Mean transverse momentum scaling at LHC energies using deep learning methods

23rd ZIMÁNYI SCHOOL

WINTER WORKSHOPON on HEAVY ION PHYSICS

04-08 12 2023

GÁBOR BÍRÓ
biro.gabor@wigner.hun-ren.hu

Gergely Gábor Barnaföldi
Gábor Papp

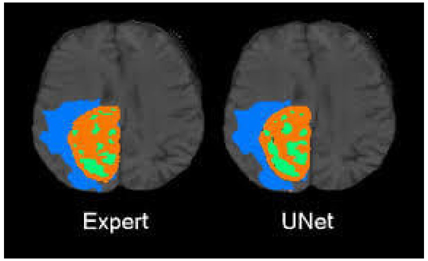
HUN REN | WIGNER | ELTE EÖTVÖS LORÁND TUDOMÁNYEGYETEM

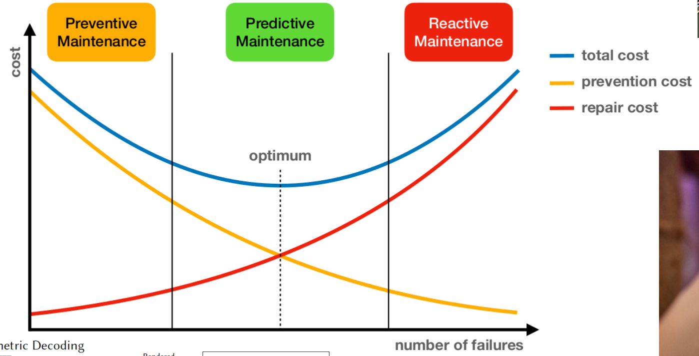
Motivaton - data, data, more data

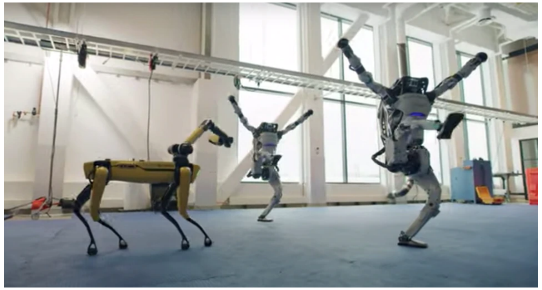
Autonomous driving
Medical imaging
Predictive maintenance
Anomaly detection, fake news detection
Search of BSM physics
Stock price prediction
Natural Language Processing
Virtual Assistants
Virtual reality
Colorization of Black and White Images
Content generation, examples:

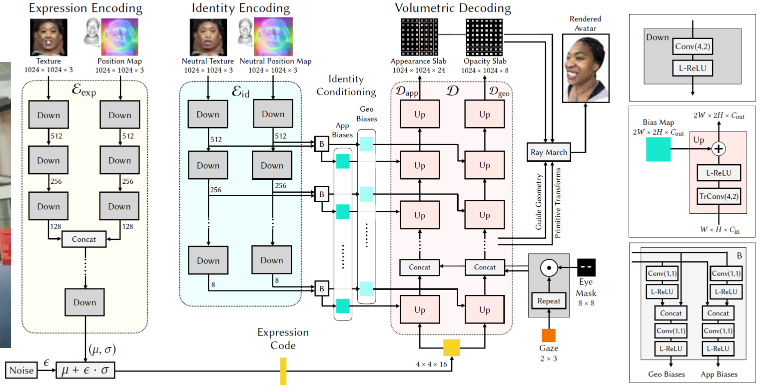
https://infiniteconversation.com/
https://huggingface.co/spaces/stabilityai/stable-diffusion

Robotics
...

