Machine Learning applications in high energy physics

V4HEP - Prague

Theory and Experiment in High Energy Physics

02-03 10 2024

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supported by
Visegrad Fund

HUN REN | Wigner | ELTE EÖTVÖS LORÁND TUDOMÁNYEGYETEM

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Former:

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Bence Tankó-Bartalis
Mihály Pocsai
Imre Barna
Gábor Demeter

History

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

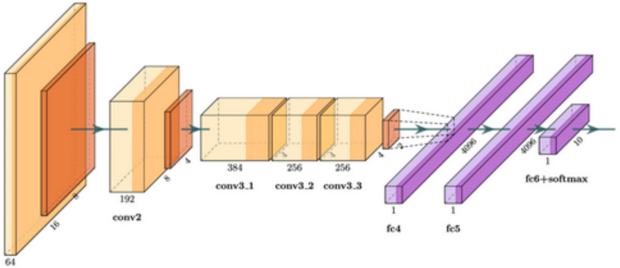
Checkers (1959) - Arthur Samuel

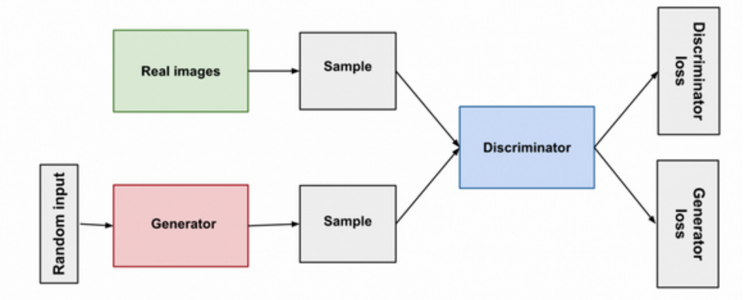
Chess (1997) - 11.38 GFLOPS

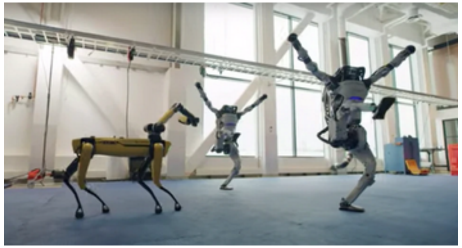
Jeopardy! (2011) - IBM Watson

Google Brain (2011)

Go (2016) - AlphaGo



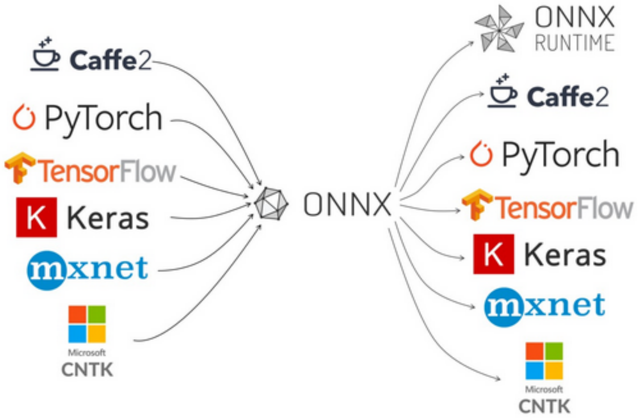




CNN (image classification, object detection, recommender systems)

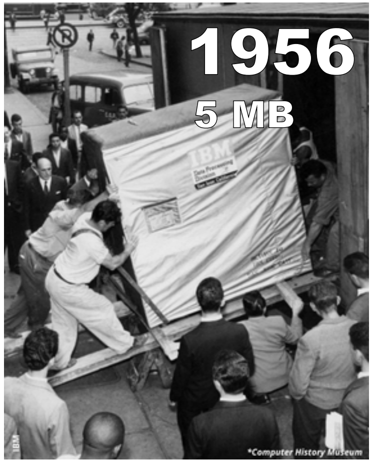
Recurrent/recursive neural networks (RNNs), sequence modeling, next word prediction, translating sounds to words, human language translation

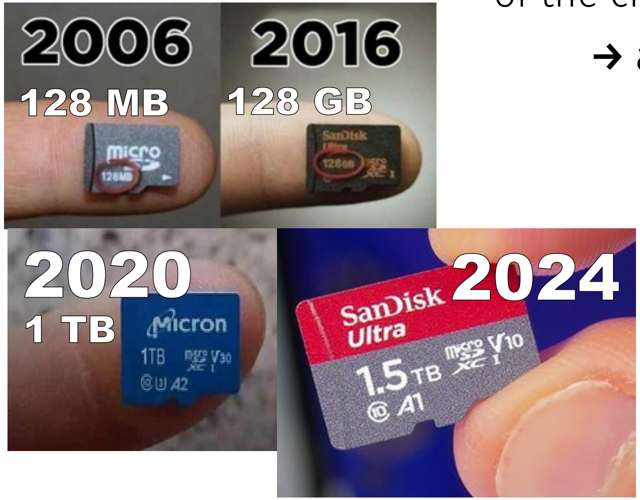
Generative models: anomaly detection, pattern recognition, reinforced learning...



https://towardsdatascience.com/onnx-preventing-framework-lock-in-9a798fb34c92

Data, data, and more data



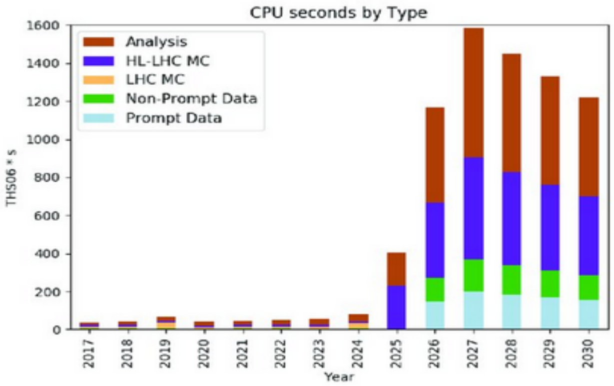


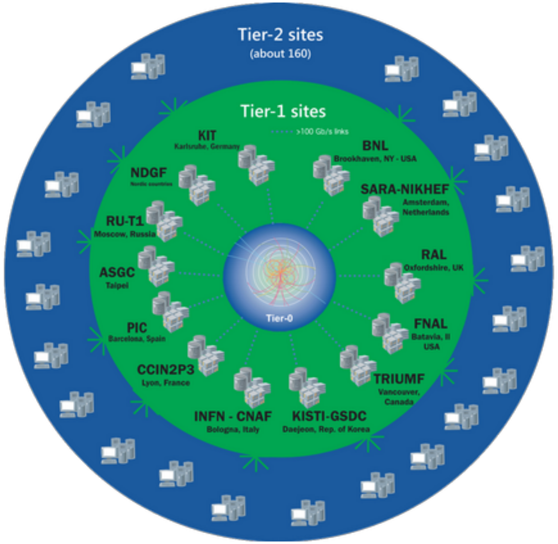
LHC in numbers: **2013** and **now:**

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 challange

→ **analysis, simulations**

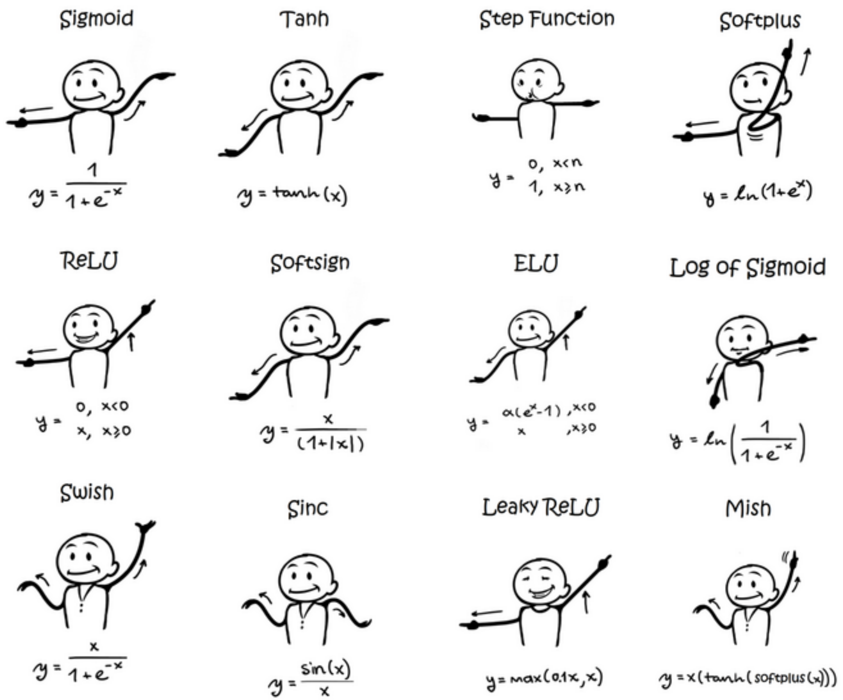


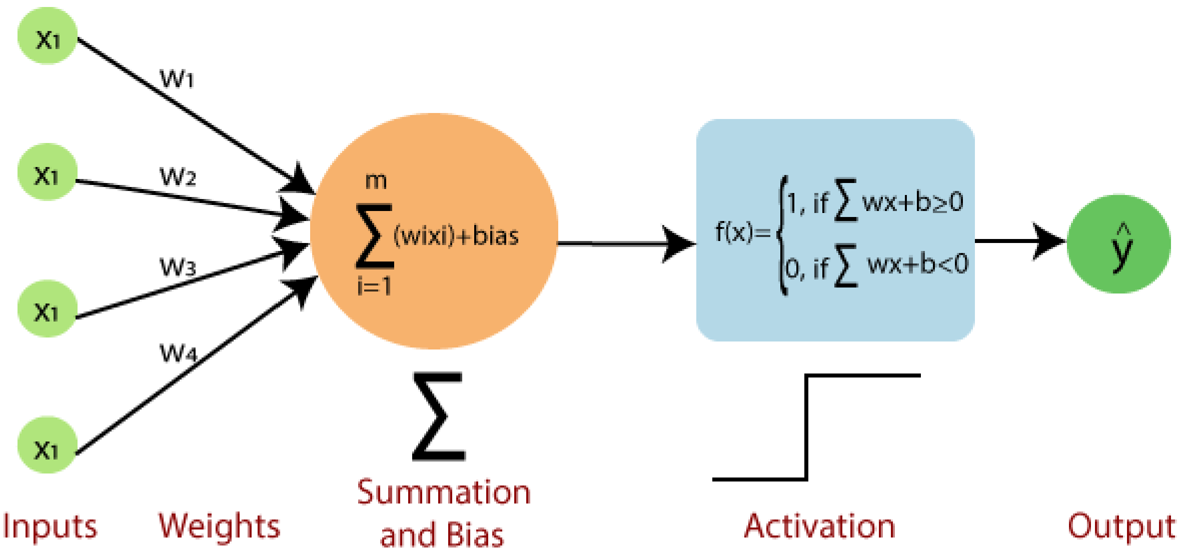


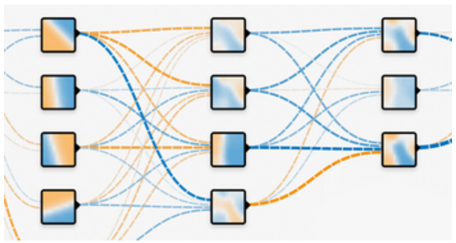
Main ingredients

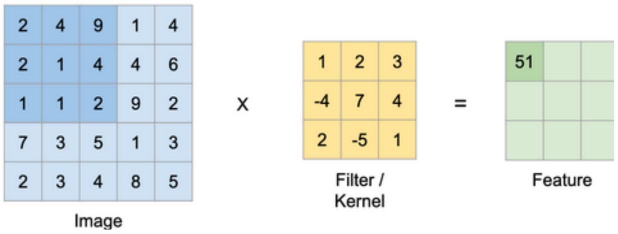
Perceptrons:

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





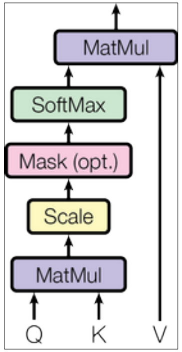




Other important components: pooling layers, regularization and normalization, recurrent layers...

https://sefiks.com/2020/02/02/dance-moves-of-deep-learning-activation-functions/

Transformers and LLMs

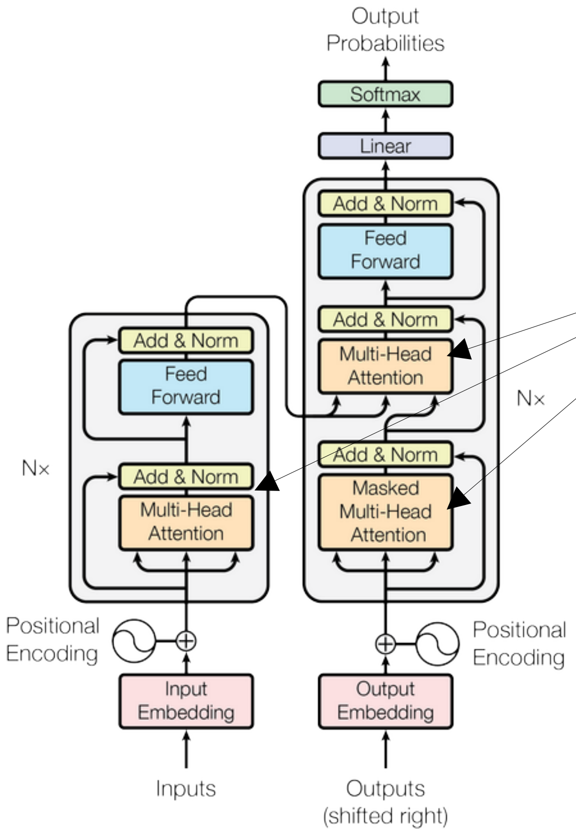


$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

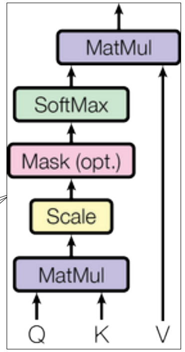
Attention layer:

