The development of a Machine Learning-based hadronization model

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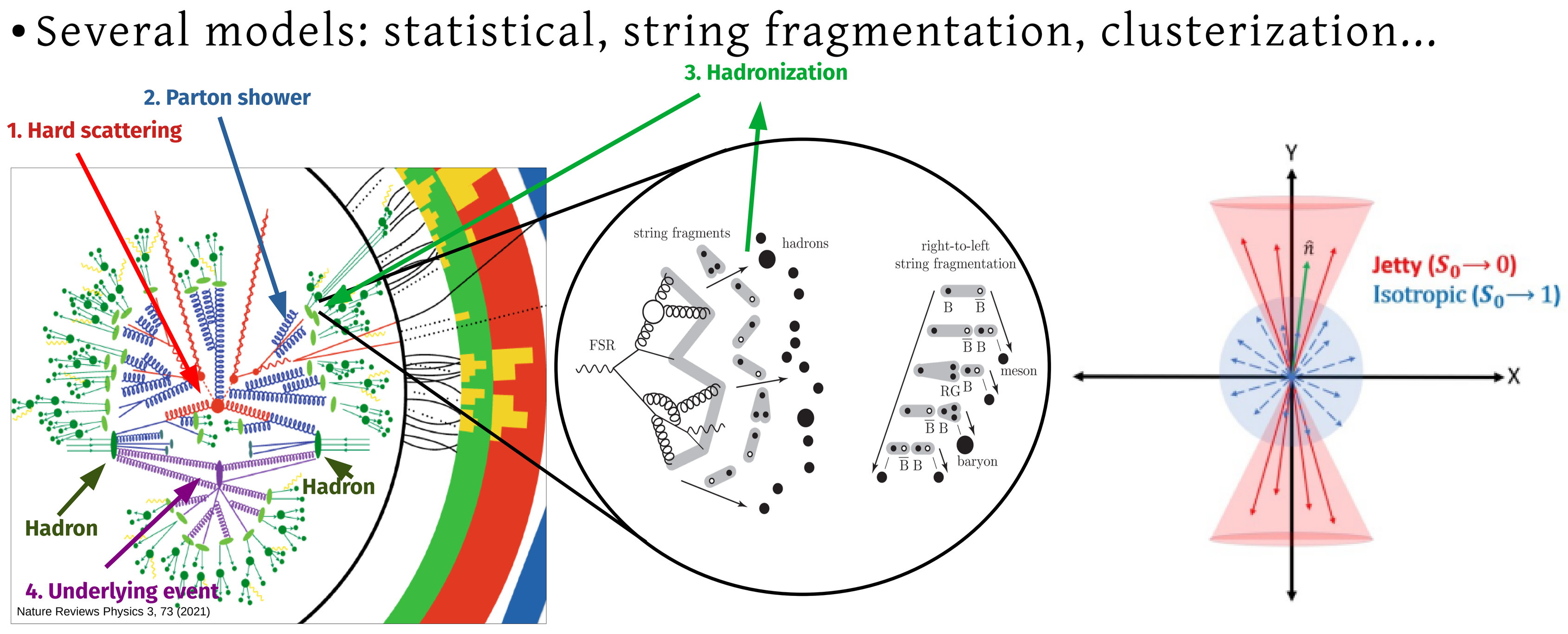
Introduction

Hadronization is a non-perturbative process, which theoretical description can not be deduced from first principles. Modeling hadron formation requires several assumptions and various phenomenological approaches. Utilizing state-of-the-art Computer Vision and Deep Learning algorithms, it is eventually possible to train neural networks to learn non-linear and non-perturbative features of the physical processes.

Hadronization

- Several models: statistical, string fragmentation, clusterization...

