

Machine Learning applications in high energy physics

V4HEP - Prague

Theory and Experiment in High Energy Physics

02-03 10 2024

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**HUN
REN**



ELTE
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Collaborators:

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Former:

Balázs Majoros

Bence Tankó-Bartalis

Mihály Pocsai

Imre Barna

Gábor Demeter



History

Main driving forces: **gaming** and **cat videos**

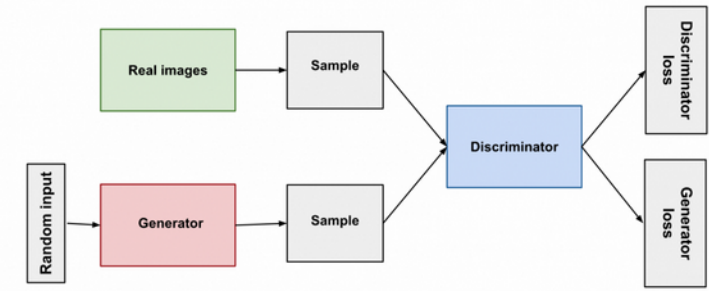
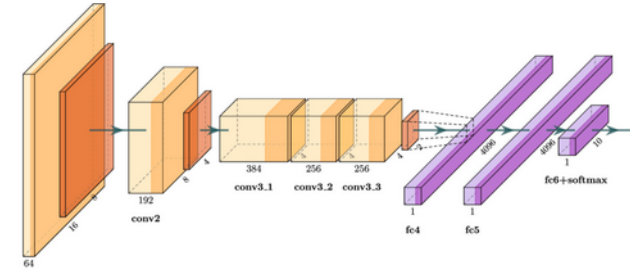
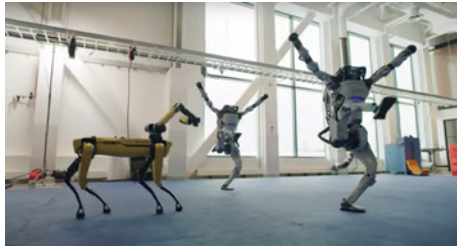
Checkers (1959) - Arthur Samuel

Chess (1997) - 11.38 GFLOPS

Jeopardy! (2011) - IBM Watson

Google Brain (2011)

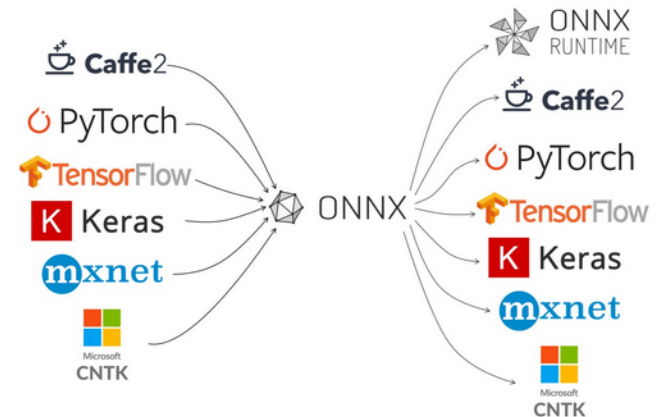
Go (2016) - AlphaGo



CNN (image classification, object detection, recommender systems)

Recurrent/recursive neural networks (RNNs), sequence modeling, next word prediction, translating sounds to words, human language translation

Generative models: anomaly detection, pattern recognition, reinforced learning...



Data, data, and more data

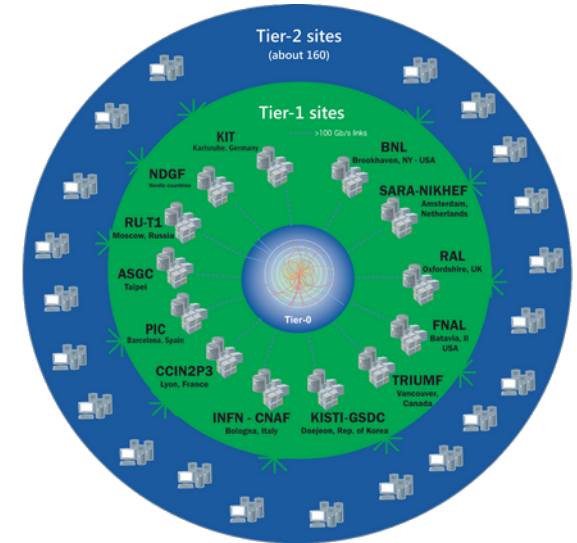


WLCG
Worldwide LHC Computing Grid



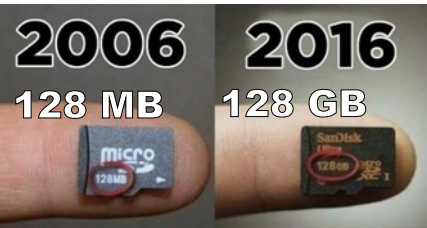
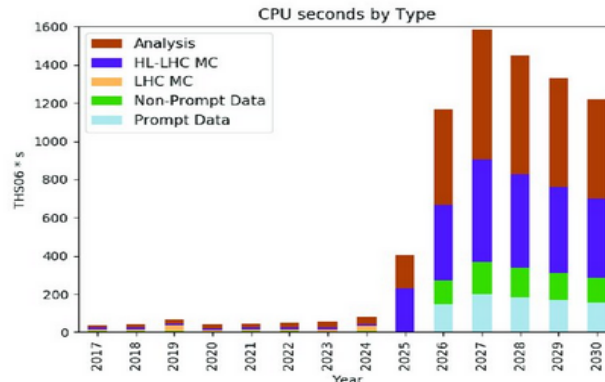
LHC in numbers: **2013** and **now**:

Data:	15 PB/year	VS	200+ PB/year
Tape:	180 PB	VS	740+ PB
Disk:	200 PB	VS	570+ PB
HS06:	2M	VS	100+ B



Storing and distributing the data is only one side of the challenge













→ analysis, simulations

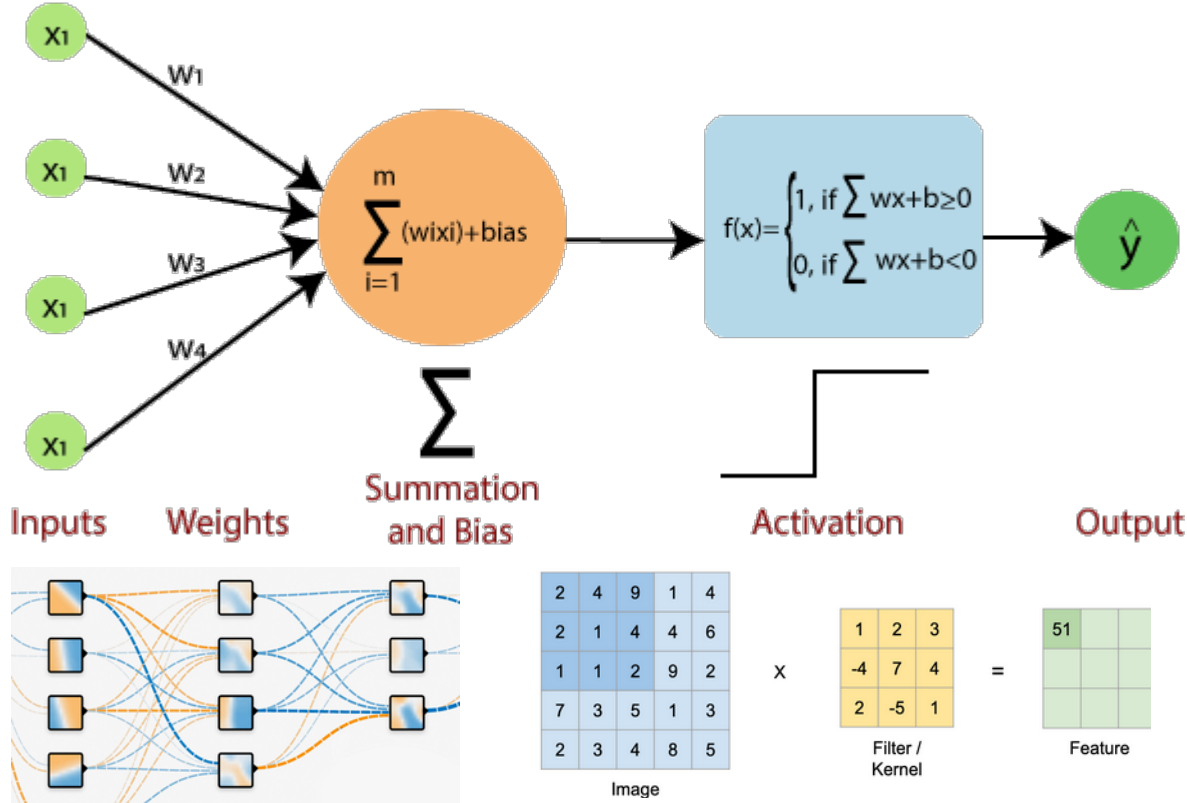


Main ingredients

Perceptrons:

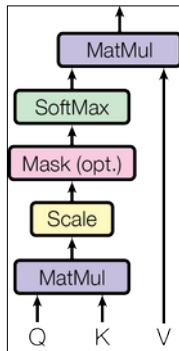
- Input value(s)
- Weight: the connection between the units
- Bias: the intercept added in a linear equation
- Activation Function

<p>Sigmoid</p>  $y = \frac{1}{1+e^{-x}}$	<p>Tanh</p>  $y = \tanh(x)$	<p>Step Function</p>  $y = \begin{cases} 0, & x < n \\ 1, & x \geq n \end{cases}$	<p>Softplus</p>  $y = \ln(1+e^x)$
<p>ReLU</p>  $y = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases}$	<p>Softsign</p>  $y = \frac{x}{(1+ x)}$	<p>ELU</p>  $y = \begin{cases} \alpha(e^x - 1), & x < 0 \\ x, & x \geq 0 \end{cases}$	<p>Log of Sigmoid</p>  $y = \ln\left(\frac{1}{1+e^{-x}}\right)$
<p>Swish</p>  $y = \frac{x}{1+e^{-x}}$	<p>Sinc</p>  $y = \frac{\sin(x)}{x}$	<p>Leaky ReLU</p>  $y = \max(\alpha x, x)$	<p>Mish</p>  $y = x(\tanh(\text{softplus}(x)))$



Other important components: pooling layers, regularization and normalization, recurrent layers...

Transformers and LLMs

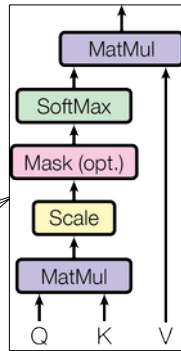
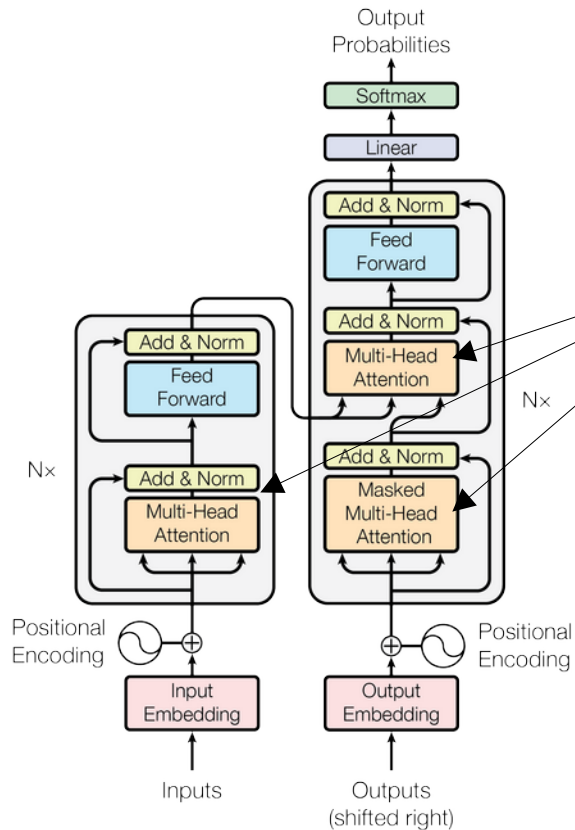


$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Attention layer:

- helps models focus on the most relevant parts of input data
- assigns weights to each part of the input, indicating how important they are for making predictions
- weighted sum of input values, where weights are determined based on similarity (usually via dot-product) between queries and keys
- allowing the model to dynamically adapt its focus