- 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



arXiv:1706.03762
(5000+ citations)



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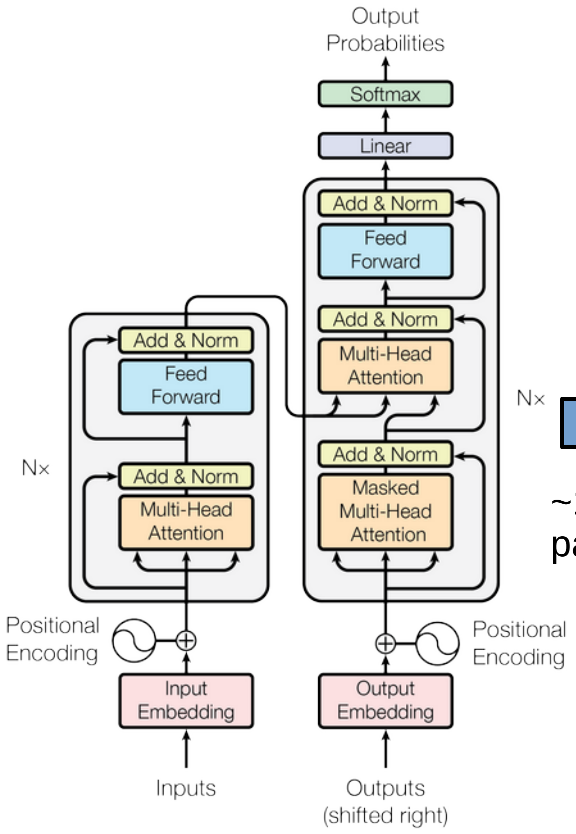
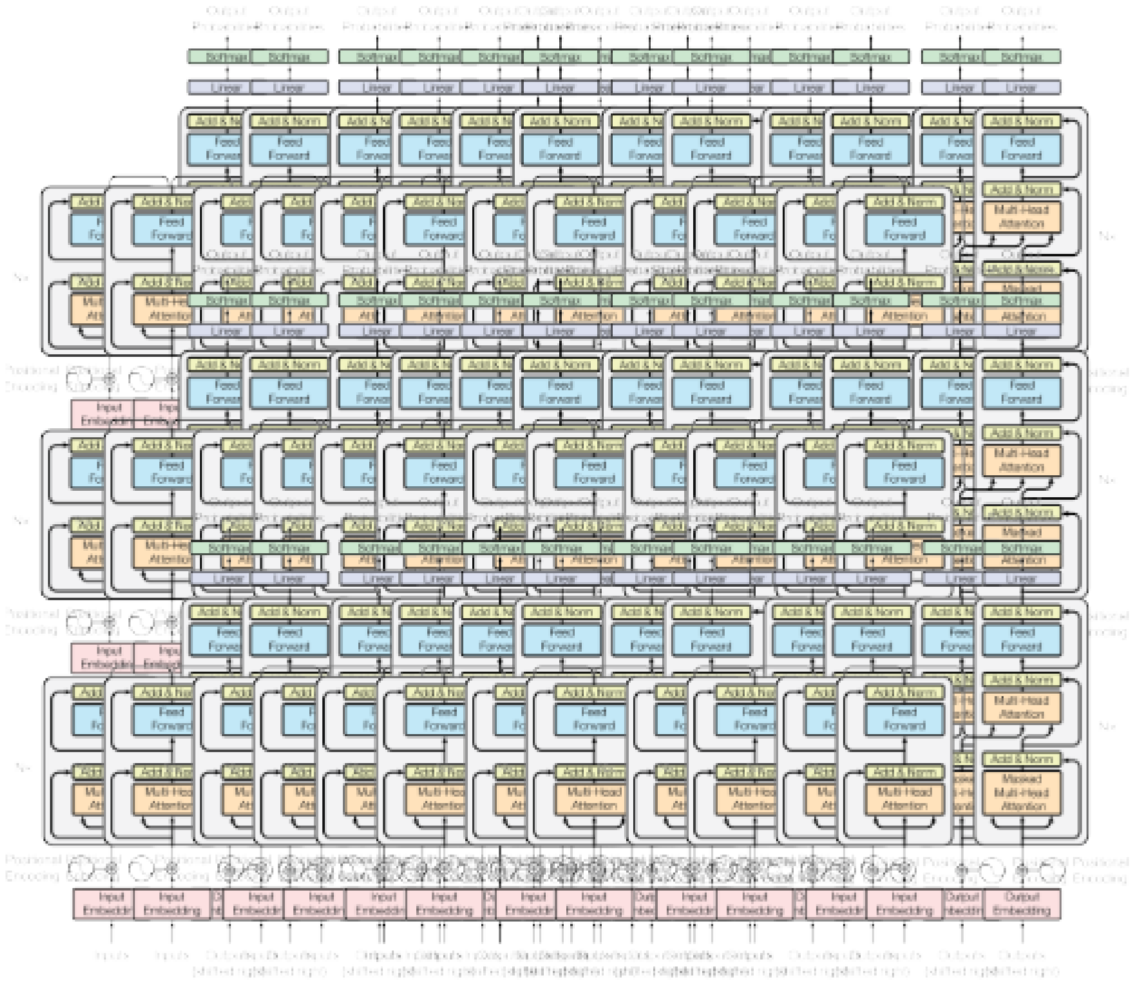
Transformers and LLMs



~1.7 **trillion**
parameters



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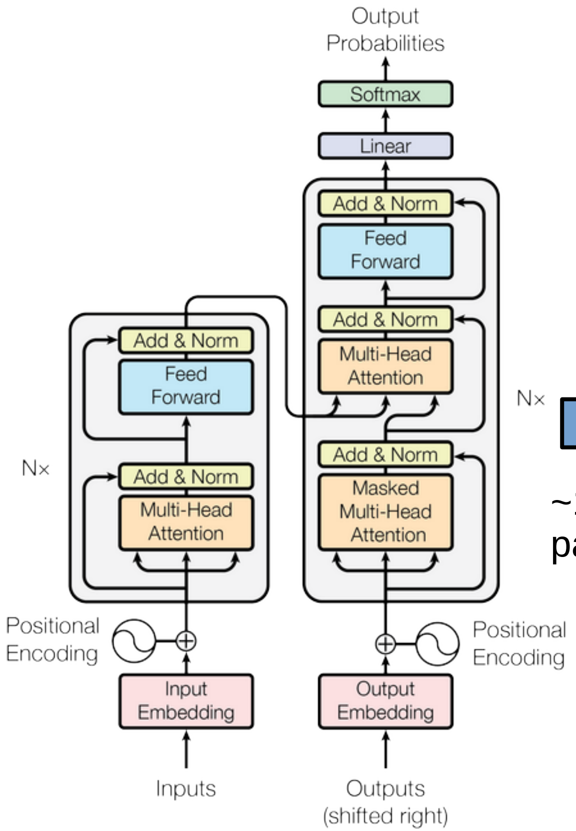
Transformers and LLMs



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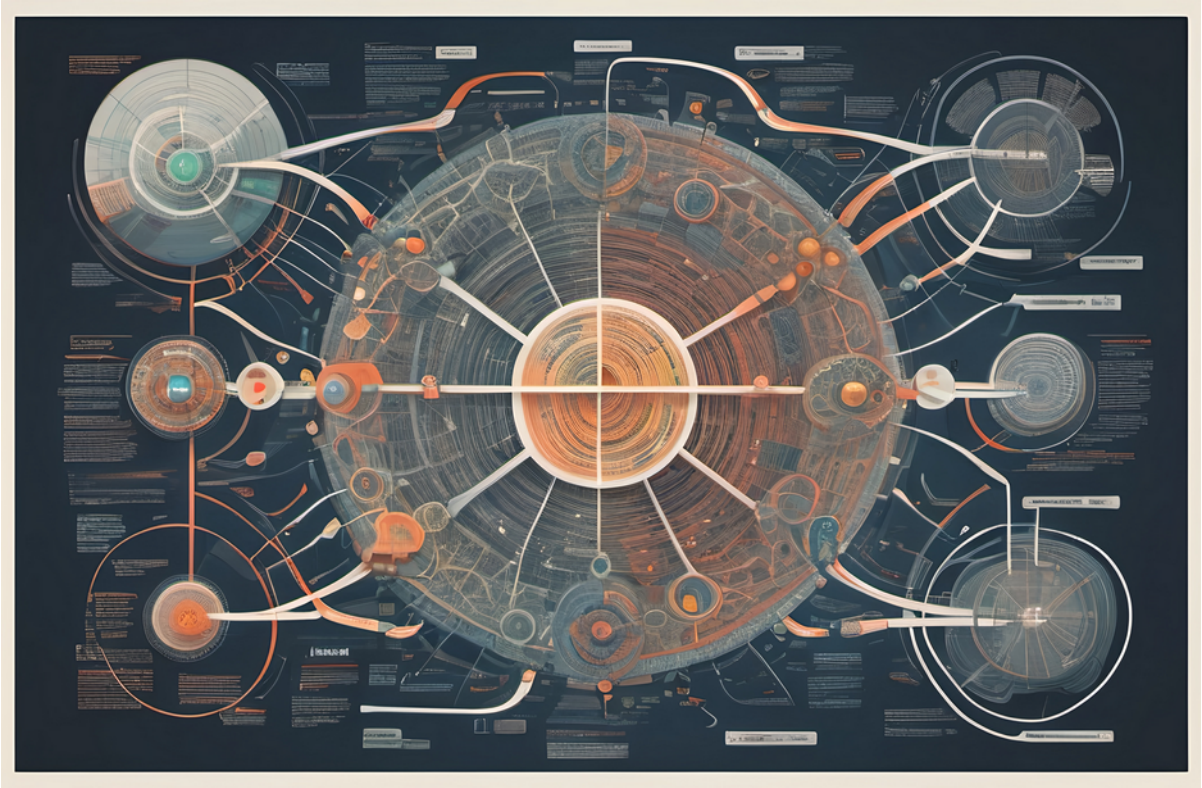

Machine Learning in HEP

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

2021 November: 568 references

2022 October: 724 references

2023 June: **849** references

Today:

- Track reconstruction
- Quark/gluon jet separation
- Jet reconstruction
- Tuning Monte Carlo event generators
- GAN of detectors
- …

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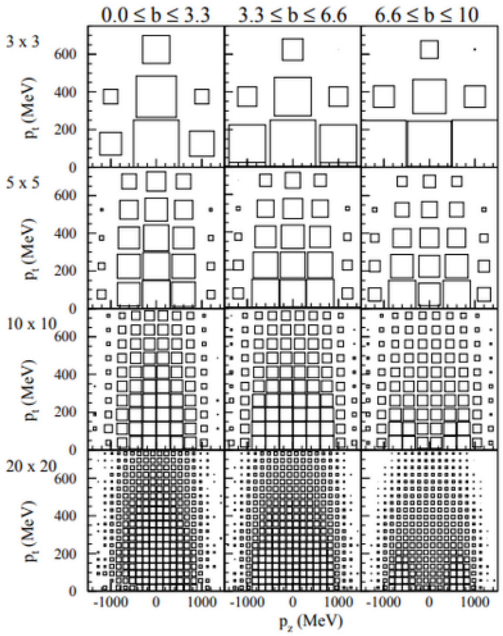
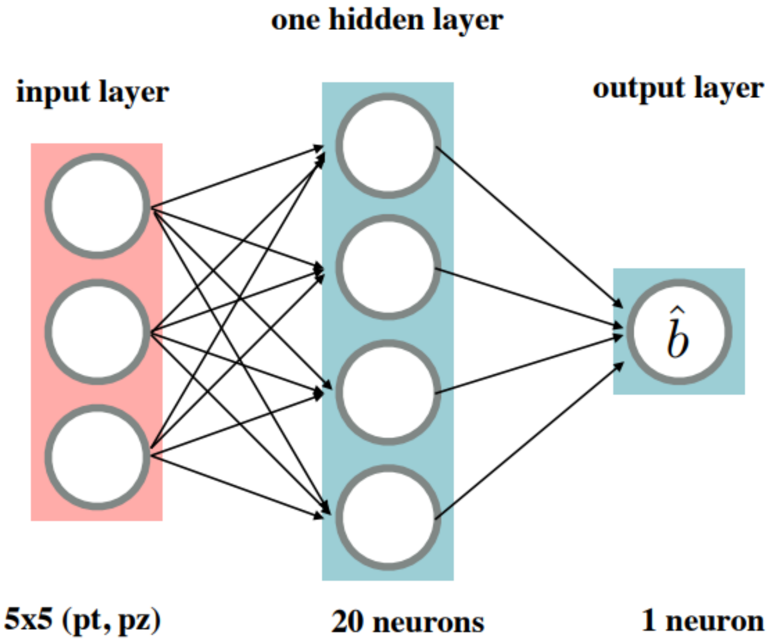
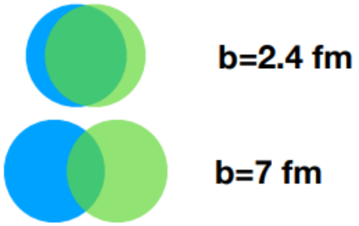
Machine Learning in HEP

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."

