Studying Hadronization by Machine Learning Techniques

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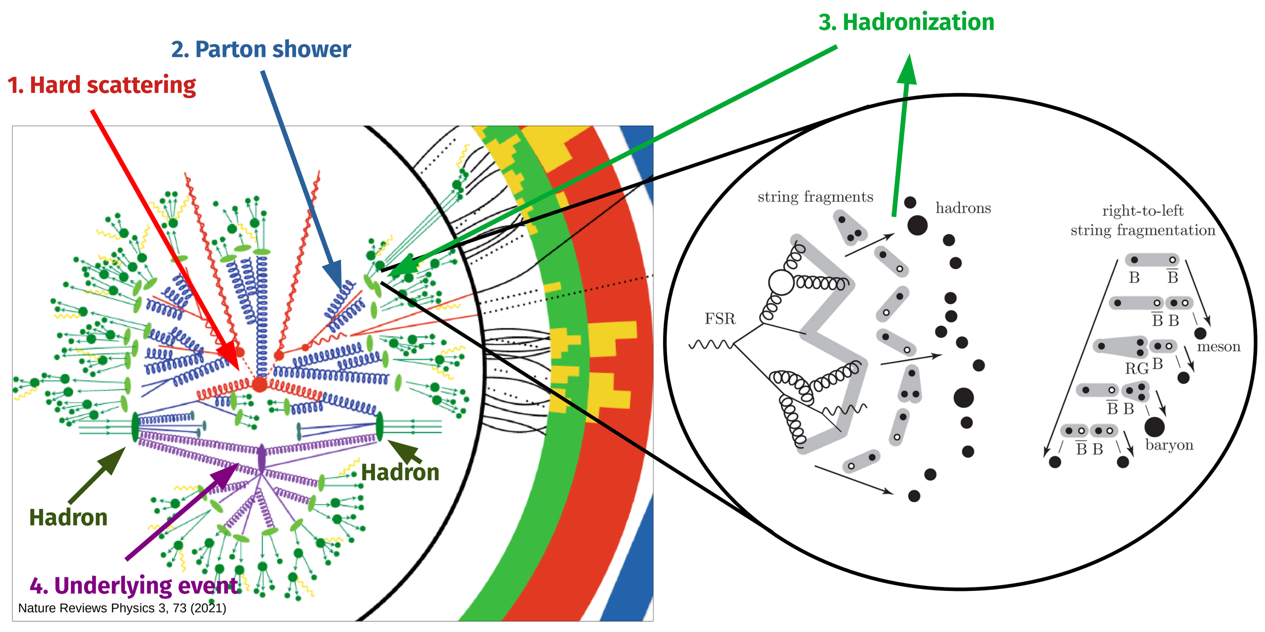
Introduction

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:

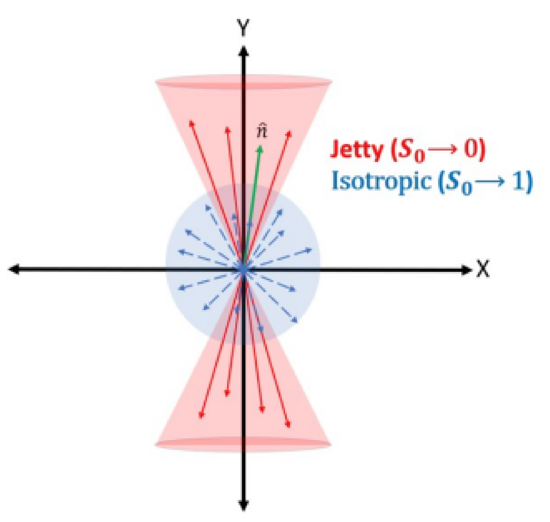
- At least 2 jets (anti-k_T), R=0.4, $p_{T,\mathrm{jet}}$>40 GeV
- All final state hadrons with $|y|<\pi$, p_T>0.15 GeV
- Event number: 750 000 (train), 100 000 (test)