Transformers and LLMs



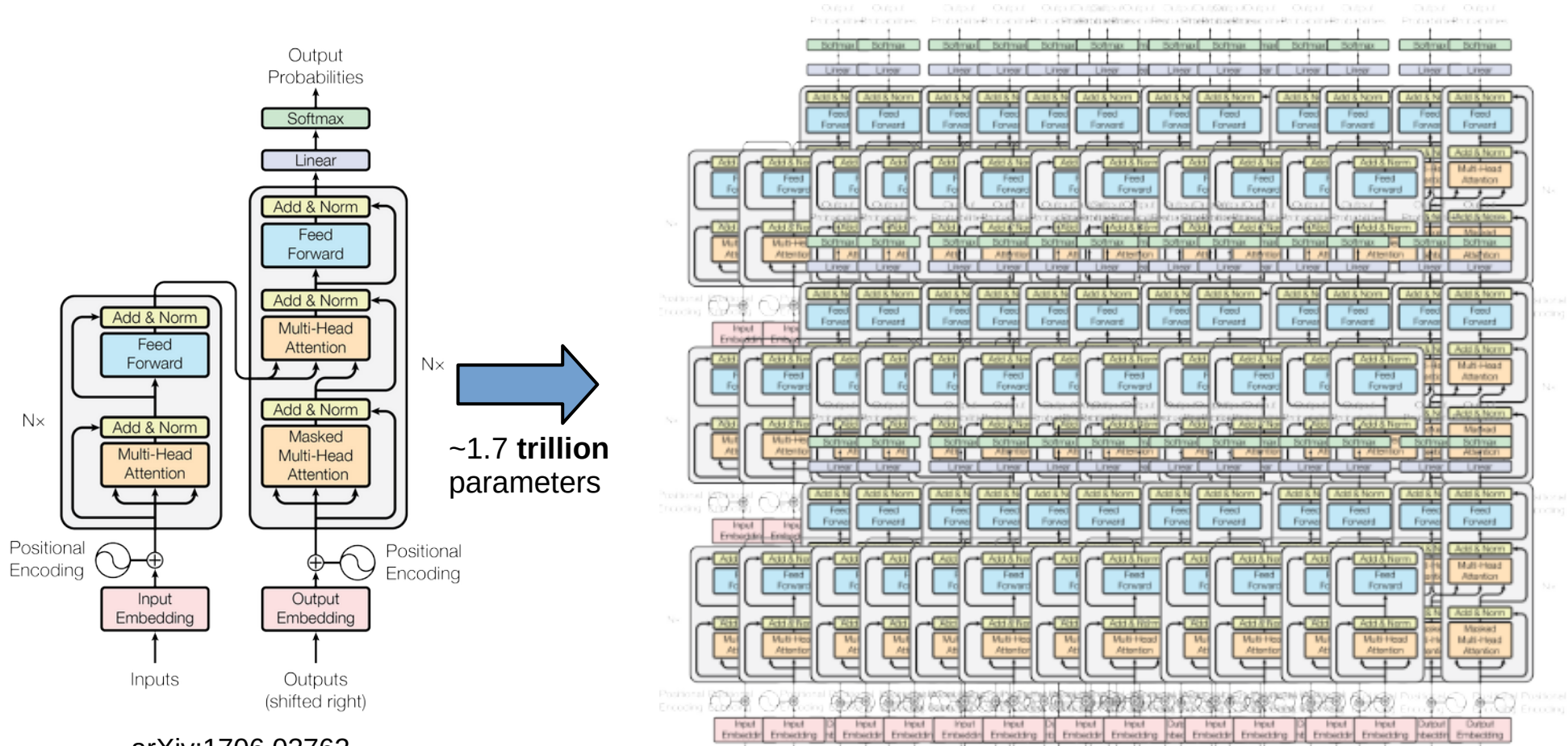
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arXiv:1706.03762
(5000+ citations)

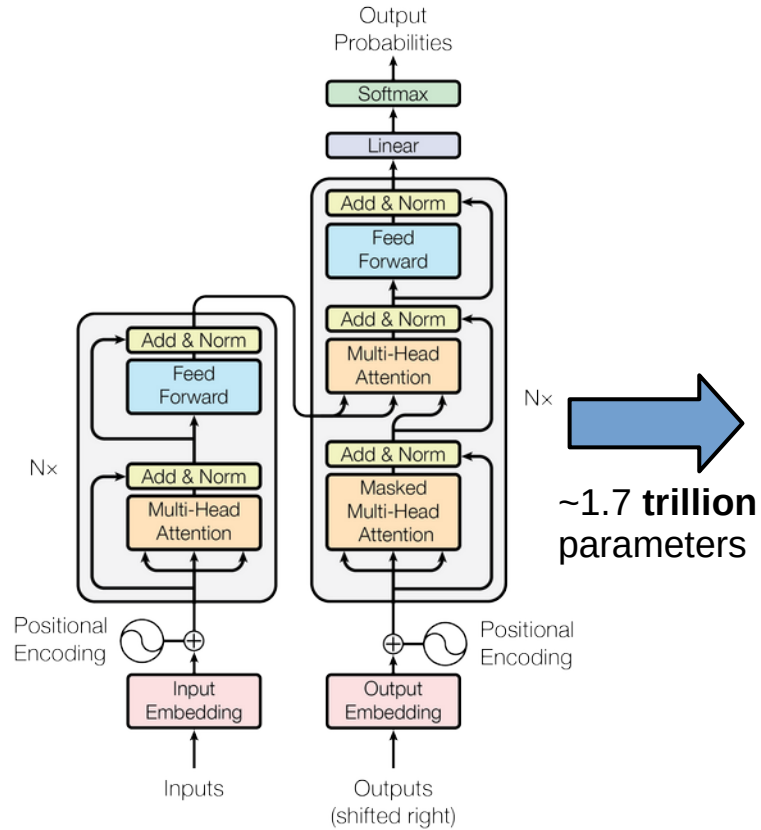
Transformers and LLMs

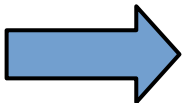


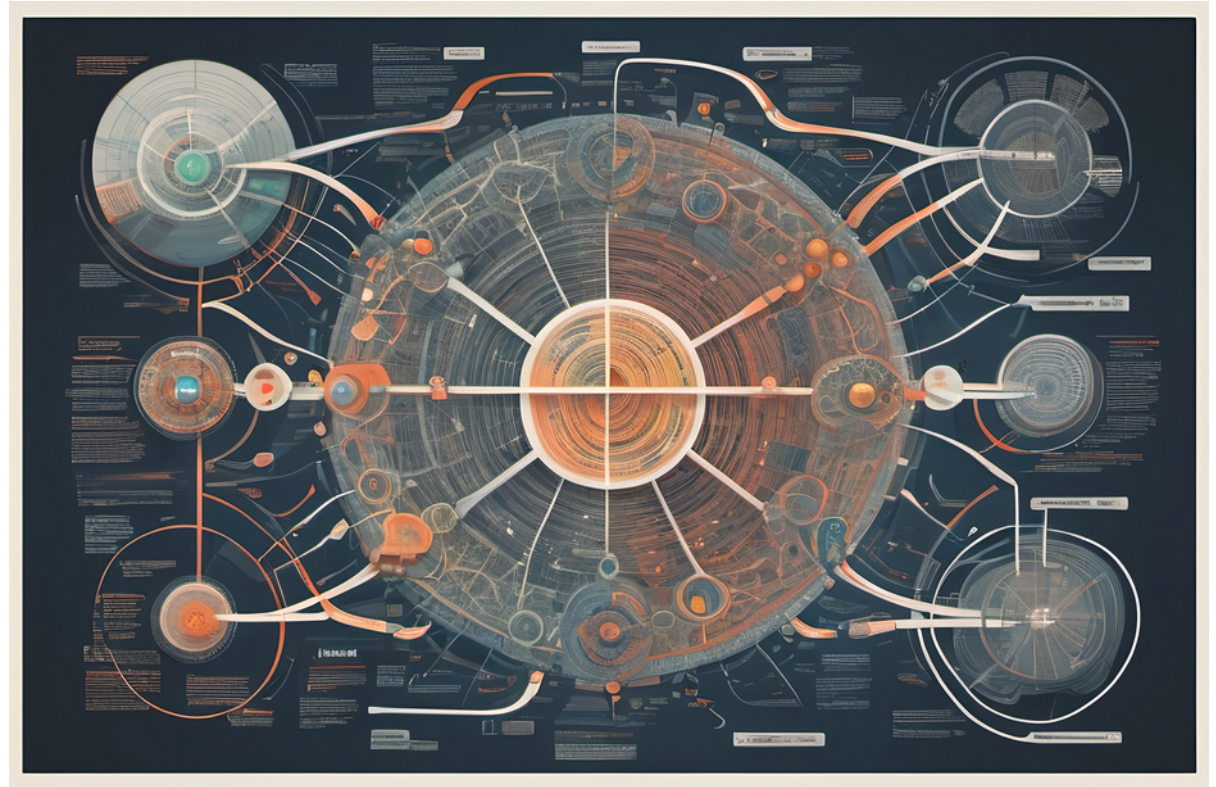
Nx  ~1.7 trillion parameters

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Transformers and LLMs



$N \times$ 
~1.7 trillion parameters



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Machine Learning in HEP

A Living Review of Machine Learning for Particle Physics

<https://iml-wg.github.io/HEPML-LivingReview/>

Matthew Feickert, Benjamin Nachman, arXiv:2102.02770

2021 May: **417** references

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- Quark/gluon jet separation
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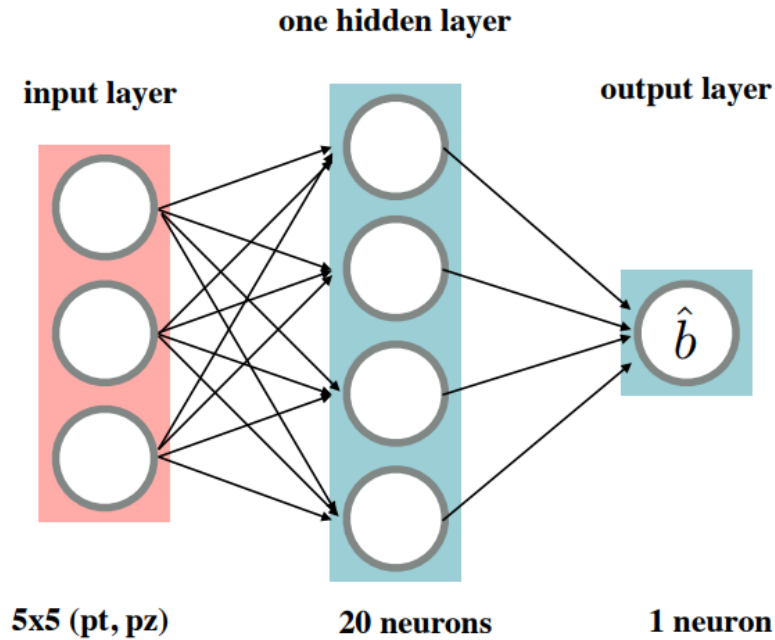
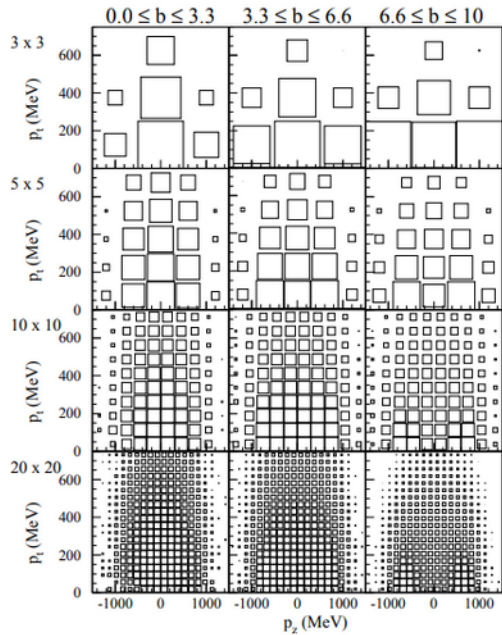
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Machine Learning in HEP

Neural Networks for Impact Parameter Determination



“The neural network approach yields an improvement in performance of a factor of two as compared to classical techniques.”

Machine Learning in HEP

Particle Track Reconstruction with Deep Learning

Steven Farrell, Paolo Calafiura, Mayur Mudigonda, Prabhat
Lawrence Berkeley National Laboratory
{SFarrell,PCalafiura,Mudigonda,Prabhat}@lbl.gov

**Dustin Anderson, Josh Bendavid, Maria Spiropoulou,
Jean-Roch Vlimant, Stephan Zheng**
California Institute of Technology
{dustinanderson111,joshbendavid,maria.spiropulu,
jeanroch.vlimant,st.t.zheng}@gmail.com

**Giuseppe Cerati, Lindsey Gray, Keshav Kapoor, Jim Kowalkowski,
Panagiotis Spentzouris, Aristeidis Tsaris, Daniel Zurawski**
Fermi National Accelerator Laboratory
{cerati,lagray,kkapoor,jbk,spentz,
atsaris,zurawski}@fnal.gov

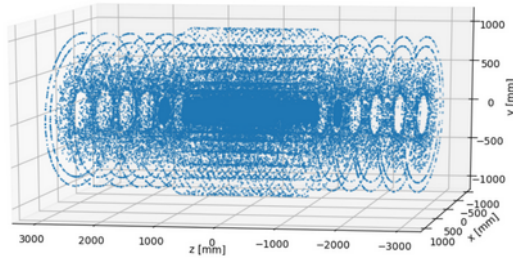


Figure 1: Distribution of particle spacepoints in a particle collision event in a generic simulated HL-LHC tracking detector.



Featured Prediction Competition

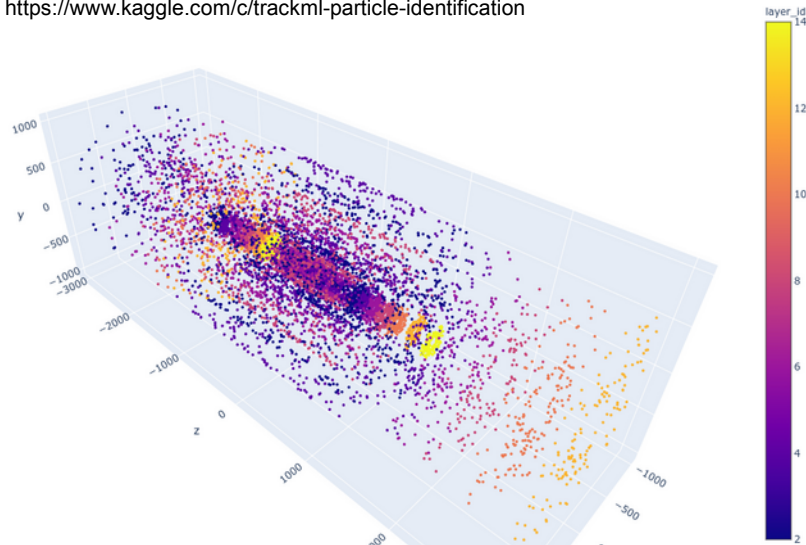
TrackML Particle Tracking Challenge

High Energy Physics particle tracking in CERN detectors

\$25,000
Prize Money

CERN · 651 teams · 3 years ago

<https://www.kaggle.com/c/trackml-particle-identification>



Machine Learning in HEP

Machine Learning based jet momentum reconstruction in heavy-ion collisions

Rüdiger Haake¹ and Constantin Loizides²

¹Yale University, Wright Laboratory, New Haven, CT, USA

²ORNL, Physics Division, Oak Ridge, TN, USA

(Dated: June 24, 2019)

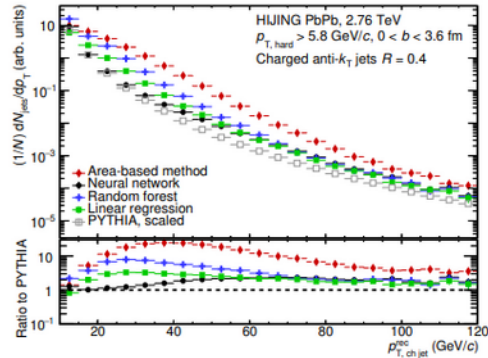


FIG. 9. Reconstructed charged jet spectra in HIJING events and the ratio to $(N_{\text{coll}}\text{-scaled})$ PYTHIA jet spectra.