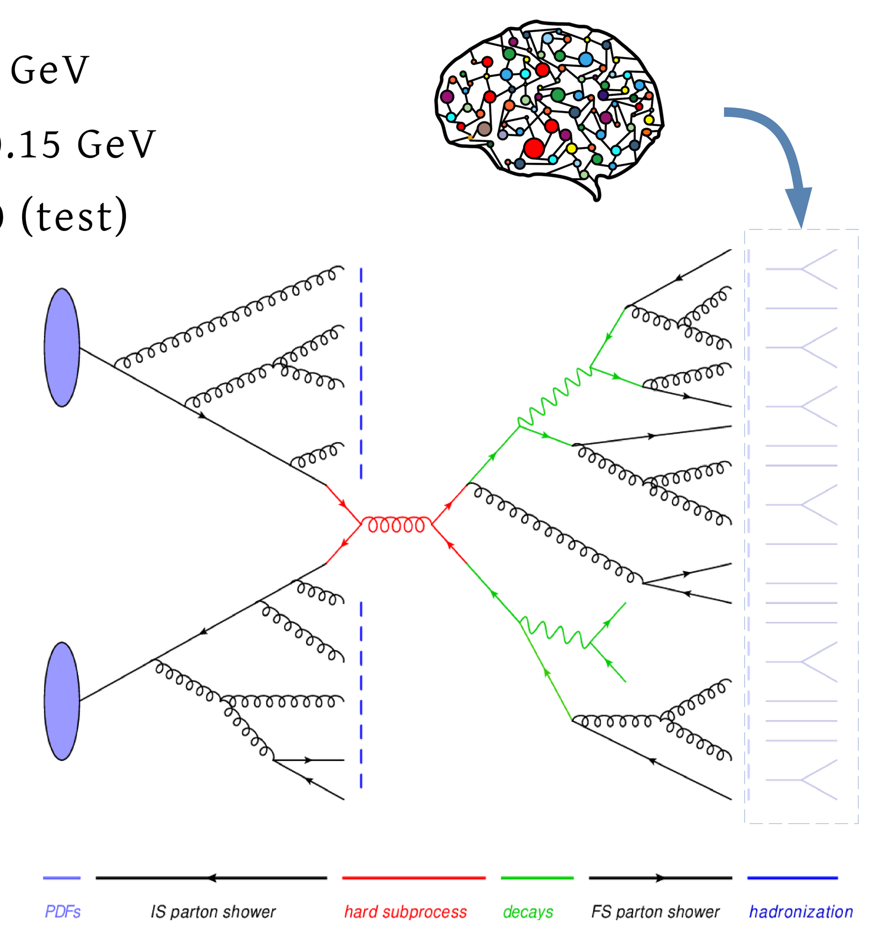


Dataset: Pythia 8.303

- Decay, rescattering turned off
- MPI, ISR, FSR on for train, on/off for validation
- Process level: SoftQCD/HardQCD with various minimum invariant p_T values

Event/particle selection:

- At least 2 jets (anti-k_T), R=0.4, $p_{T,jet}$>40 GeV
- All final state hadrons with $|y|<\pi$, p_T>0.15 GeV
- Event number: 750 000 (train), 100 000 (test)



Parton level:

- Discretized in the (y, ϕ) plane: p_T, m, multiplicity (CM energy)
- $y \in [\pi, \pi]$, $\phi \in [0, 2\pi]$, 32x32 grid

Hadron level:

- (Charged) event multiplicities, transverse sphericity, charged hadron p_T, jet p_T, jet mass, jet width, jet multiplicity, jet number

Method: Machine Learning

Consider the task as a modified image processing problem

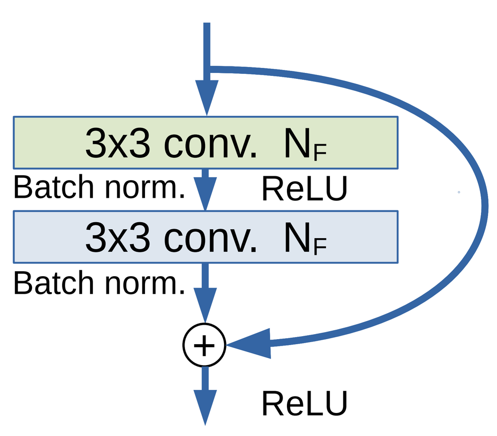
- Reproduce the hadronic statistics from a partonic image

