Studying hadronization with Machine Learning techniques

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arXiv:2111.15655
arXiv:2210.10548

ACAT 2022
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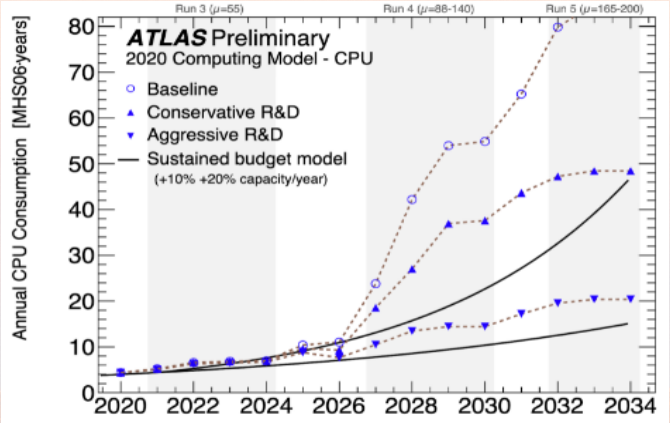
Data, data, and more data

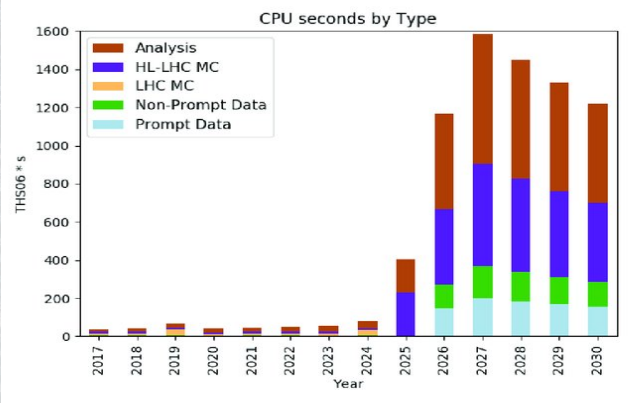
LHC numbers in **2013** vs. now:

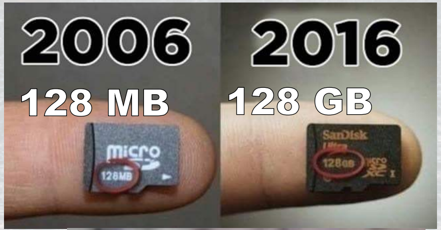
Data:	15 PB/y	vs	200+ PB/y
Tape:	180 PB	vs	740+ PB
Disk:	200 PB	vs	570+ PB
HS06 hours:	2M	vs	100+ B



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

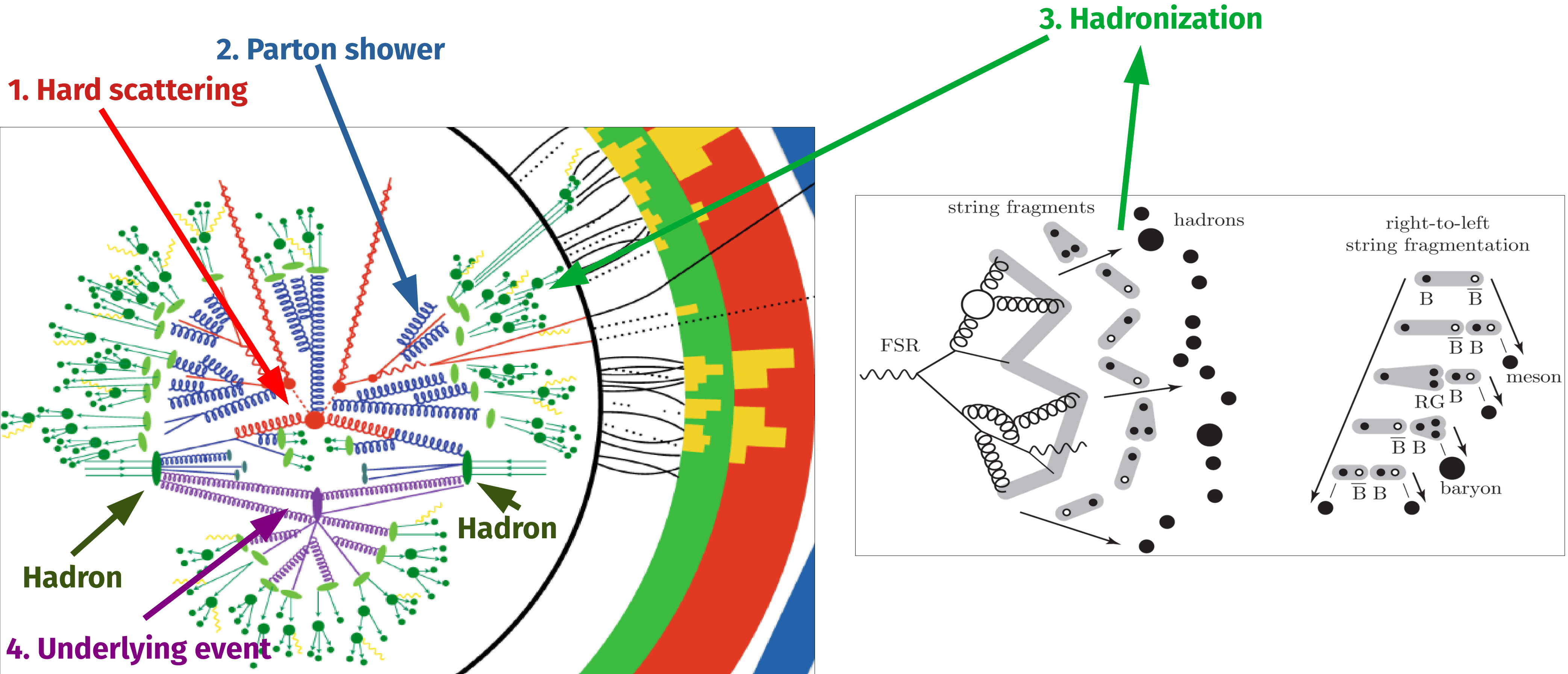
- Track reconstruction
- Quark/gluon jet separation
- Jet reconstruction
- Tuning Monte Carlo event generators
- GAN of detectors
- …

- 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

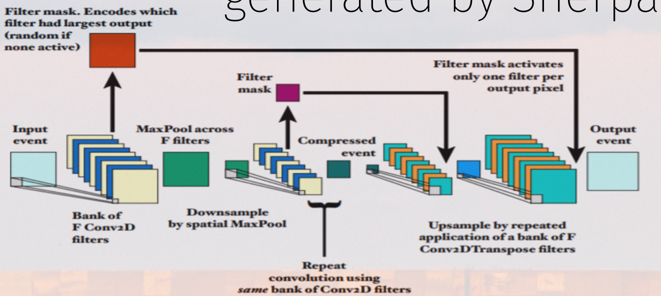


Nature Reviews Physics 3, 73 (2021)