<https://doi.org/10.1103/PhysRevC.99.064904>

Feature	Score	Feature	Score
Jet p_T (no corr.)	0.1355	$p_{T, \text{const}}^1$	0.0012
Jet mass	0.0007	$p_{T, \text{const}}^2$	0.0039
Jet area	0.0005	$p_{T, \text{const}}^3$	0.0015
Jet p_T (area-based corr.)	0.7876	$p_{T, \text{const}}^4$	0.0011
LeSub	0.0004	$p_{T, \text{const}}^5$	0.0009
Radial moment	0.0005	$p_{T, \text{const}}^6$	0.0009
Momentum dispersion	0.0007	$p_{T, \text{const}}^7$	0.0008
Number of constituents	0.0008	$p_{T, \text{const}}^8$	0.0007
Mean of const. p_T	0.0585	$p_{T, \text{const}}^9$	0.0006
Median of const. p_T	0.0023	$p_{T, \text{const}}^{10}$	0.0007

Jet reconstruction

Machine Learning based jet momentum reconstruction in Pb–Pb collisions measured with the ALICE detector

Rüdiger Haake* for the ALICE Collaboration

Yale University, Wright Laboratory, New Haven, CT, USA

E-mail: ruediger.haake@cern.ch

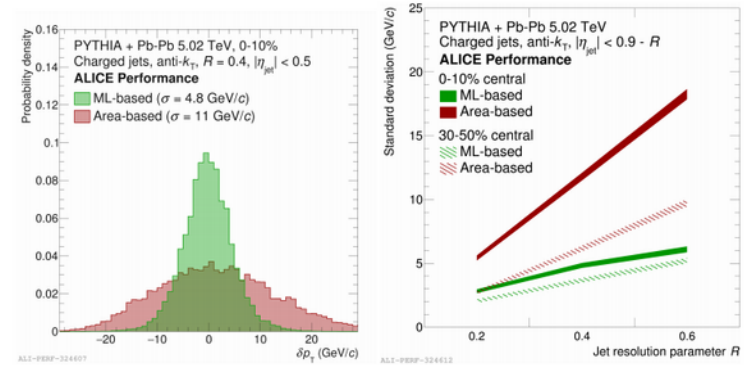


Figure 1: Residual p_T -distributions of embedded jet probes of known transverse momentum.

<https://doi.org/10.22323/1.364.0312>

Machine Learning in HEP

Beam Background Detection in ALICE ITS Data Using Machine Learning

CERN Summer Student Report

Zsófia Jólesz*
Eötvös Loránd University Budapest

Supervisors: Matteo Concas and Fabio Catalano
CERN
(Dated: 27.09.24)

The Inner Tracking System (ITS) is a crucial detector within the ALICE (A Large Ion Collider Experiment) at CERN's LHC, which explores quark-gluon plasma properties through heavy-ion collisions. With the onset of Run 3, the ITS generates a massive influx of data, presenting new challenges in processing and analysis. One key issue is data pollution, caused by residuals from the beam hitting the detector, which can compromise data quality.

This project focuses on developing and testing a machine learning-based approach to detect beam-related background in the context of a Summer Student Project. By automating the detection of such anomalies, the project aims to establish a foundation for more advanced anomaly detection systems in the future. This first step will help evaluate the feasibility of identifying specific features with machine learning, ultimately leading to improved detection of malfunctions, data integrity issues, and unanticipated phenomena affecting the detector's performance.

Keywords: ALICE; Beam Background; Anomaly Detection; CNN

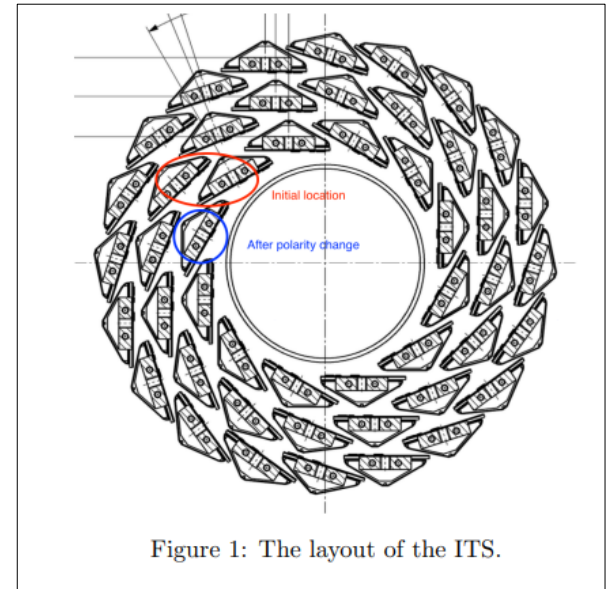
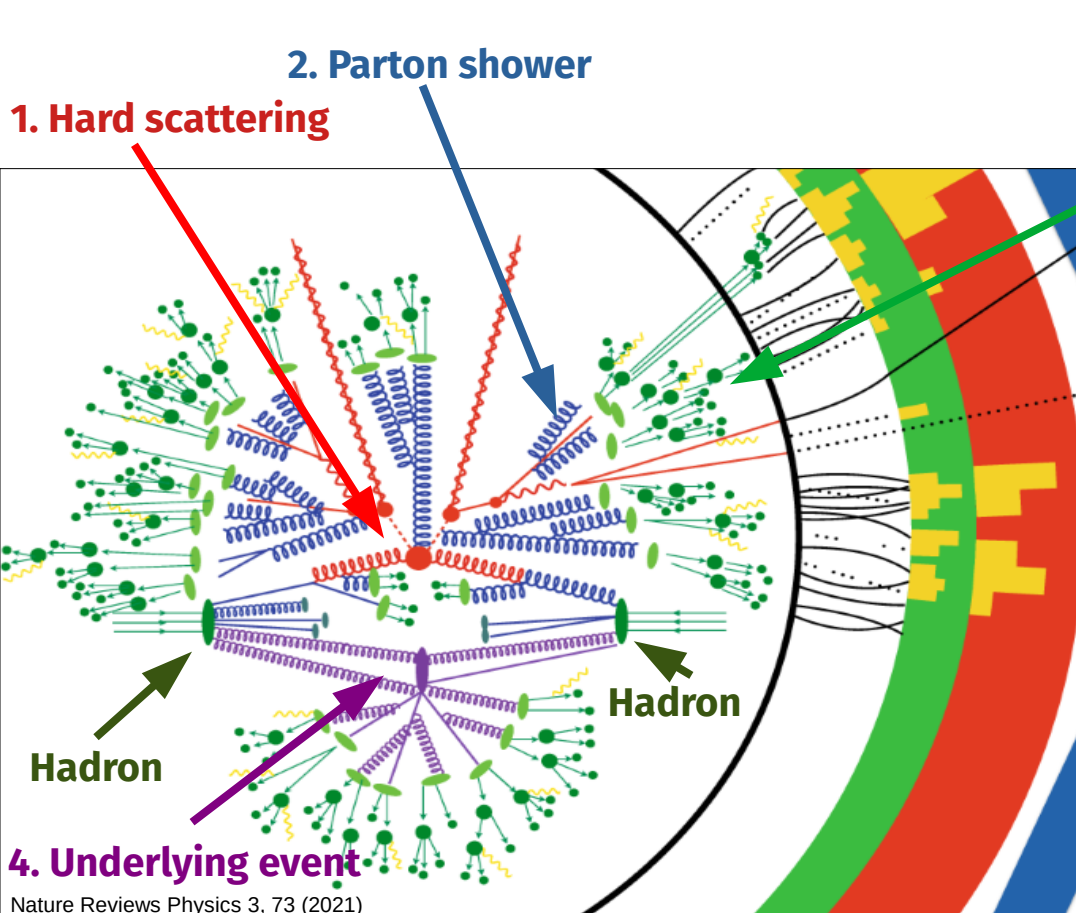


Figure 1: The layout of the ITS.

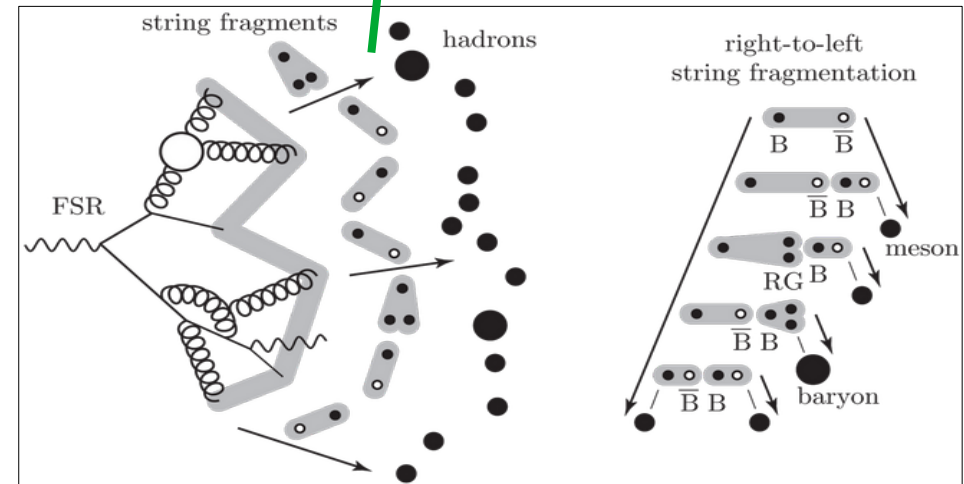
Selected topics

- **Hadronization and scaling studies**
- Proton computed tomography for hadron therapy
- Tuning of Monte Carlo event generators
- Monitoring of plasma channel

Parton shower and hadronization



3. Hadronization



arXiv:2408.17130
arXiv:2303.05422
arXiv:2210.10548

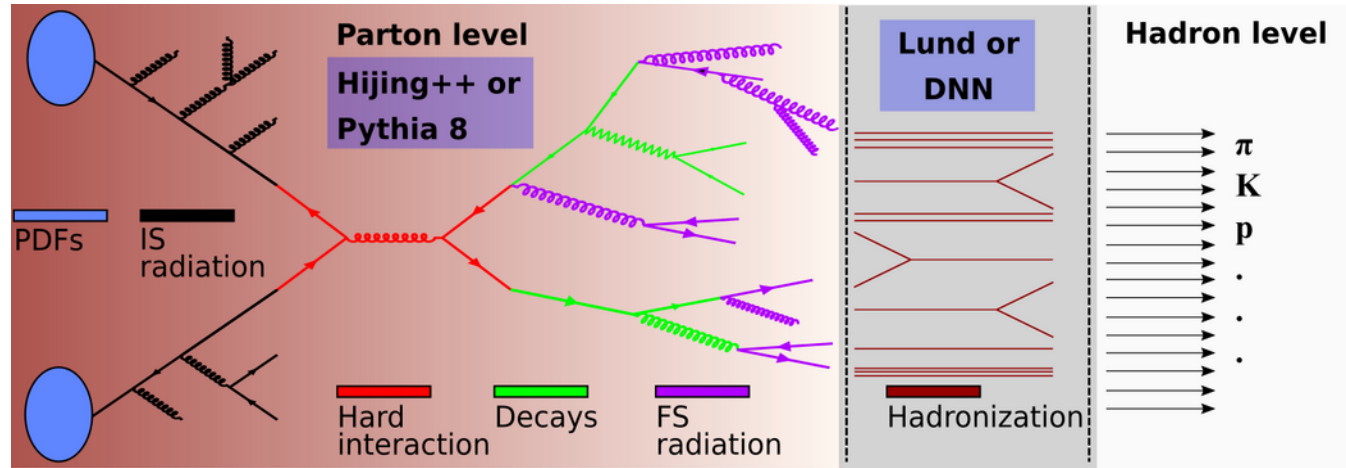
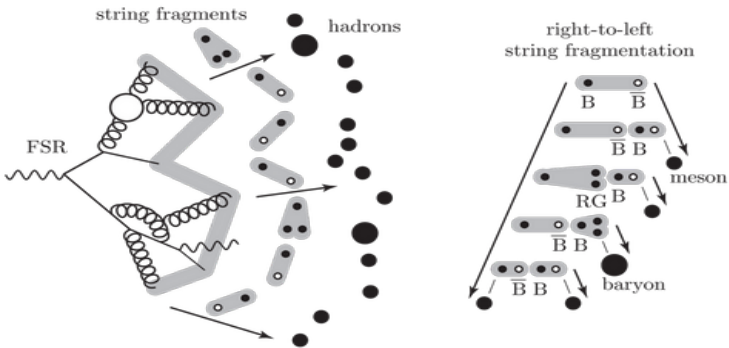
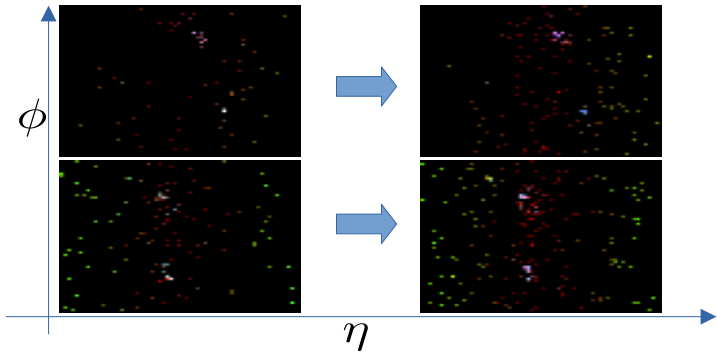
Hadronization