PRC 53 2358 (1996), Bass, S. A.; Bischoff, A.; Maruhn, J. A.; Stöcker, H.; Greiner, W.c

Machine Learning in HEP

Particle Track Reconstruction with Deep Learning

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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

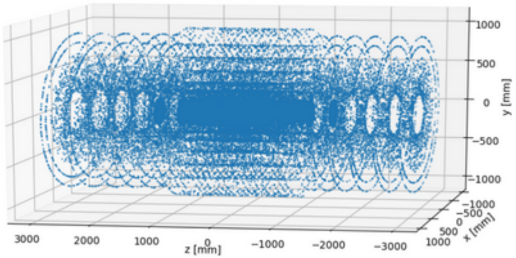
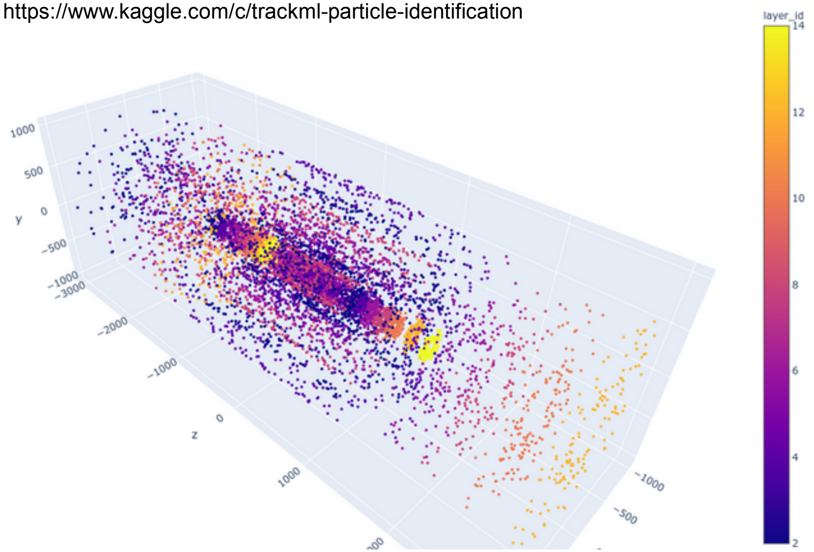


Figure 1: Distribution of particle spacepoints in a particle collision event in a generic simulated HL-LHC tracking detector.

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



Machine Learning in HEP

Jet reconstruction

Machine Learning based jet momentum reconstruction in heavy-ion collisions

Rüdiger Haake[1] and Constantin Loizides[2]
[1] *Yale University, Wright Laboratory, New Haven, CT, USA*
[2] *ORNL, Physics Division, Oak Ridge, TN, USA*
(Dated: June 24, 2019)

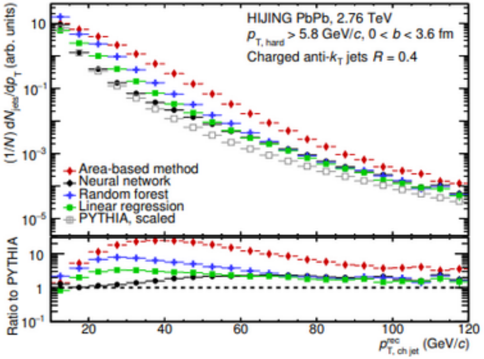


FIG. 9. Reconstructed charged jet spectra in HIJING events and the ratio to (N_{coll}-scaled) PYTHIA jet spectra.

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

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

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

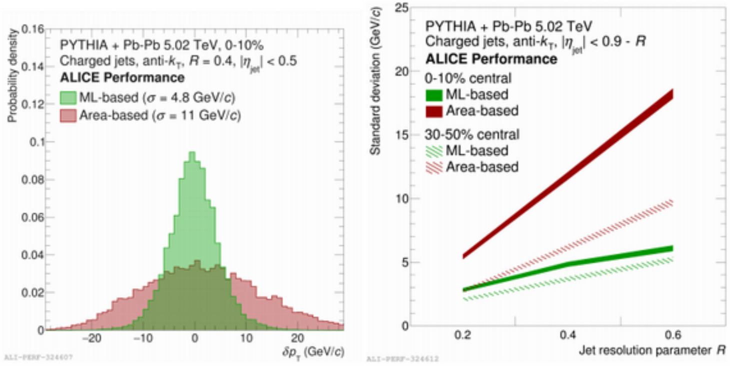
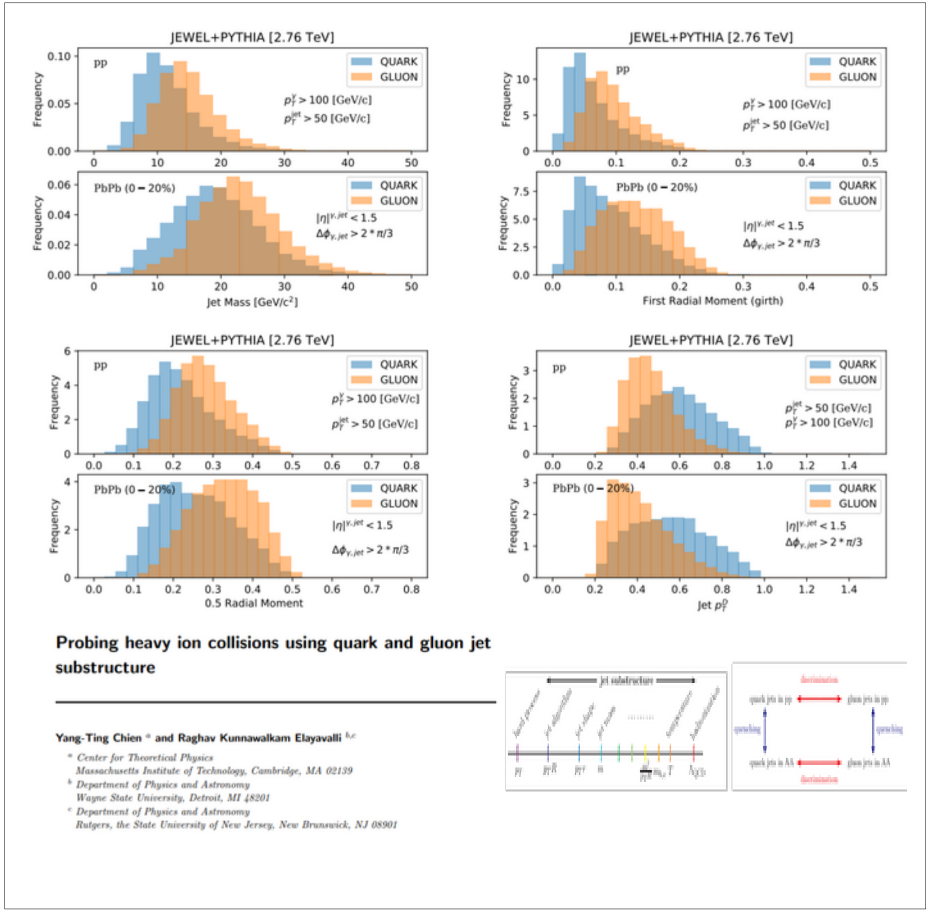


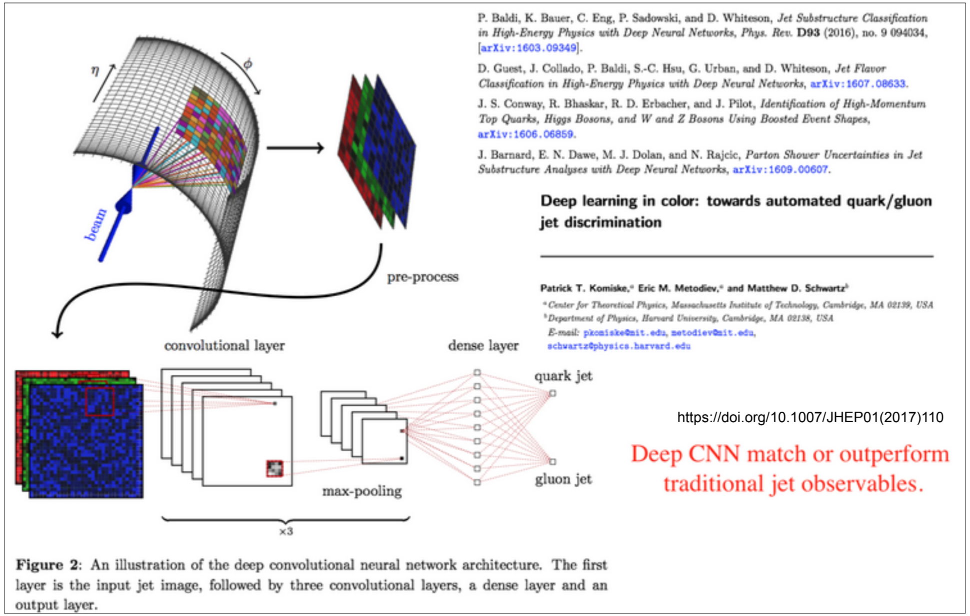
Figure 1: Residual p_T-distributions of embedded jet probes of known transverse momentum.

https://doi.org/10.22323/1.364.0312

Machine Learning in HEP



Separation of quark/gluon jets



https://doi.org/10.1007/JHEP01(2017)110

Deep CNN match or outperform traditional jet observables.

I. Csabai et al. Nucl.Phys.B 374 (**1992**) 288-308

I. Csabai et al. Phys.Rev.D 44 (**1991**) 1905-1908

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

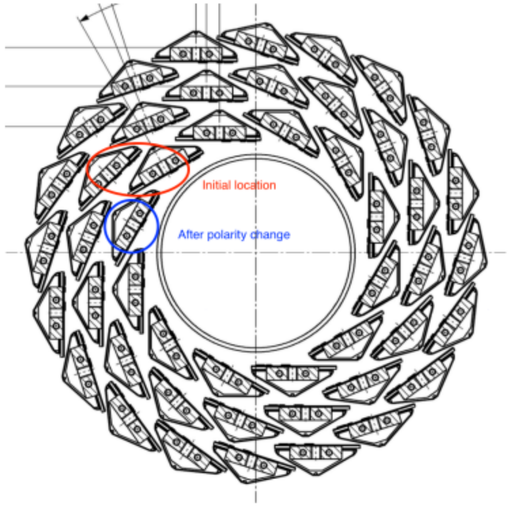


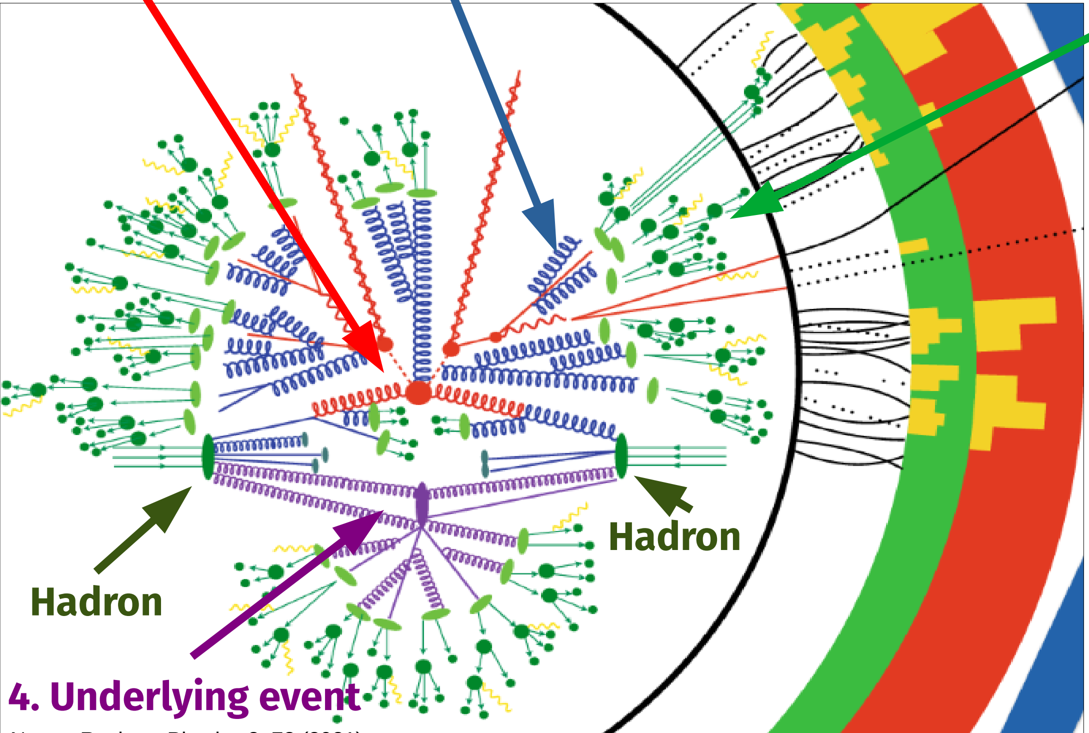
Figure 1: The layout of the ITS.