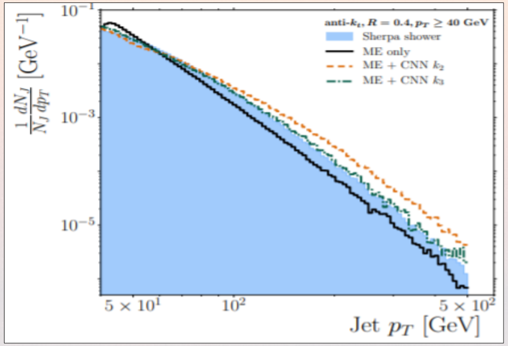
The goal of this study

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

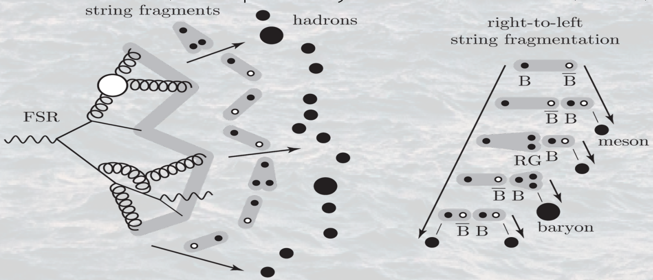


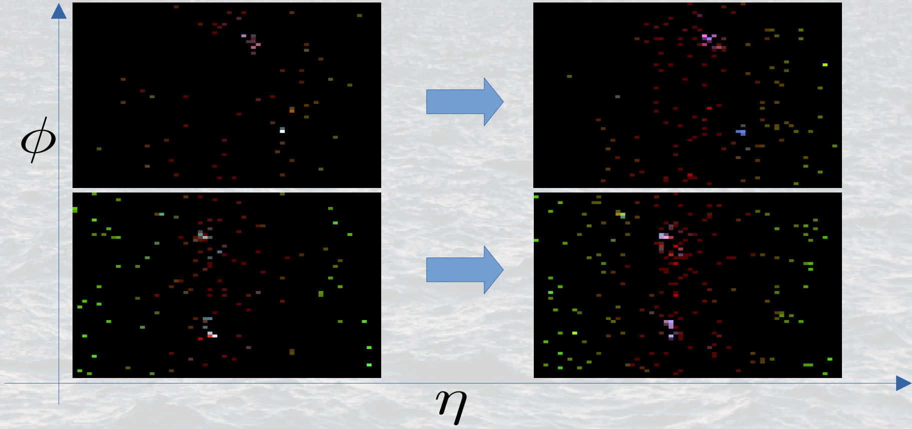
Hadronization

Partons → hadrons

Non-perturbative process

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





ML: a great tool...

ML: a great tool...

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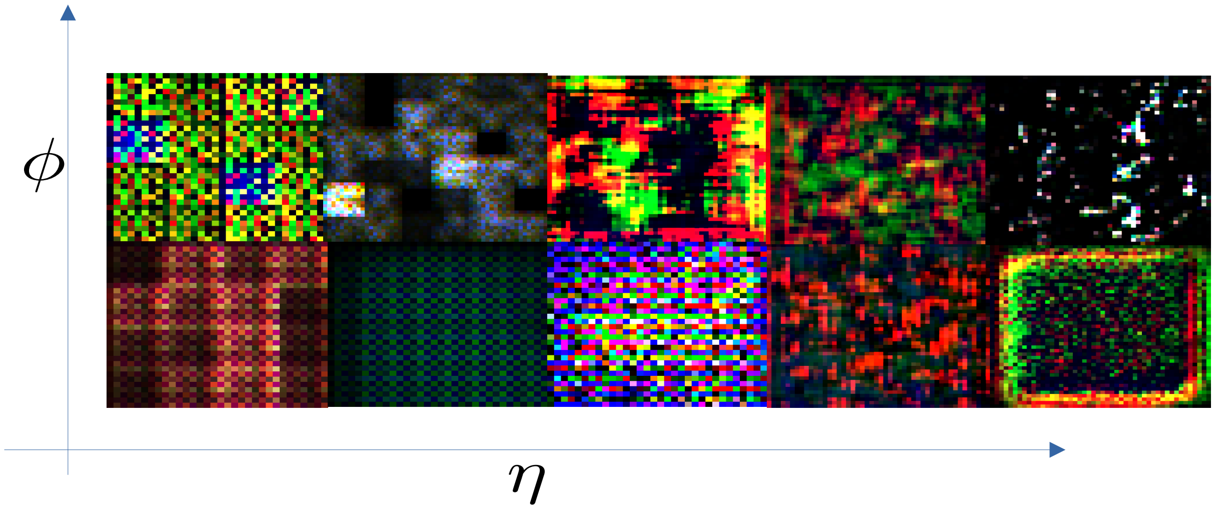
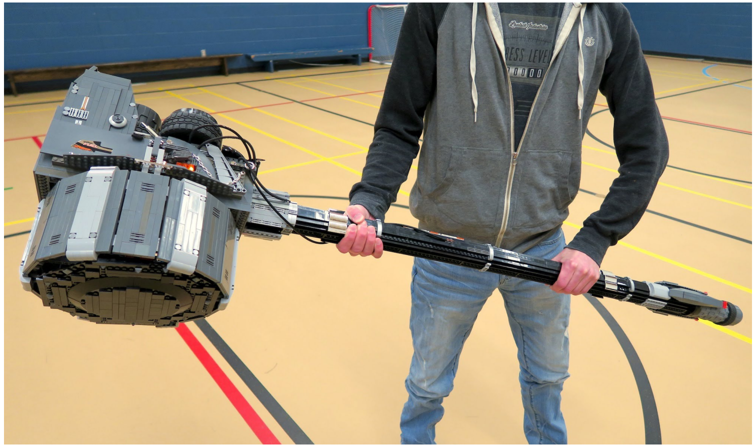




https://www.youtube.com/watch?v=WhvMvbqWNYo

“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

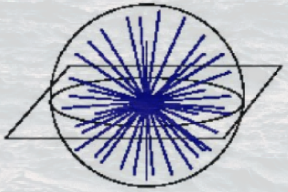
Monash tune
Rescattering and decays turned off
ISR, FSR, MPI: turned on (*)
Selection:

- 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, $\sqrt{s}$ = 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: $\lambda_1 > \lambda_2 > \lambda_3$ $\quad \sum_i \lambda_i = 1$

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

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

Models

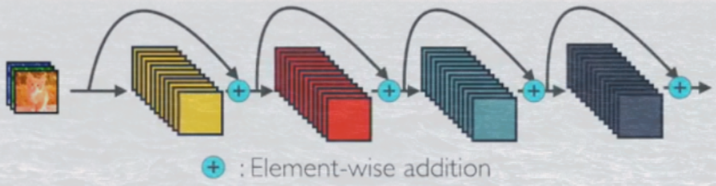
Stacking more layers: solve complex problems more efficiently, get highly accurate results

BUT:

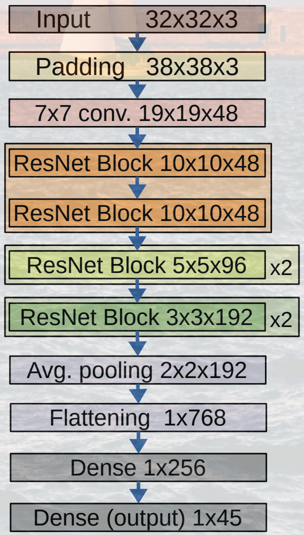
Vanishing/exploding gradients

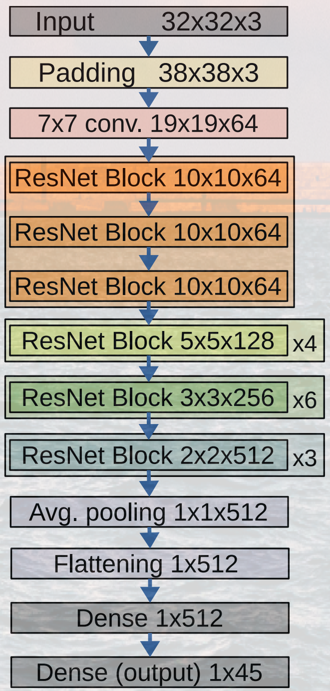
ResNet:

Residual blocks with "skip connections"