Partons → hadrons

Non-perturbative process

Lund-fragmentation (Comput.Phys.Commun. 27 (1982) 243)

$$f(z) = \frac{1}{z} (1 - z)^a e^{-\frac{bm^2}{z}}$$



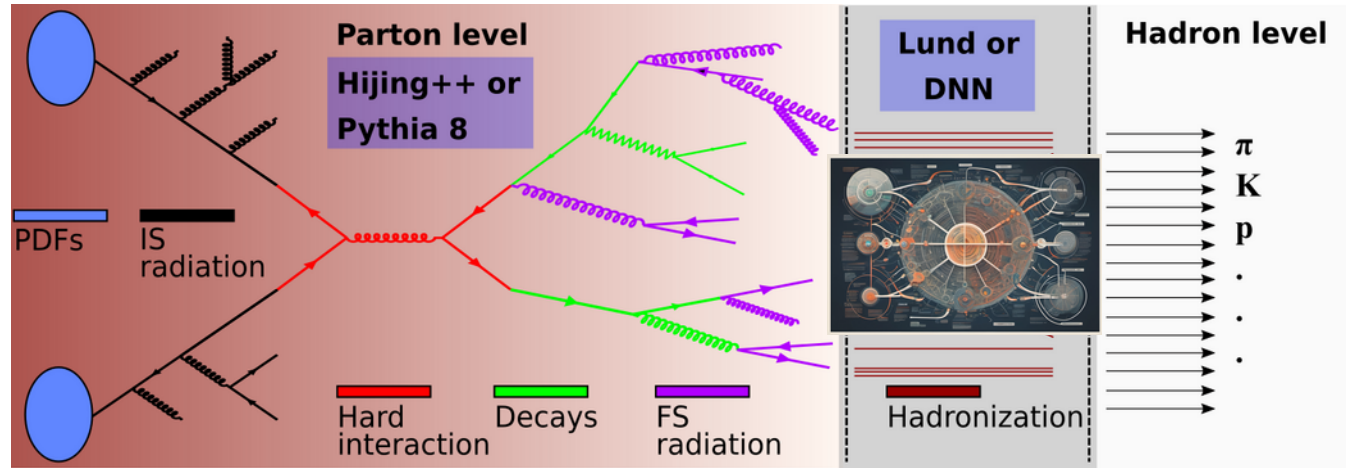
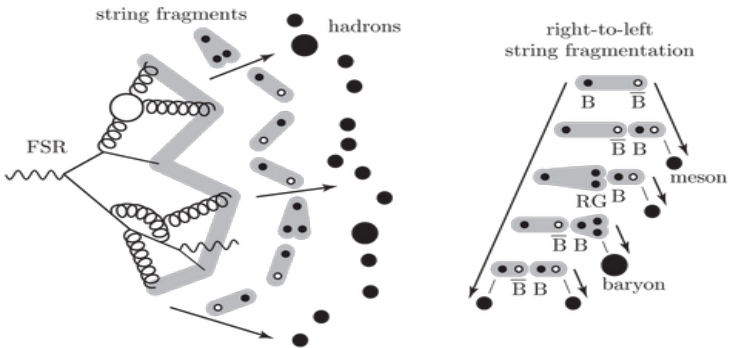
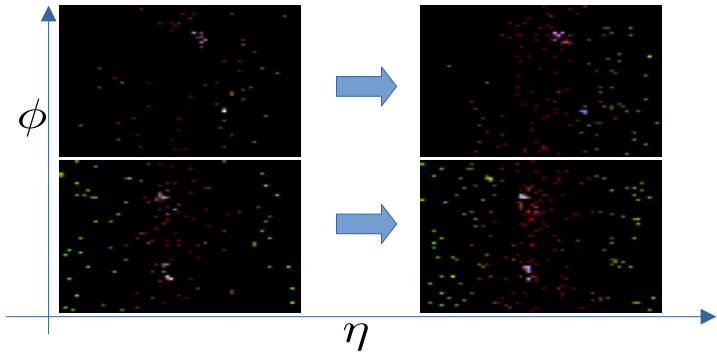
Hadronization

Partons → hadrons

Non-perturbative process

Lund-fragmentation (Comput.Phys.Commun. 27 (1982) 243)

$$f(z) = \frac{1}{z} (1 - z)^a e^{-\frac{bm^2}{z}}$$



Train and validation sets

Monte Carlo data: Pythia 8.303

Monash tune

Rescattering and decays turned off
CR, ISR, FSR, MPI: turned on

Selection:

- All final particles with $|y| < 4.0$

Event number:

- Train: 5M events, $\sqrt{s} = 7 \text{ TeV}$
 - ~uniform multiplicity distribution

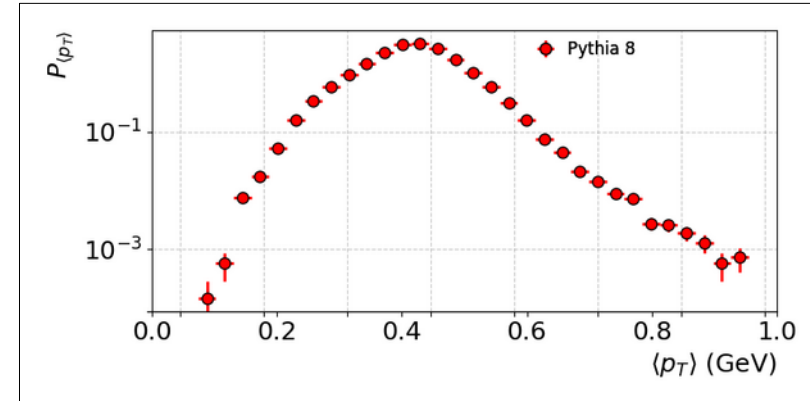
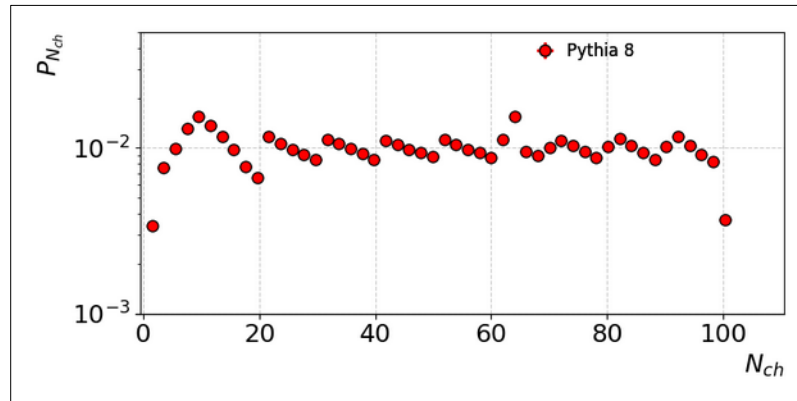
- ~30 GB raw data

Parton level, before the hadronization process

Standardized η , φ , p_T , m variables

Charged event multiplicity, mean event transverse momentum

η, φ, p_T, m
η, φ, p_T, m
η, φ, p_T, m
η, φ, p_T, m
η, φ, p_T, m
η, φ, p_T, m
η, φ, p_T, m
η, φ, p_T, m



Models

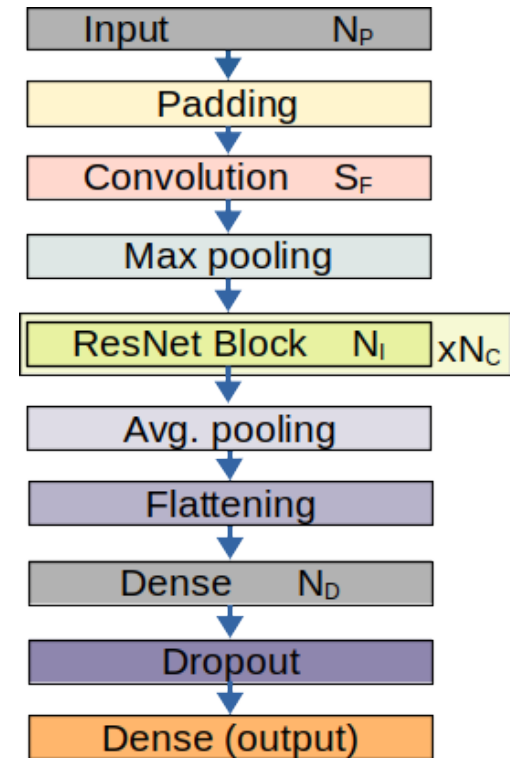
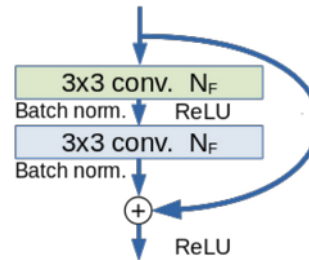
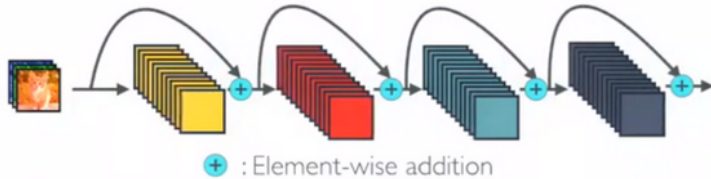
Stacking more layers: solve complex problems more efficiently, get highly accurate results

BUT:

Vanishing/exploding gradients

ResNet:

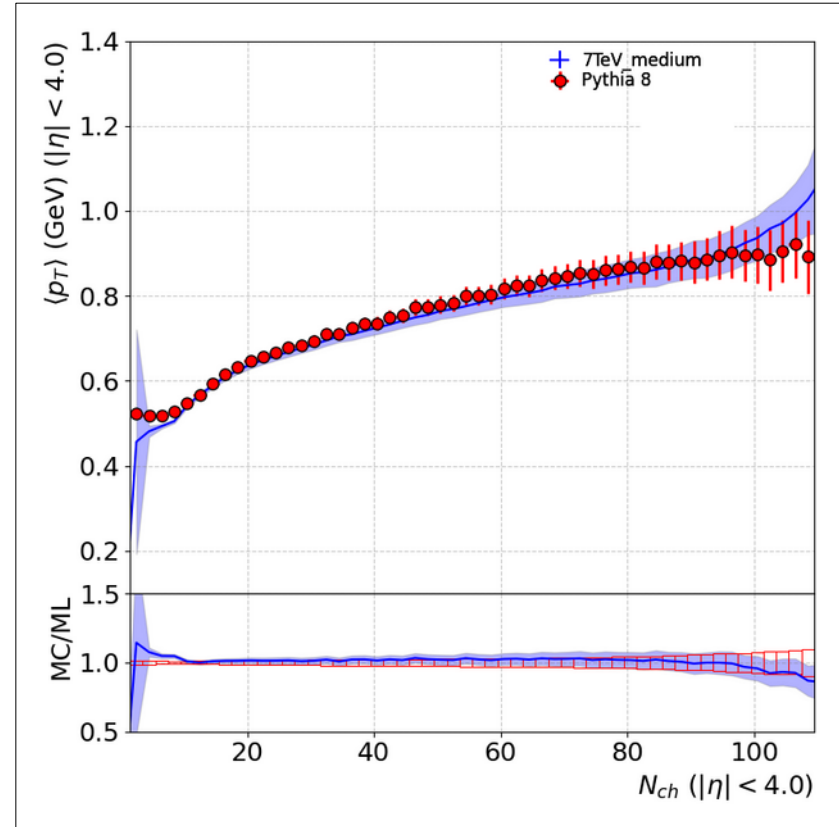
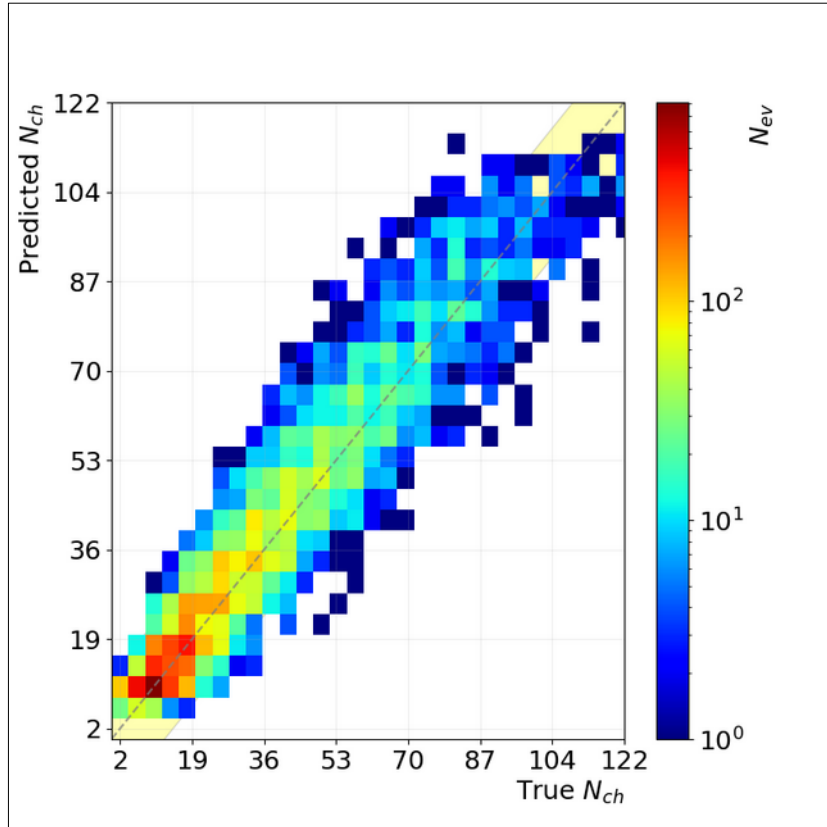
Residual blocks with “skip connections”



Used hardwares: Nvidia Tesla T4, GeForce GTX 1080
@ Wigner Scientific Computing Laboratory