Zsófia Jólesz, CERN-STUDENTS-Note-2024-170

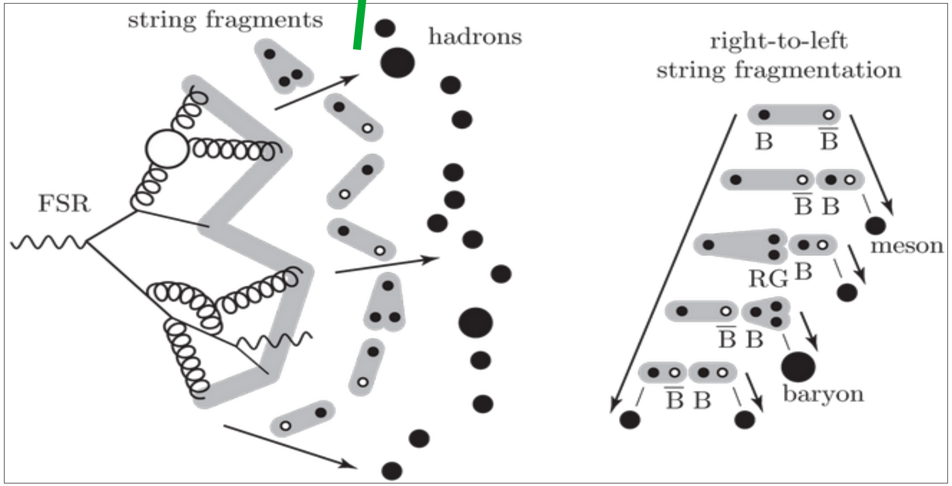
Selected topics

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

Parton shower and hadronization



Nature Reviews Physics 3, 73 (2021)



arXiv:2408.17130
arXiv:2303.05422
arXiv:2210.10548

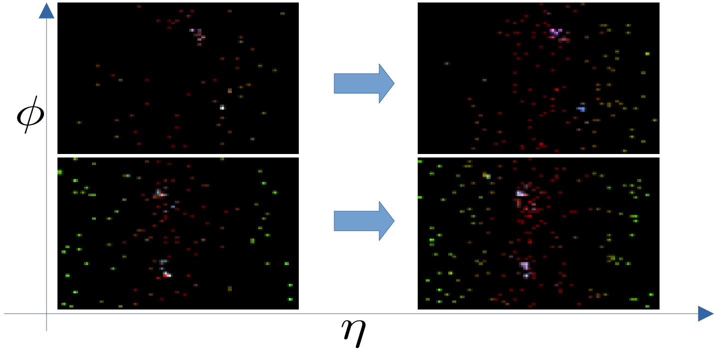
Hadronization

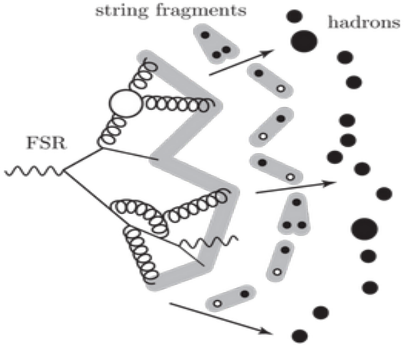
Partons → hadrons

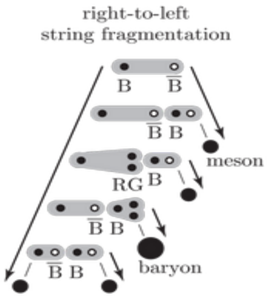
Non-perturbative process

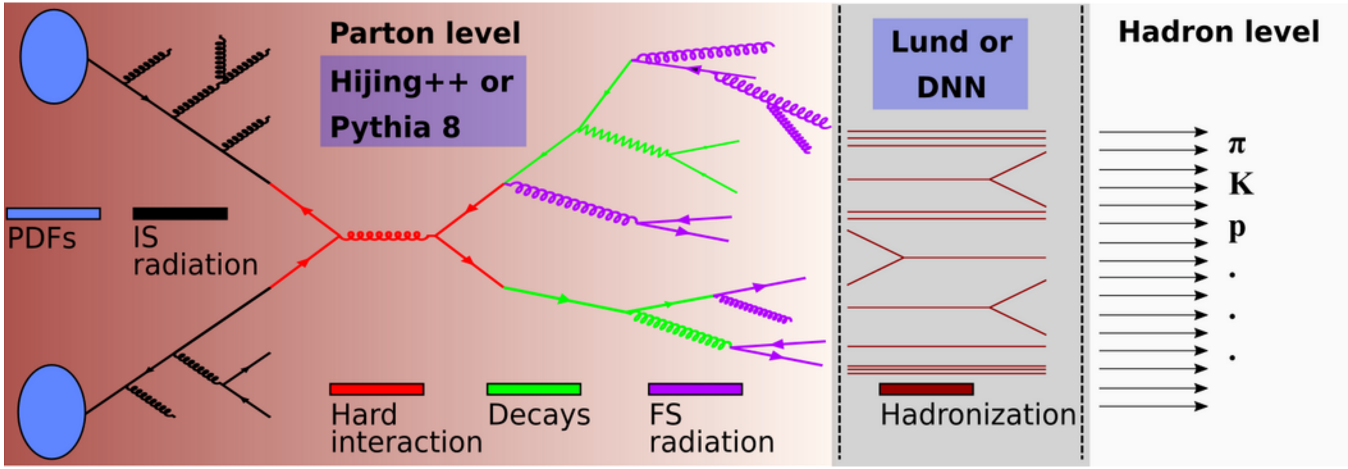
Lund-fragmentation (Comput.Phys.Commun. 27 (1982) 243)

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









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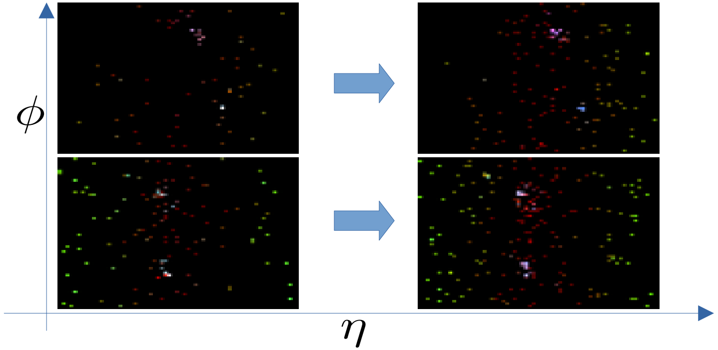
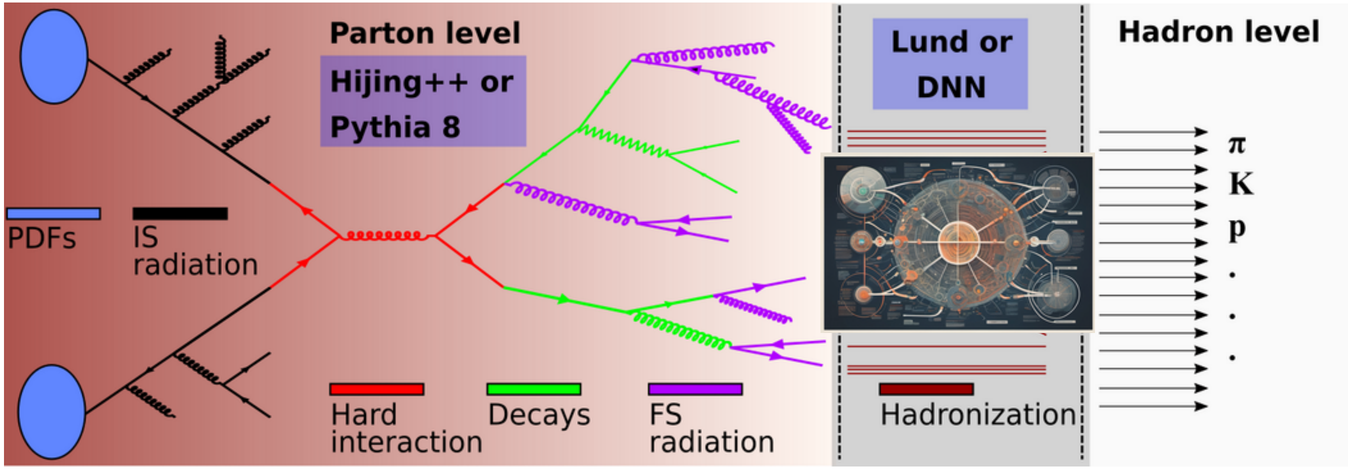
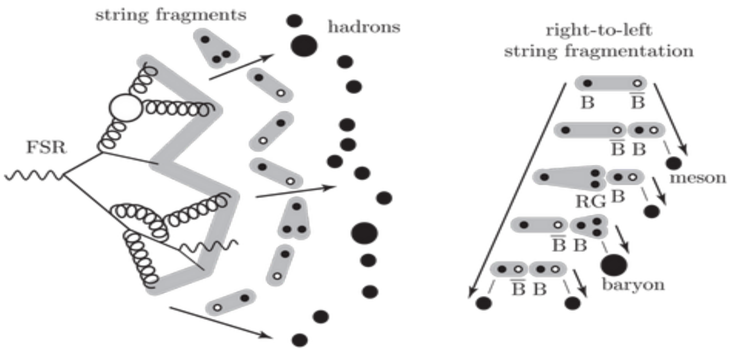






Train and validation sets

Monte Carlo data: Pythia 8.303

Monash tune
Rescattering and decays turned off
CR, ISR, FSR, MPI: turned on
Selection:
- All final particles with $|y| < 4.0$

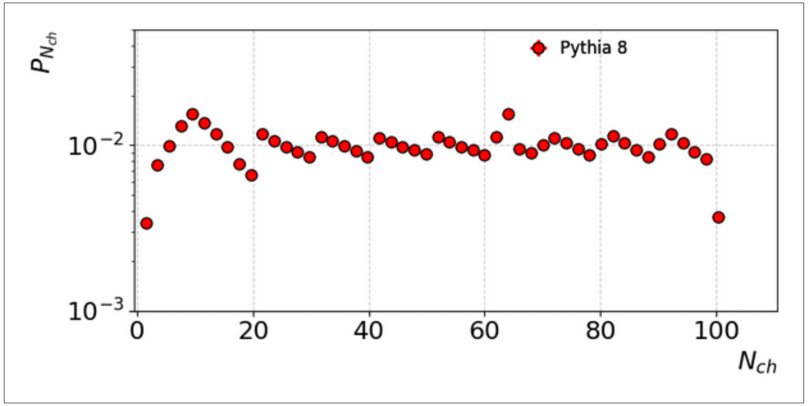
Event number:
- Train: 5M events, **$\sqrt{s}$ = 7 TeV**
  - ~uniform multiplicity distribution
- ~30 GB raw data

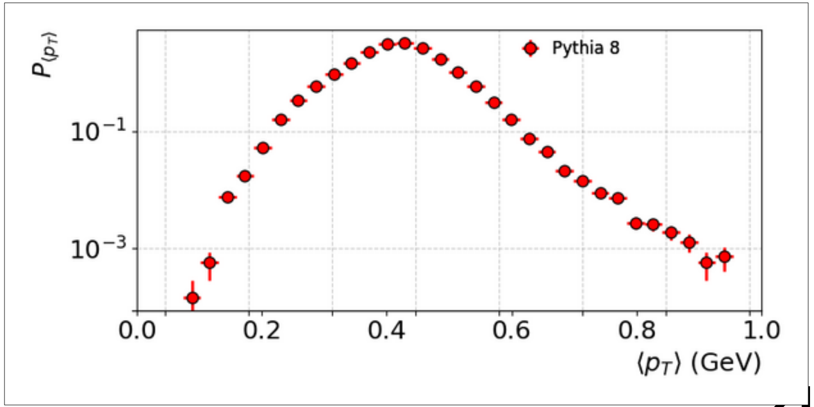
Parton level, before the hadronization process

Standardized η, φ, p_T, m variables

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

Charged event multiplicity, mean event transverse momentum





Models

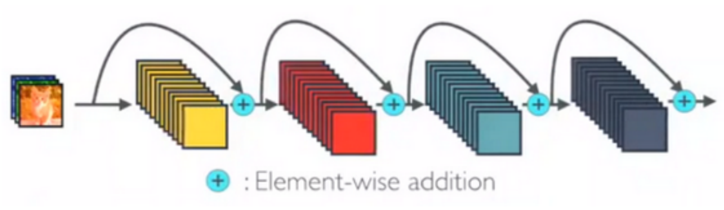
Stacking more layers: solve complex problems more efficiently, get highly accurate results

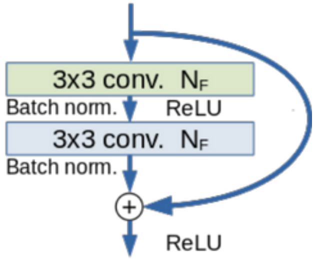
BUT:

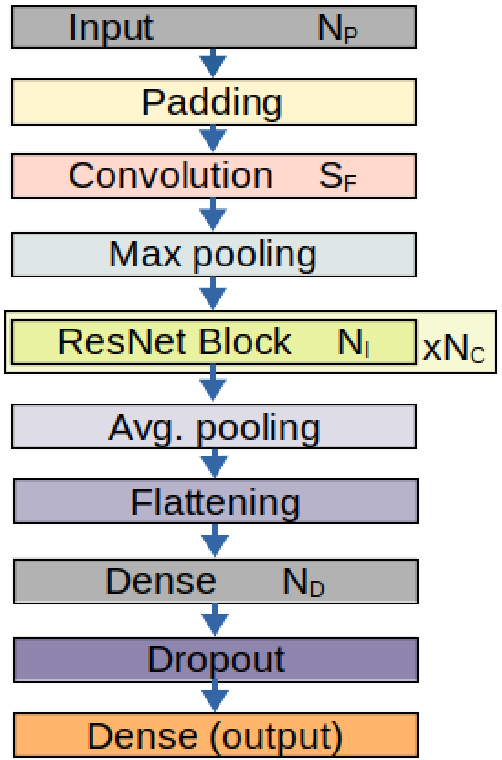
Vanishing/exploding gradients

ResNet:

Residual blocks with “skip connections”



