Studying hadronization with Machine Learning techniques

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GÁBOR BÍRÓ
biro.gabor@wigner.hu

Gergely Gábor Barnaföldi
Bence Tankó-Bartalis

arXiv:2111.15655
arXiv:2210.10548

ACAT 2022
BARI

WIGNER

UNIVERSITY OF OXFORD

Data, data, and more data

LHC numbers in **2013** vs. **now:**

Data: **15 PB/y** vs **200+ PB/y**

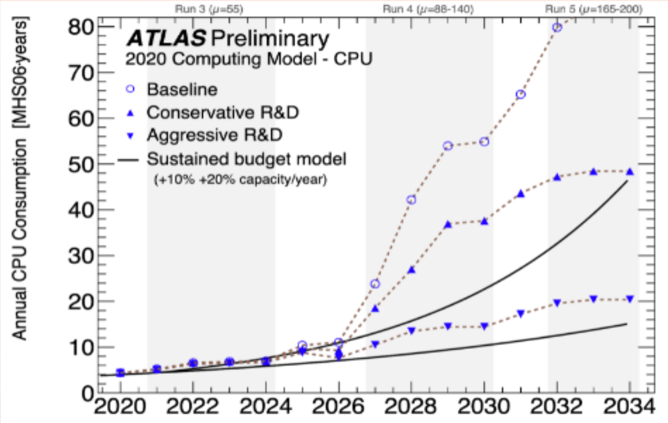
Tape: **180 PB** vs **740+ PB**

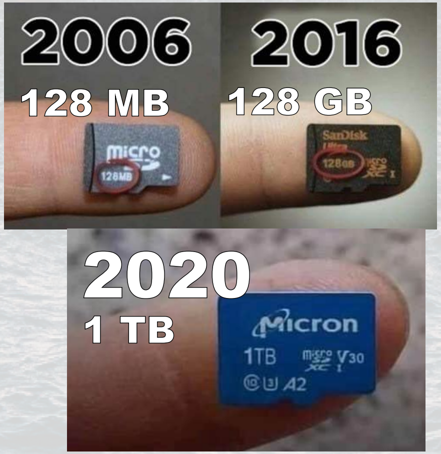
Disk: **200 PB** vs **570+ PB**

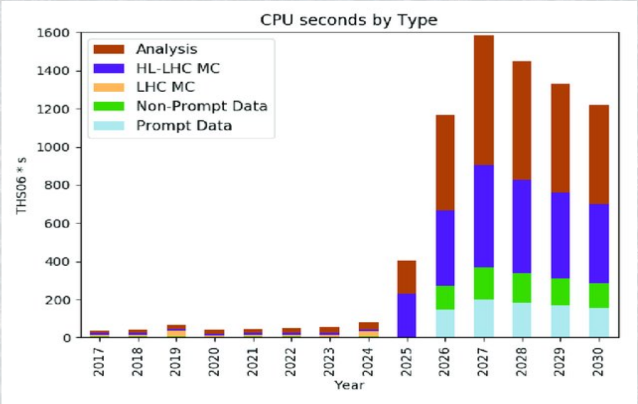
HS06 hours: **2M** vs **100+ B**

Storing the data is not the only challange

→ **analysis, simulation**







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

Today: **724** references

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

  - Accelerated Charged Particle Tracking with Graph Neural Networks on FPGAs
  - Particle Track Reconstruction using Geometric Deep Learning
  - Jet tagging in the Lund plane with graph networks [DOI]
  - Vertex and Energy Reconstruction in JUNO with Machine Learning Methods
  - MLPF: Efficient machine-learned particle-flow reconstruction using graph neural networks
  - 25th International Conference on Computing in High-Energy and Nuclear Physics
  - 25th International Conference on Computing in High-Energy and Nuclear Physics
  - Graph Neural Network for Object Reconstruction in Liquid Argon Time Projection Chambers
  - Instance Segmentation GNNs for One-Shot Conformal Tracking at the LHC
  - Charged particle tracking via edge-classifying interaction networks
  - Jet characterization in Heavy Ion Collisions by QCD-Aware Graph Neural Networks
  - Graph Generative Models for Fast Detector Simulations in High Energy Physics
  - Segmentation of EM showers for neutrino experiments with deep graph neural networks
- Sets (point clouds)
  - Energy Flow Networks: Deep Sets for Particle Jets [DOI]
  - ParticleNet: Jet Tagging via Particle Clouds [DOI]
  - ABCNet: An attention-based method for particle tagging [DOI]
  - Secondary Vertex Finding in Jets with Neural Networks
  - Equivariant Energy Flow Networks for Jet Tagging
  - Permutationless Many-Jet Event Reconstruction with Symmetry Preserving Attention Networks
  - Zero-Permutation Jet-Parton Assignment using a Self-Attention Network
  - Learning to Isolate Muons
  - Point Cloud Transformers applied to Collider Physics
- Physics-inspired basis
  - Automating the Construction of Jet Observables with Machine Learning [DOI]
  - How Much Information is in a Jet? [DOI]
  - Novel Jet Observables from Machine Learning [DOI]
  - Energy flow polynomials: A complete linear basis for jet substructure [DOI]
  - Deep-learned Top Tagging with a Lorentz Layer [DOI]
  - Resurrecting $b\bar{b}h$ with kinematic shapes
- W/Z tagging
  - Jet-images — deep learning edition [DOI]
  - Parton Shower Uncertainties in Jet Substructure Analyses with Deep Neural Networks [DOI]
  - QCD-Aware Recursive Neural Networks for Jet Physics [DOI]
  - Identification of heavy, energetic, hadronically decaying particles using machine-learning techniques [DOI]
  - Boosted W and Z tagging with jet charge and deep learning [DOI]
  - Supervised Jet Clustering with Graph Neural Networks for Lorentz Boosted Bosons [DOI]
  - Jet tagging in the Lund plane with graph networks [DOI]
  - A $W^\pm$ polarization analyzer from Deep Neural Networks
- $H\rightarrow b\bar{b}$
  - Automating the Construction of Jet Observables with Machine Learning [DOI]
  - Boosting $H\to b\bar b$ with Machine Learning [DOI]
  - Interaction networks for the identification of boosted $H \rightarrow b\overline{b}$ decays [DOI]
  - Interpretable deep learning for two-prong jet classification with jet spectra [DOI]
  - Identification of heavy, energetic, hadronically decaying particles using machine-learning techniques [DOI]
  - Disentangling Boosted Higgs Boson Production Modes with Machine Learning
  - Benchmarking Machine Learning Techniques with Di-Higgs Production at the LHC
  - The Boosted Higgs Jet Reconstruction via Graph Neural Network
  - Extracting Signals of Higgs Boson From Background Noise Using Deep Neural Networks
  - Learning to increase matching efficiency in identifying additional b-jets in the $\text{t}\bar{\text{t}}\text{b}\bar{\text{b}}$ process
- quarks and gluons
  - Quark versus Gluon Jet Tagging Using Jet Images with the ATLAS Detector
  - Deep learning in color: towards automated quark/gluon [DOI]
  - Recursive Neural Networks in Quark/Gluon Tagging [DOI]
  - DeepJet: Generic physics object based jet multiclass classification for LHC experiments
  - Probing heavy ion collisions using quark and gluon jet substructure
  - JEDI-net: a jet identification algorithm based on interaction networks [DOI]
  - Quark-Gluon Tagging: Machine Learning vs Detector [DOI]
  - Towards Machine Learning Analytics for Jet Substructure [DOI]
  - Quark Gluon Jet Discrimination with Weakly Supervised Learning [DOI]