	Model S	Model K
Trainable parameters	1.7 M	20 M



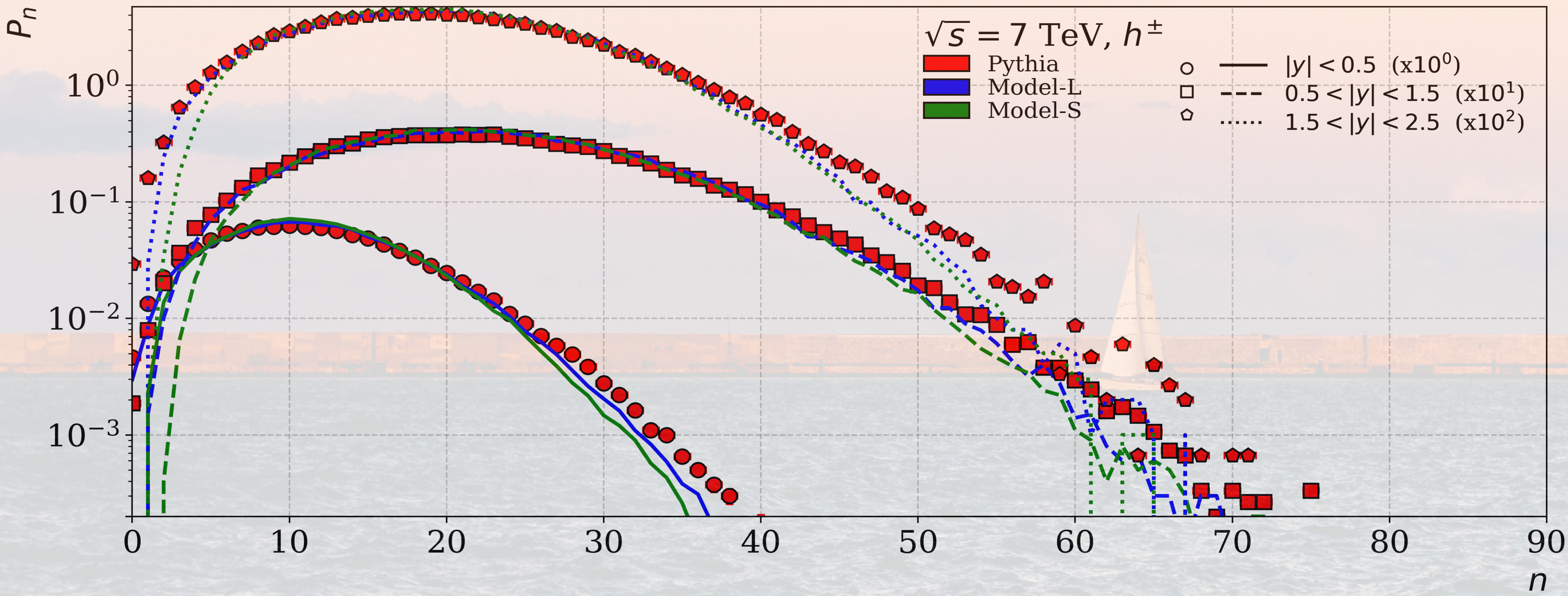


Used hardwares: Nvidia Tesla T4, GeForce GTX 1080
@ Wigner Scientific Computing Laboratory

Framework: Tensorflow 2.4.1, Keras 2.4.0

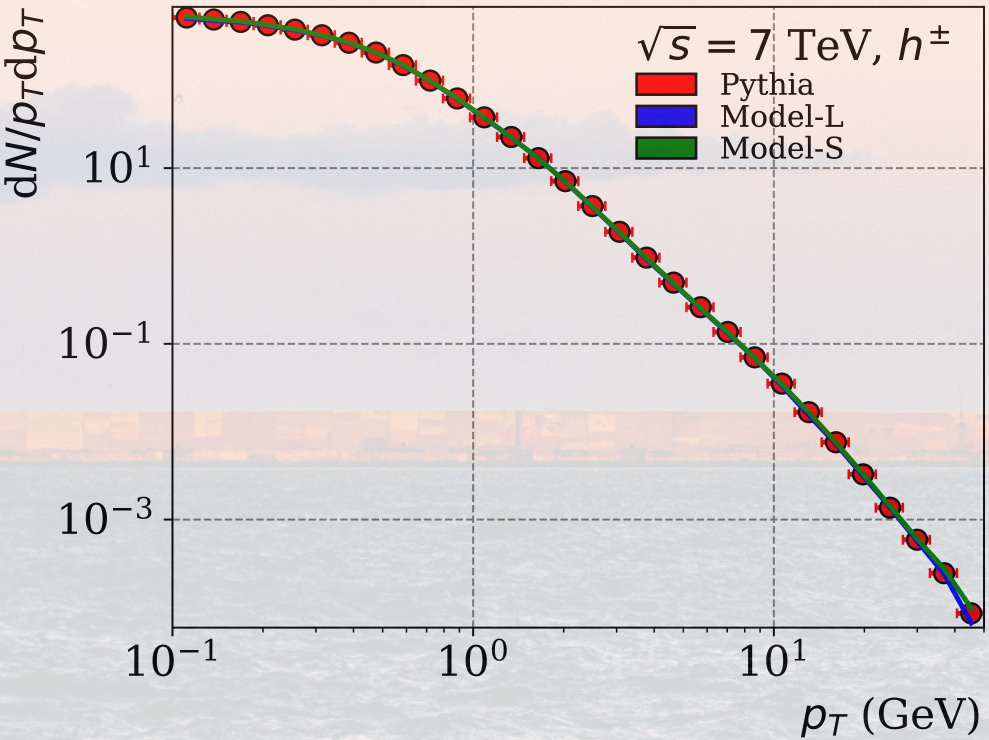
Results

Proton-proton @ 7 TeV, Training + Validation



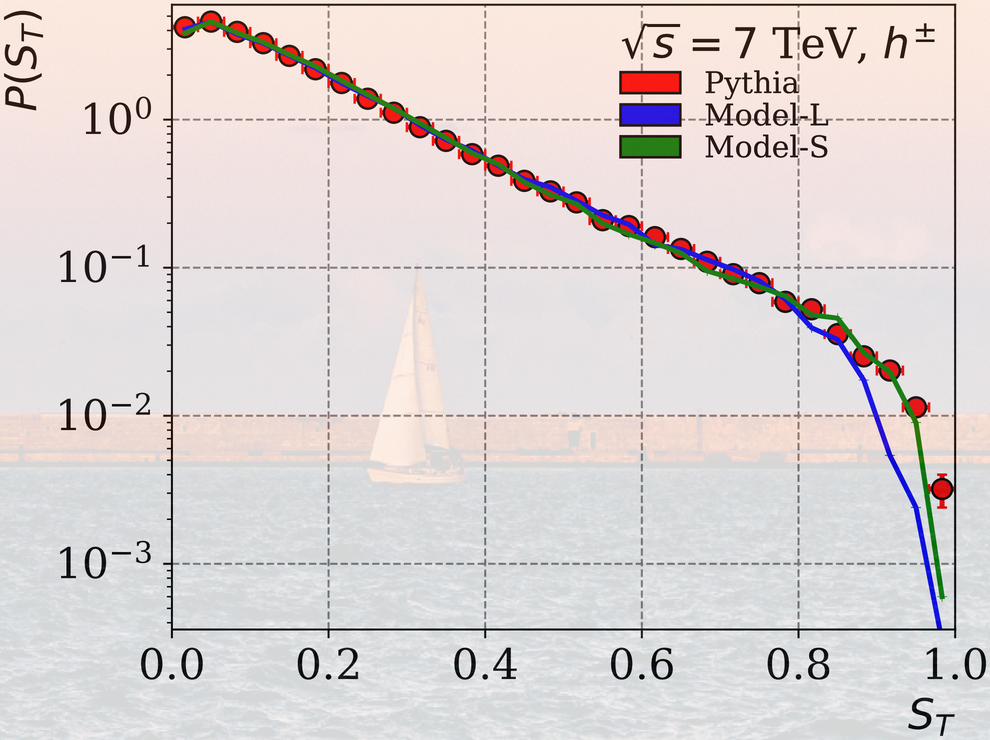
Charged hadron multiplicity at various rapidity windows
Comparison to reference MC model
Good agreement for both models