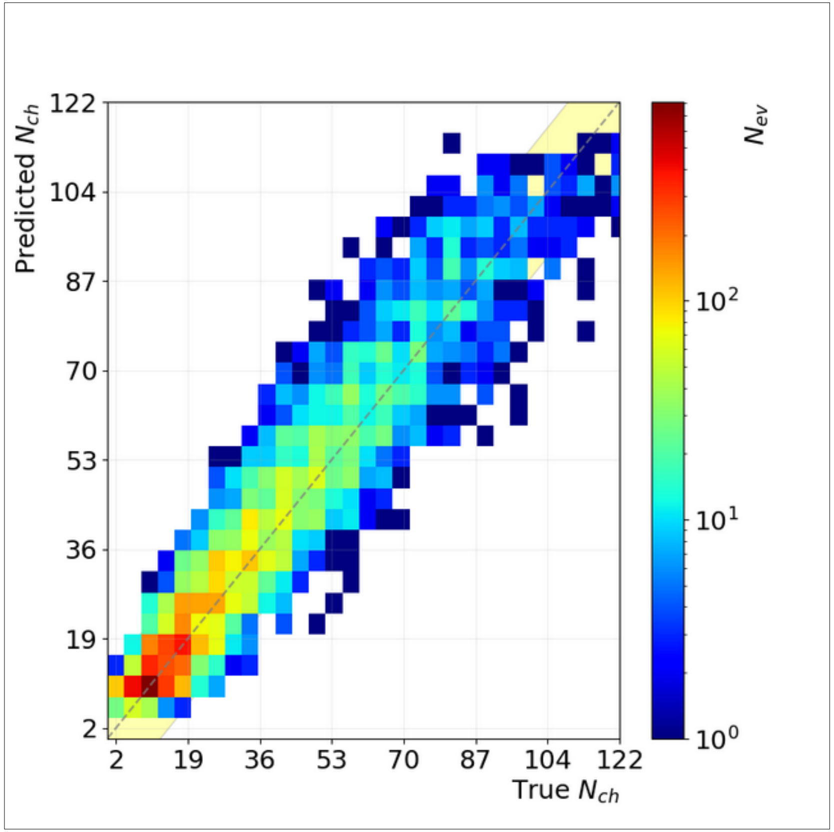


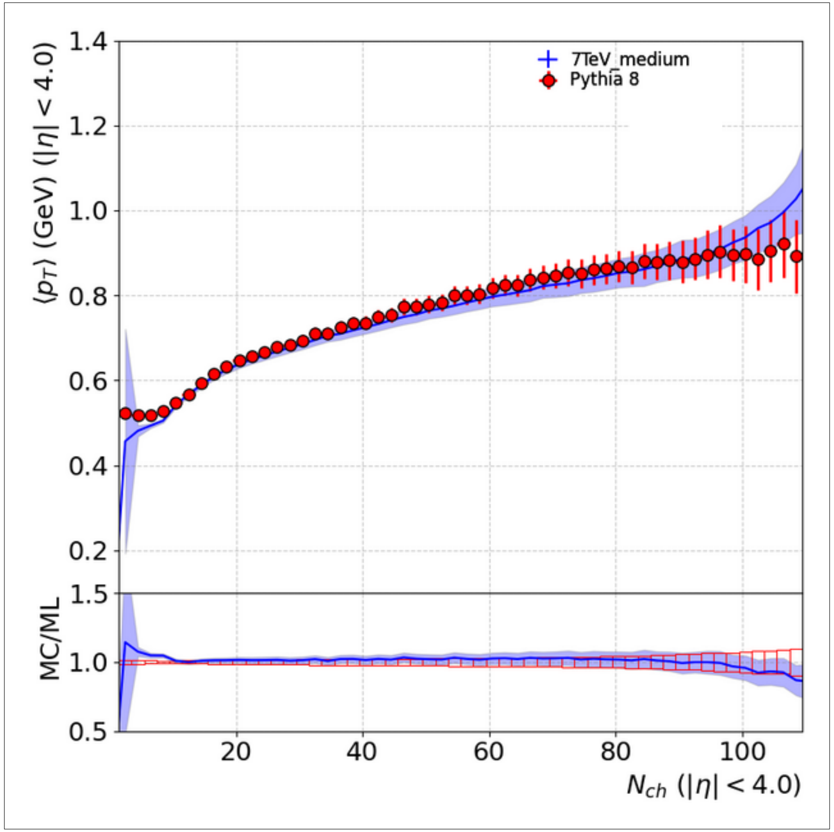


Used hardwares: Nvidia Tesla T4, GeForce GTX 1080
@ Wigner Scientific Computing Laboratory

Framework: Tensorflow 2.4.1, Keras 2.4.0

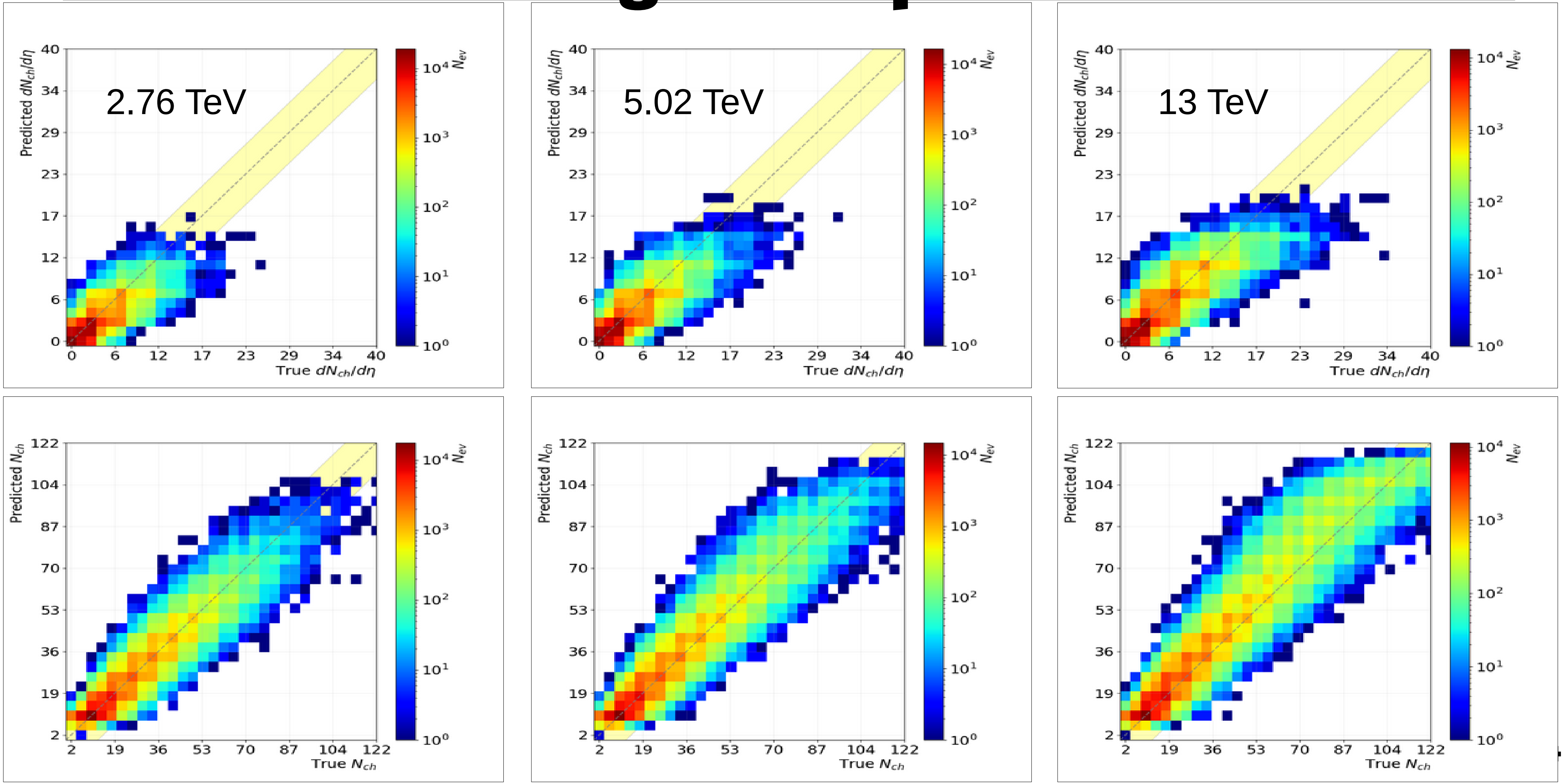
Proton-proton @ 7 TeV, Training + Validation





Total event multiplicity: ✓
Mean transverse momentum vs event multiplicity: ✓

Test of KNO-scaling for the predictions



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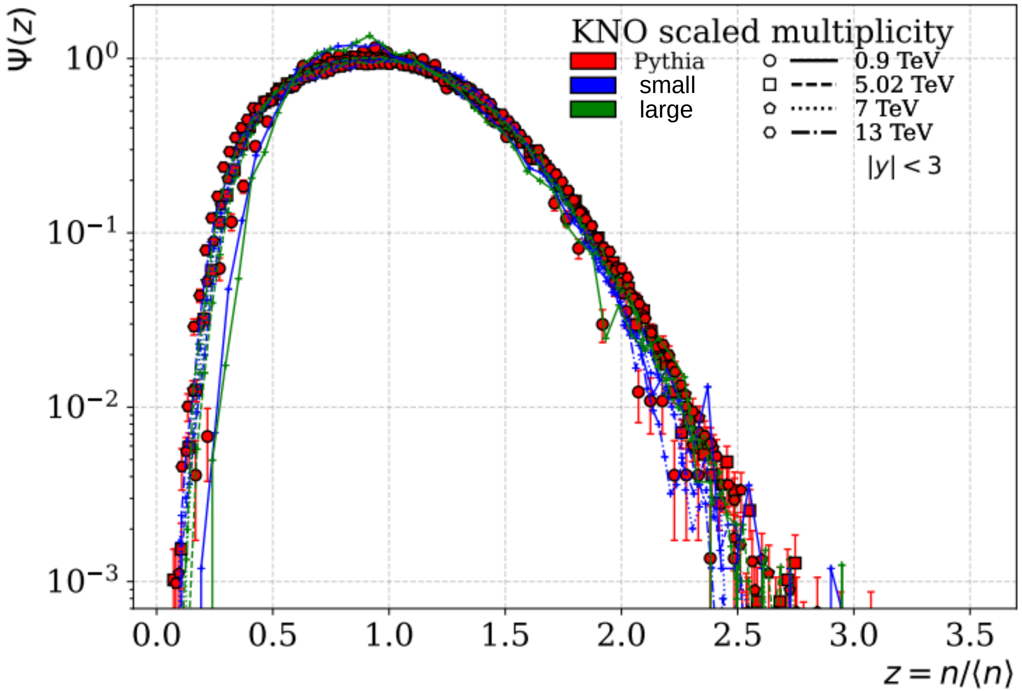

Scaling function for multiplicities at various energies: $P_n = \frac{1}{\langle n \rangle} \Psi \left(\frac{n}{\langle n \rangle} \right)$

Charged hadron multiplicities: good overlap and agreement

Nucl.Phys.B Proc.Suppl. 92 (2001) 122-129

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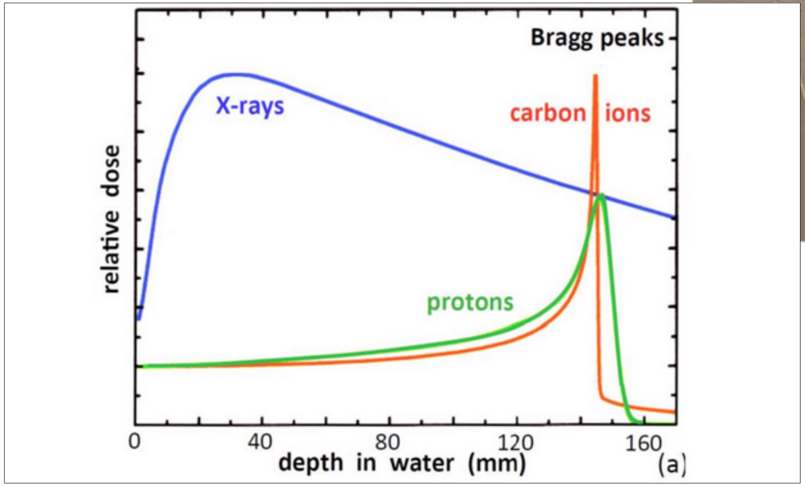
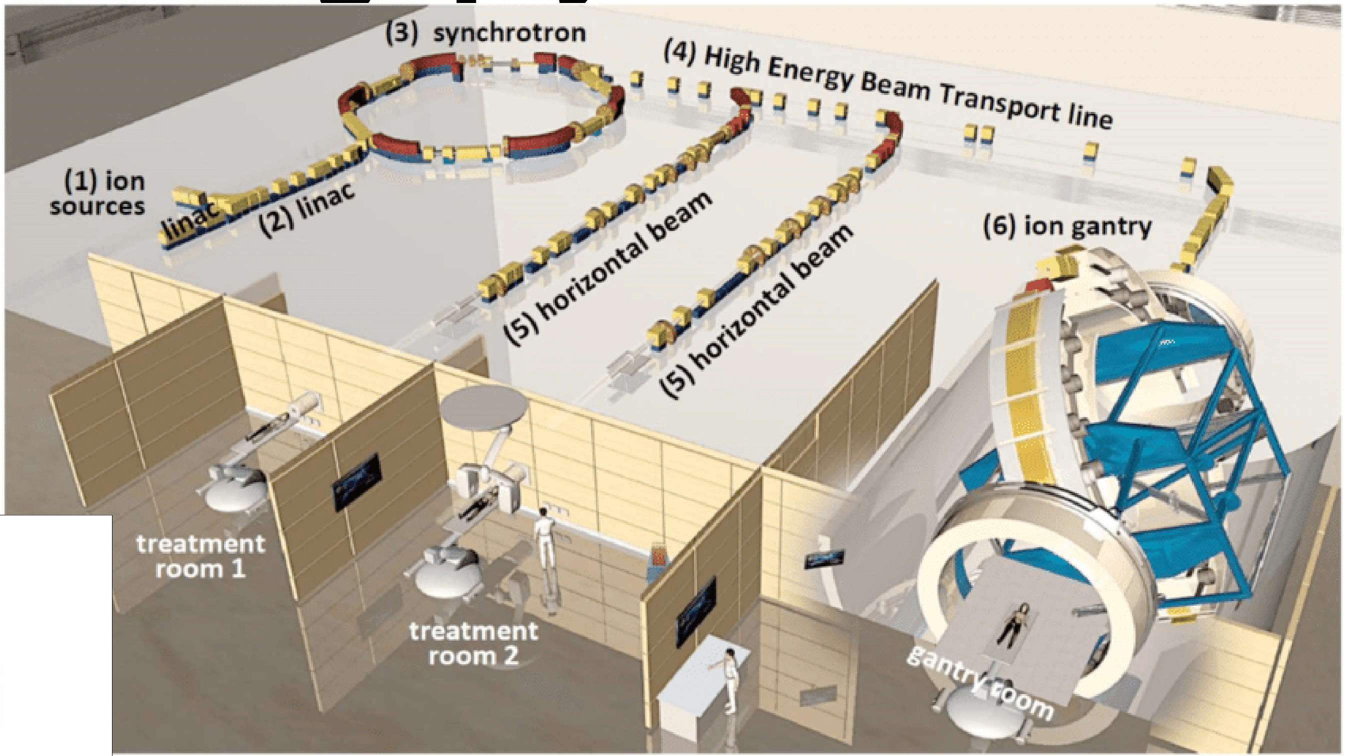
Proton Computed Tomography