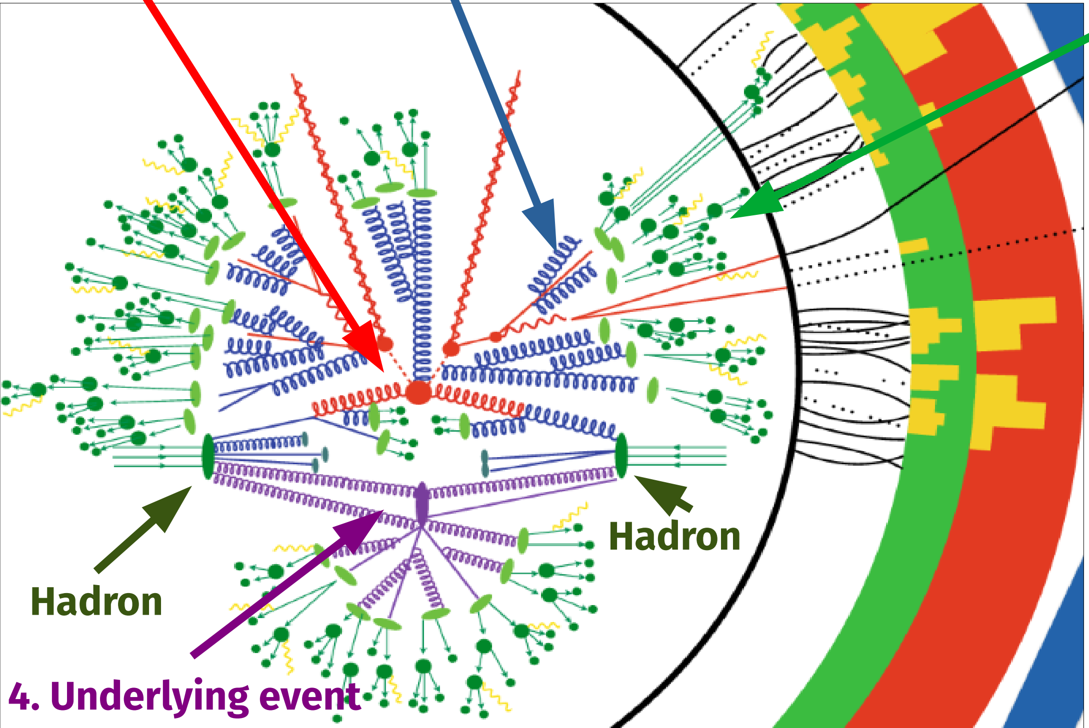
- Classification
  - Parameterized classifiers
    - Parameterized neural networks for high-energy physics [DOI]
    - Approximating Likelihood Ratios with Calibrated Discriminative Classifiers
    - E Pluribus Unum Ex Machina: Learning from Many Collider Events at Once
    - Jet images
      - How to tell quark jets from gluon jets
      - Jet-Images: Computer Vision Inspired Techniques for Jet Tagging [DOI]
      - Playing Tag with ANN: Boosted Top Identification with Pattern Recognition [DOI]
      - Jet-images — deep learning edition [DOI]
      - Quark versus Gluon Jet Tagging Using Jet Images with the ATLAS Detector
      - Boosting $H\to b\bar b$ with Machine Learning [DOI]
      - Learning to classify from impure samples with high-dimensional data [DOI]
      - Parton Shower Uncertainties in Jet Substructure Analyses with Deep Neural Networks [DOI]
      - Deep learning in color: towards automated quark/gluon [DOI]
      - Deep-learning Top Taggers or The End of QCD? [DOI]
      - Pulling Out All the Tops with Computer Vision and Deep Learning [DOI]
      - Reconstructing boosted Higgs jets from event image segmentation
      - An Attention Based Neural Network for Jet Tagging
      - Quark-Gluon Jet Discrimination Using Convolutional Neural Networks [DOI]
      - Learning to Isolate Muons
      - Deep learning jet modifications in heavy-ion collisions
    - Event images
      - Topology classification with deep learning to improve real-time event selection at the LHC [DOI]
      - Convolutional Neural Networks with Event Images for Pileup Mitigation with the ATLAS Detector
      - Boosting $H\to b\bar b$ with Machine Learning [DOI]
      - End-to-End Physics Event Classification with the CMS Open Data: Applying Image-based Deep Learning on Detector Data to Directly Classify Collision Events at the LHC [DOI]
      - Disentangling Boosted Higgs Boson Production Modes with Machine Learning
      - Identifying the nature of the QCD transition in relativistic collision of heavy nuclei with deep learning [DOI]
    - Sequences
      - Jet Flavor Classification in High-Energy Physics with Deep Neural Networks [DOI]
      - Topology classification with deep learning to improve real-time event selection at the LHC [DOI]
      - Jet Flavour Classification Using DeepJet [DOI]
      - Development of a Vertex Finding Algorithm using Recurrent Neural Network
      - Sequence-based Machine Learning Models in Jet Physics
    - Trees
      - QCD-Aware Recursive Neural Networks for Jet Physics [DOI]
      - Recursive Neural Networks in Quark/Gluon Tagging [DOI]
    - Graphs
      - Neural Message Passing for Jet Physics
      - Graph Neural Networks for Particle Reconstruction in High Energy Physics detectors
      - Probing stop pair production at the LHC with graph neural networks [DOI]
      - Pileup mitigation at the Large Hadron Collider with graph neural networks [DOI]
      - Unveiling CP property of top-Higgs coupling with graph neural networks at the LHC [DOI]
      - JEDI-net: a jet identification algorithm based on interaction networks [DOI]
      - Learning representations of irregular particle-detector geometry with distance-weighted graph networks [DOI]
      - Interpretable deep learning for two-prong jet classification with jet spectra [DOI]
      - Neural Network-based Top Tagger with Two-Point Energy Correlations and Geometry of Soft Emissions [DOI]
      - Probing triple Higgs coupling with machine learning at the LHC
      - Casting a graph net to catch dark showers [DOI]
      - Graph neural networks in particle physics [DOI]
      - Distance-Weighted Graph Neural Networks on FPGAs for Real-Time Particle Reconstruction in High Energy Physics [DOI]
      - Supervised Jet Clustering with Graph Neural Networks for Lorentz Boosted Bosons [DOI]
      - Track Seeding and Labelling with Embedded-space Graph Neural Networks
      - Graph neural network for 3D classification of ambiguities and optical crosstalk in scintillator-based neutrino detectors [DOI]

Parton shower and hadronization

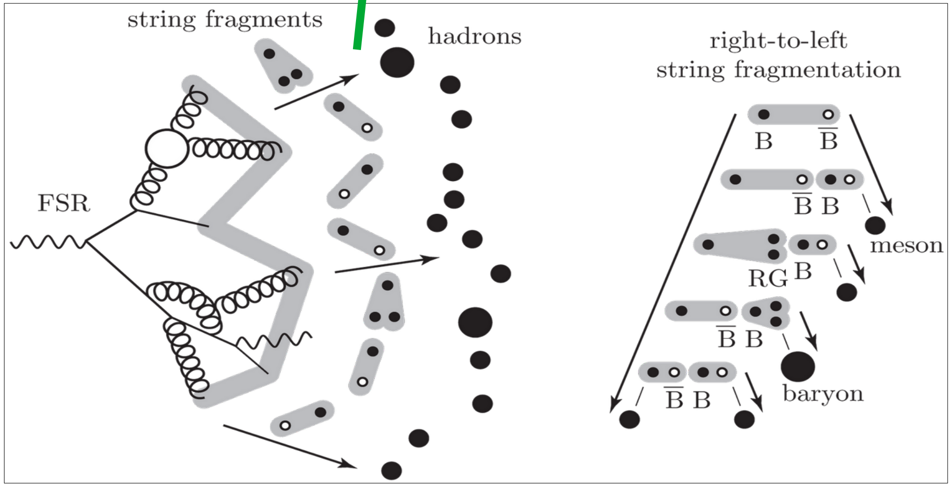
3. Hadronization

2. Parton shower

1. Hard scattering



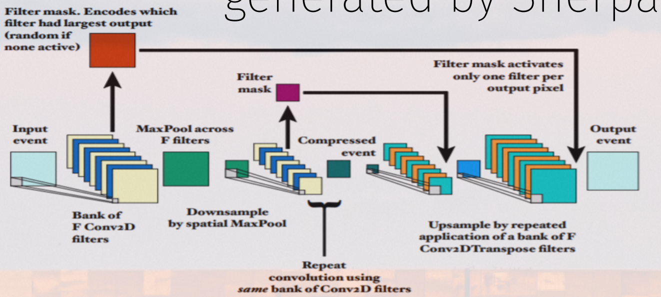
Nature Reviews Physics 3, 73 (2021)



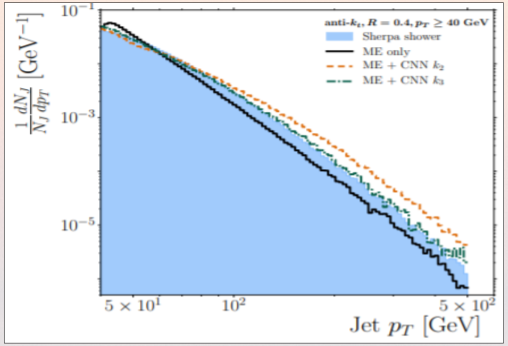
The goal of this study

J.W. Monk: Deep Learning as a Parton Shower (arXiv:1807.03685)

Dataset: 500 000 QCD pp event @ 7 TeV, generated by Sherpa



parameter	model k_2	model k_3
Kernel size, k	2	3
Input image size, N	64	81
Size of filter bank, F	9	7
Levels of decomposition	5	3
Regularisation, λ	500	300
Learning rate	5×10^{-5}	1×10^{-5}
Loss weight w_1	5	4
Loss weight w_2	2	2
Loss weight w_3	1	1
Total number of trained weights	72	126

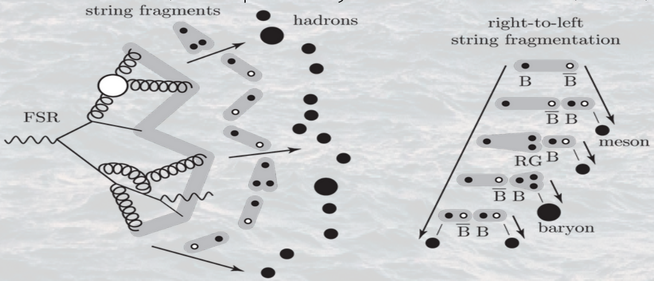


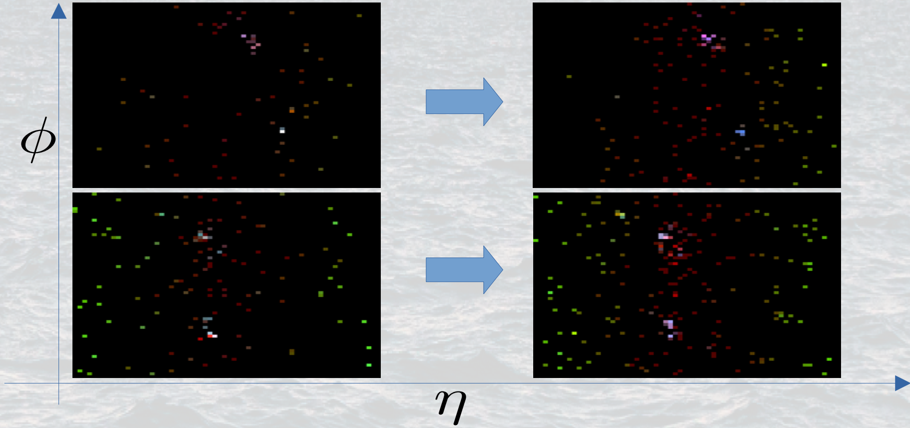
Hadronization

Partons → hadrons

Non-perturbative process

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





ML: a great tool...