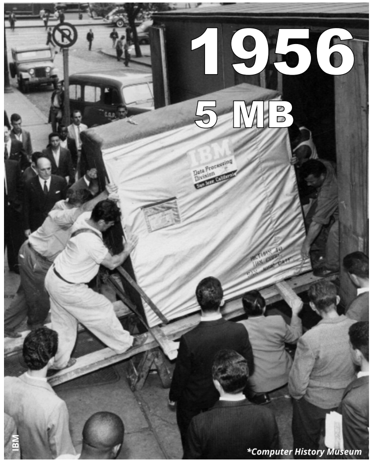


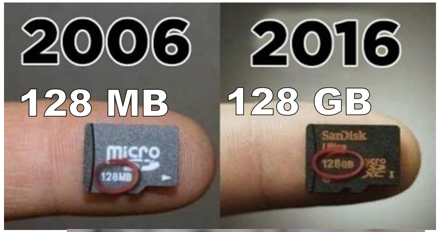


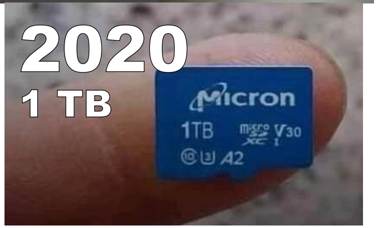




Motivaton - data, data, more data





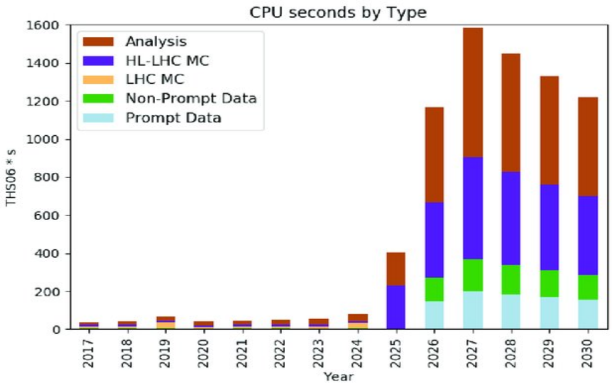


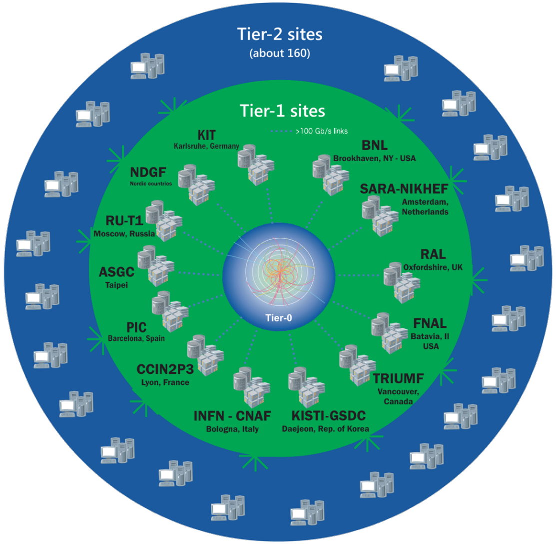
LHC in numbers: 2013 and **now:**

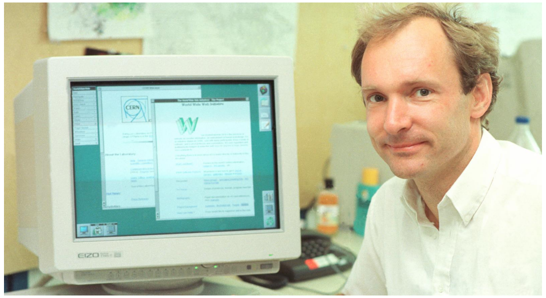
Data:	15 PB/year	vs	200+ PB/year
Tape:	180 PB	vs	740+ PB
Disk:	200 PB	vs	570+ PB
HS06:	2M	vs	100+ B