Proton-proton @ 7 TeV, Training + Validation



Charged hadron transverse momentum

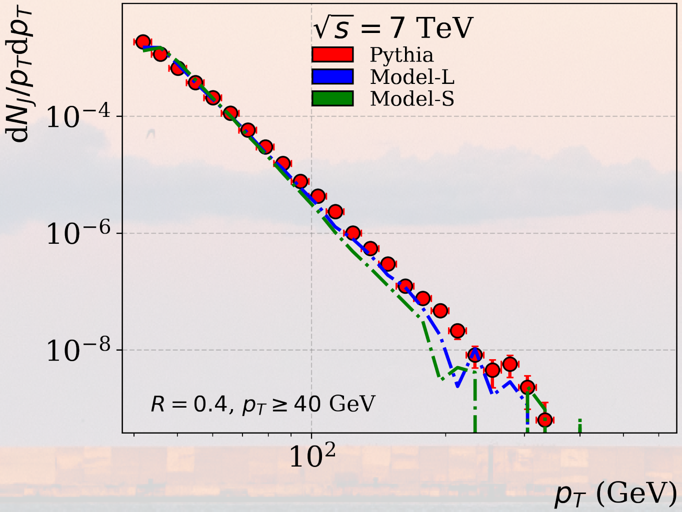
0.1 GeV ≤ p_T ≤ 50 GeV



Event transverse sphericity

The smaller model performs better

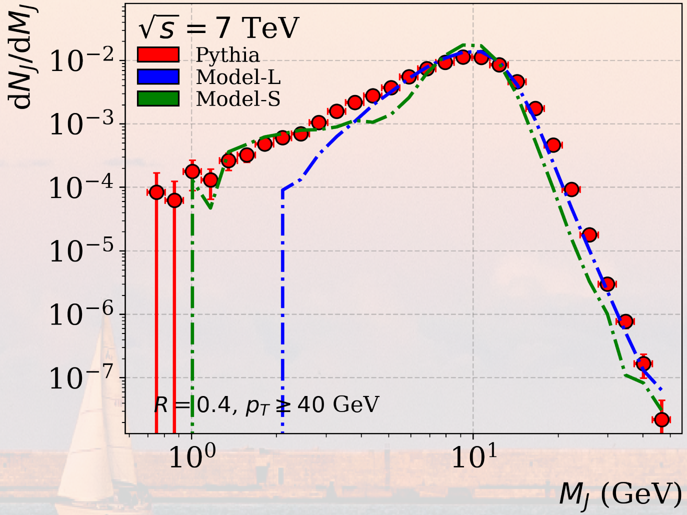
Proton-proton @ 7 TeV, Training + Validation

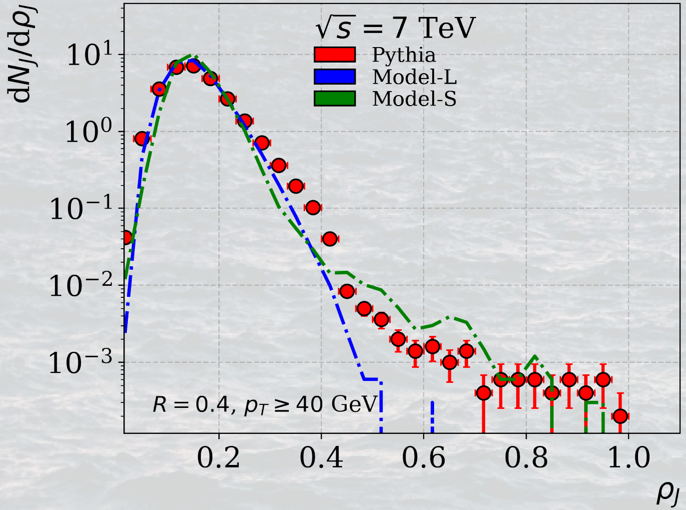


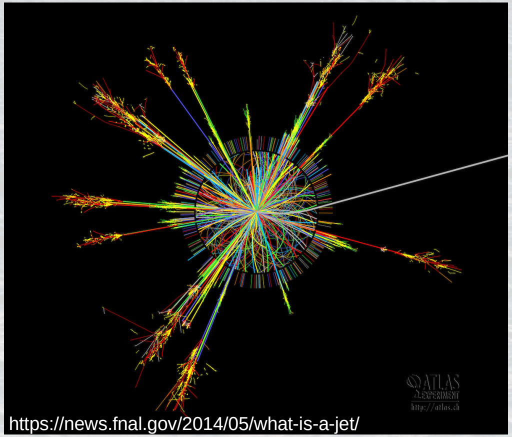
Jets:

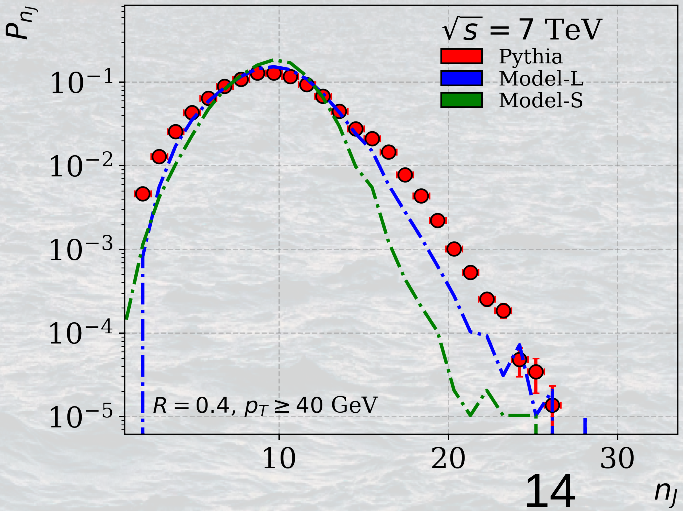
- Mean $p_T \leq 400$ GeV
- Mean mass $p_T \leq 400$ GeV
- Mean multiplicity
- Mean width