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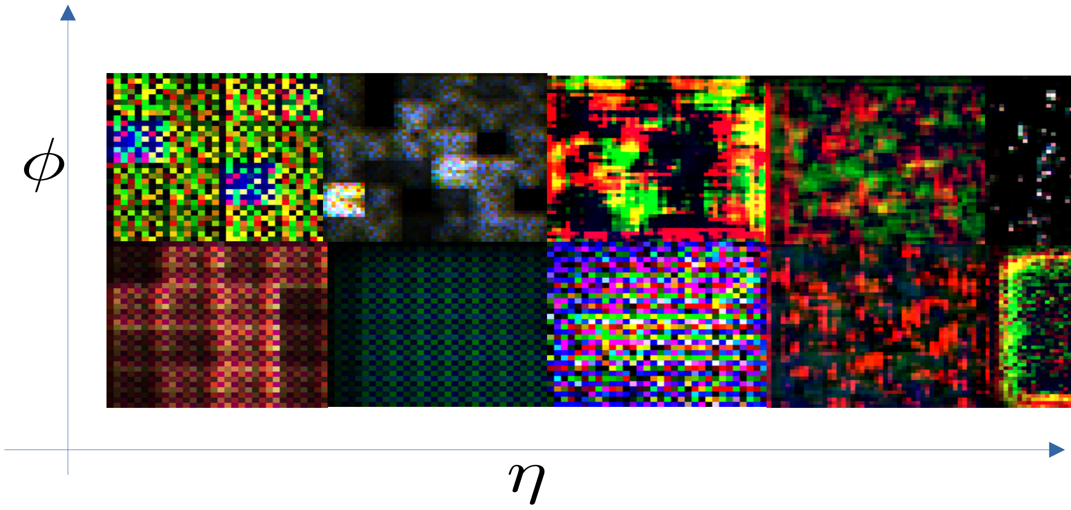
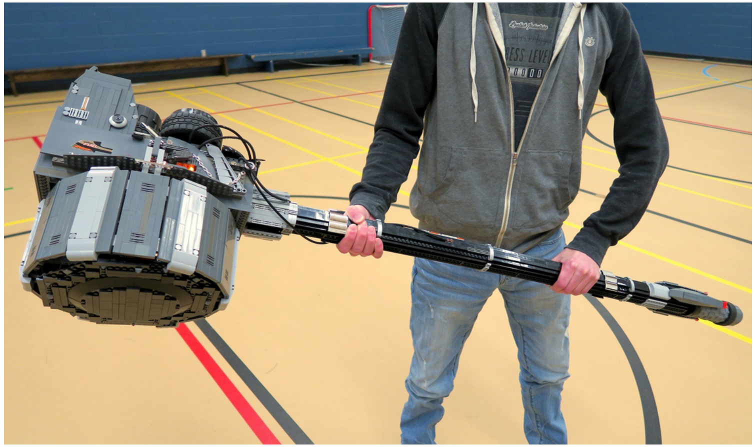
ML: a great tool...





https://www.youtube.com/watch?v=WhvMvbqWNYo

“The nice thing about artificial intelligence is that at least it’s better than artificial stupidity.”

Terry Pratchett, Stephen Baxter: The Long War

Train and validation sets

Monte Carlo data: Pythia 8.303

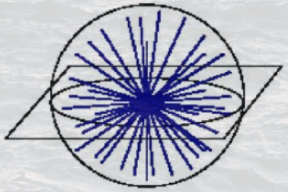
Monash tune
Rescattering and decays turned off
ISR, FSR, MPI: turned on **(*)**
Selection:

- All final particles with $|y| < \pi$
- At least 2 jets
  - Anti-k_T
  - R=0.4
  - p_T>40 GeV

Event number:

- Train: 750 000, **√s = 7 TeV**
- Validation and test: 100 000
- ~20 GB raw data

S=3/4 A=0



S=1 A=1/2

Input:

Parton level

Discretized in the (y, ϕ) plane: p_T, m, multiplicity $\times\sqrt{s}/1GeV$

$y \in [\pi, \pi]$ 32 bins
$\phi \in [0, 2\pi]$, 32 bins

Hadron level output:

(Charged) event multiplicity, (tr-)sphericity, mean jet p_T, -mass, -width, -multiplicity

$$M_{xyz} = \sum_i \begin{pmatrix} p_{xi}^2 & p_{xi}p_{yi} & p_{xi}p_{zi} \\ p_{yi}p_{xi} & p_{yi}^2 & p_{yi}p_{zi} \\ p_{zi}p_{xi} & p_{zi}p_{yi} & p_{zi}^2 \end{pmatrix}$$

Eigenvalues: $\lambda_1 > \lambda_2 > \lambda_3$ $\sum_i \lambda_i = 1$

Sphericity: $S = \frac{3}{2}(\lambda_2 + \lambda_3)$

Transverse sphericity: $S_\perp = \frac{2\lambda_2}{\lambda_1+\lambda_2}$

Models

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

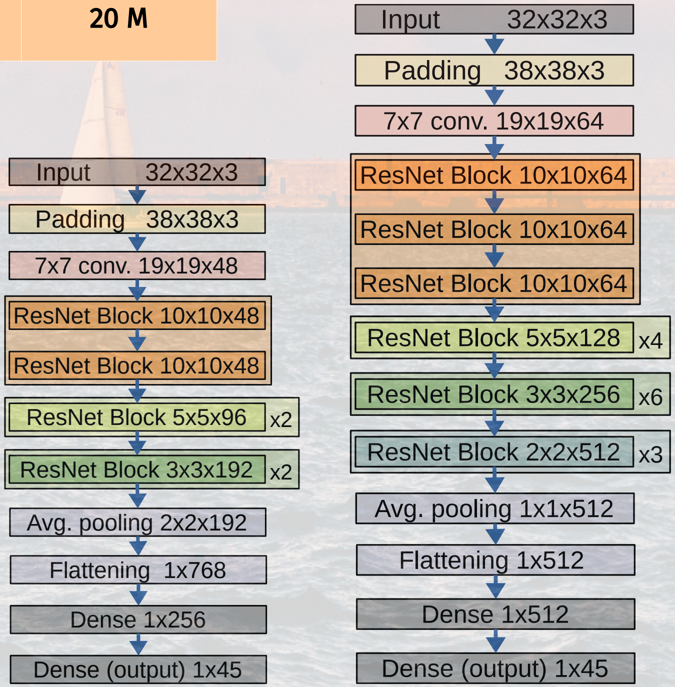
BUT:

Vanishing/exploding gradients

ResNet:

Residual blocks with "skip connections"