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

→ analysis, simulations

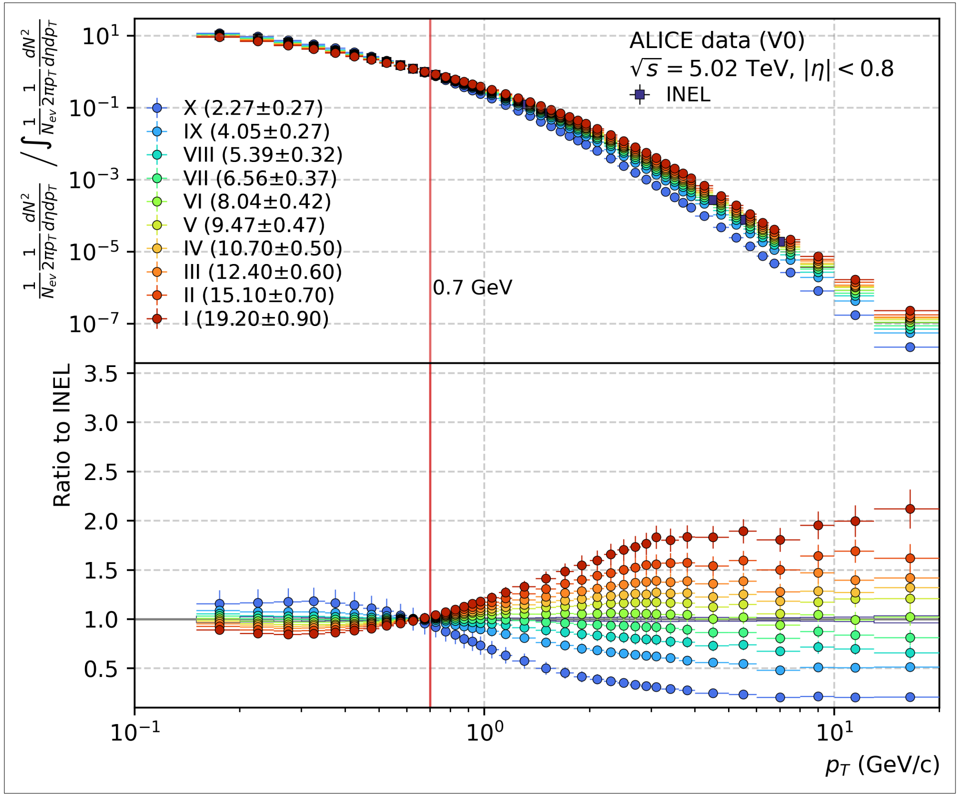


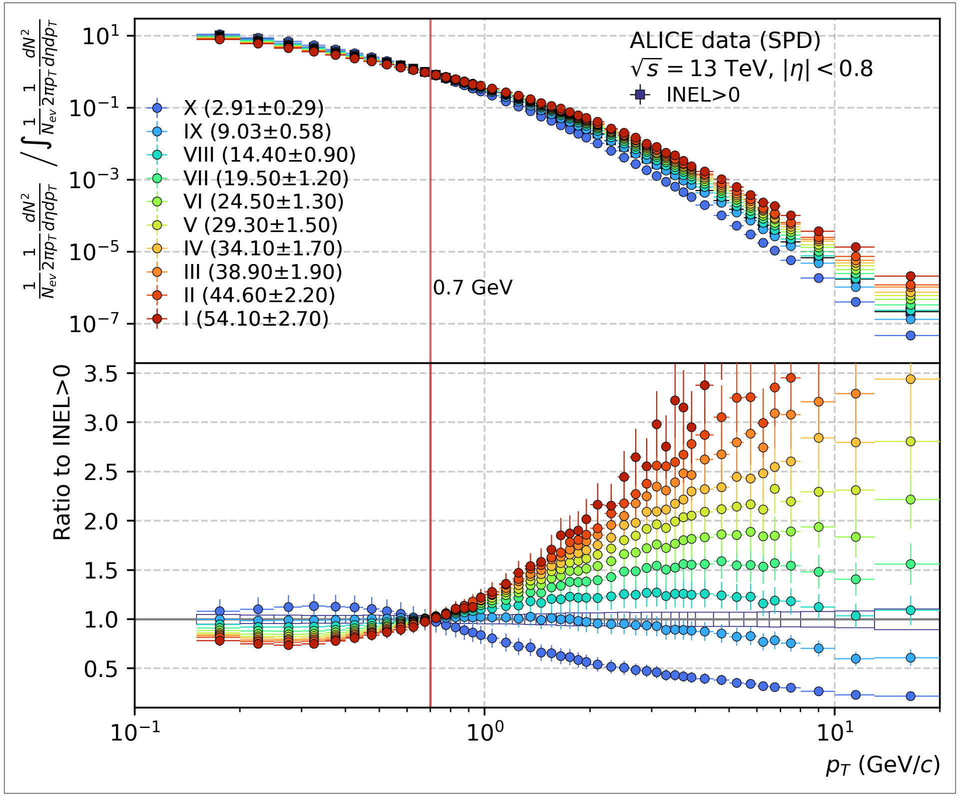




Scaling of p_T with event multiplicity

From experimental data:



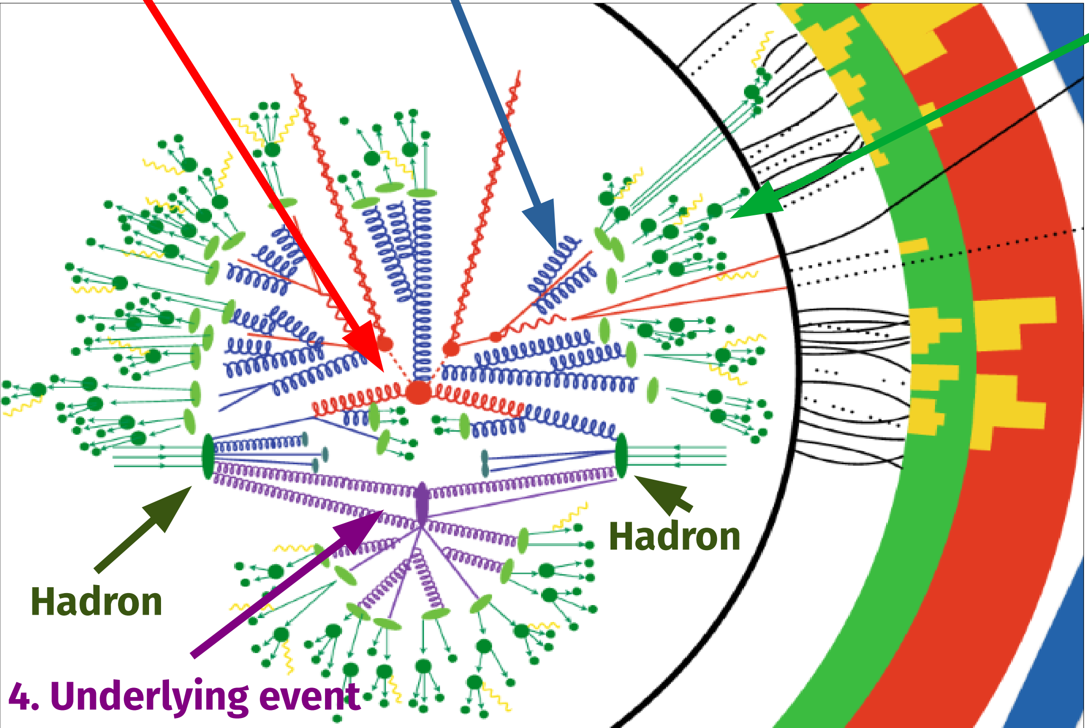


Parton shower and hadronization

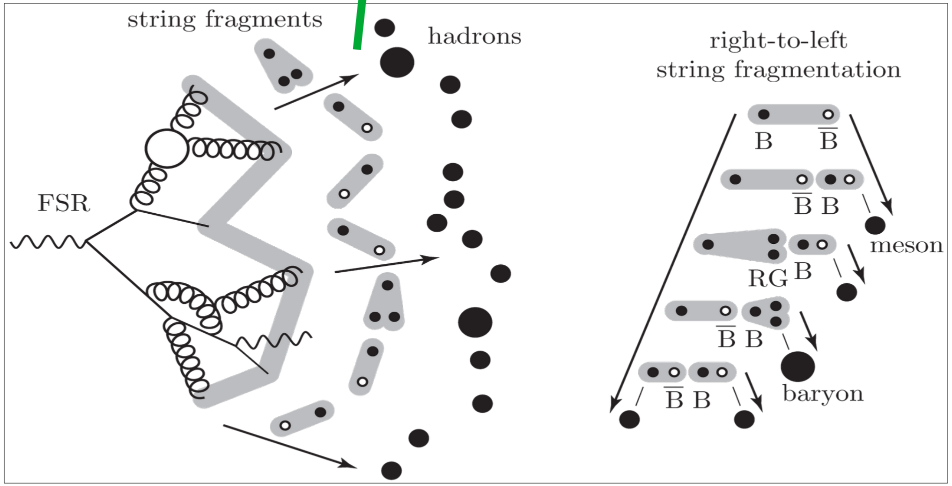
3. Hadronization

2. Parton shower

1. Hard scattering



Nature Reviews Physics 3, 73 (2021)