Framework: Tensorflow 2.4.1, Keras 2.4.0

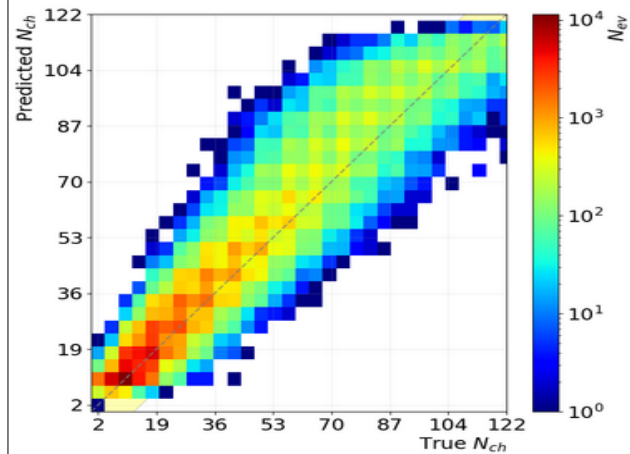
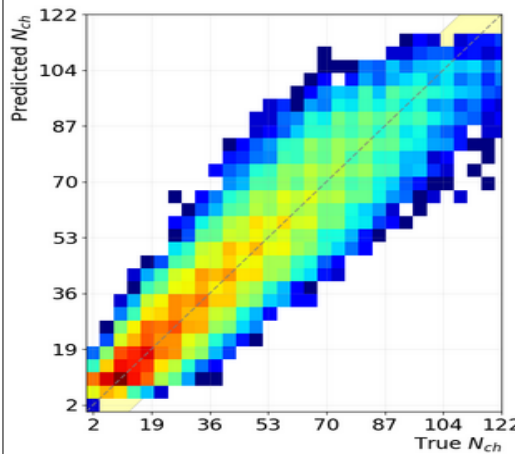
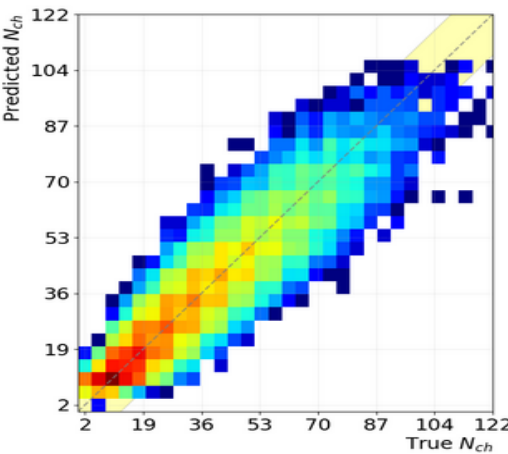
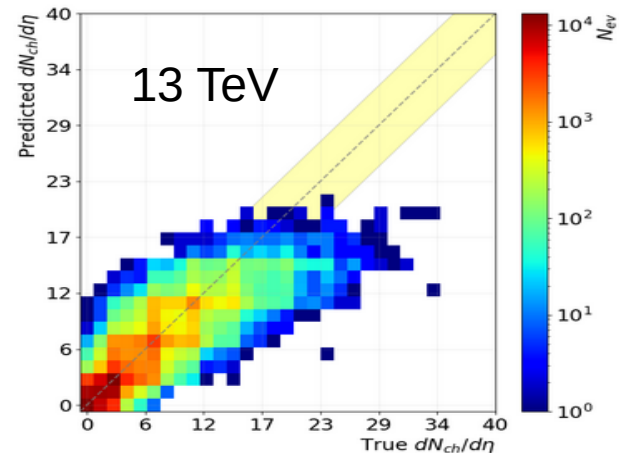
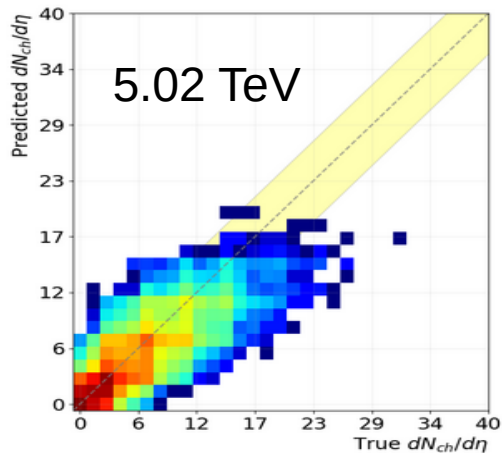
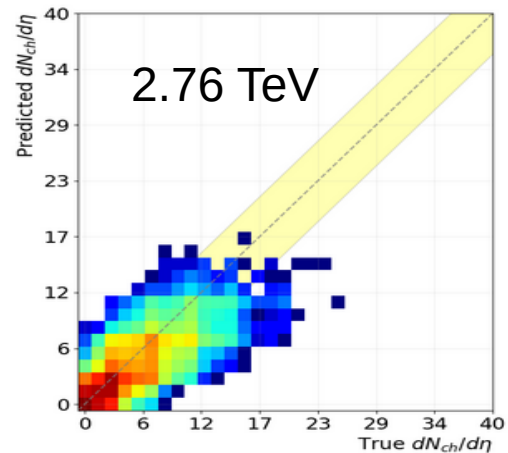
Proton-proton @ 7 TeV, Training + Validation



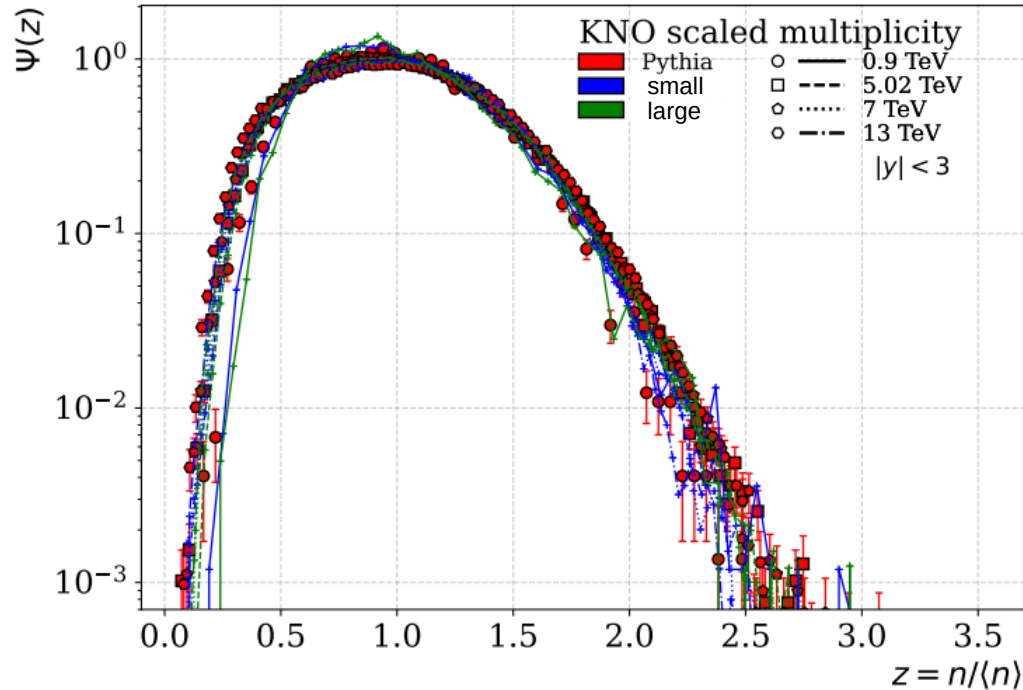
Total event multiplicity: ✓

Mean transverse momentum vs event multiplicity: ✓

Test of KNO-scaling for the predictions



Test of KNO-scaling for the predictions



Scaling function for multiplicities at various energies: $P_n = \frac{1}{\langle n \rangle} \Psi \left(\frac{n}{\langle n \rangle} \right)$

Charged hadron multiplicities: good overlap and agreement

Selected topics

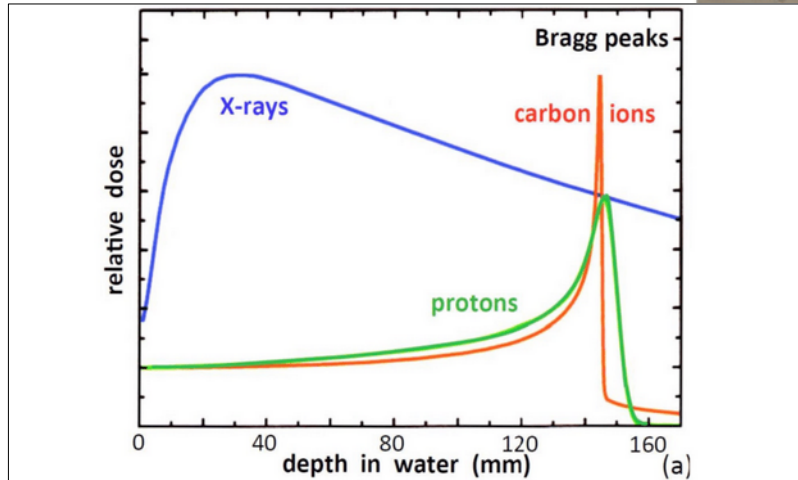
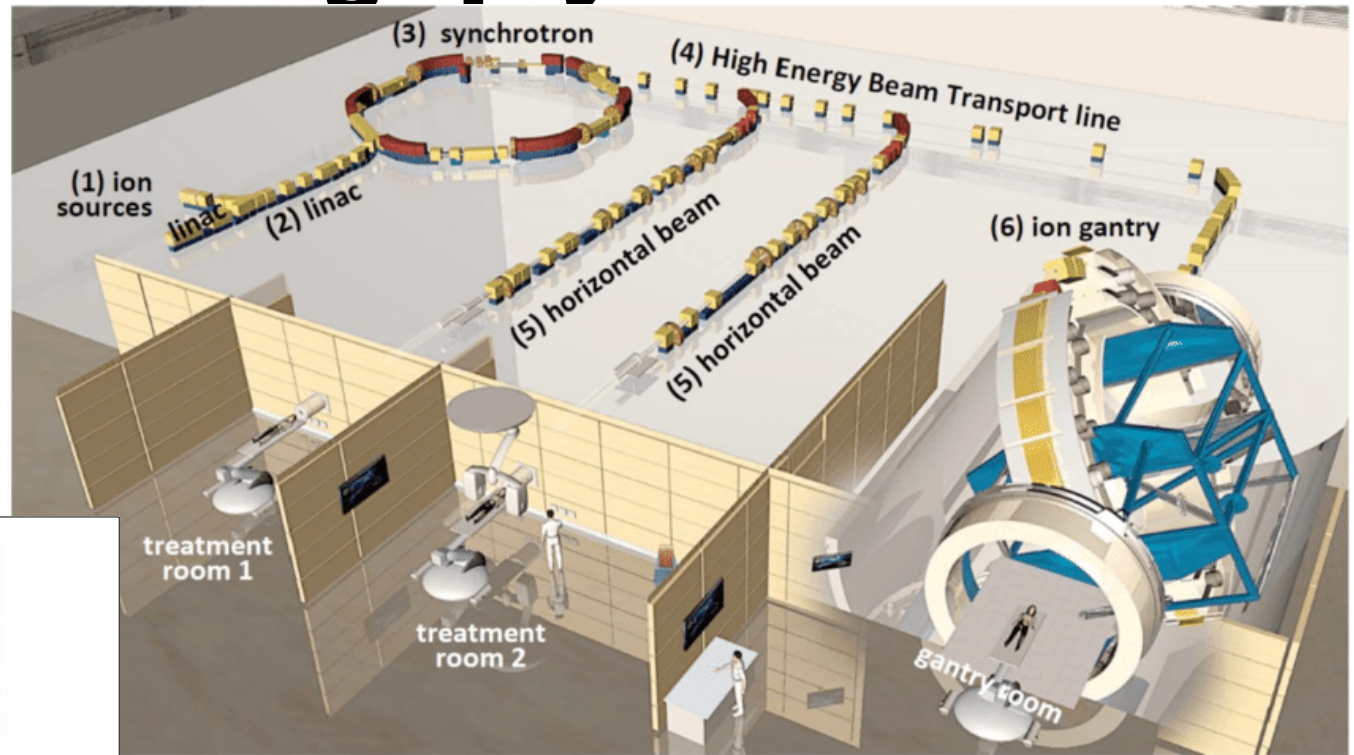
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- **Proton computed tomography for hadron therapy**
- Tuning of Monte Carlo event generators
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Proton Computed Tomography

- Cancer treatment: surgery, chemotherapy, radiotherapy, immunotherapy
- Radiotherapy: uses ionizing particles

arXiv:2212.00126

arXiv:2410.<...>



Layout figure of HIT Centre (Heidelberg)

Difficulty: difference between the absorption of photons and the energy loss of protons → conversion is not accurate between Hounsfield units and relative stopping power

Proton Computed Tomography

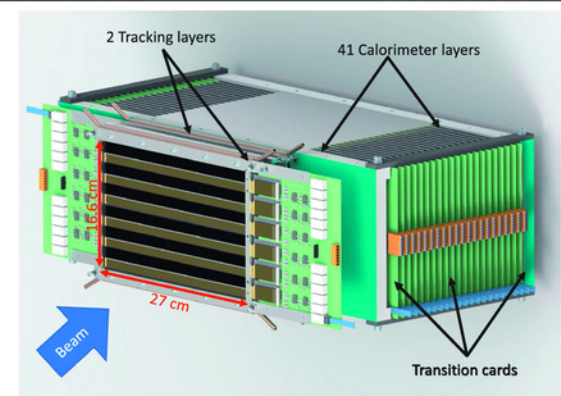
Irradiating the phantom with high energy (~100 MeV) protons