	Model S	Model K
Trainable parameters	1.7 M	20 M

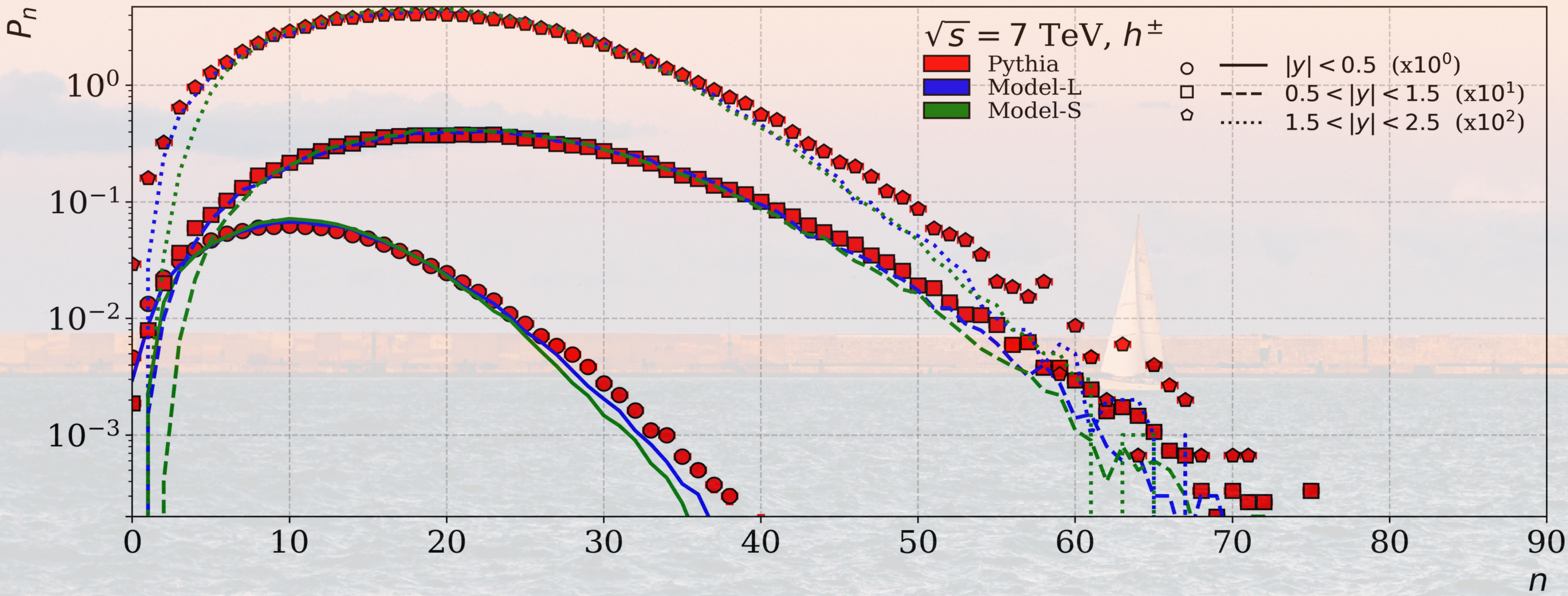


Used hardwares: Nvidia Tesla T4, GeForce GTX 1080
@ Wigner Scientific Computing Laboratory

Framework: Tensorflow 2.4.1, Keras 2.4.0

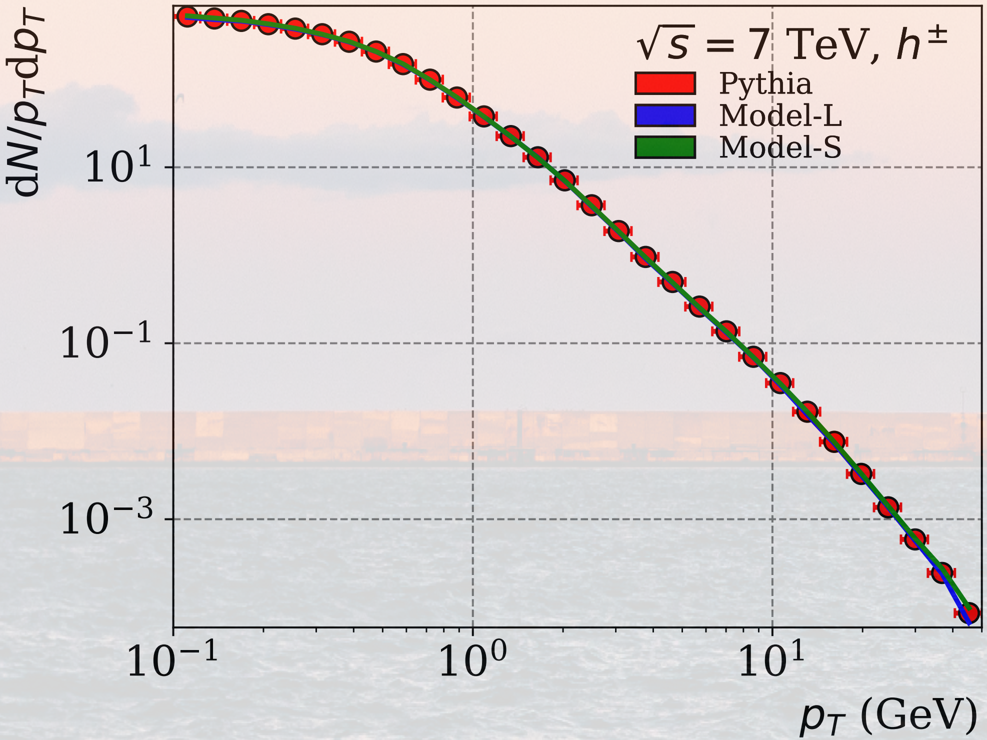
Results

Proton-proton @ 7 TeV, Training + Validation



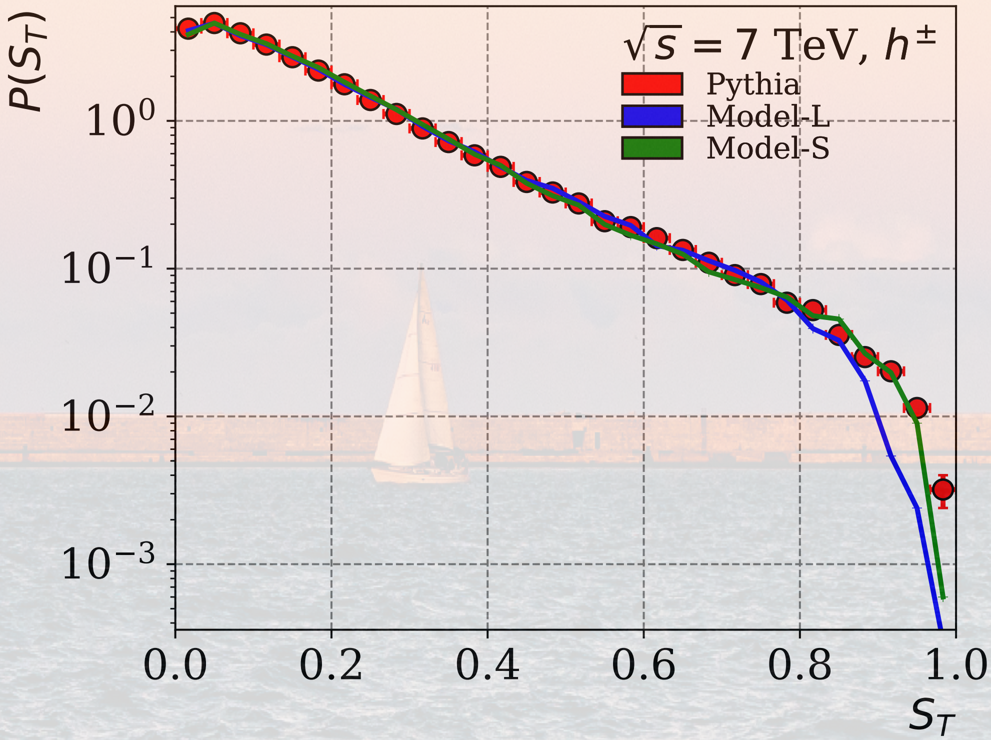
Charged hadron multiplicity at various rapidity windows
Comparison to reference MC model
Good agreement for both models

Proton-proton @ 7 TeV, Training + Validation



Charged hadron transverse momentum

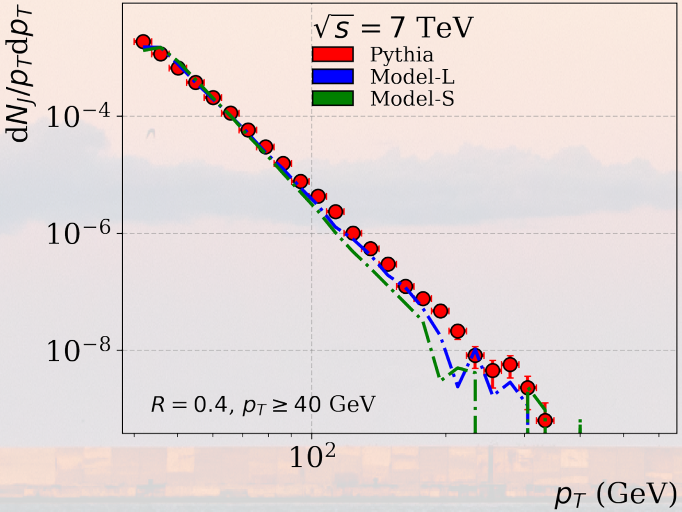
0.1 GeV ≤ p_T ≤ 50 GeV



Event transverse sphericity

The smaller model performs better

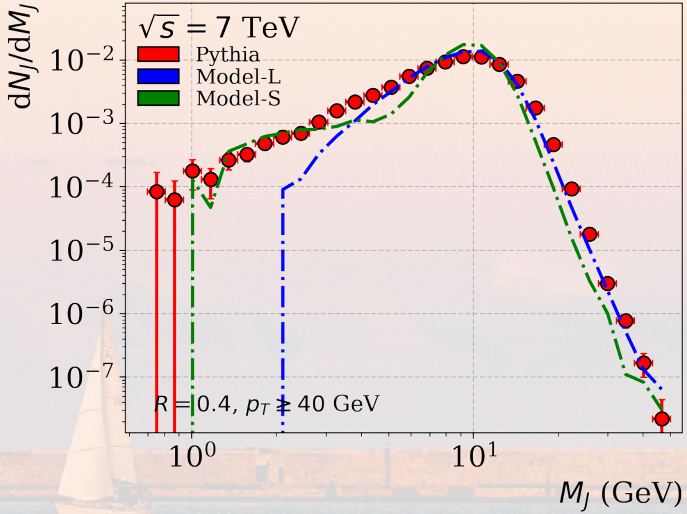
Proton-proton @ 7 TeV, Training + Validation