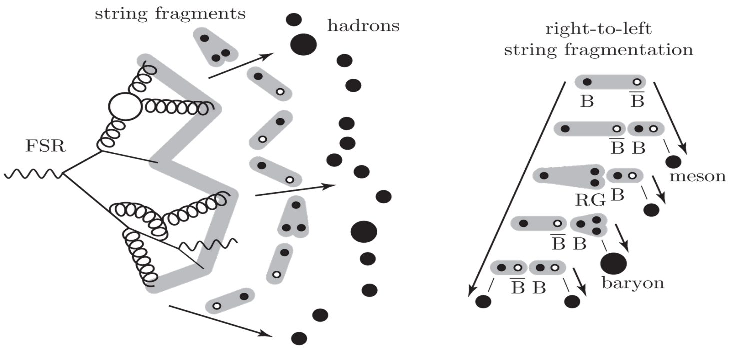
Hadronization

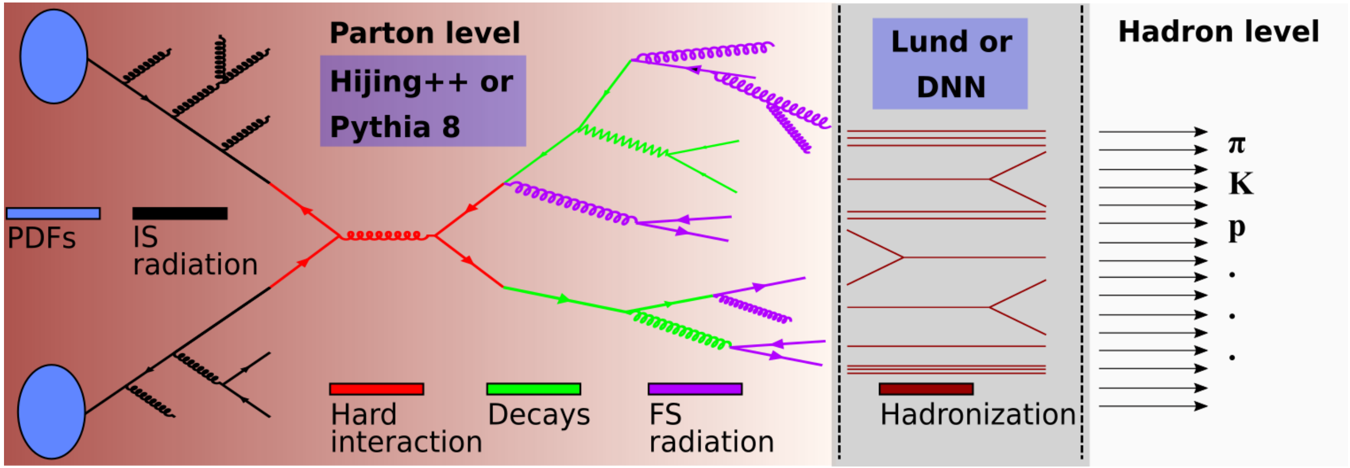
Partons → hadrons

Non-perturbative process

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

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





Train and validation sets

Monte Carlo data: Pythia 8.303

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

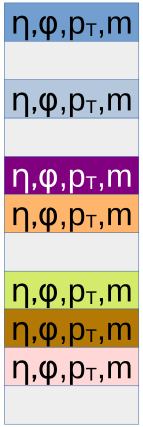
- All final particles with $|y| < 4.0$

Event number:

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

- ~30 GB raw data

Input:

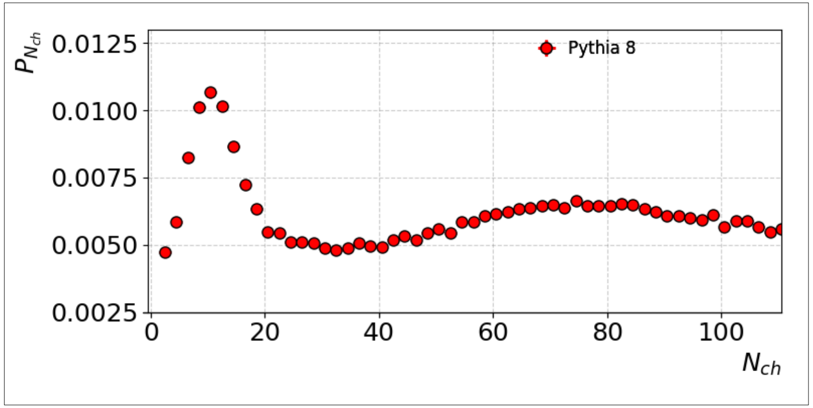


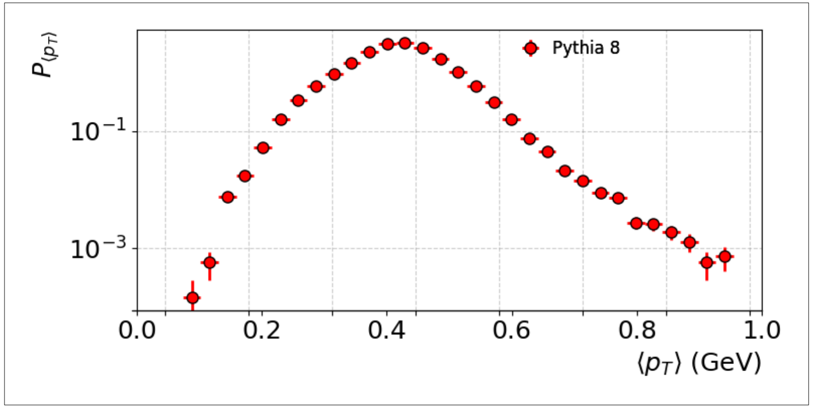
Parton level, before the hadronization process