Detector system senses the signals

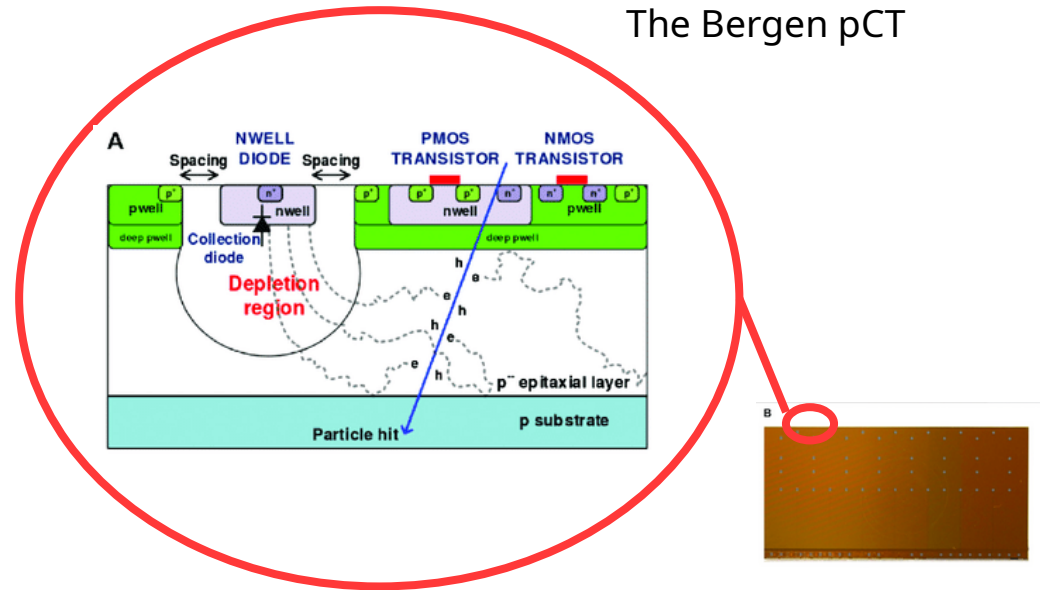
Processing the signals

Reconstructing the image

- Bergen pCT Collaboration
- Goal: proton CT based on the high-energy particle detectors used in the CERN ALICE collaboration (technology transfer)
- The detector system is based on the ALPIDE chip



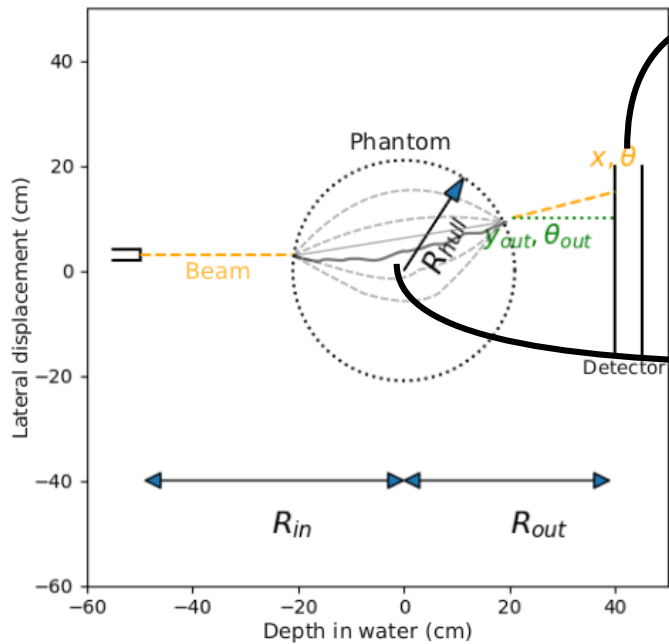
The Bergen pCT



The cross-sectional image (A) and the photograph (B) of the ALPIDE chip

Proton Computed Tomography

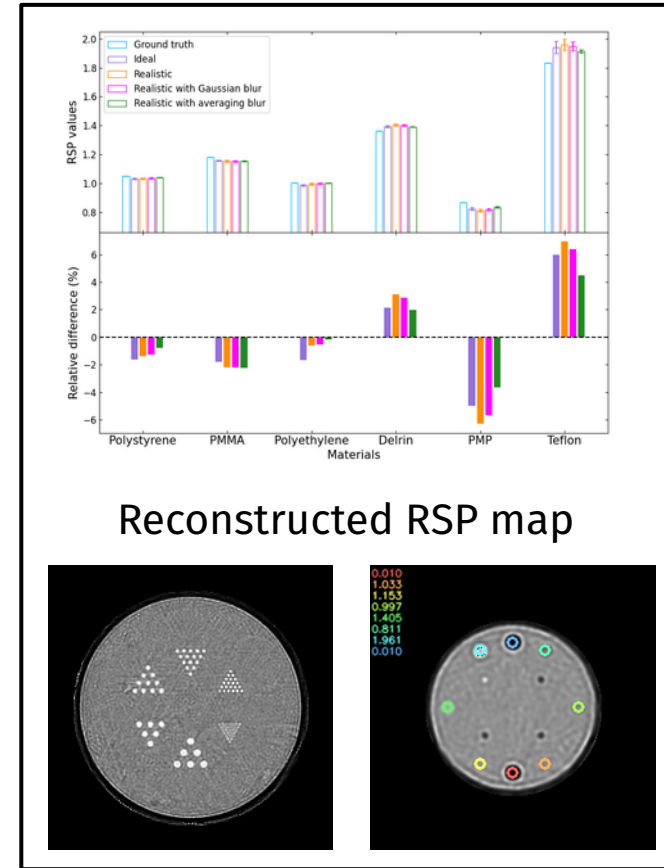
Track reconstruction
from detector signals



Most likely path
determination



Image
reconstruction



Selected topics

- Hadronization and scaling studies
- Proton computed tomography for hadron therapy
- **Tuning of Monte Carlo event generators**
- Monitoring of plasma channel

Monte Carlo parameter tuning

Simulation of one proton-proton collision event: complicated...

1) Perturbative QCD calculations

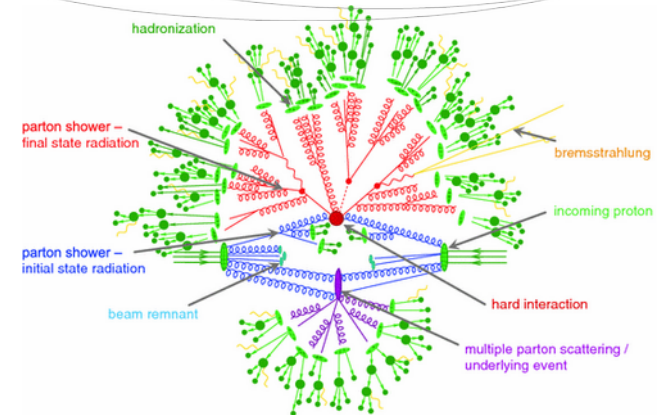
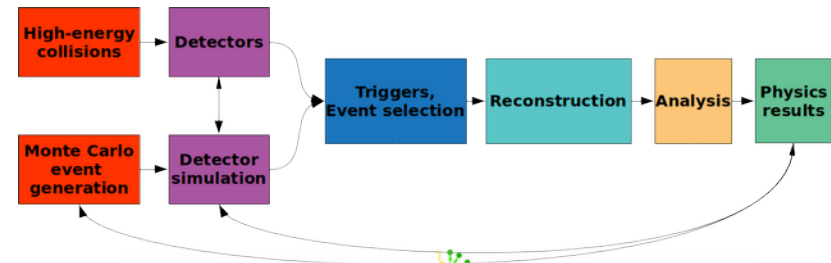
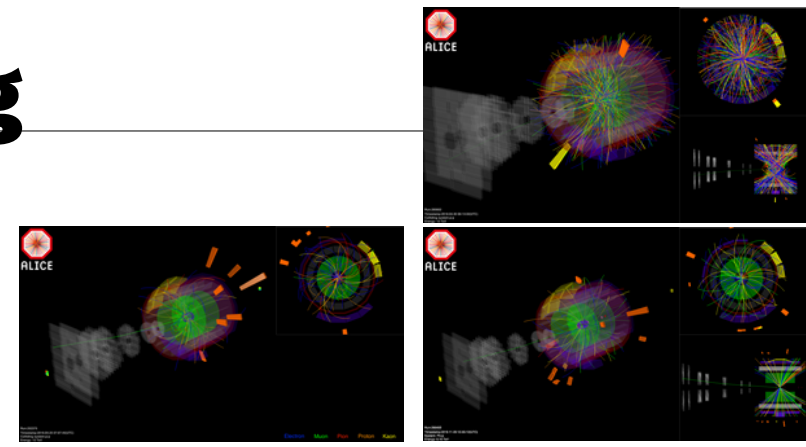
$$\frac{d^2\sigma^{lP\rightarrow hX}}{dx dQ^2} = \sum_{i=q,\bar{q},g} \int_x^1 \frac{dz}{z} f_i(z, \mu) d\hat{\sigma}_{il\rightarrow iX} \left(\frac{x}{z}, \frac{Q}{\mu} \right) D_i^h(z)$$

2) Additional phenomenological processes: MPI, colour reconnection, hadronization scheme...

3) Compromise: computational time \leftrightarrow precision

- Tons of random numbers

4) Empirical parameters: need to be tuned



Monte Carlo parameter tuning

Simulation of one **heavy-ion** collision event: **even more** complicated...

1) Perturbative QCD calculations

$$\frac{d^2\sigma^{lP\rightarrow hX}}{dx dQ^2} = \sum_{i=q,\bar{q},g} \int_x^1 \frac{dz}{z} f_i(z, \mu) d\hat{\sigma}_{il\rightarrow iX} \left(\frac{x}{z}, \frac{Q}{\mu} \right) D_i^h(z)$$

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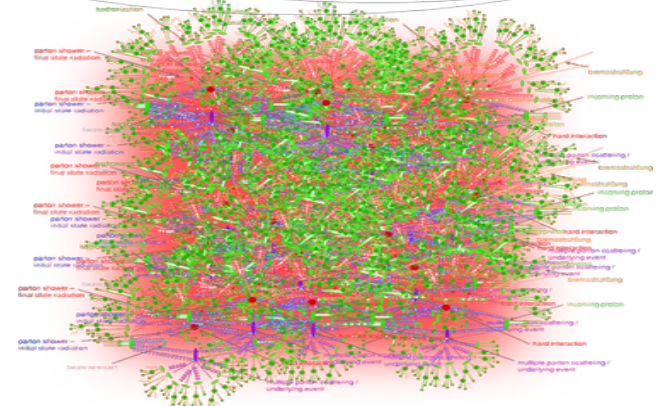
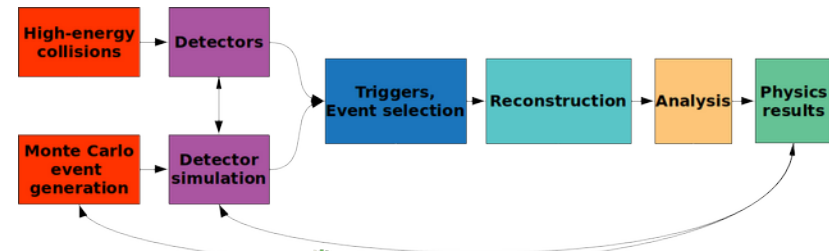
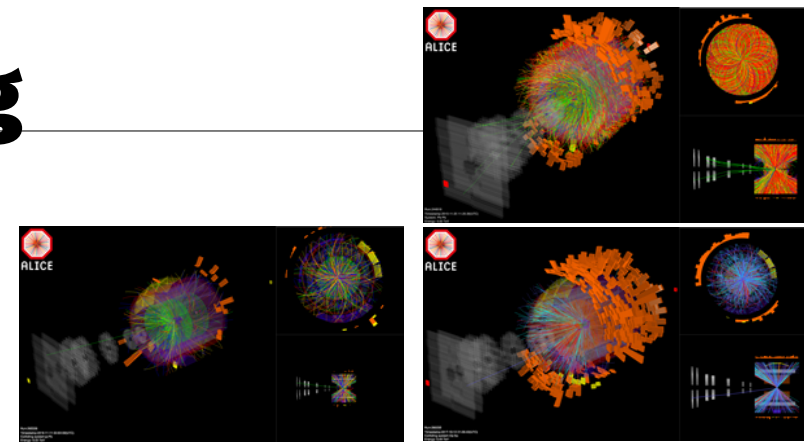
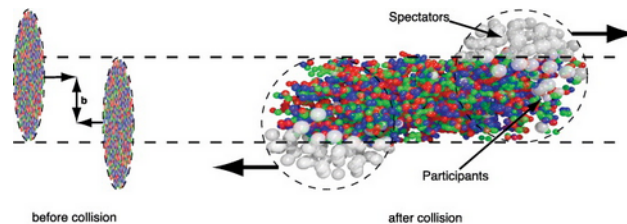
- **Tons** of random numbers

4) Empirical parameters: need to be tuned

5) Multiple nucleon-nucleon interactions

6) Additional nuclear effects: jet quenching, Cronin enhancement,

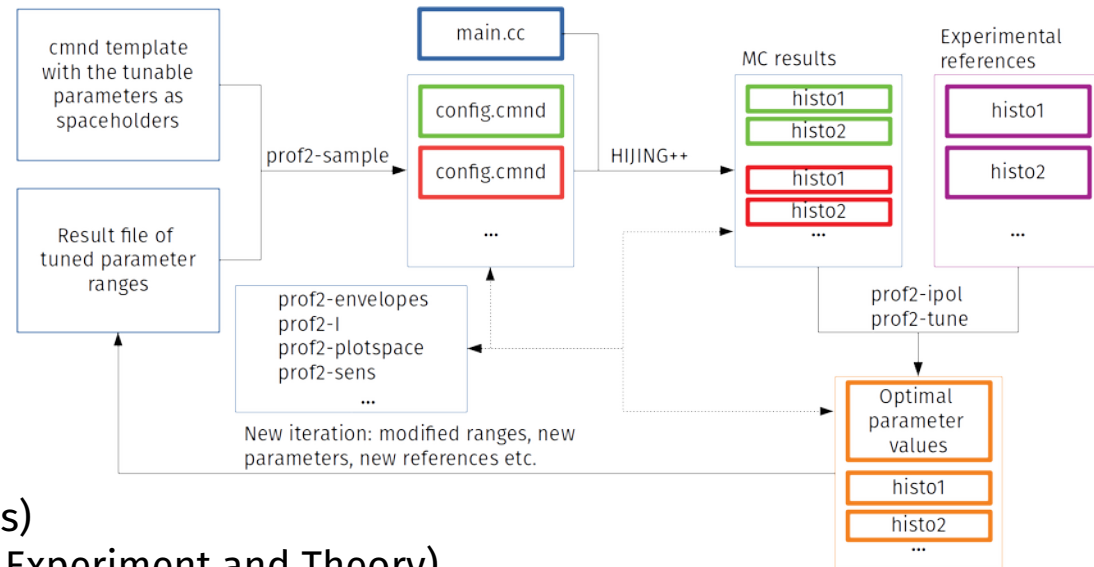
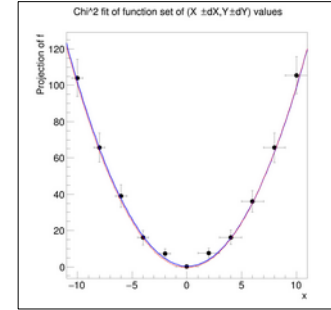
7) shadowing..