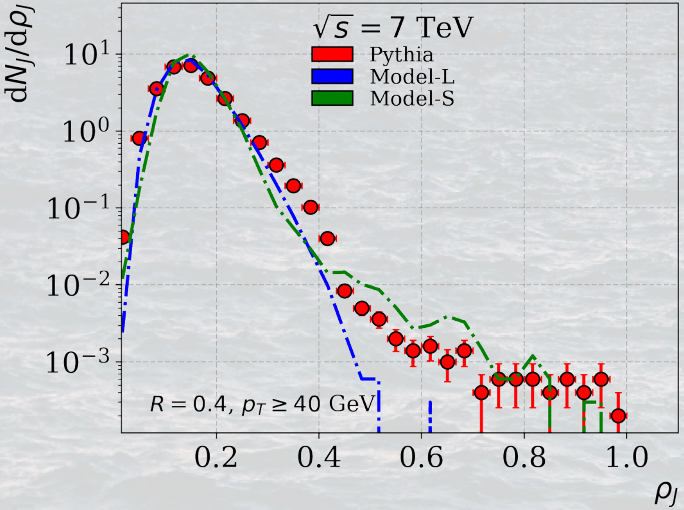


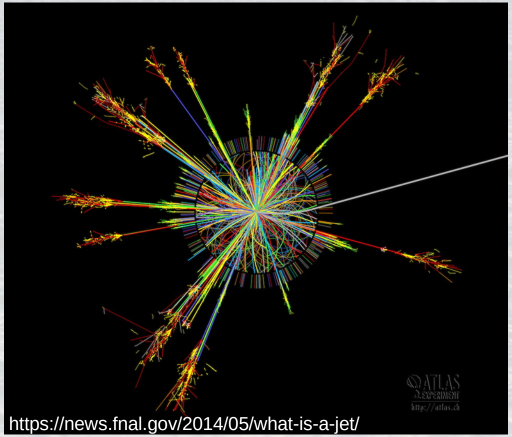
Jets:

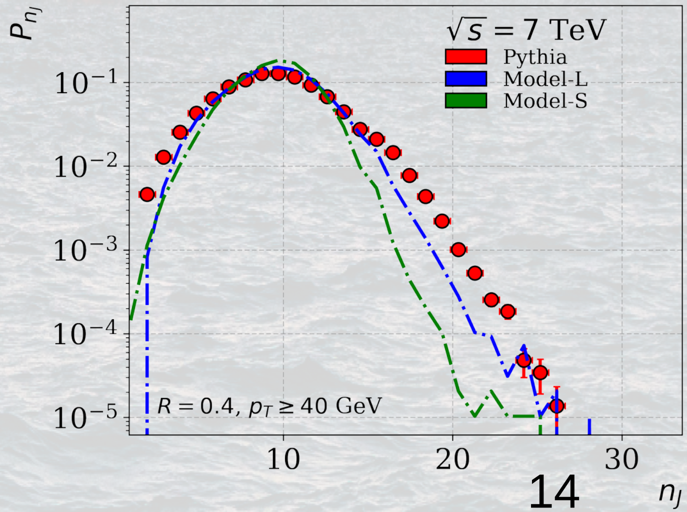
- Mean $p_T \leq 400$ GeV
- Mean mass $p_T \leq 400$ GeV
- Mean multiplicity
- Mean width

The smaller model performs better



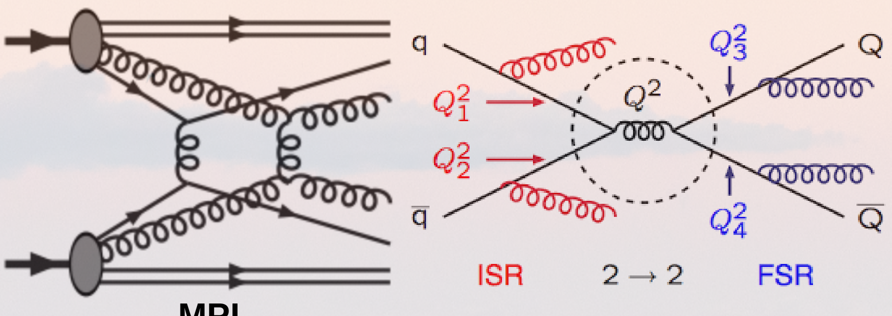




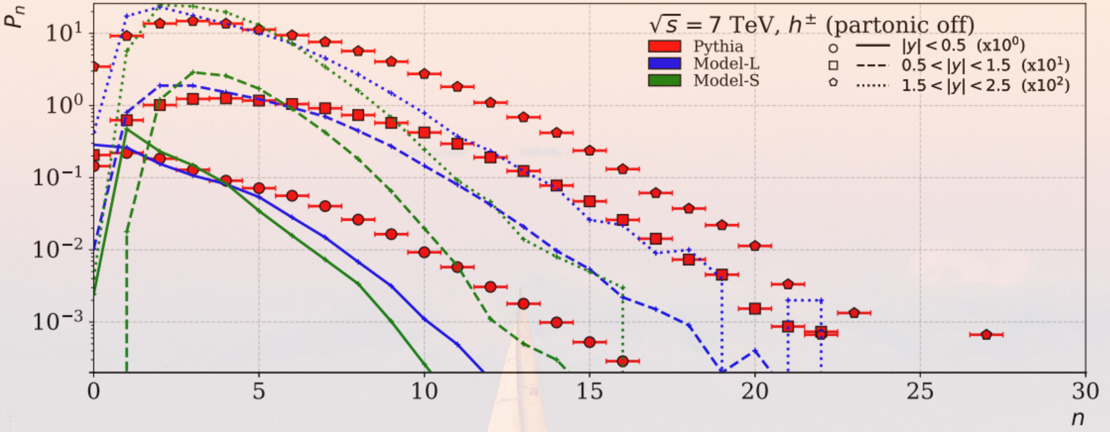


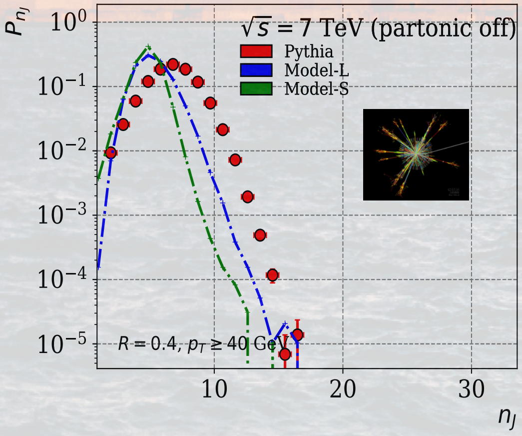
Proton-proton @ 7 TeV, Training + Validation

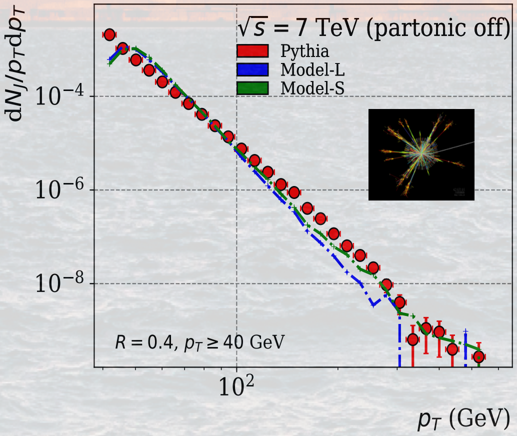
(*) What about the partonic processes?

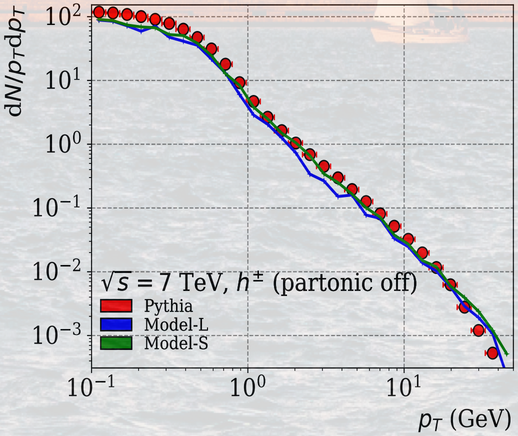


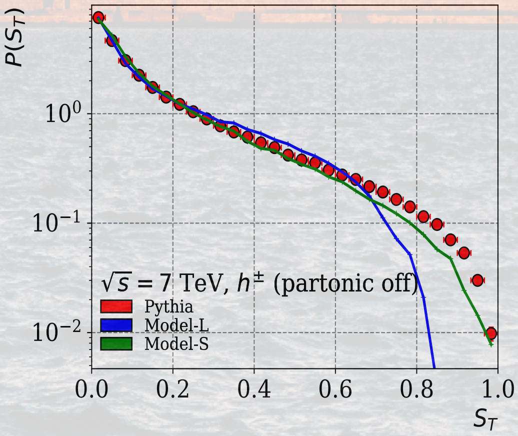
http://home.thep.lu.se/~torbjorn/talks/cern18cosmic.pdf