- Cancer treatment: surgery, chemotherapy, <u>radiotherapy</u>, 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

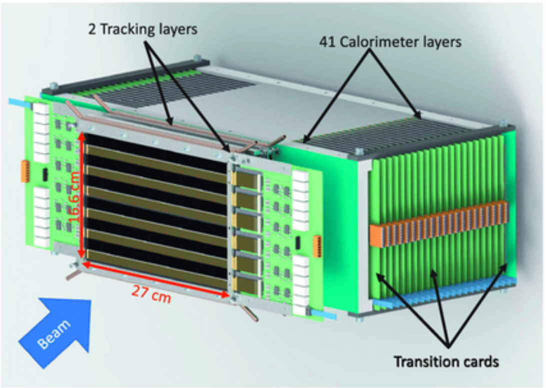
↓

Processing the signals

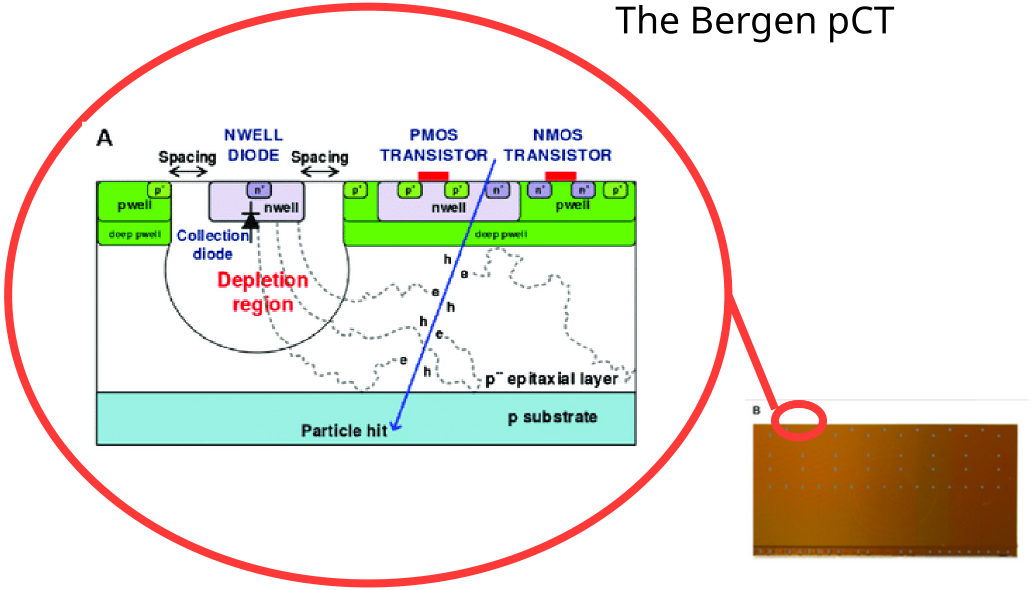
↓

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

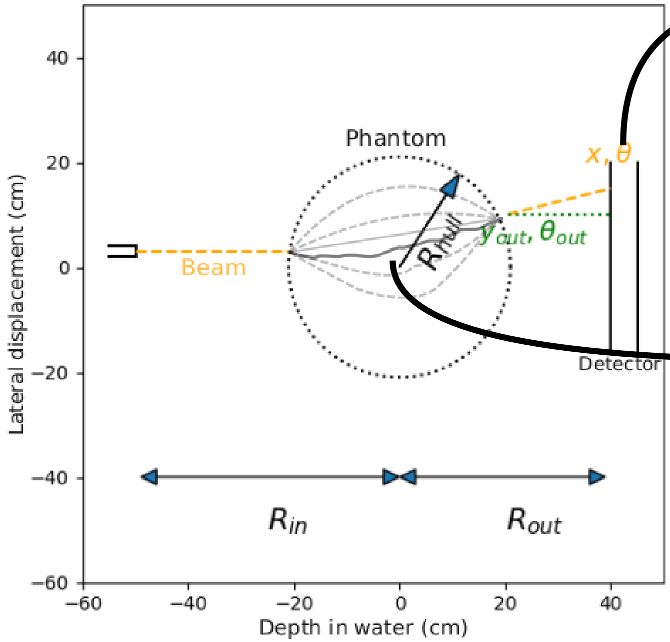


The Bergen pCT



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

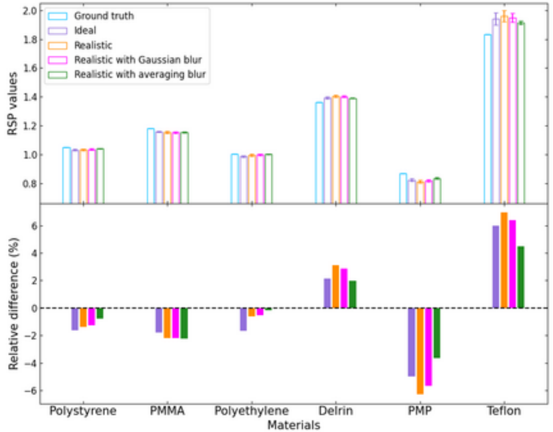
Proton Computed Tomography



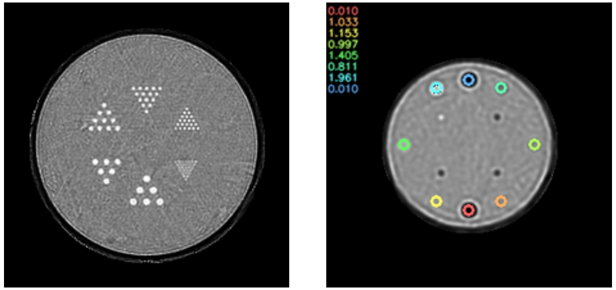
Track reconstruction from detector signals

Most likely path determination

Image reconstruction



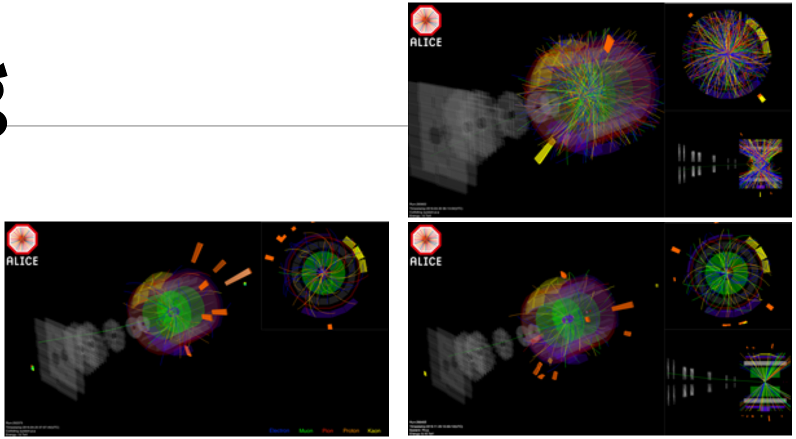
Reconstructed RSP map



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

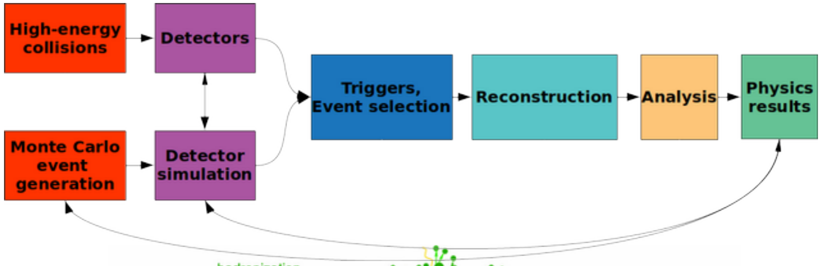


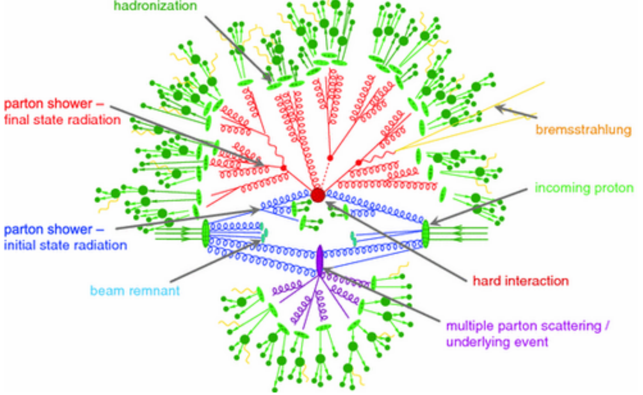
Simulation of one proton-proton collision event: complicated…

1) Perturbative QCD calculations

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

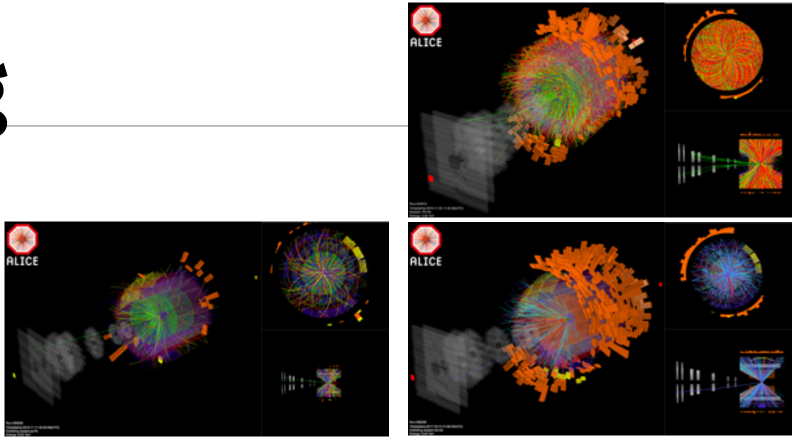
2) Additional phenomenological processes: MPI, colour reconnection, hadronization scheme…
3) Compromise: computational time ←→ precision
   - Tons of random numbers
4) Empirical parameters: need to be tuned





arXiv:1901.04220
arXiv:1811.02131

Monte Carlo parameter tuning

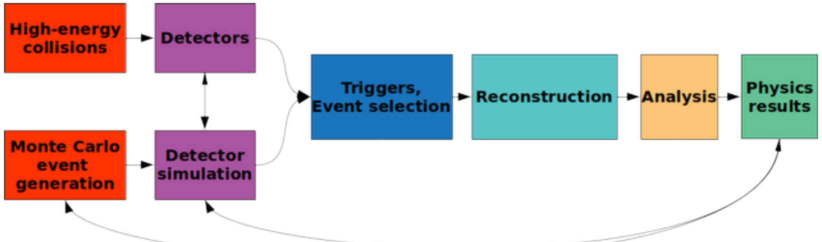


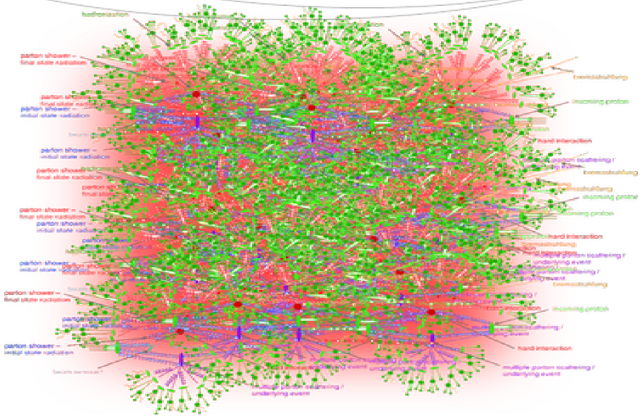
Simulation of one **heavy-ion** collision event: **even more** complicated…

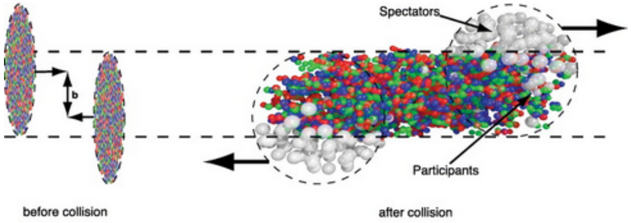
1) Perturbative QCD calculations

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

2) Additional phenomenological processes: MPI, colour reconnection, hadronization scheme…
3) Compromise: computational time ←→ precision
   - **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..