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

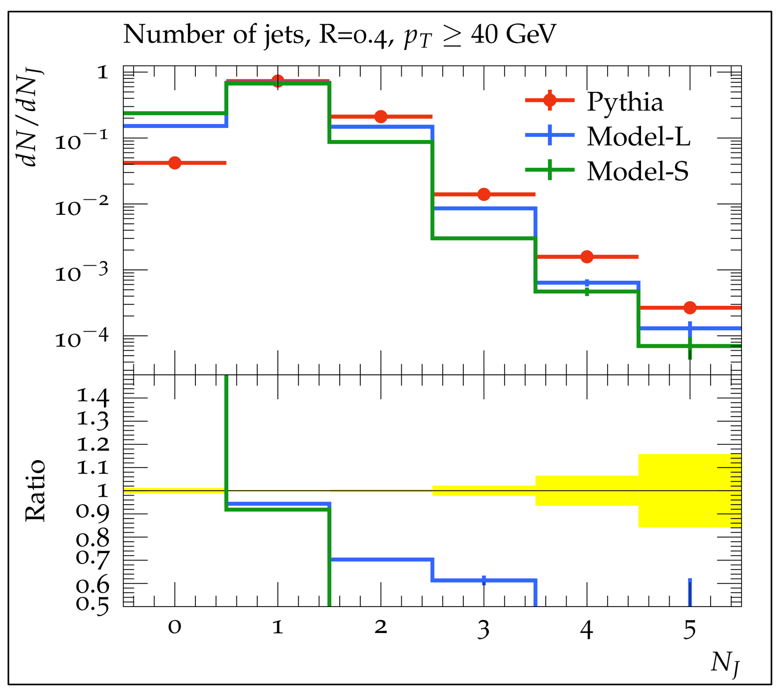


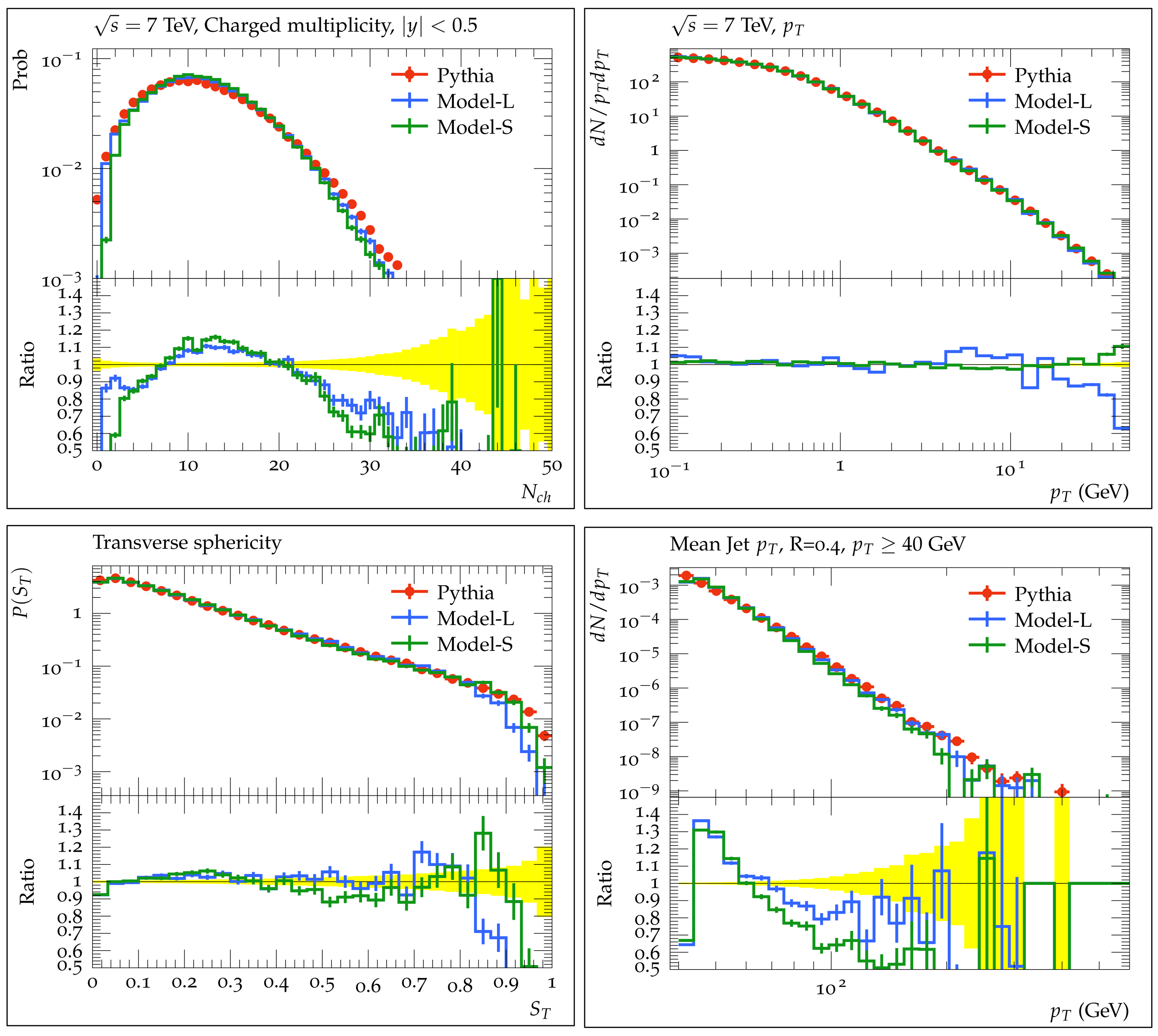
Results

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

Good agreement with the reference Monte Carlo data