The smaller model performs better



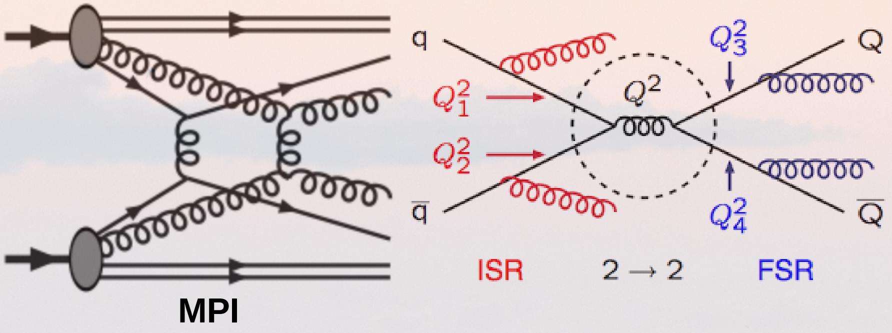




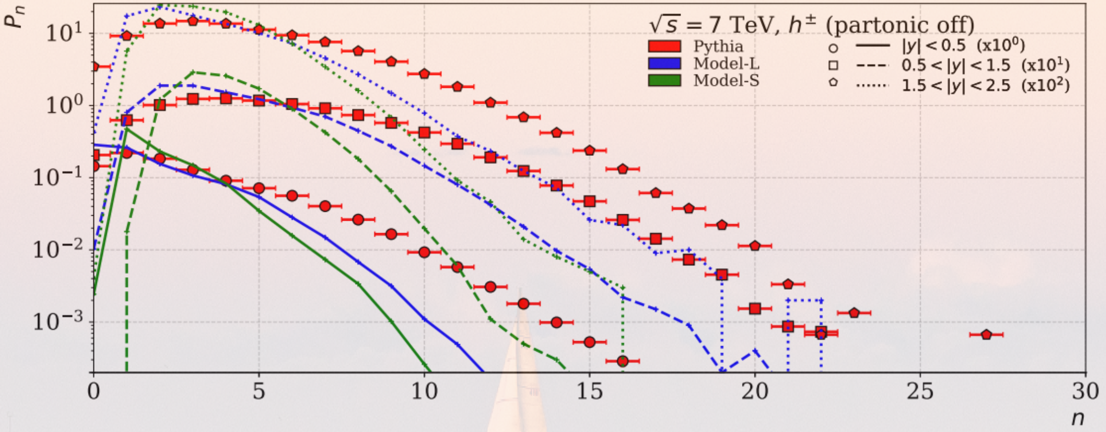


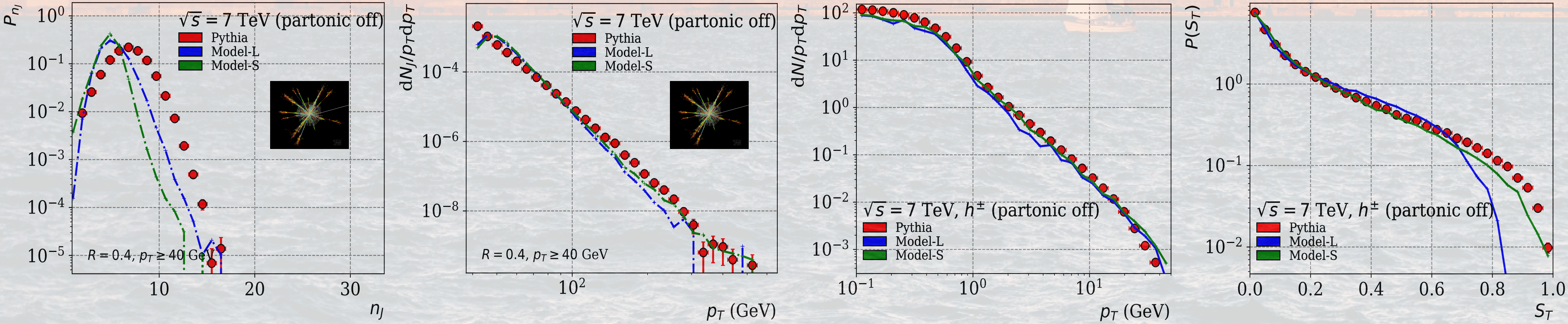
Proton-proton @ 7 TeV, Training + Validation

(*) What about the partonic processes?



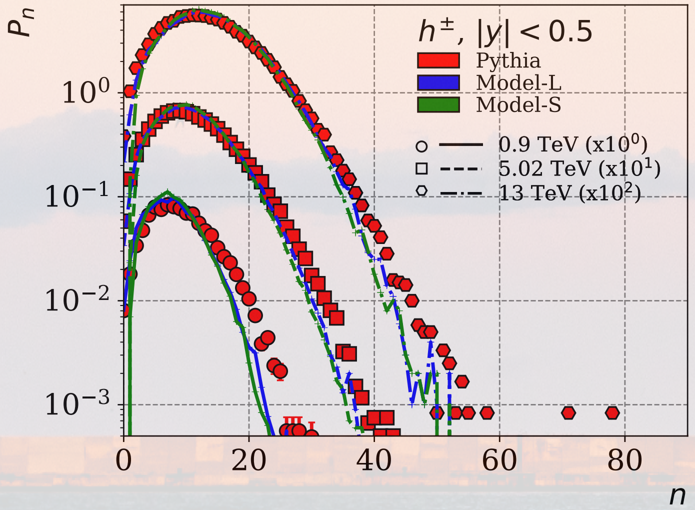
http://home.thep.lu.se/~torbjorn/talks/cern18cosmic.pdf