Monte Carlo parameter tuning

Tuning: set the empirical parameters to fit the experimental data
→ basically „just” an iterative χ^2 minimization

sample → **calculate** → minimize → repeat

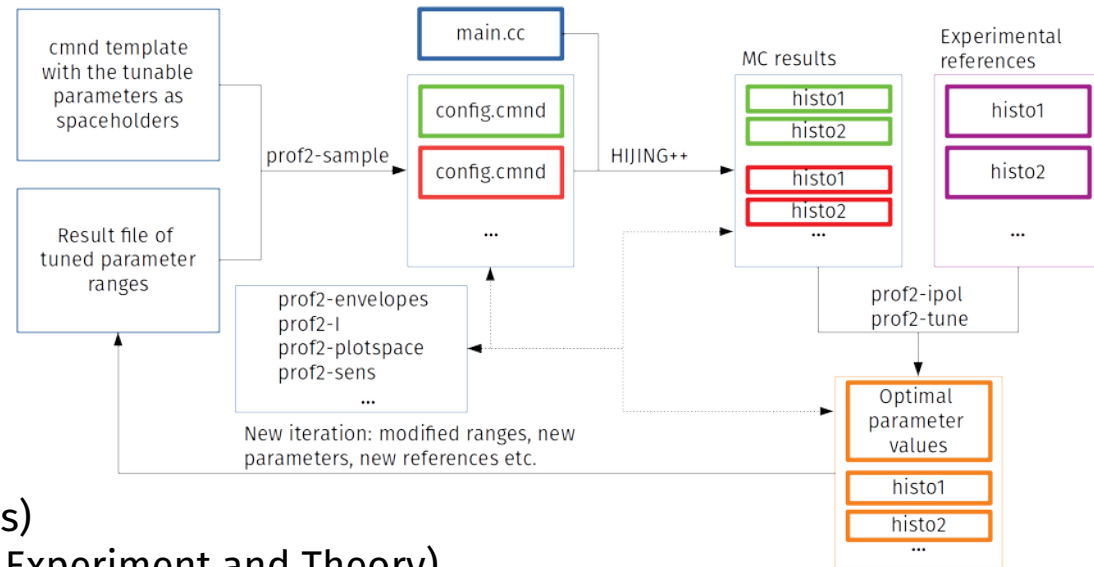
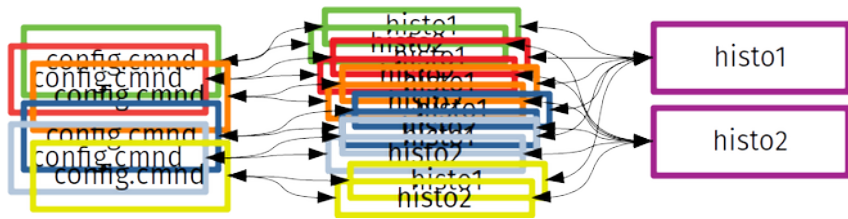
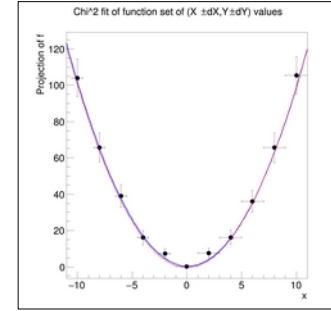


YODA (YODA – Yet more Objects for Data Analysis)
Rivet (Rivet – Robust Independent Validation of Experiment and Theory)
Professor (Tuning tool for Monte Carlo event generators)

Monte Carlo parameter tuning

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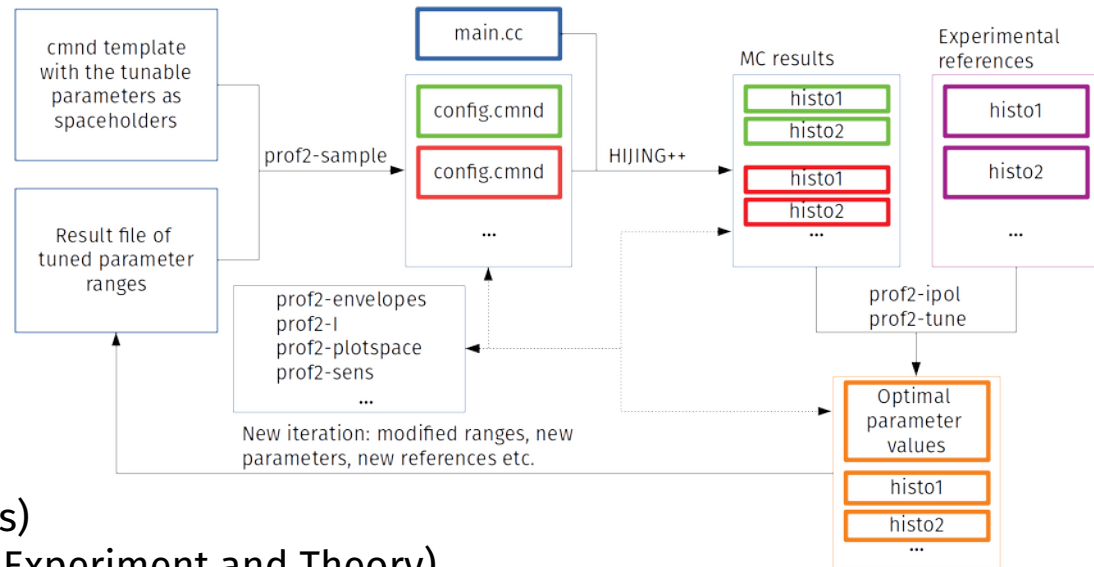
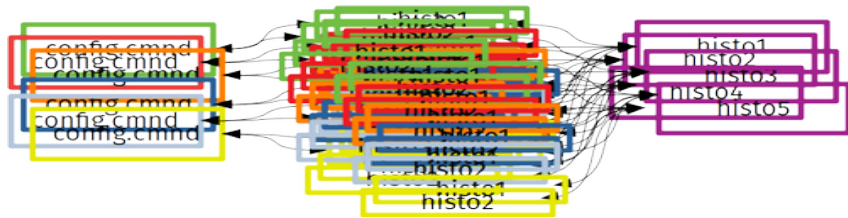
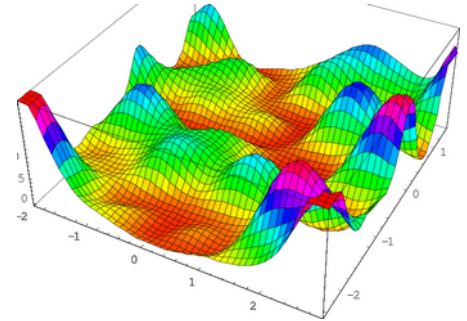


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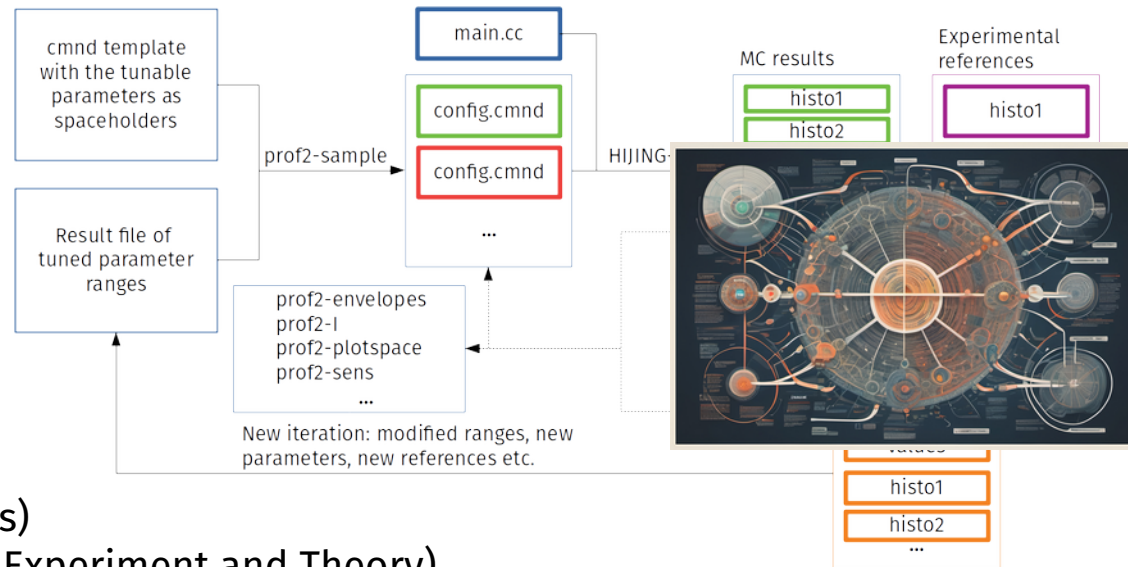
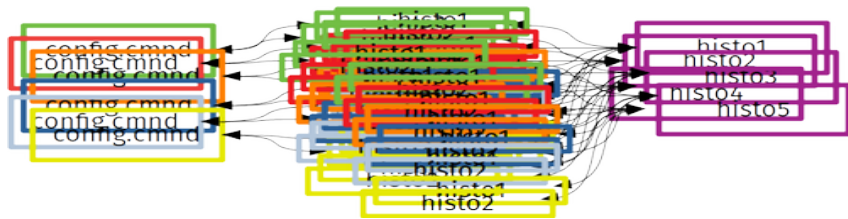
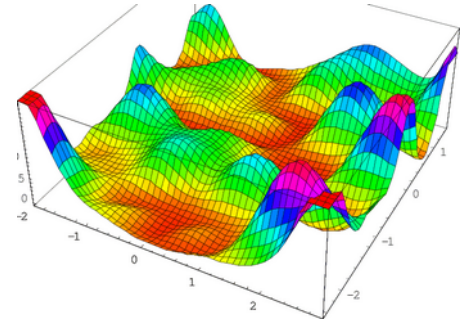


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Monte Carlo parameter tuning

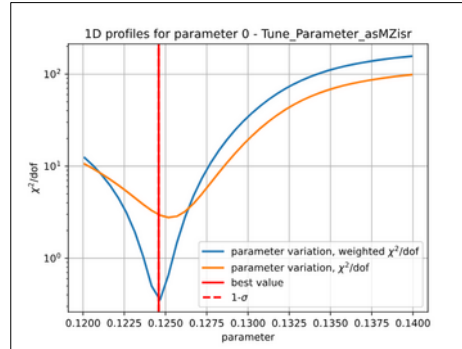
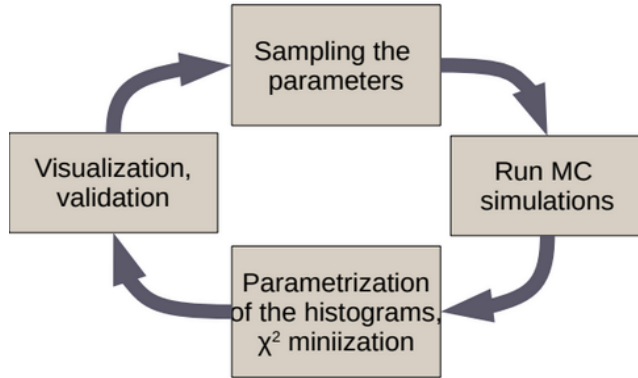
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Monte Carlo parameter tuning



Accelerating Science with Generative Adversarial Networks: An Application to 3D Particle Showers in Multi-Layer Calorimeters

Michela Paganini,^{1,2,*} Luke de Oliveira,^{1,†} and Benjamin Nachman^{1,‡}
¹Lawrence Berkeley National Laboratory, Berkeley, CA 94720
²Yale University, New Haven, CT 06520

<https://doi.org/10.1103/PhysRevLett.120.042003>

Neural Networks for Full Phase-space Reweighting and Parameter Tuning

Anders Andreassen^{1,2,*} and Benjamin Nachman^{2,†}

¹Department of Physics, University of California, Berkeley, CA 94720, USA

²Physics Division, Lawrence Berkeley National Laboratory, Berkeley, CA 94720, USA

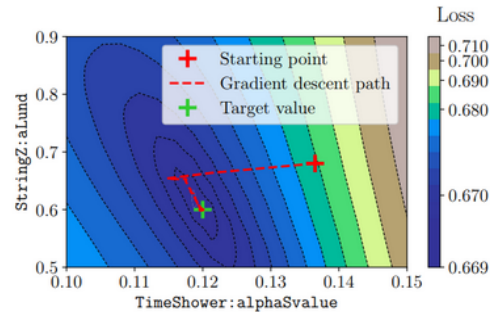


Figure 1: An illustration of the parametrisation of the generator response as implemented in the Per Bin Model.

Figure 2: An illustration of the Inverse Model strategy.

MCNNTUNES: tuning Shower Monte Carlo generators with machine learning

Marco Lazzarin^a, Simone Alioli^b, Stefano Carrazza^a

^aTIF Lab, Dipartimento di Fisica, Università degli Studi di Milano and INFN Sezione di Milano, Milan, Italy.
^bDipartimento di Fisica, Università degli Studi di Milano Bicocca and INFN Sezione di Milano Bicocca, Milan, Italy.