Standardized η, φ, p_T, m variables

Hadron level output:

Charged event multiplicity, mean event transverse momentum





Models

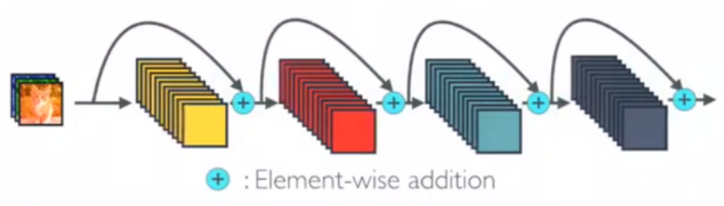
Stacking more layers: solve complex problems more efficiently, get highly accurate results

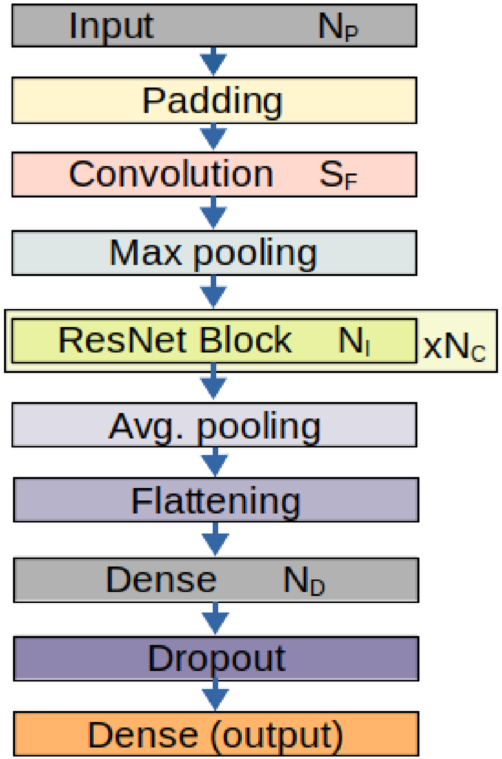
BUT:

Vanishing/exploding gradients

ResNet:

Residual blocks with “skip connections”