Architecture base: ResNet

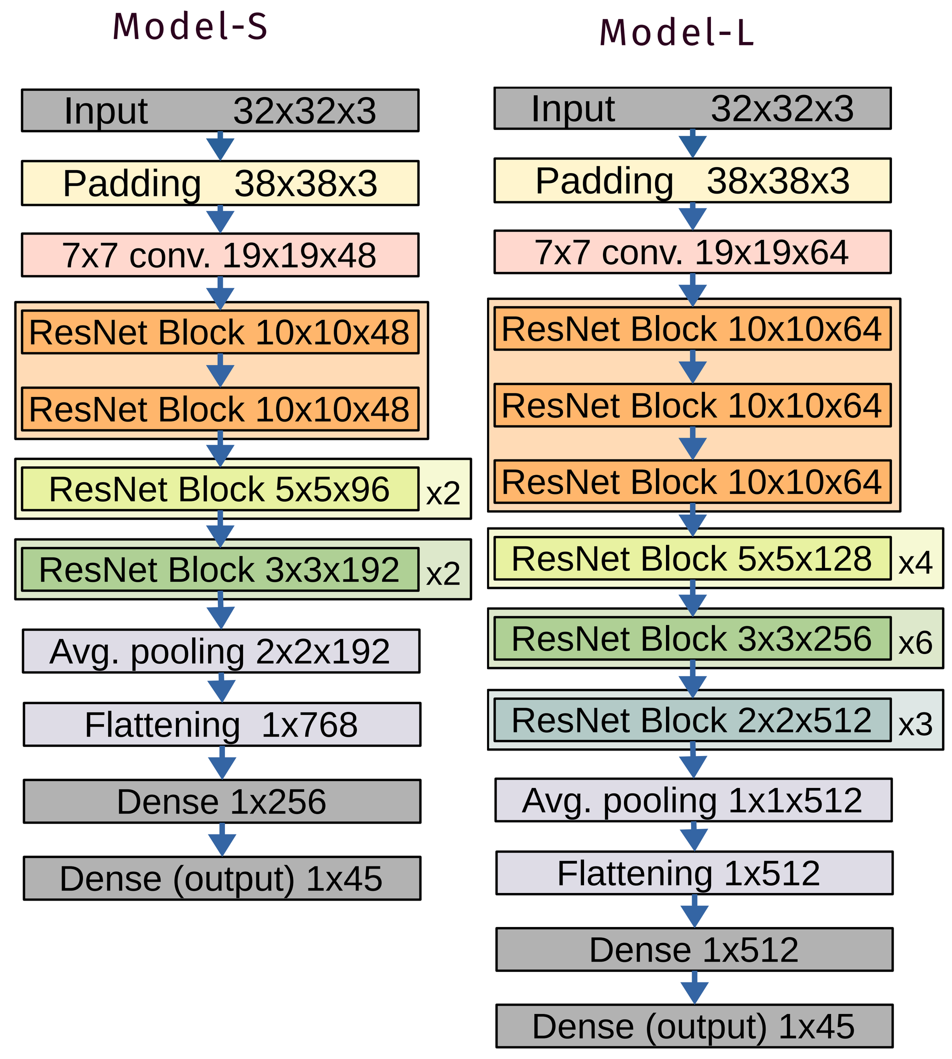
- Input: 32x32x3, scaled into the [0,1] region
- Output: 45 histogram bin, scaled into the [0,1] region
- Loss: Binary Cross-entropy:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N} y_i \cdot \log\left(p(y_i)\right) + (1-y_i)\cdot\log\left(1-p(y_i)\right)$$

A ResNet block



- Optimizer: adam
- Batch size: 512
- Metrics: mean absolute error
- Other properties: Batch normalization, ReLU activation, sigmoid output, decaying learning rate



Tested models:

- Model-S: 14 layers, 1.7M trainable parameters
- Model-L: 34 layers, 21.5M trainable parameters

Hardware and Software:

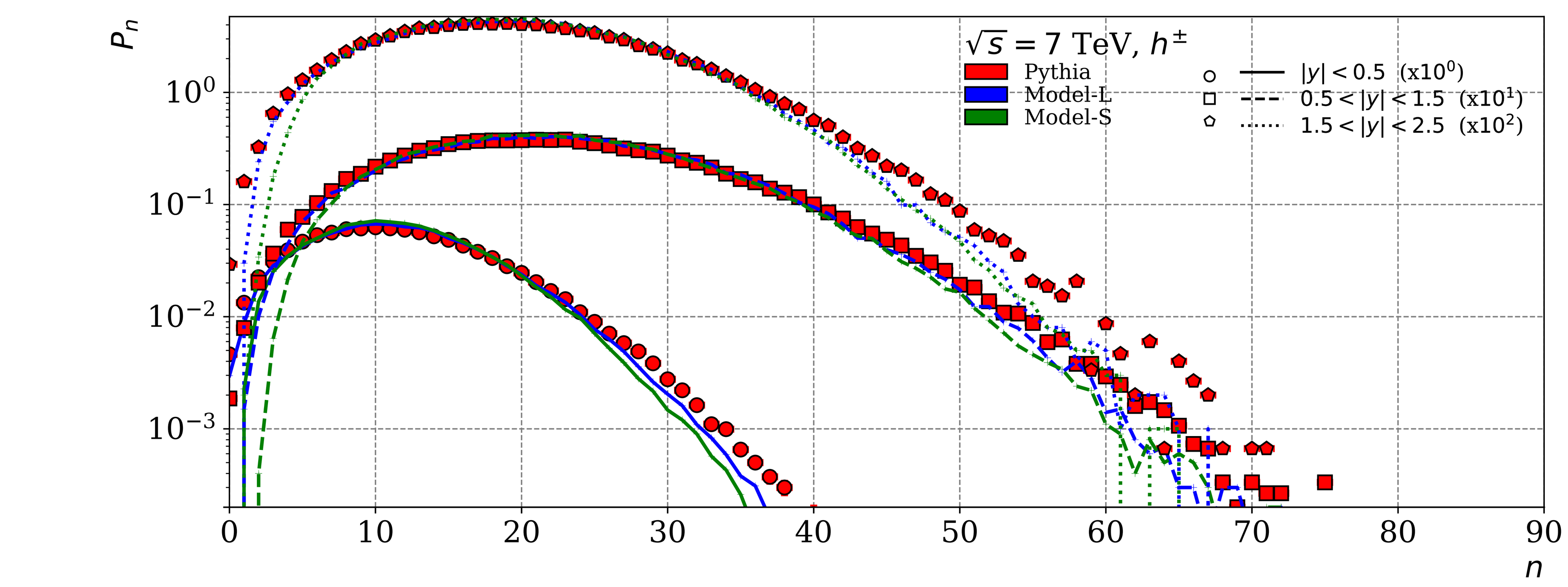
Used hardwares: NVIDIA A100, Tesla T4, GeForce GTX 1080 @ Wigner Scientific Computing Laboratory