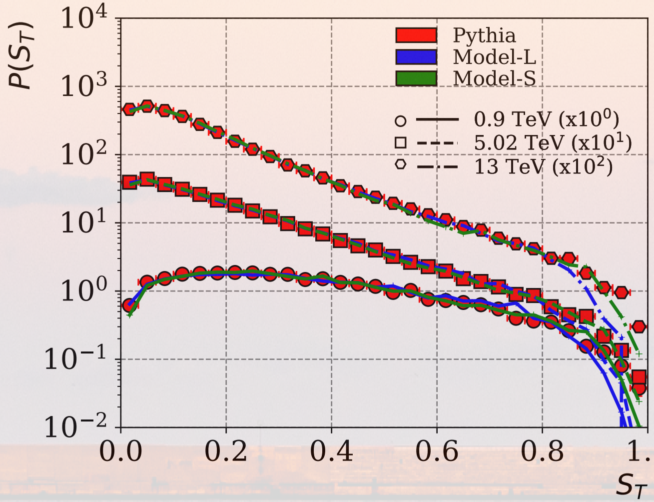


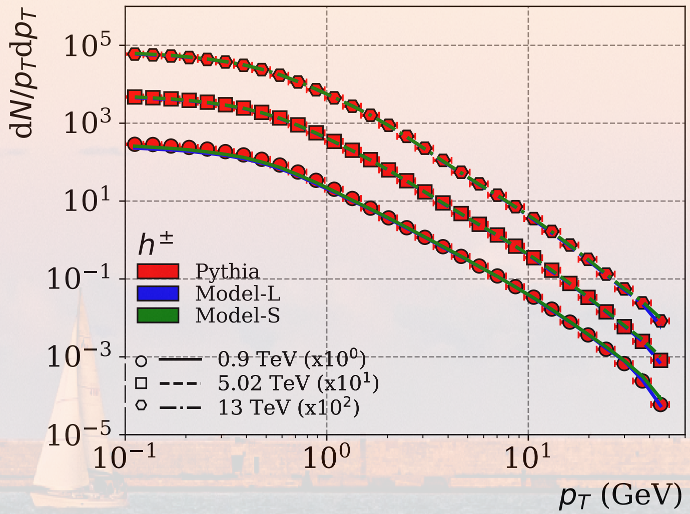


Qualitative agreement → the models adopted the hadronization properties

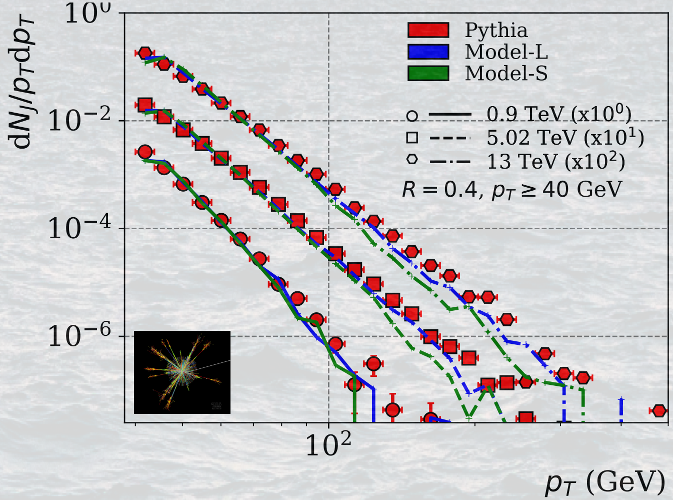
Proton-proton @ 0.9-13 TeV, Predictions



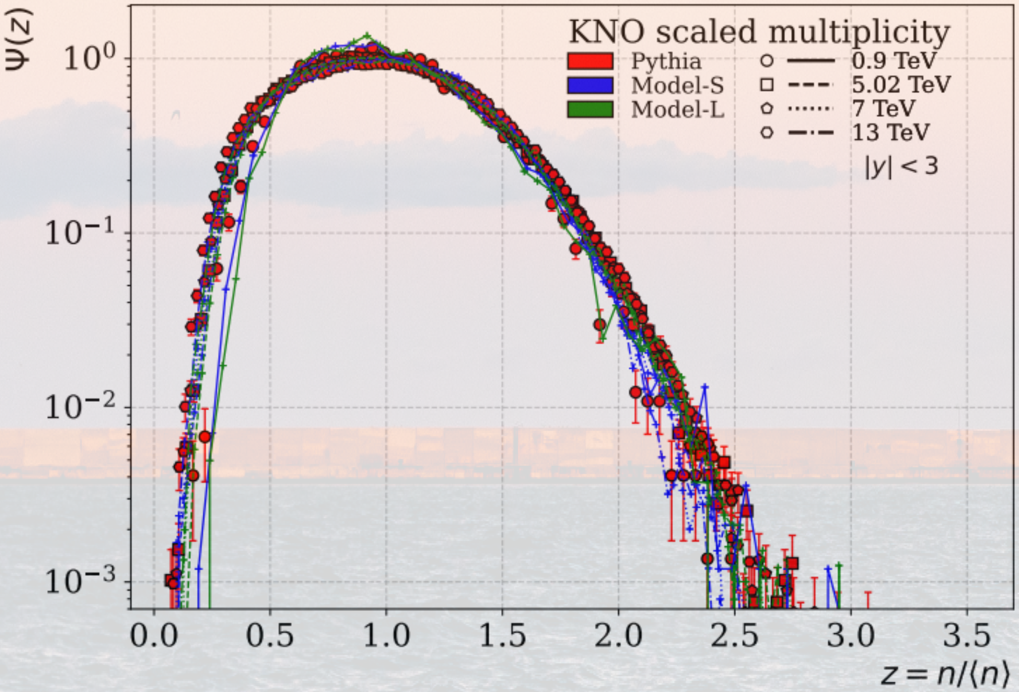


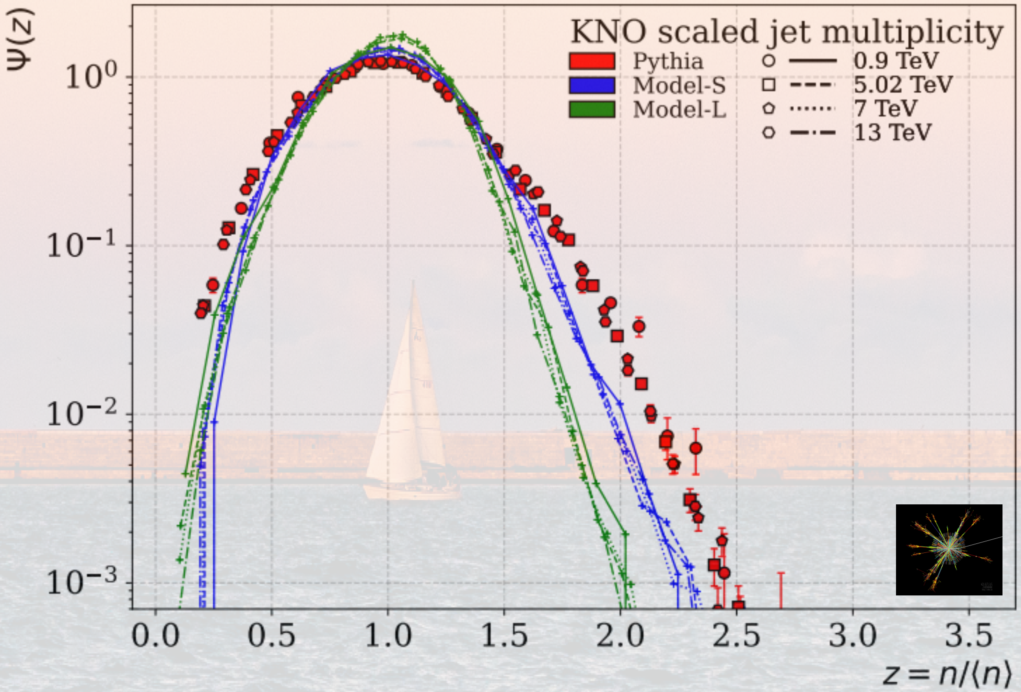


- So far: everything at √s = 7 TeV → the **ONLY** energy, where the models were trained
  - Good agreement for all observable quantities as **predictions** for other LHC energies
- **Multiplicity scaling?**



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

ACAT 2022

24–28 OCTOBER 2022

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, NKFIH 2019-2.1.11-TÉT-2019-00078, 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

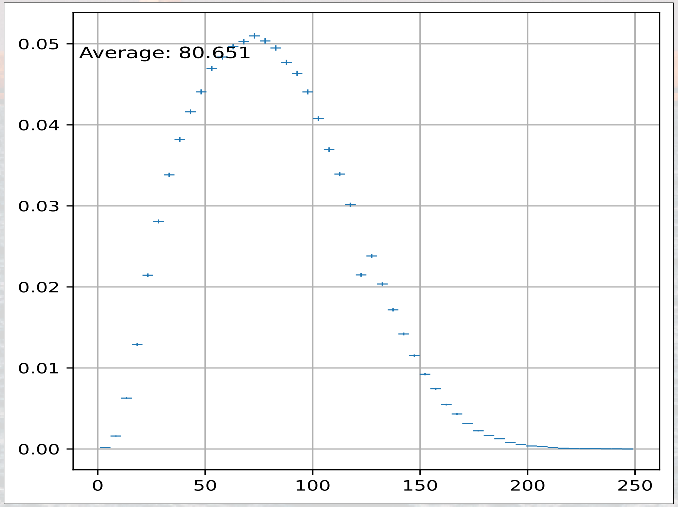
Discretized in the (y, ϕ) plane: p_T,m, multiplicity

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

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

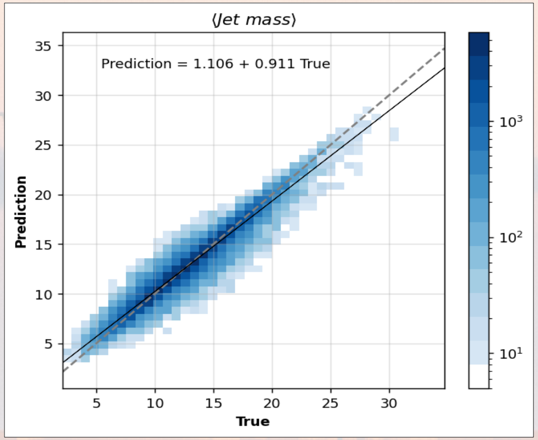
$$M \approx \sum_{i=1}^{r} \sigma_i u_i v_i^T + \mathcal{O}(\epsilon), \quad r \leq \min\{n, m\}$$