No significant difference between the models

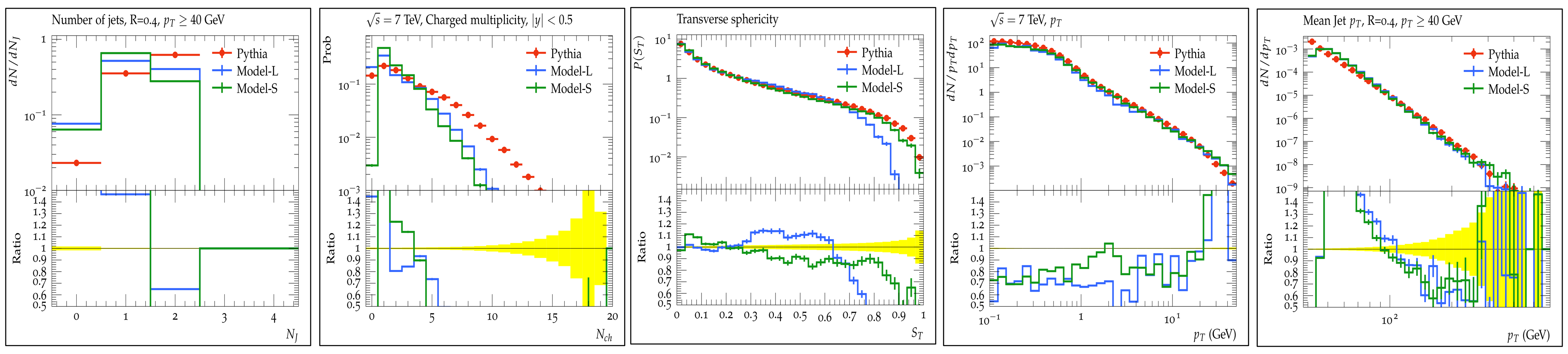




With partonic interactions OFF:

Qualitative (and some quantitative) agreement with reference

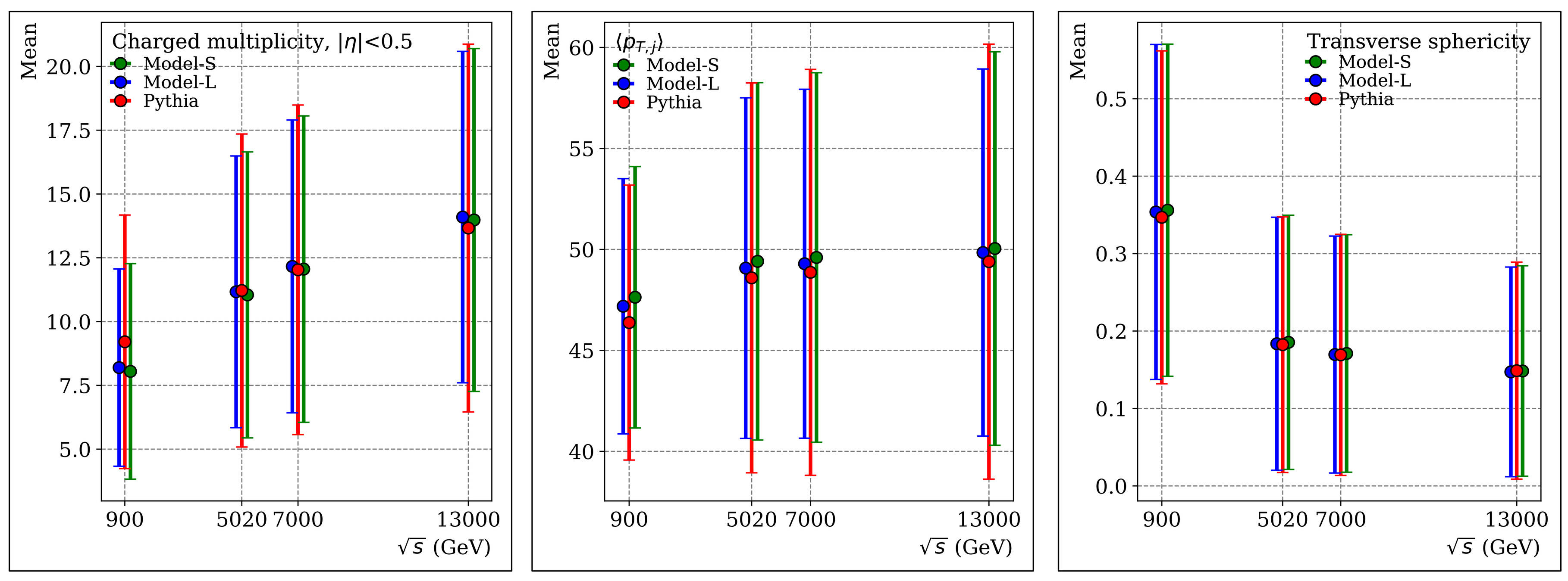
Indicates that the hadronization process is captured indeed