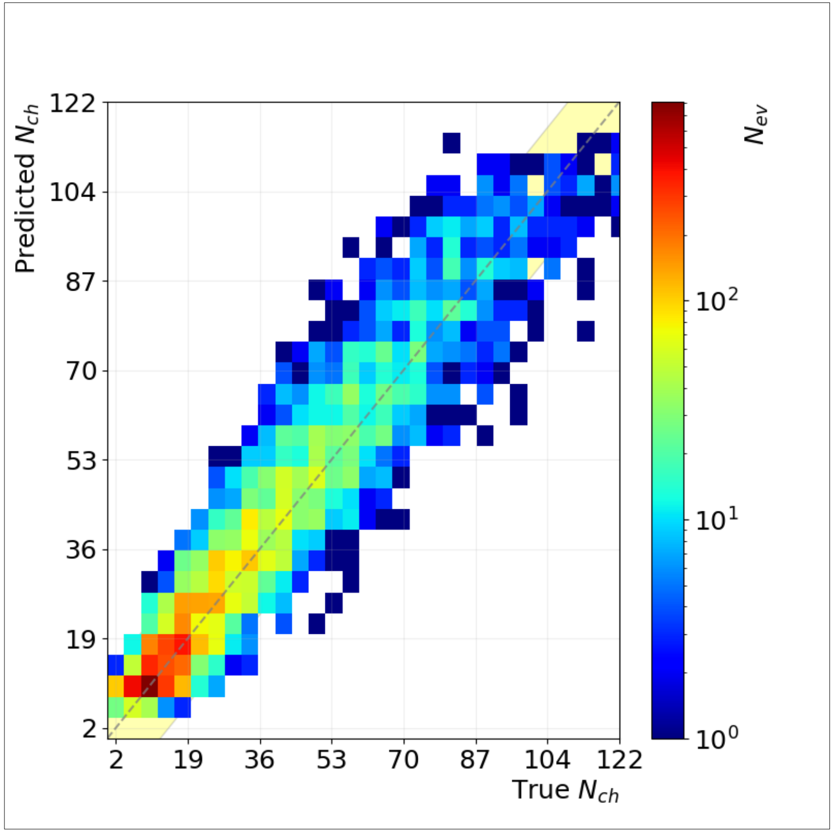


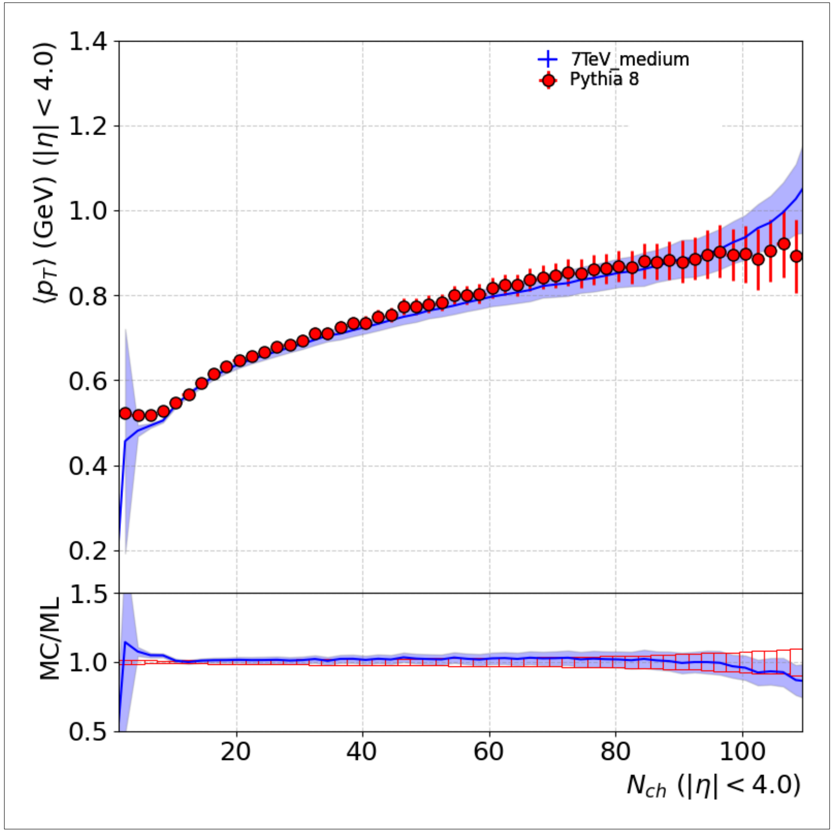
Used hardwares: Nvidia Tesla T4, GeForce GTX 1080
@ Wigner Scientific Computing Laboratory

Framework: Tensorflow 2.4.1, Keras 2.4.0

Results

Proton-proton @ 7 TeV, Training + Validation





Total event multiplicity: ✓

Mean transverse momentum vs event multiplicity: ✓

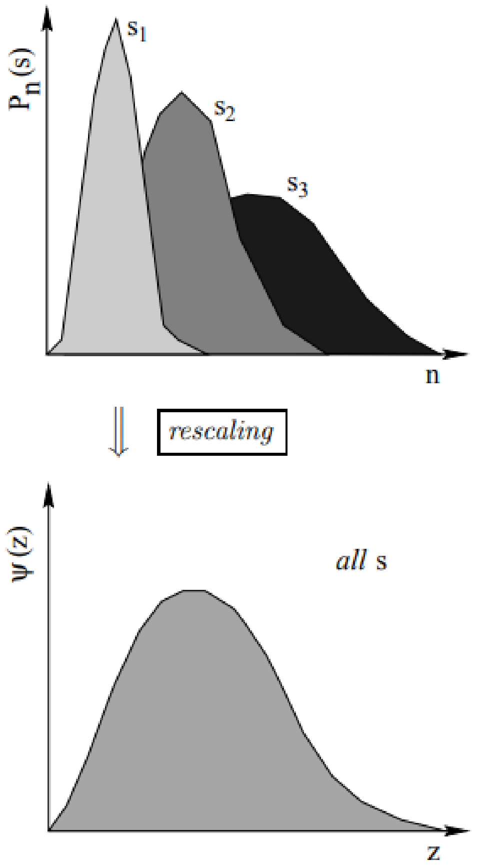
KNO-scaling

The collapse of multiplicity distributions $\mathbf{P_n}$ onto a universal scaling curve:

$$P_n = \frac{1}{\langle n \rangle} \Psi \left(\frac{n}{\langle n \rangle} \right)$$

The scale parameters governed by leading particle effects and the growth of average multiplicity

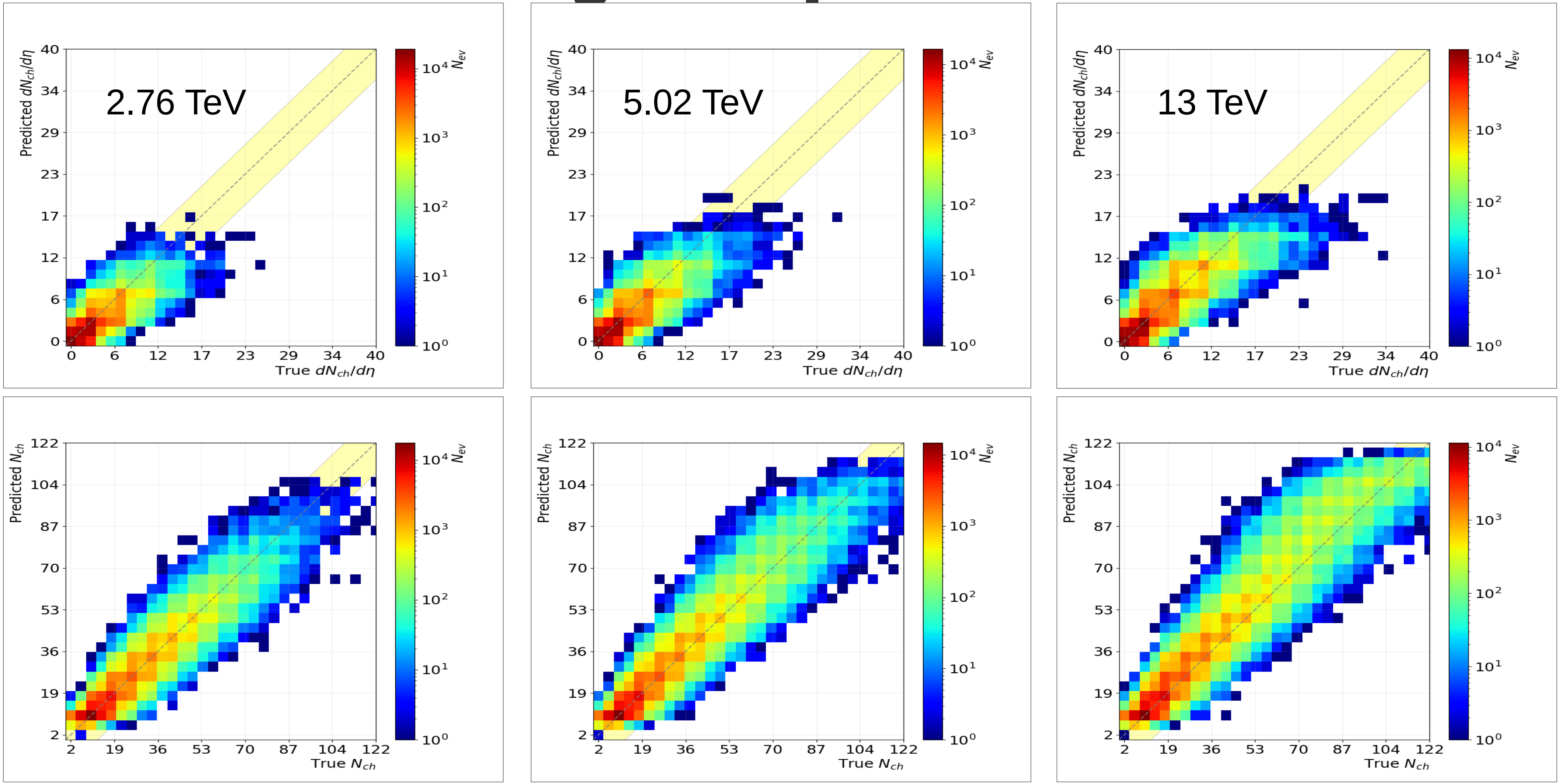
Violation of the scaling at high CM energies: not fully understood (relation to MPI?)