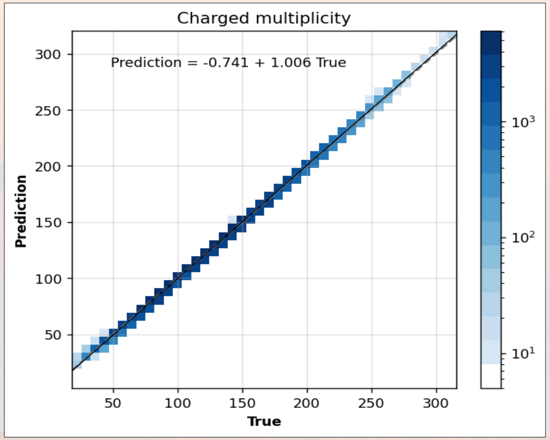
Reduce the input to $\mathcal{O}(10^2)$

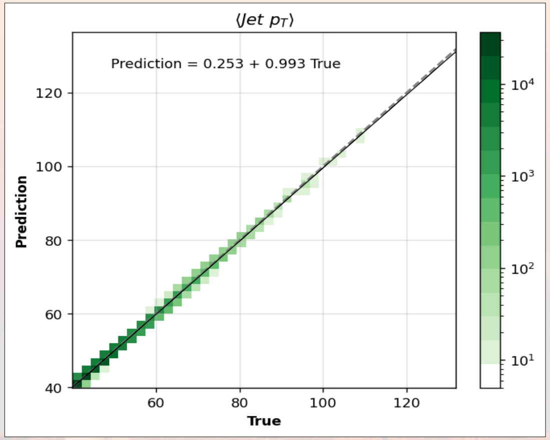
doi:10.1007/BF02288367

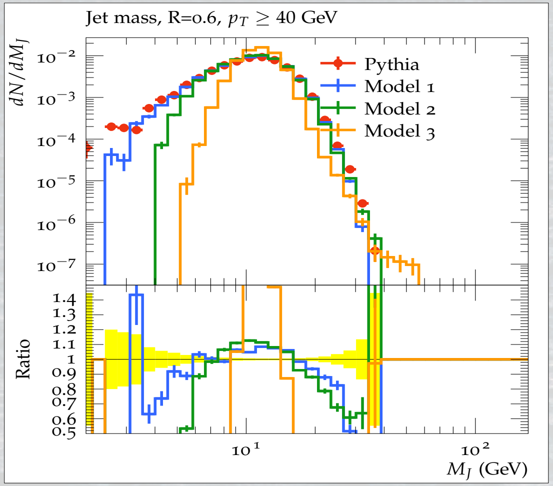
Data-Driven Science and Engineering (S. L. Brunton, J. N. Kutz)

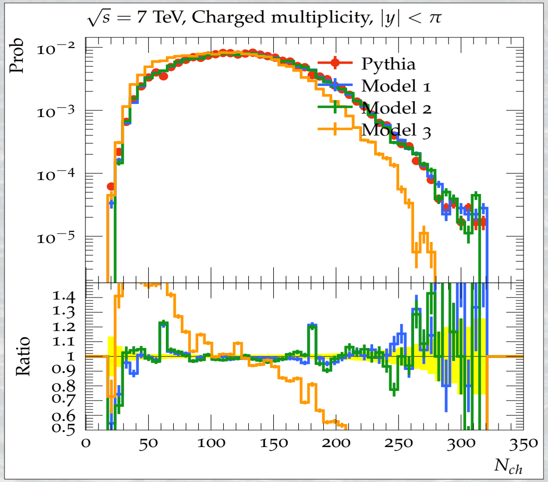
Dimensionality (work in progress)