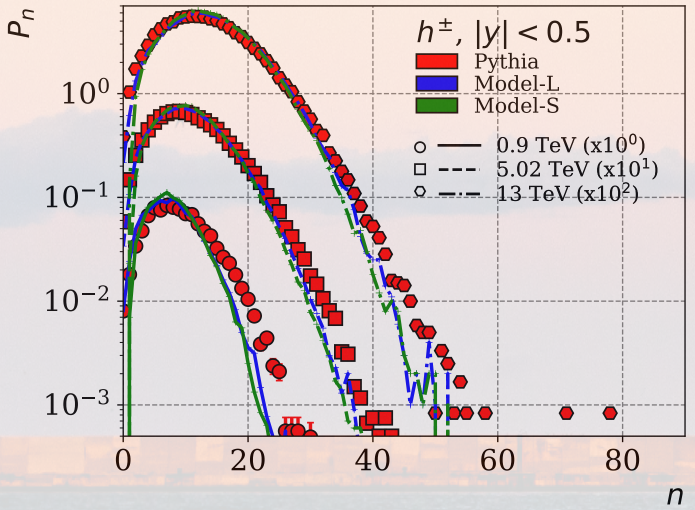


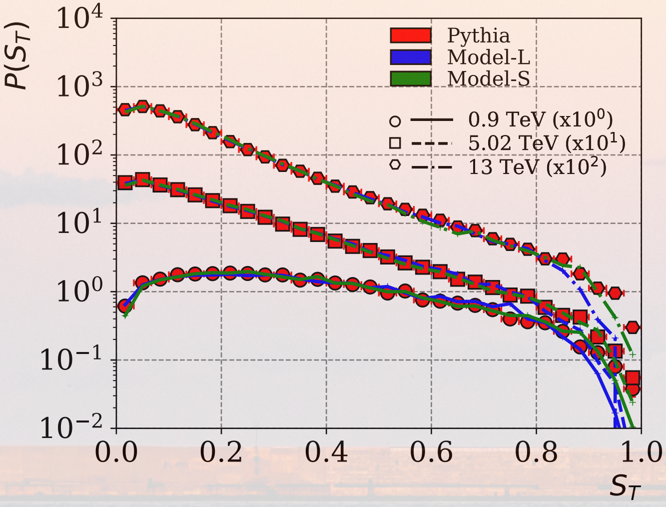


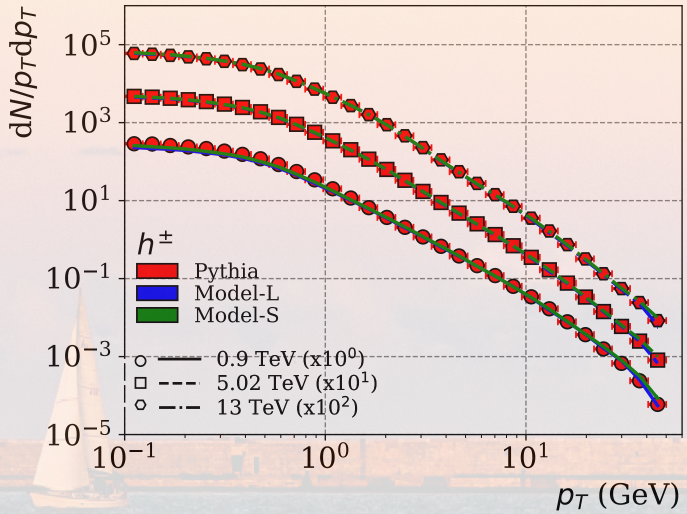


Qualitative agreement → the models adopted the hadronization properties

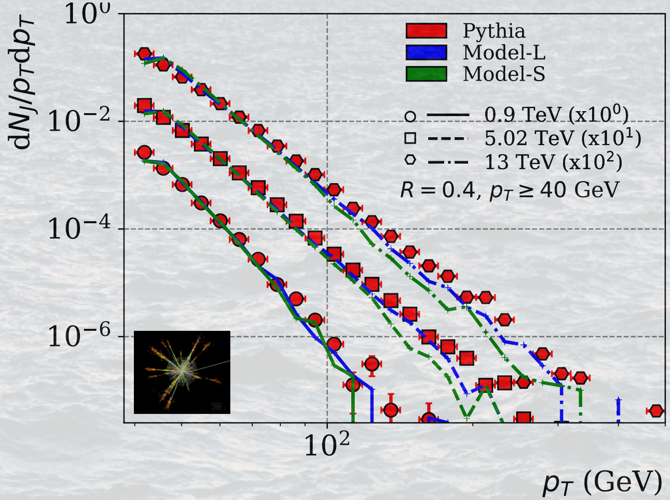
Proton-proton @ 0.9-13 TeV, Predictions



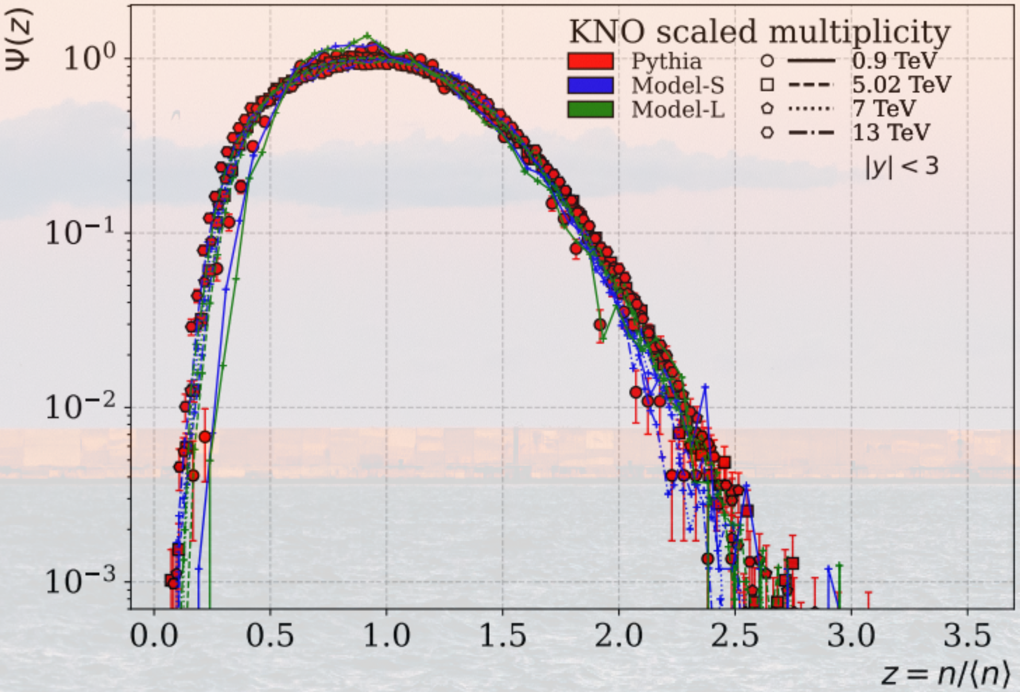


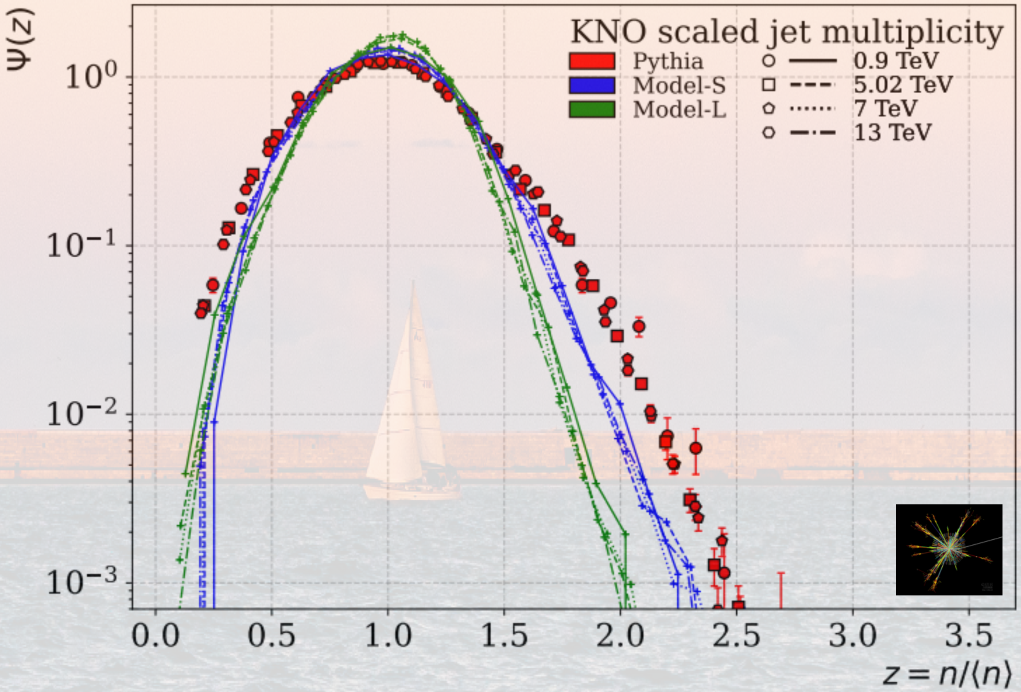


- So far: everything at √s = 7 TeV → the **ONLY** energy, where the models were trained
  - Good agreement for all observable quantities as **predictions** for other LHC energies
- **Multiplicity scaling?**



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 in **jetty** events: good overlap and agreement

Mean jet multiplicities: different scaling for the models

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

Summary

Developed hadronization models with different complexities

Traditional computer vision algorithms capture the main features of high-energy event variables successfully → training only at a single c.m. energy, predictions at other energies

Generalization to other CM energies: KNO scaling in jetty events

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, 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.