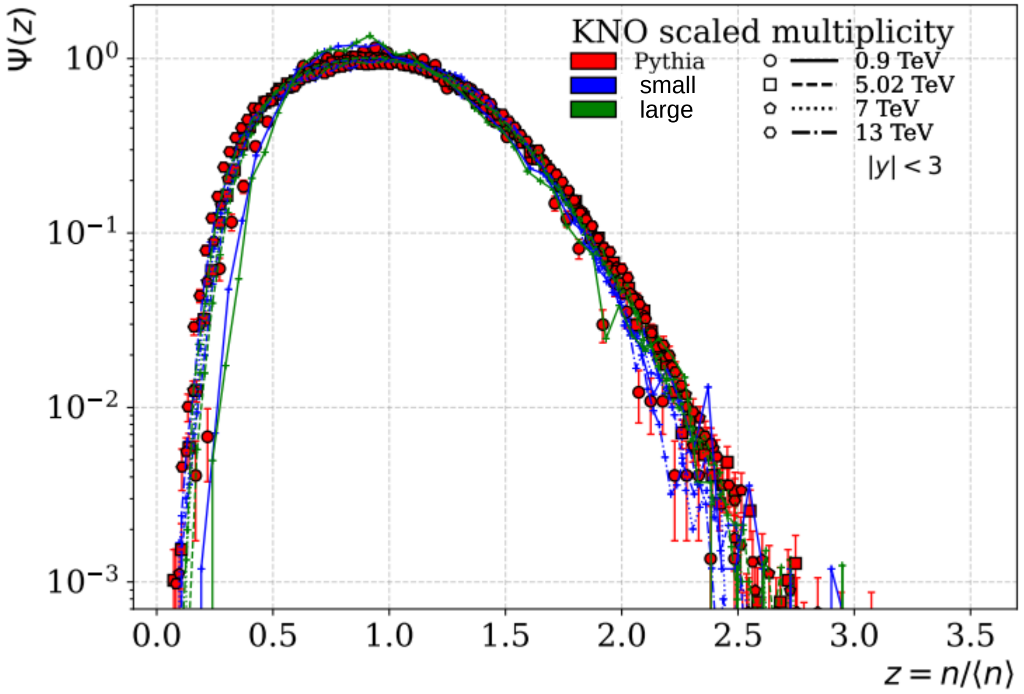
Nuclear Physics B 40 (1972), 317–334.

