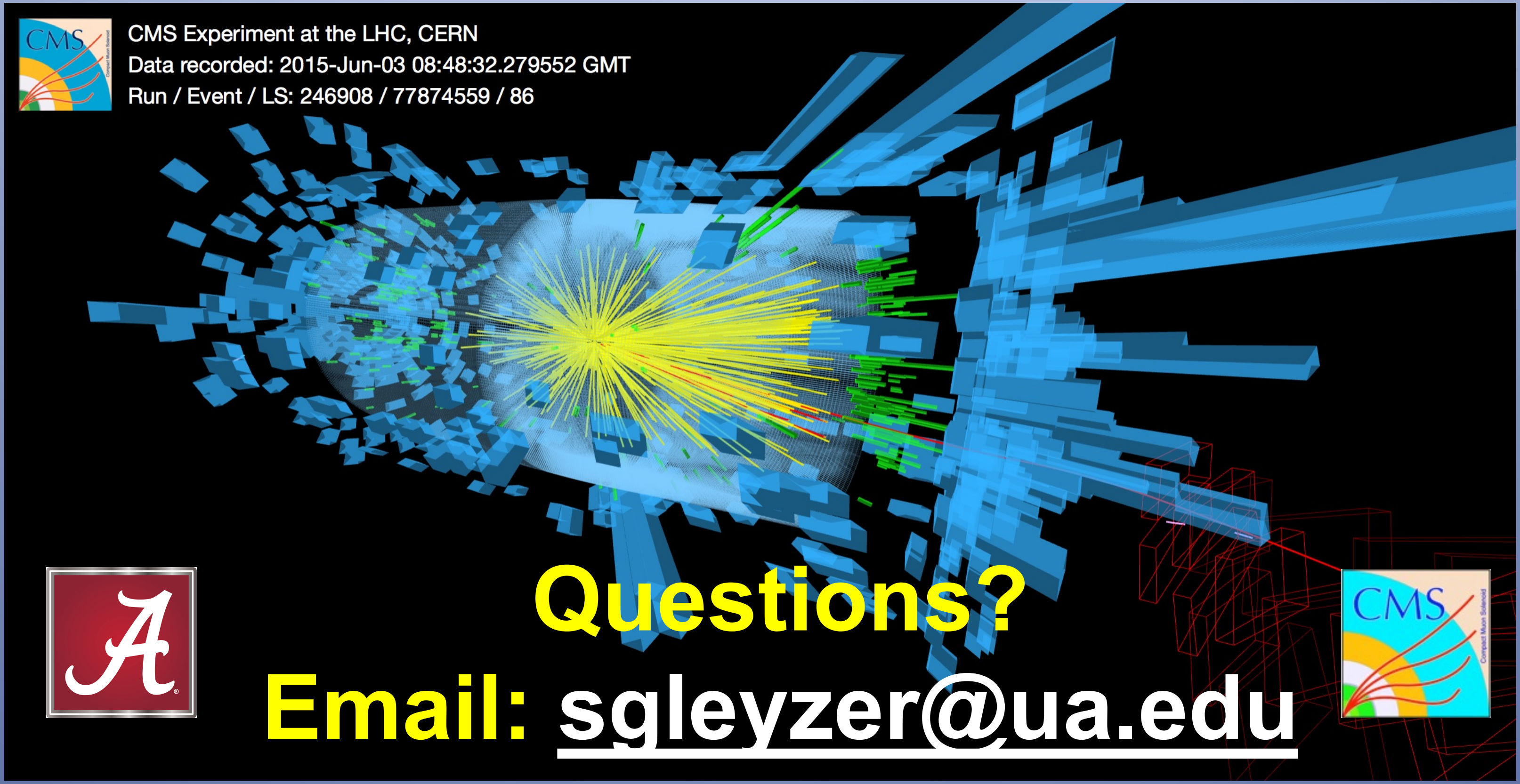
Summary

- We are taking steps towards answering fundamental questions across all frontiers

- Will require progress to extract all the knowledge we seek from the data at the HEP experiments

- Advanced Deep Learning is a powerful tool to help us achieve these goals for reconstruction, simulation and realtime applications

THANK YOU


CMS Experiment at the LHC, CERN
Data recorded: 2015-Jun-03 08:48:32.279552 GMT
Run / Event / LS: 246908 / 77874559 / 86
Questions?
Email: sgleyzer@ua.edu