Dimensionality

Input:
Parton level

Discretized in the (y, ϕ) plane: p_T,m, multiplicity

$$\left.\begin{array}{ll} y \in [\pi, \pi], & \text{32 bins} \\ \phi \in [0, 2\pi], & \text{32 bins} \end{array}\right\} := M$$

$\mathcal{O}(10^3 - 10^4)$ Total pixels

vs $\mathcal{O}(10^2)$

Pixels with information

Reduction with Singular Value Decomposition:

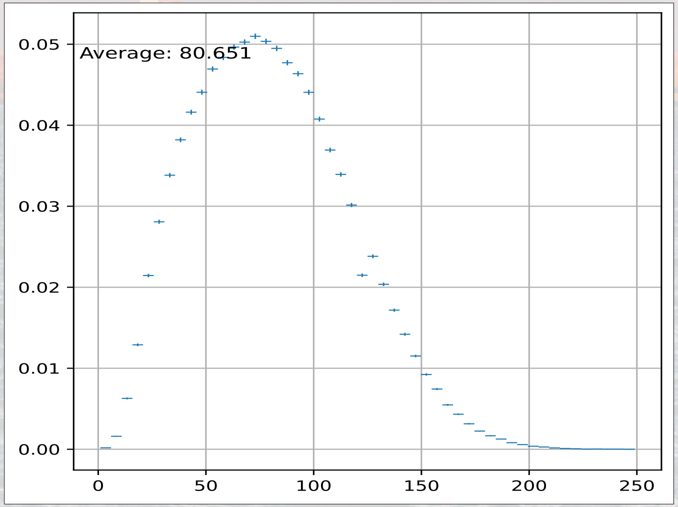
$$M_{n\times m} = U_{n\times n}\Sigma_{n\times m}V^T_{m\times m}$$

- Unitarity
- Ordered by importance
- Guaranteed to exist, unique

$$M \approx \sum_{i=1}^{r} \sigma_i u_i v_i^T + \mathcal{O}(\epsilon), \quad r \leq \min\{n, m\}$$

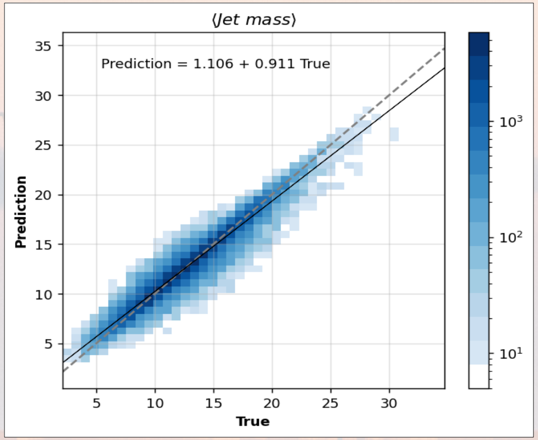
Reduce the input to $\mathcal{O}(10^2)$

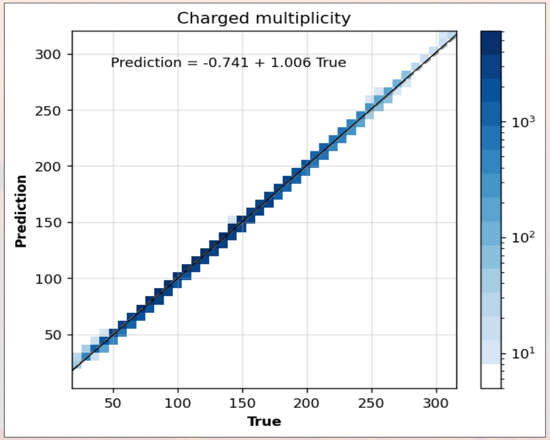
doi:10.1007/BF02288367

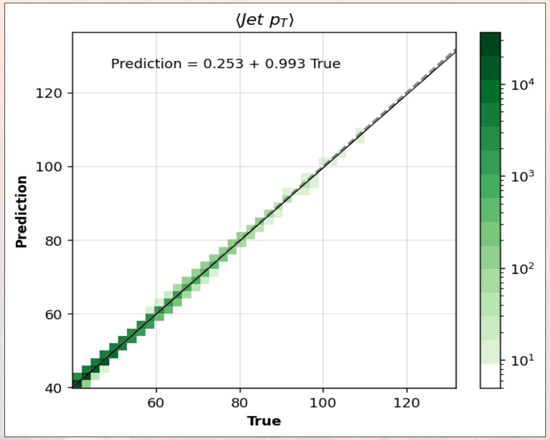


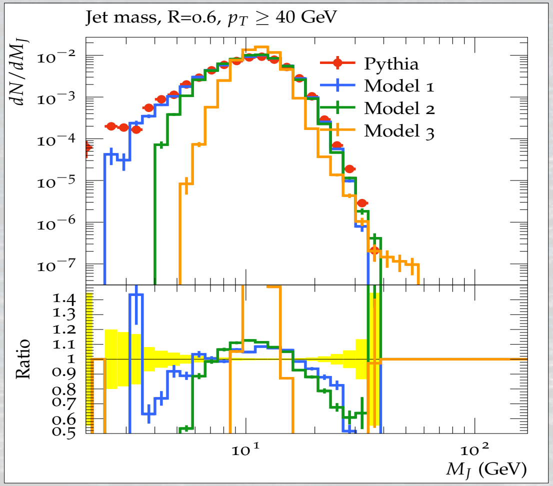
Data-Driven Science and Engineering (S. L. Brunton, J. N. Kutz)

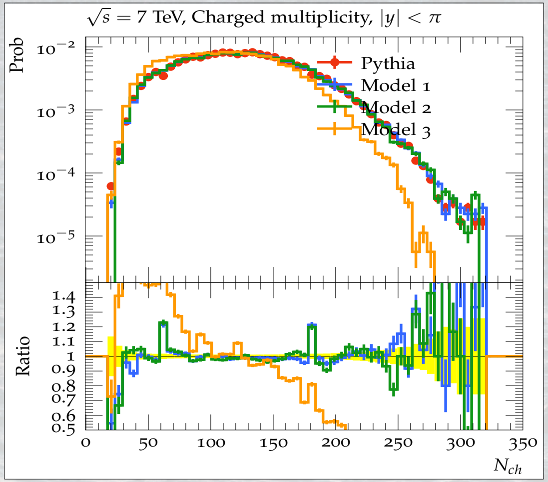
Dimensionality (work in progress)

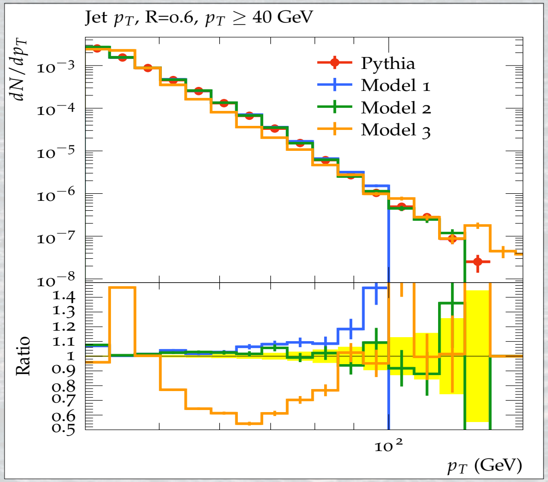






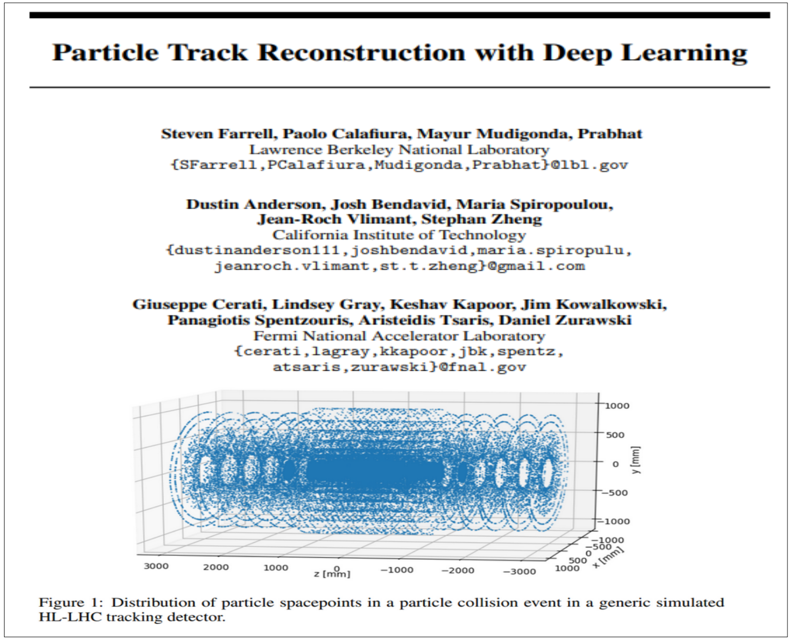






Machine Learning in HEP

Track reconstruction



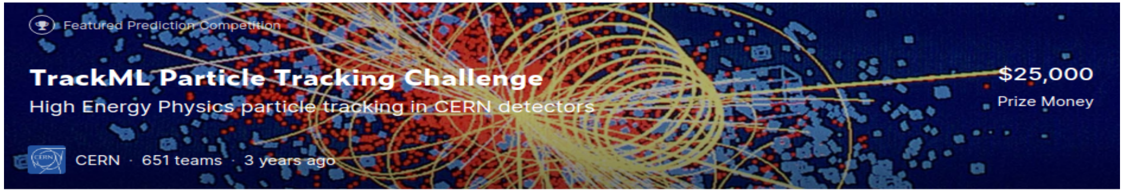
Particle Track Reconstruction with Deep Learning