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

Test of KNO-scaling for the predictions



Test of KNO-scaling for the predictions

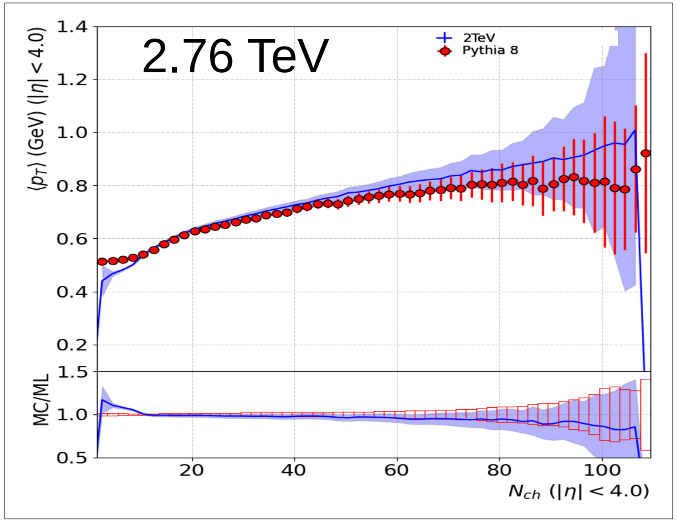


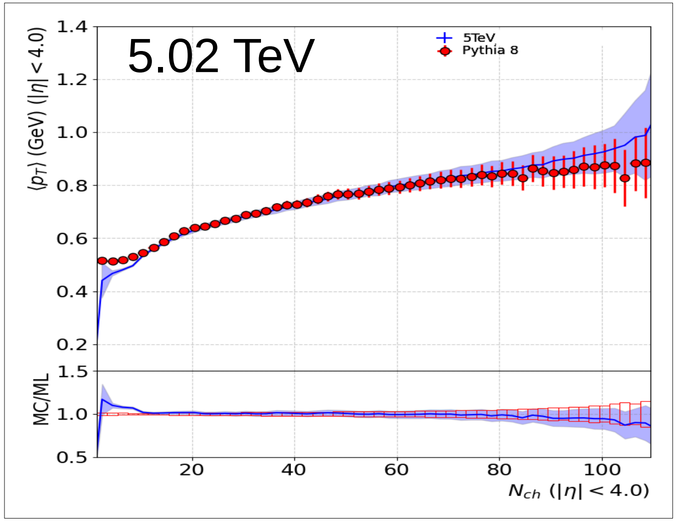
Scaling function for multiplicities at various energies: $P_n = \frac{1}{\langle n \rangle} \Psi \left(\frac{n}{\langle n \rangle} \right)$

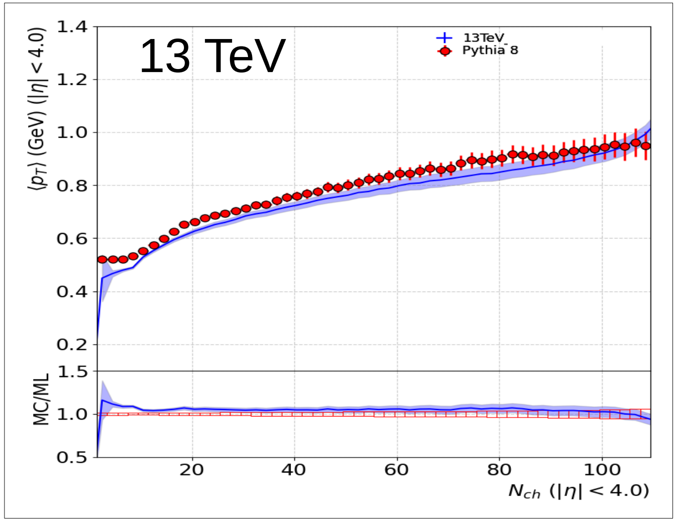
Charged hadron multiplicities: good overlap and agreement

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

Test of <p_T> scaling for the predictions

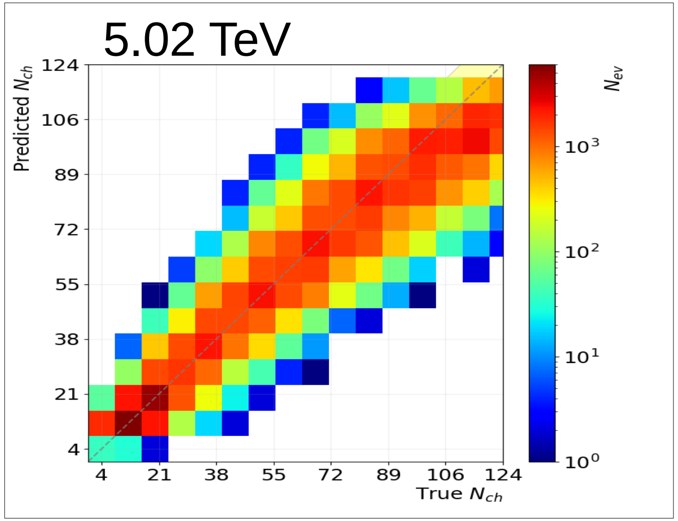


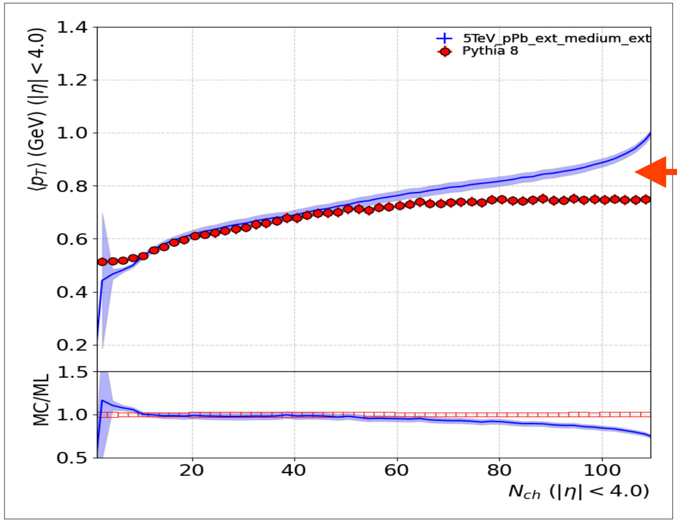




What about larger (small) systems?

Test of scaling properties for the predictions for p-Pb





Total event multiplicity: ✓

Mean transverse momentum: deviation at higher multiplicity

Summary

Developed hadronization models with different complexities to test scaling properties

Training only at a single c.m. energy, predictions at other energies

Generalization to other CM energies: KNO and $\langle p_T \rangle$ scaling

Valuable input for MC developments

Prospects

Architecture variations (hyperparameter fine-tuning)

Heavy ion (centralities, collective effects...)

Thank you for your attention!

The research was supported by OTKA grants K135515, NKFIH 2019-2.1.6-NEMZKI-2019-00011, 2019-2.1.11-TÉT-2019-00078, 2019-2.1.11-TÉT-2019-00050, 2020-2.1.1-ED-2021-00179, the Wigner Scientific Computating Laboratory (former Wigner GPU Laboratory) and RRF-2.3.1-21-2022-00004 within the framework of the Artificial Intelligence National Laboratory.