arXiv:1901.04220
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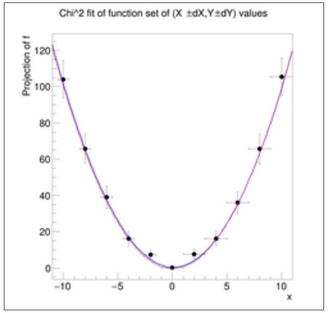
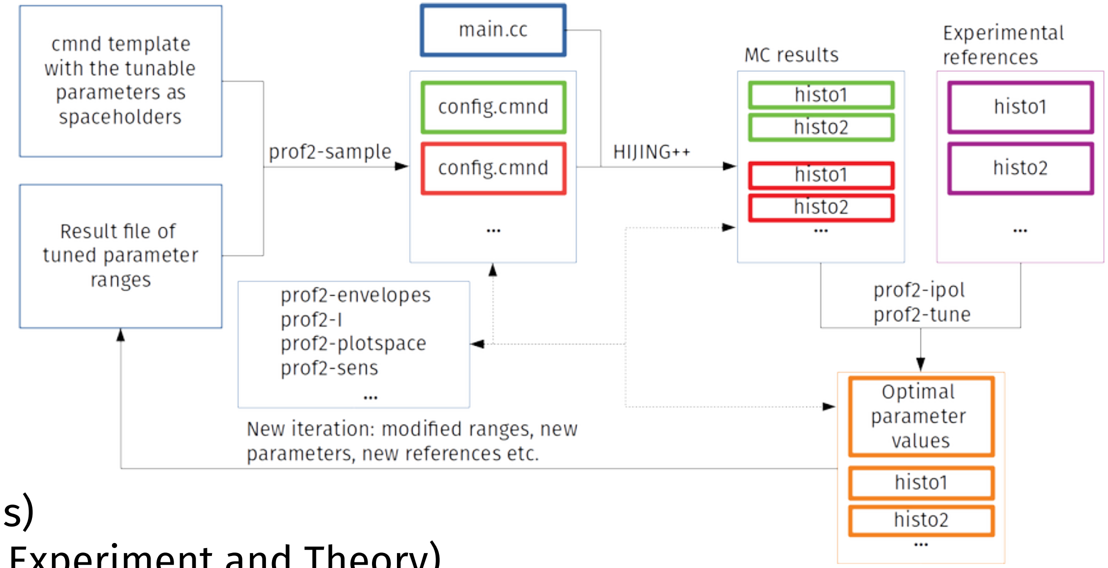
Monte Carlo parameter tuning

Tuning: set the empirical parameters to fit the experimental data
→ basically „just” an iterative χ2 minimization

sample→**calculate**→minimize→repeat





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Rivet (Rivet – Robust Independent Validation of Experiment and Theory)
Professor (Tuning tool for Monte Carlo event generators)

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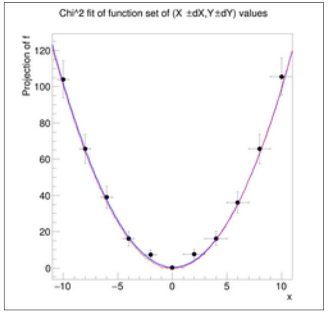

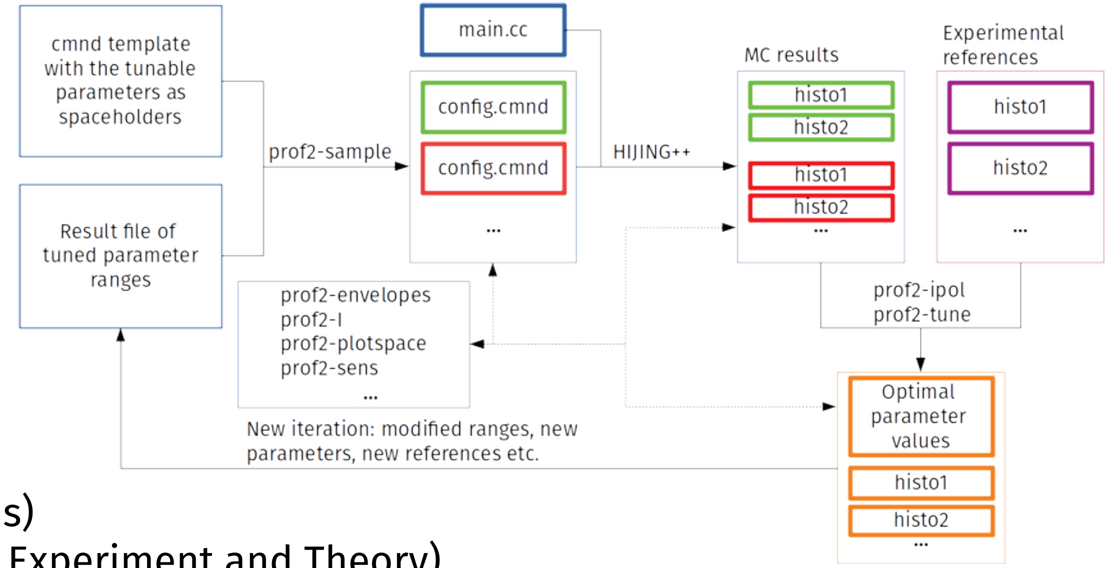

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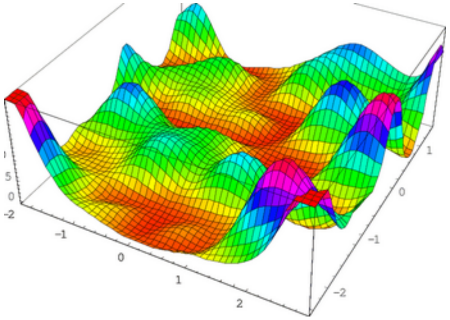

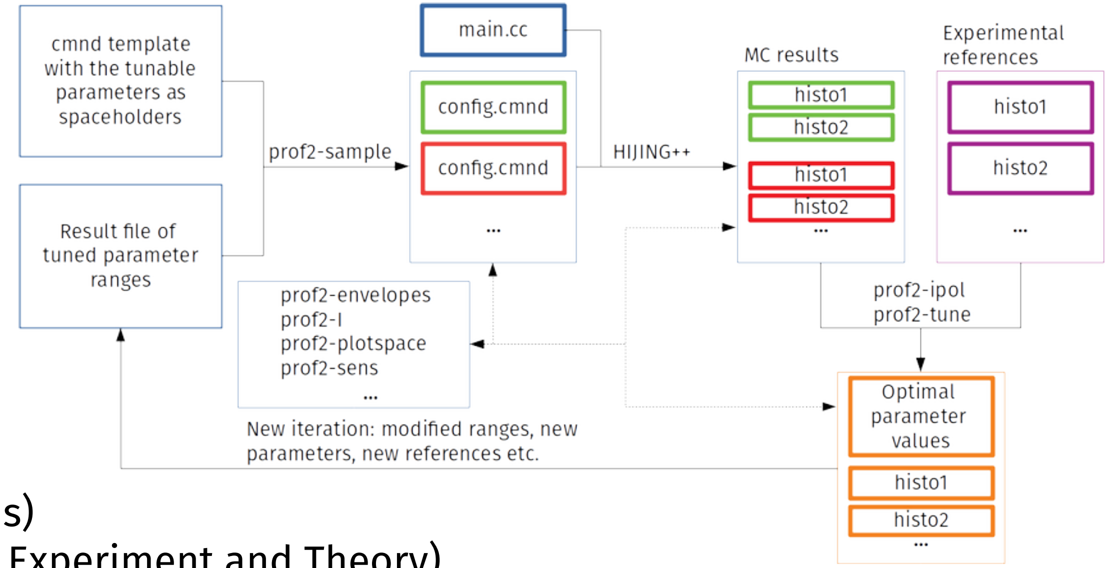

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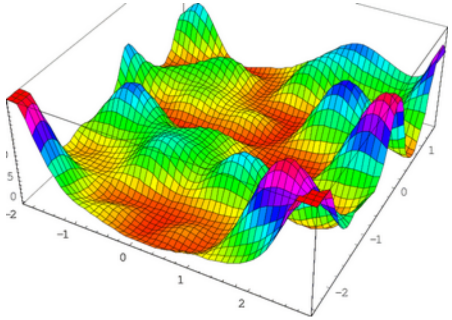

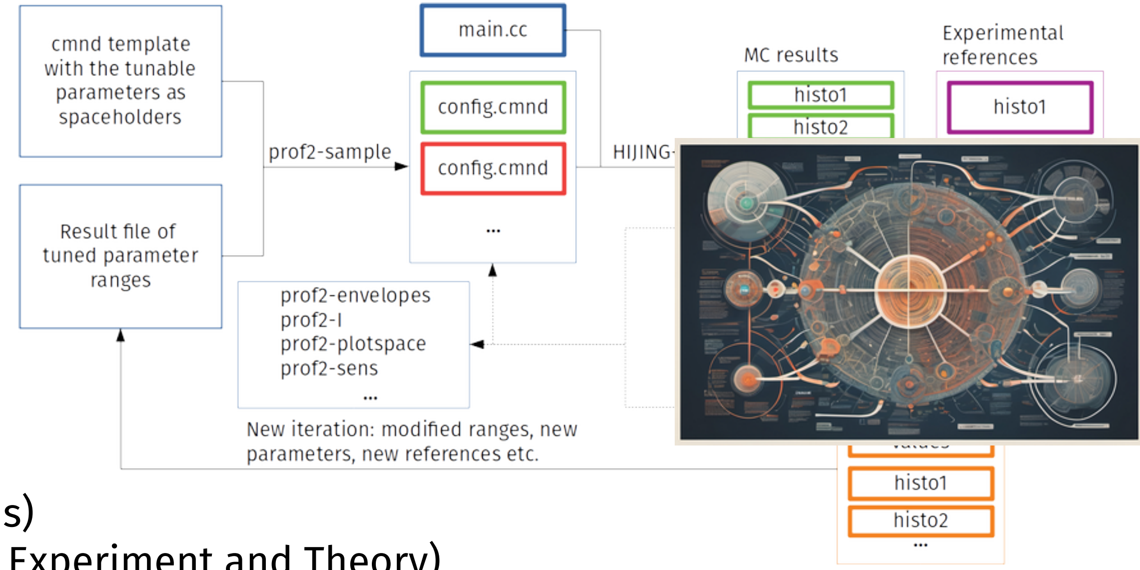

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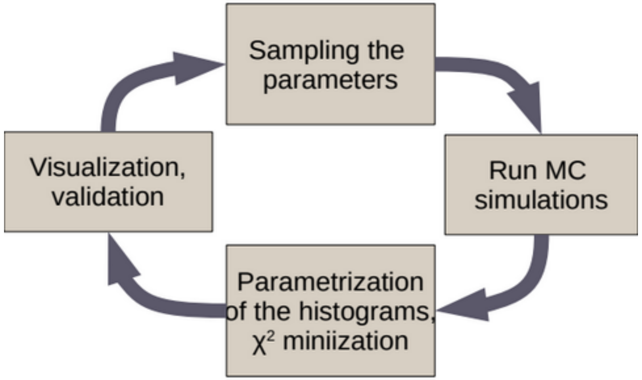
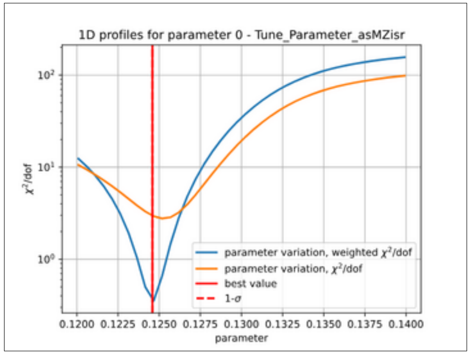




Accelerating Science with Generative Adversarial Networks: An Application to 3D Particle Showers in Multi-Layer Calorimeters

Michela Paganini,[1,2,*] Luke de Oliveira,[1,†] and Benjamin Nachman[1,‡]

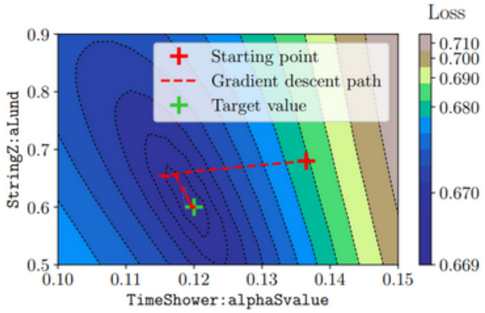
[1] *Lawrence Berkeley National Laboratory, Berkeley, CA 94720*
[2] *Yale University, New Haven, CT 06520*

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,†]

[1] *Department of Physics, University of California, Berkeley, CA 94720, USA*
[2] *Physics Division, Lawrence Berkeley National Laboratory, Berkeley, CA 94720, USA*



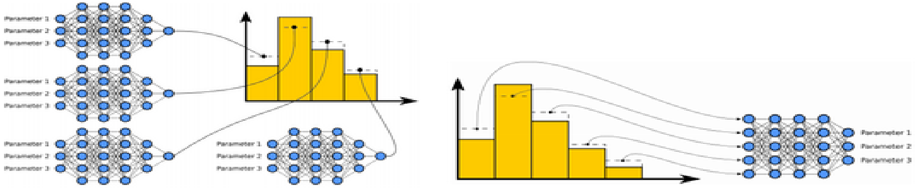


Figure 1: An illustration of the parametrisation of the generator response as implemented in the Per Bin Model.