Scaling with the center-of-mass energy:

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

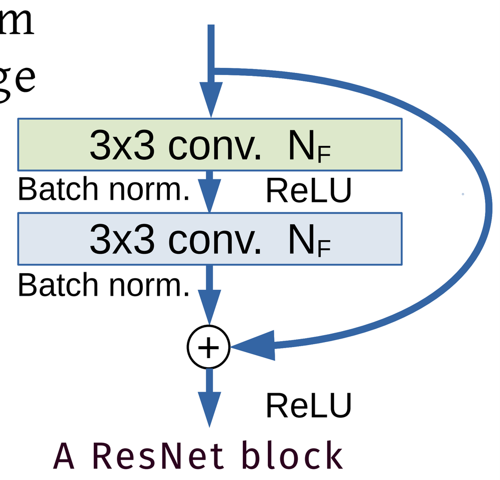
Inherent feature: $dN_{ch}/d\eta \propto \sqrt{s}$



Method: Machine Learning

Consider the task as a modified image processing problem

- Reproduce the hadronic statistics from a partonic image

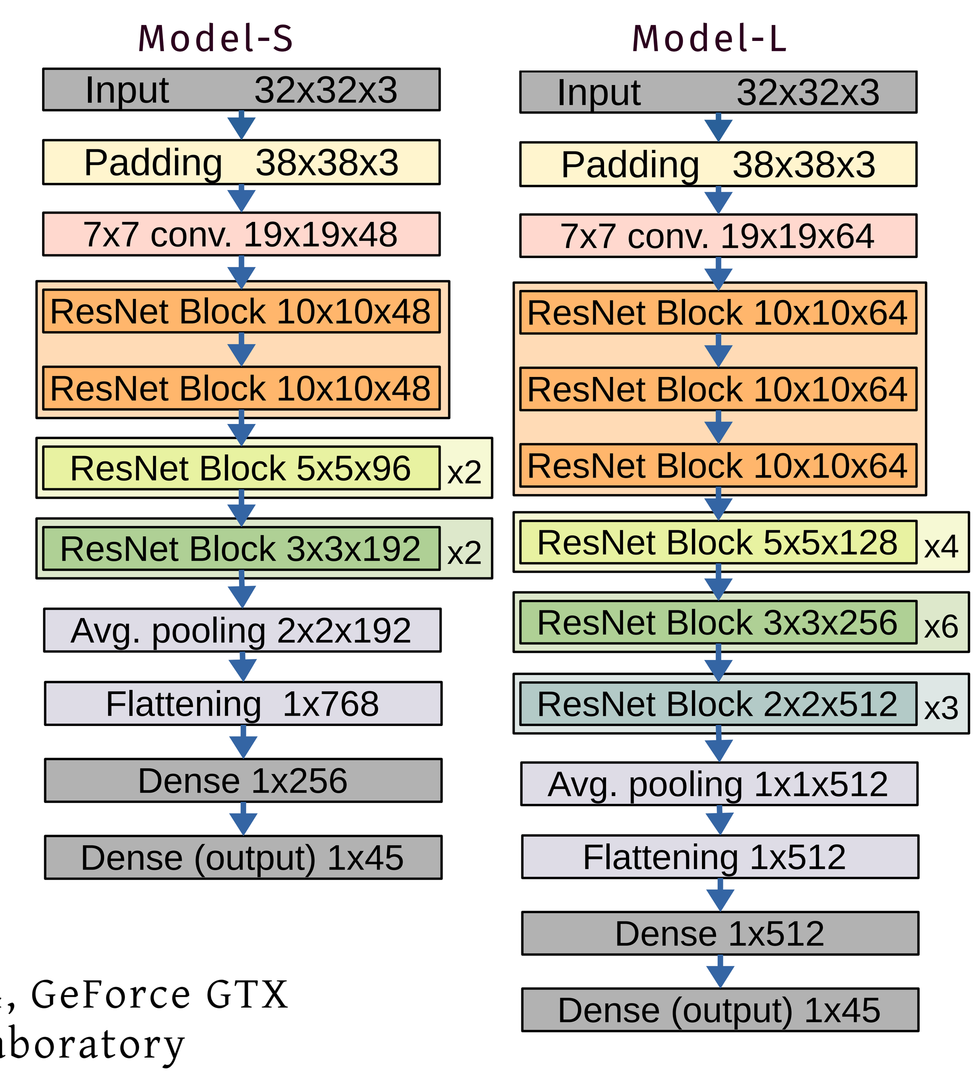


Architecture base: ResNet

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

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

- 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

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?

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