<https://doi.org/10.1016/j.cpc.2021.107908>

Selected topics

- Hadronization and scaling studies
- Proton computed tomography for hadron therapy
- Tuning of Monte Carlo event generators
- **Monitoring of plasma channel**

Monitoring plasma channel

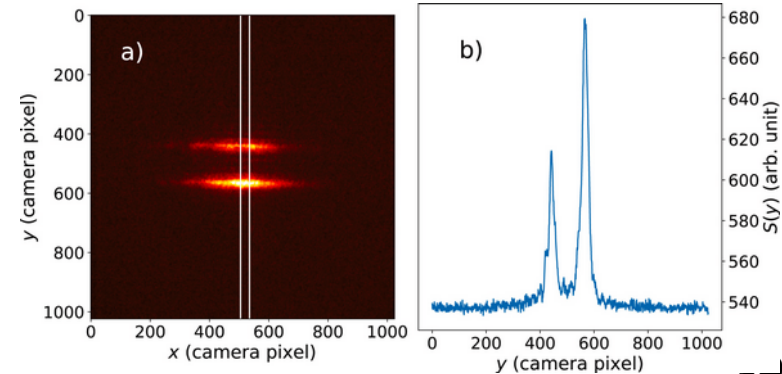
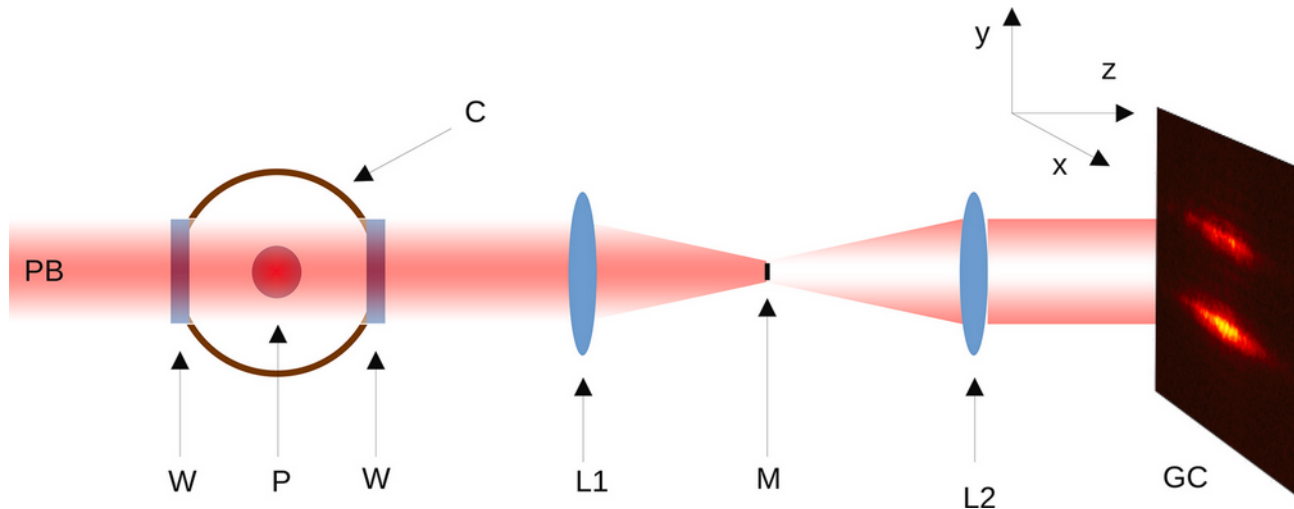
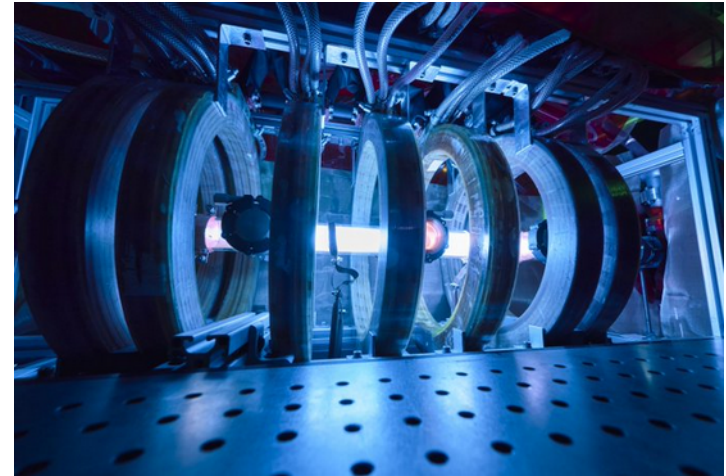
CERN-AWAKE Experiment: accelerate electrons in the wake field of proton

Microbunches: Nuclear Instruments and Methods in Physics Research Section A, 829 (2016) 76-82

Accelerating medium: Rb plasma: 10 m length, $10^{14} - 10^{15} \text{ cm}^{-3}$ density. Chamber diameter: 4 cm

Experiment motivation: determine plasma parameters via Schlieren imaging

arXiv:2205.12731



Monitoring plasma channel

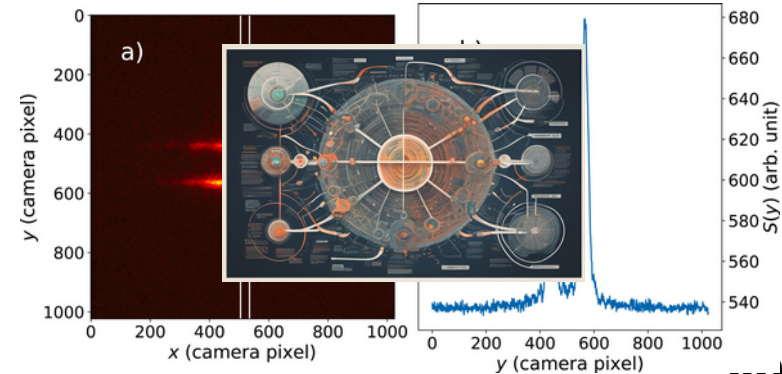
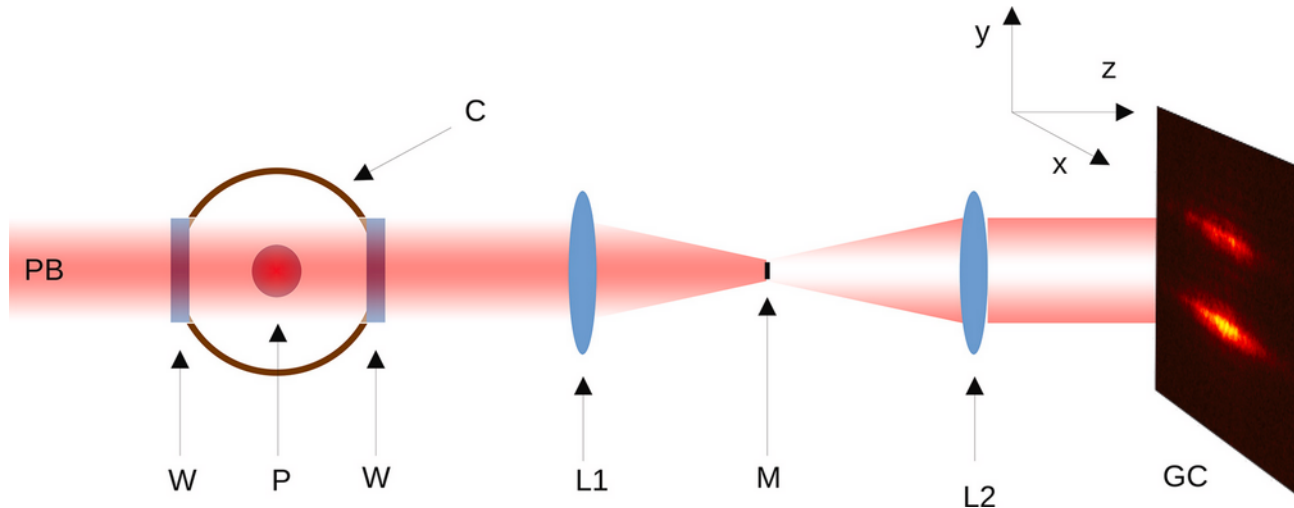
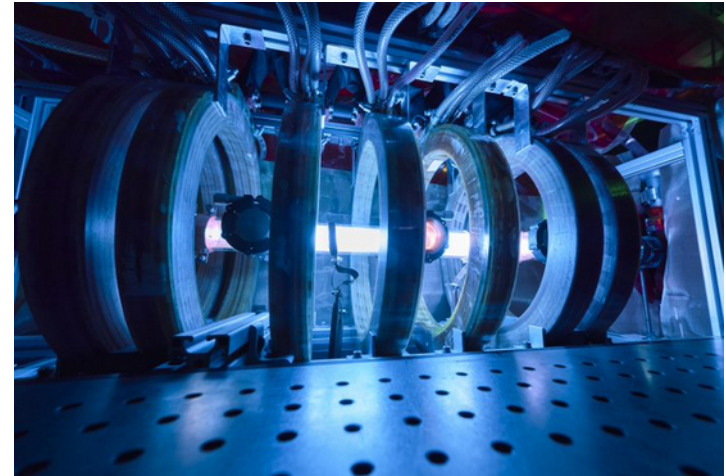
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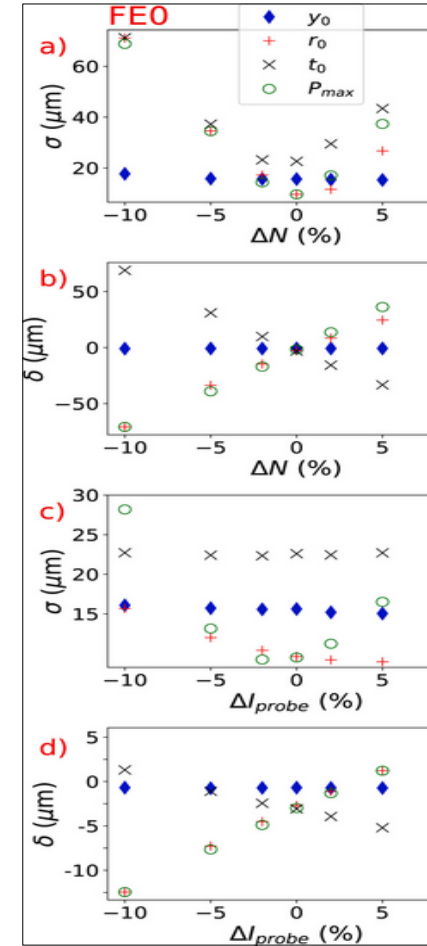
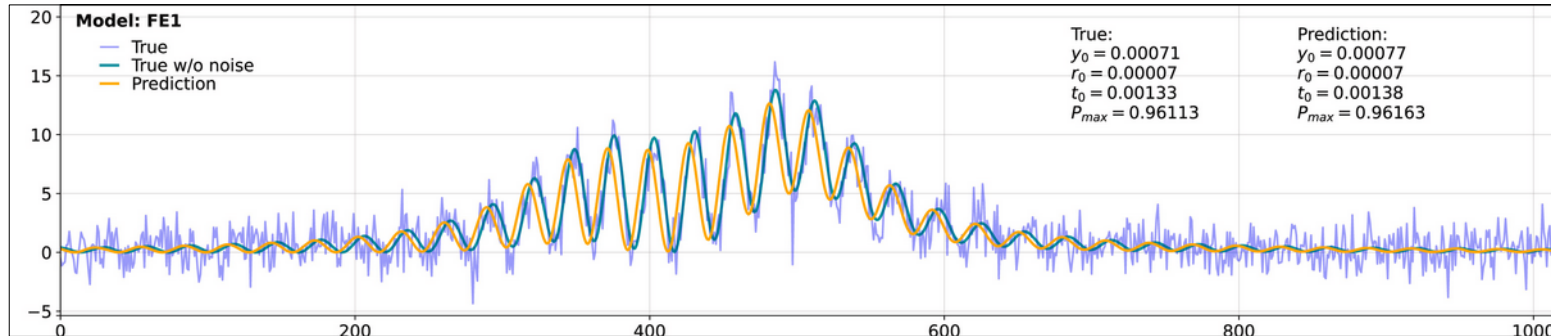
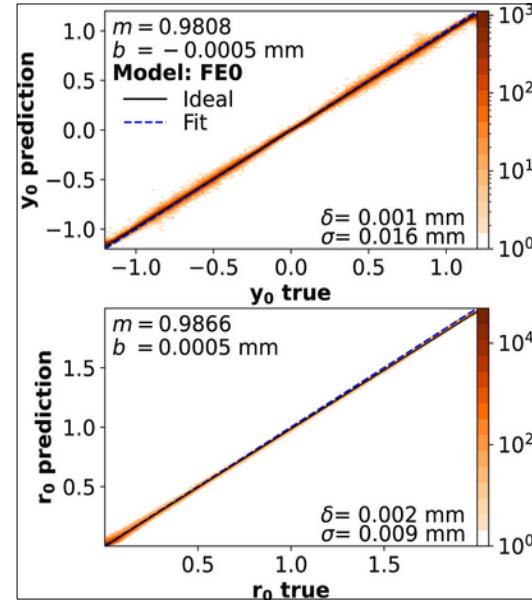
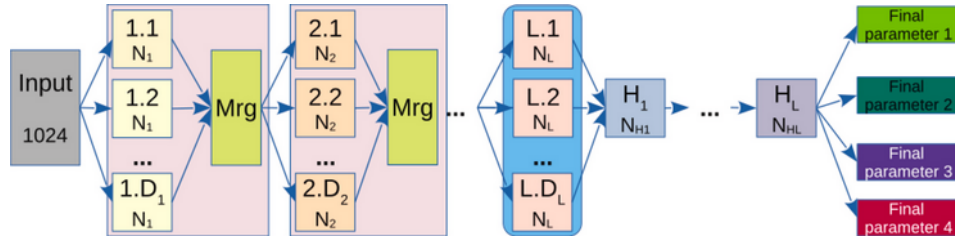


Monitoring plasma channel

Flexible network design

Precise prediction of the plasma parameters

Robust for variable experimental conditions



Summary

Advanced machine learning applications are booming (in HEP)

Getting more and more accessible

Selected topics (among others) related to our research group:

- Hadronization and scaling studies
- Proton computed tomography for hadron therapy
- Tuning of Monte Carlo event generators
- Monitoring of plasma channel



Thank you for your attention!

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