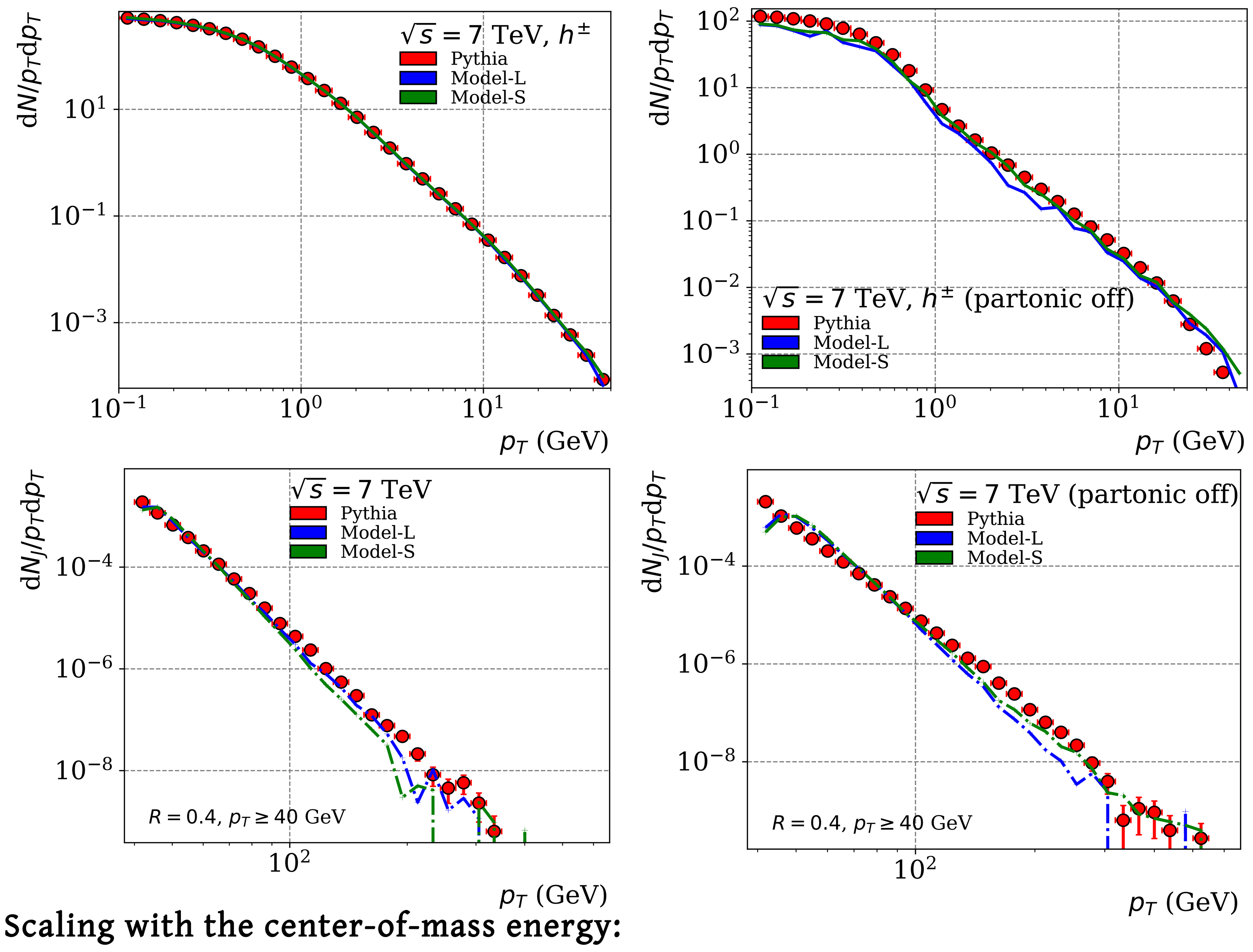
Framework: Tensorflow 2.4.1, Keras 2.4.0