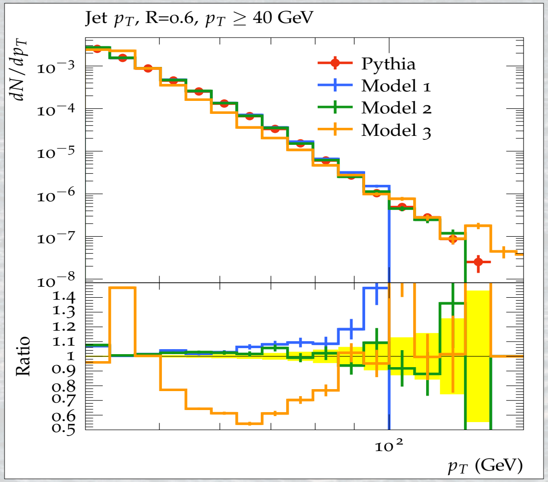






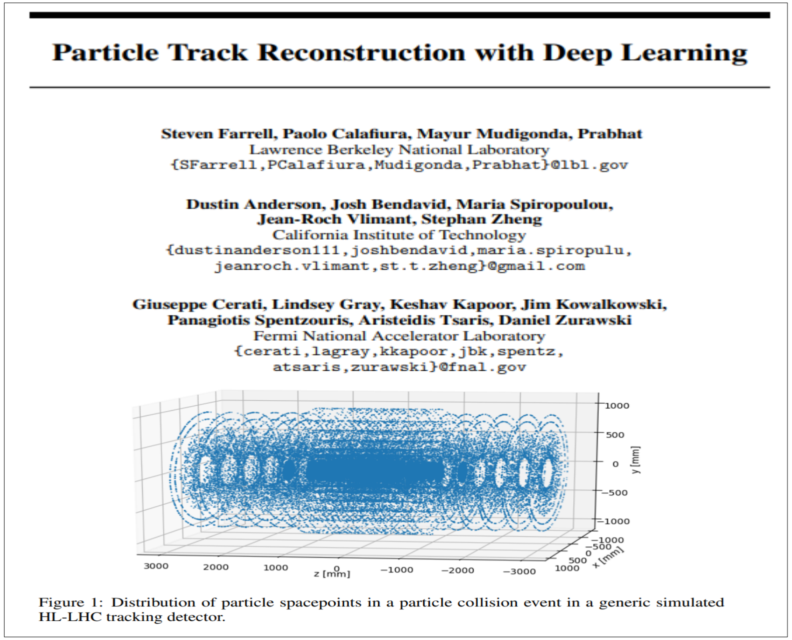






Machine Learning in HEP

Track reconstruction



Particle Track Reconstruction with Deep Learning

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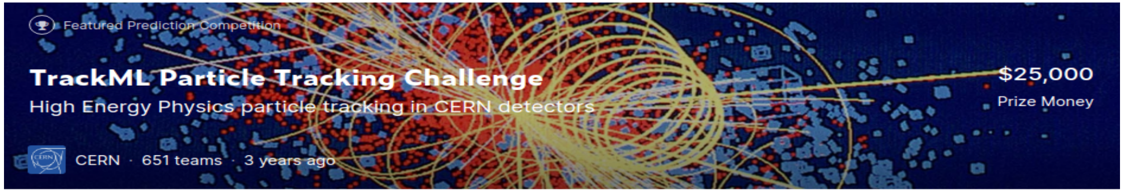
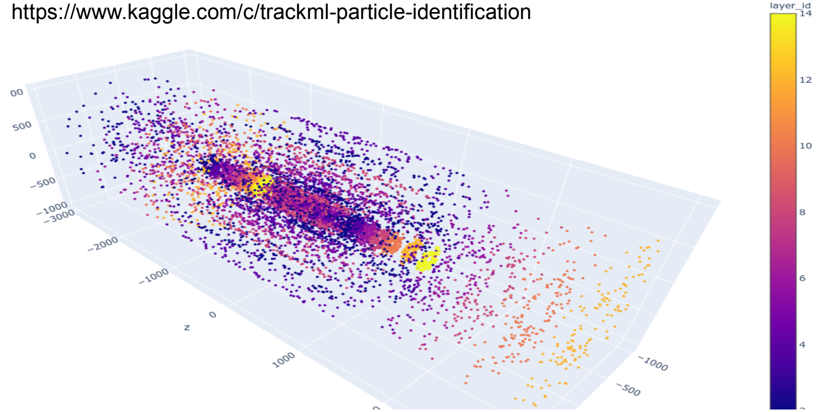
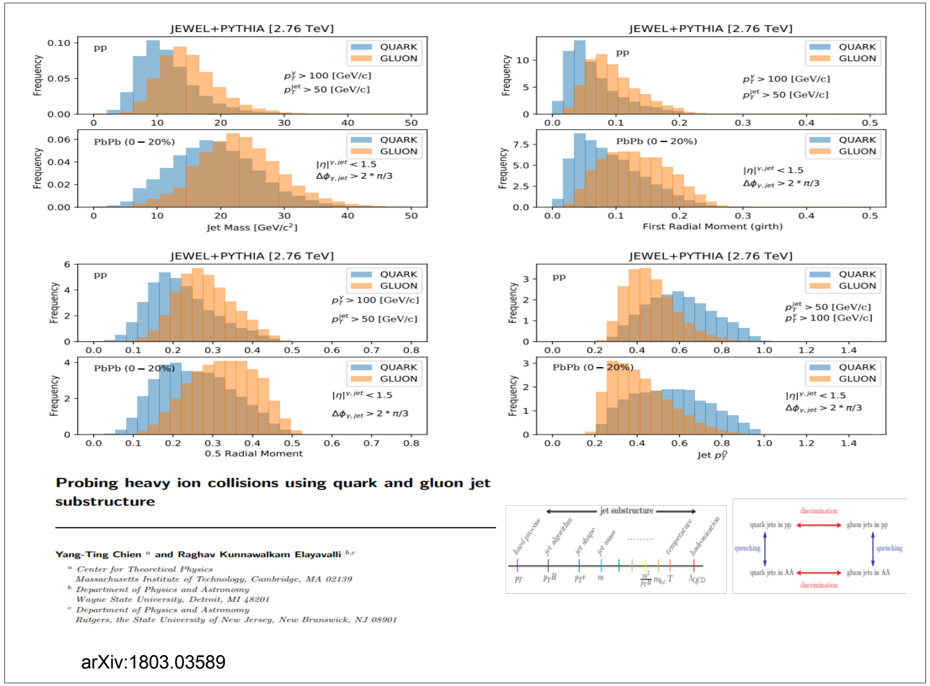
Figure 1: Distribution of particle spacepoints in a particle collision event in a generic simulated HL-LHC tracking detector.



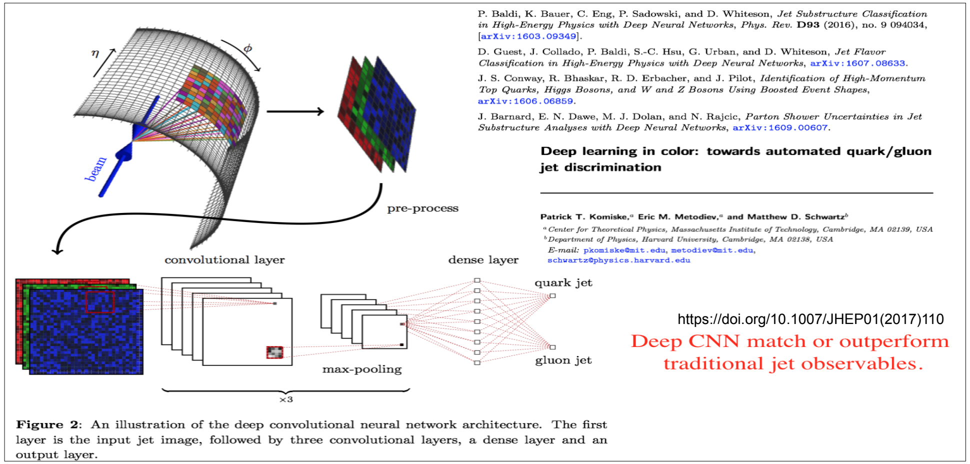
https://www.kaggle.com/c/trackml-particle-identification



Machine Learning in HEP



Quark/gluon jet separation



Machine Learning in HEP

Machine Learning based jet momentum reconstruction in heavy-ion collisions

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[2] ORNL, Physics Division, Oak Ridge, TN, USA
(Dated: June 24, 2019)

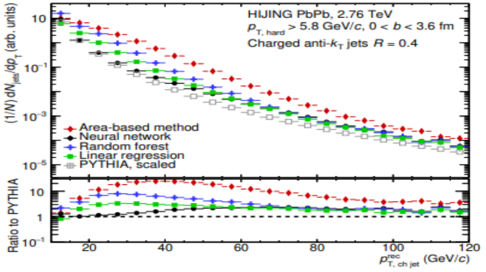

FIG. 9. Reconstructed charged jet spectra in HIJING events and the ratio to (N_{coll}-scaled) PYTHIA jet spectra.

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

Jet reconstruction

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

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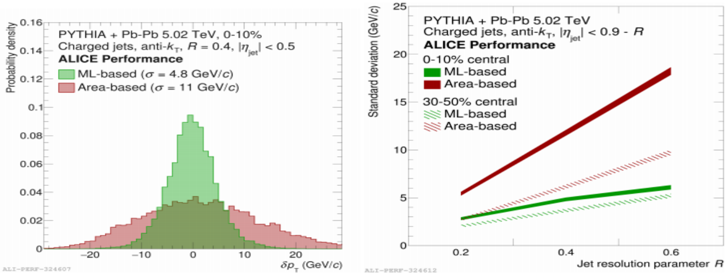
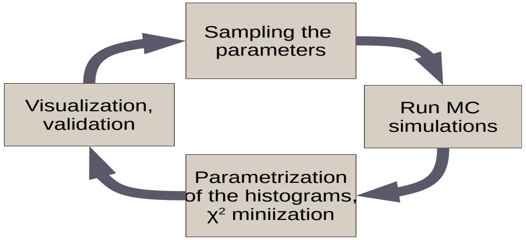


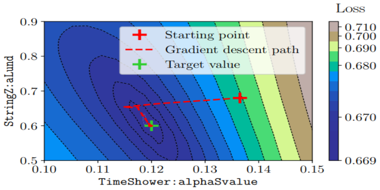
Figure 1: Residual p_T-distributions of embedded jet probes of known transverse momentum.

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

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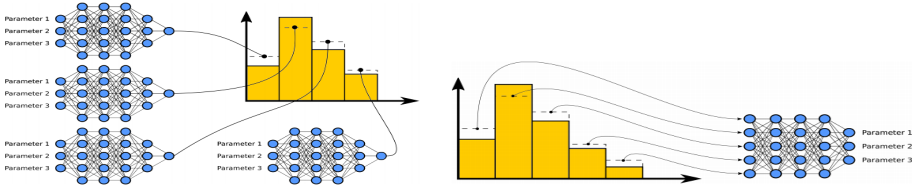

Figure 1: An illustration of the parametrisation of the generator response as implemented in the Per Bin Model.

Figure 2: An illustration of the Inverse Model strategy.

MCNNTUNES: tuning Shower Monte Carlo generators with machine learning

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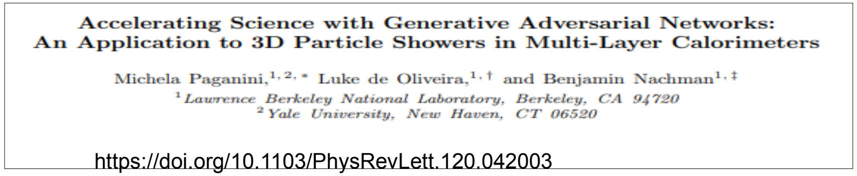
https://doi.org/10.1016/j.cpc.2021.107908



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

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