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]

[a] *TIF Lab, Dipartimento di Fisica, Università degli Studi di Milano and INFN Sezione di Milano, Milan, Italy.*
[b] *Dipartimento 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

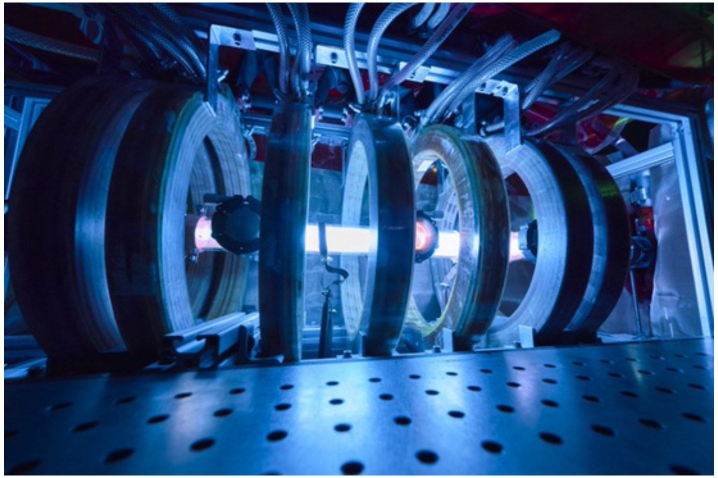
CERN–AWAKE Experiment: accelerate electrons in the wake field of proton

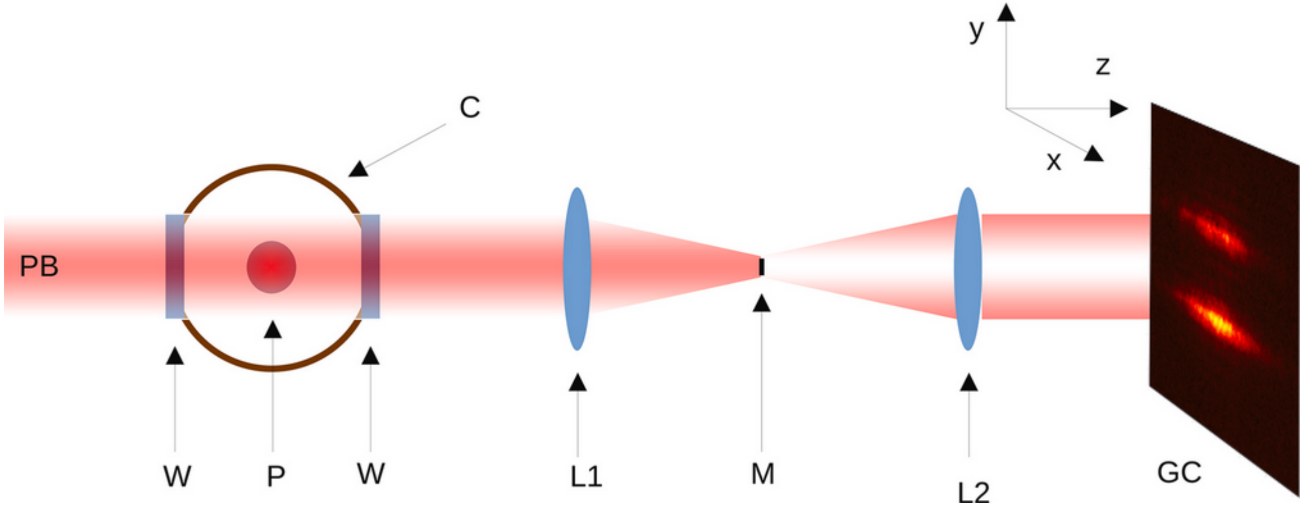
Microbunches: Nuclear Instruments and Methods in Physics Research Section A, 829 (2016) 76-82

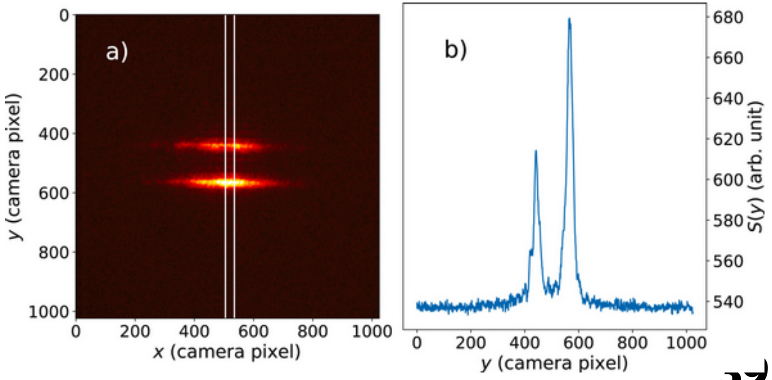
Accelerating medium: Rb plasma: 10 m length, 1014 – 1015 cm^{-3} density. Chamber diameter: 4 cm

Experiment motivation: determine plasma parameters via Schlieren imaging

arXiv:2205.12731







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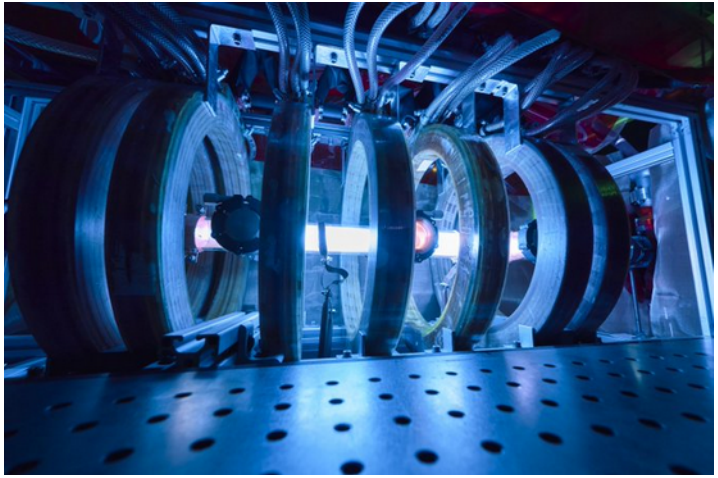
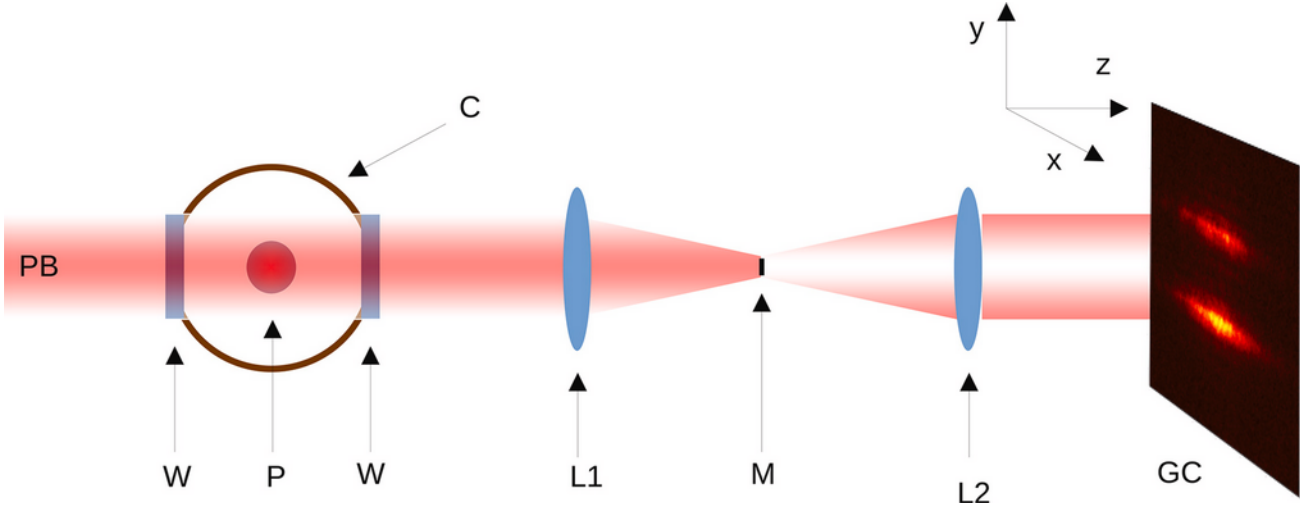
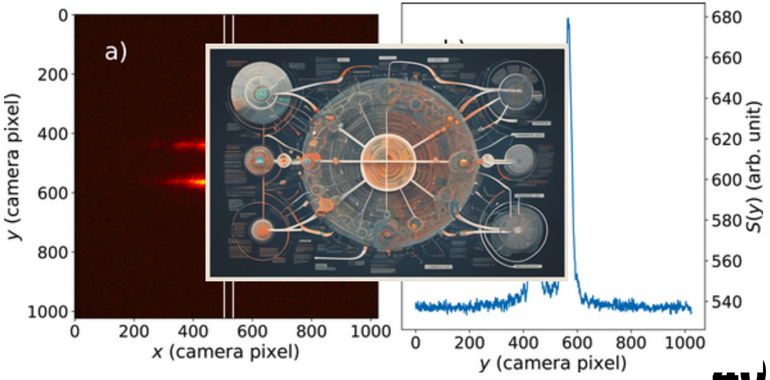




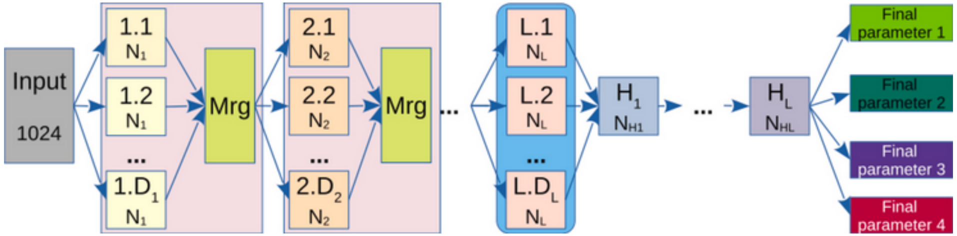


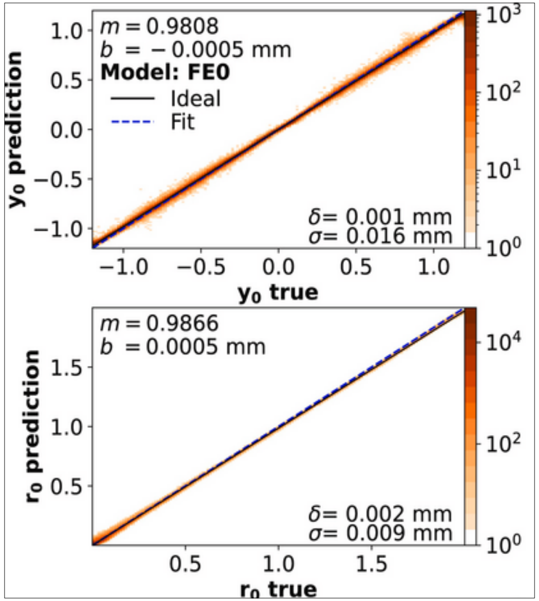
Monitoring plasma channel

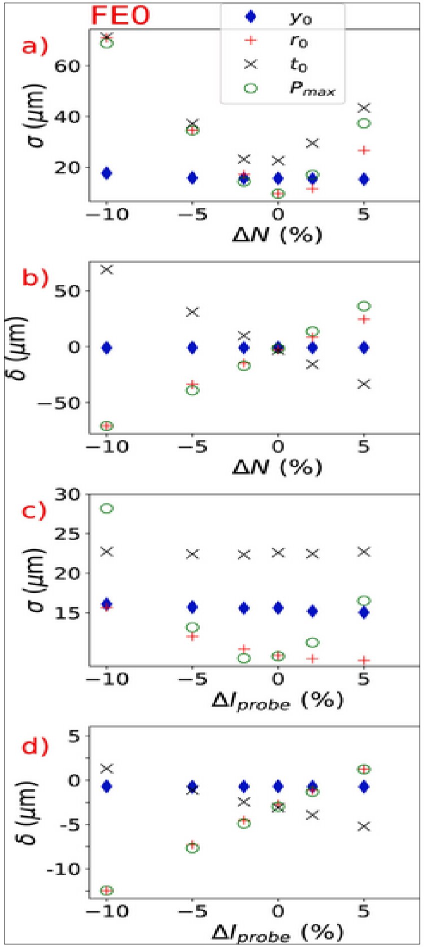
Flexible network design

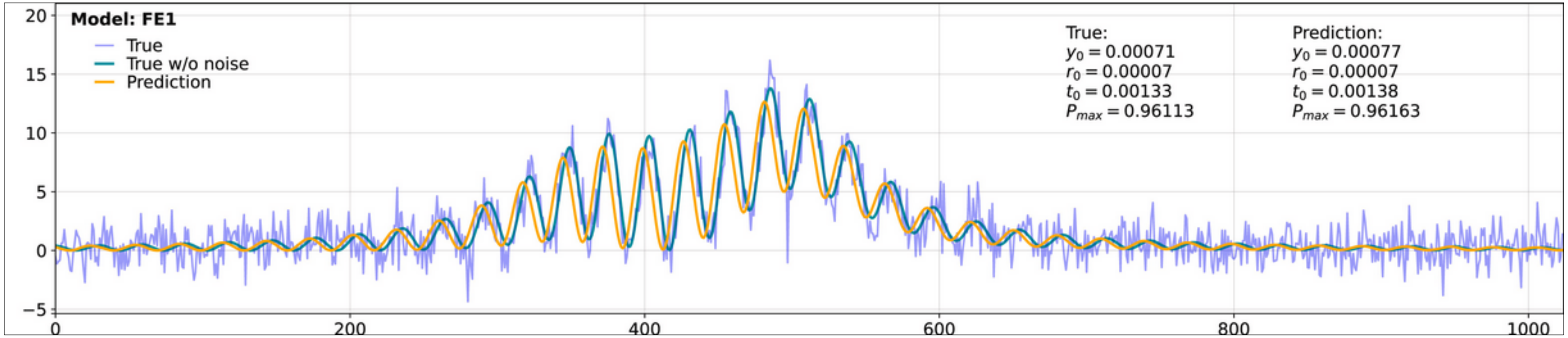
Precise prediction of the plasma parameters

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

supported by Visegrad Fund

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