Results

Validation at the training energy: $\sqrt{s} = 7$ TeV, proton-proton collisions

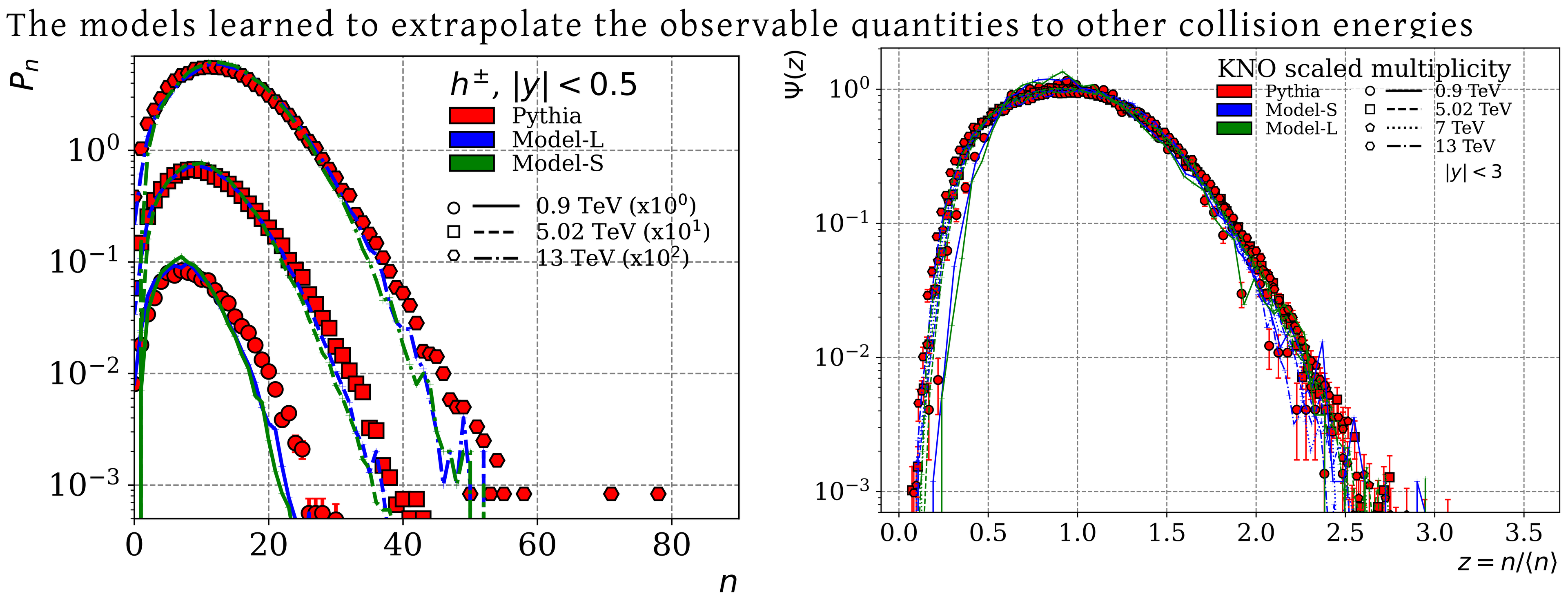
Good Qualitative (and some quantitative) agreement with the reference Monte Carlo data
No significant difference between the models
Indicates that the hadronization process is captured indeed





Scaling with the center-of-mass energy:

The models learned to extrapolate the observable quantities to other collision energies



Summary

- Machine learning method for investigating hadronization: transform the partonic state into hadronic event-by-event statistical quantities
- Two model complexities: no significant difference
- Partonic interactions turned off: good qualitative agreement
- Accurate extrapolation to other center-of-mass energies
- Open questions:
  - Other collision systems and energies, observables?
  - Network complexity? Dimensionality?

Acknowledgement

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