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

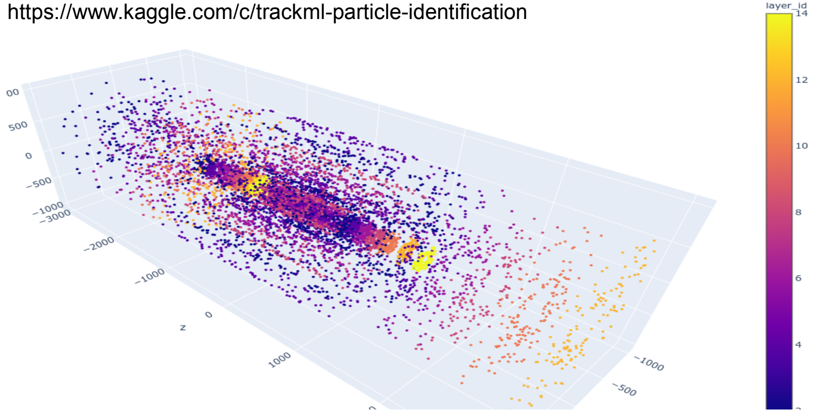
Dustin Anderson, Josh Bendavid, Maria Spiropoulou,
Jean-Roch Vlimant, Stephan Zheng
California Institute of Technology
{dustinanderson111,joshbendavid,maria.spiropulu,
jeanroch.vlimant,st.t.zheng}@gmail.com

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

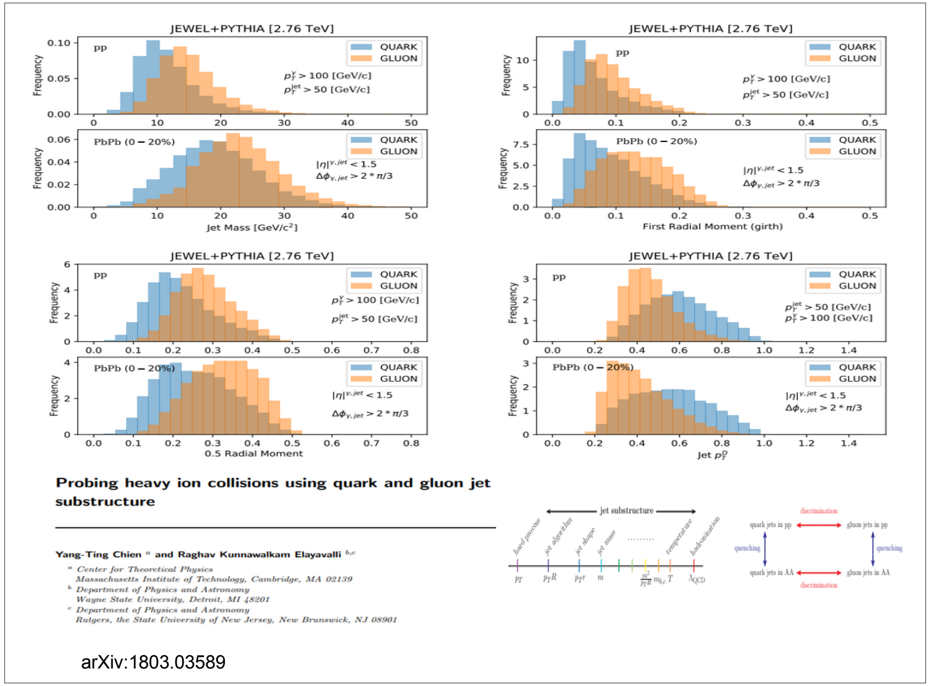
Figure 1: Distribution of particle spacepoints in a particle collision event in a generic simulated HL-LHC tracking detector.



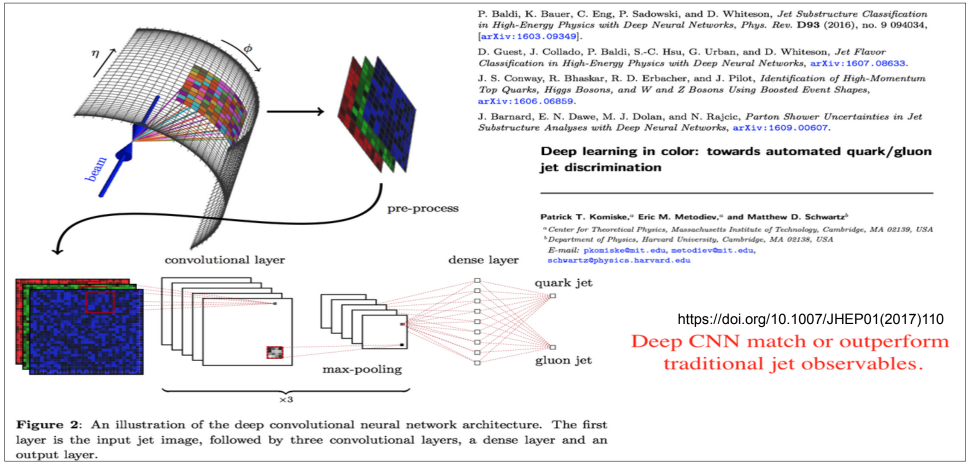
https://www.kaggle.com/c/trackml-particle-identification



Machine Learning in HEP



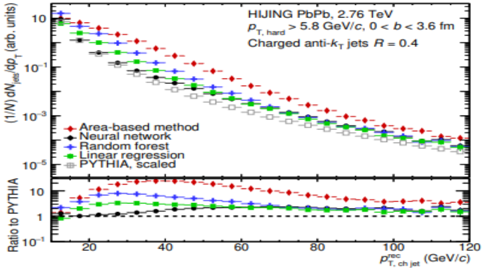
Quark/gluon jet separation



Machine Learning in HEP

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)



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

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

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

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

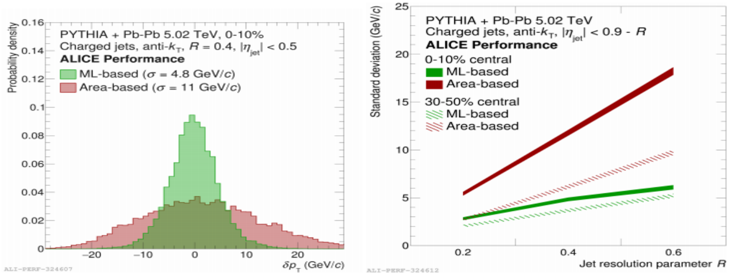
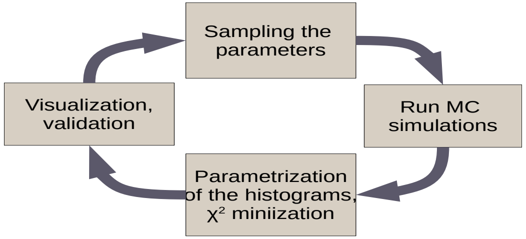


Figure 1: Residual p_T-distributions of embedded jet probes of known transverse momentum.

https://doi.org/10.22323/1.364.0312

Machine Learning in HEP

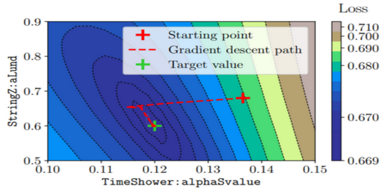
Tuning Monte Carlo event generators



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*



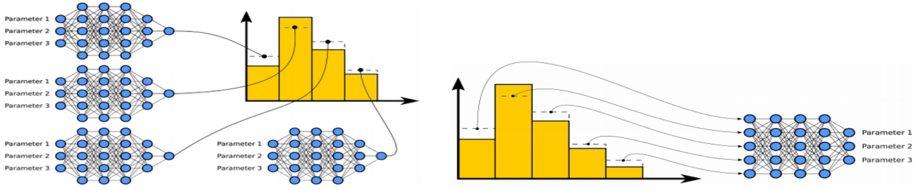


Figure 1: An illustration of the parametrisation of the generator response as implemented in the Per Bin Model.

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

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