Studying Hadronization by Machine Learning Techniques

G.G. Barnaföldi, G. Bíró (Wigner FK), and B. Tankó-Bartalis (University of Oxford)

Ref: arXiv:2111.15655

SQM2022, Busan, South Korea, 14th June 2022
Modeling hadronization in $e^+e^-$ collisions

Final state processes & hadronization
Hadronization models – history

The evolution of hadronization models

Feynman-Field

pair production

Lund model

cluster model

\[ f(z) \propto \left[ z \left( 1 - \frac{1}{z} - \frac{\epsilon}{1-z} \right)^2 \right]^{-1} \]

pQCD models

Non-pQCD models

PYTHIA/HIJING

HERWIG
Idea & motivation

Three key layers

- **Input**: Takes the features

- **Hidden layers**: Connects to each neuron through different weights

- **Output**: Gives the result as a number or class
Building up the ML structure

Algorithms behind: ResNet

- **Weights** dictate the importance of an input → more important features get more weights

- **Activation function**: mathematical function that guides the outcome at each node → Standardize the values

- **Cost function**: Evaluates the accuracy between machine prediction and true value

- **Optimizer**: Method (or algorithm) that minimizes the cost function by automatically updating the weights
Input/output of the ML structure

**Simulated data at parton/hadron level**
- Event properties (now from PYTHIA)
- Inputs → Parton/hadron level input
- (η-φ) space is the primary input space
Training & validation of the model

**ML: training, optimization, validation**

- **Training:** PYTHIA 8.303 Monash tune, All final particles, at least 2 jet, Anti-$k_T$ $R=0.6$ $p_T > 40$ GeV/c, $|y| < \pi$

- **Input:** parton/hadron: $(p_x, p_y, p_z, E, m)$
  - 62 bin ($\phi \in [0, 2\pi]$)
  - 31 bin ($y \in [\pi, \pi]$)

- **Epoch:** 300

- **Training/Validation:** 150k events (20 GB)

- **Machine:** Used hardwares: Nvidia Tesla T4, GeForce GTX 1080, GeForce GTX 980 @ Wigner Scientific Computational Laboratory

- **Framework:** Tensorflow 2.4.1, Keras 2.4.0

- **Features:** Multiplicity/Jet distributions, Jet/$p_T$ spectra, Event properties: Sphericity Transverse spherosity,

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Trainable parameters</strong></td>
<td>1.13 M</td>
<td>1.90 M</td>
</tr>
</tbody>
</table>

![Loss and Accuracy Graph]

G.G. Barnafoldi: SQM2022 Busan, South Korea
Results on ML-hadronization

Training and validation pp@7 TeV

G.G. Barnafoldi: SQM2022 Busan, South Korea
Results on ML-hadronization

Predictions pp@13 TeV

$\sqrt{s} = 13$ TeV, Charged multiplicity, $|y| < \pi$

$\sqrt{s} = 13$ TeV, Sphericity

$\sqrt{s} = 13$ TeV, Jet multiplicity, $R=0.6, p_T \geq 40$ GeV

$\sqrt{s} = 13$ TeV, Jet width, $R=0.6, p_T \geq 40$ GeV

$\sqrt{s} = 13$ TeV, Event multiplicity, $|y| < \pi$

$\sqrt{s} = 13$ TeV, Transverse sphericity

$\sqrt{s} = 13$ TeV, Jet mass, $R=0.6, p_T \geq 40$ GeV

G.G. Barnafoldi: SQM2022 Busan, South Korea
Conclusions

- **Aim: modeling hadronization by ML**
  - Highly non-linear/non-perturbative problem
  
  - Many features are fitted well: multiplicity distributions, jet/pT distributions, sphericity, transverse sphericity, etc

  - Preserved scaling in multiplicity on a wide energy range

- **Work in progress...**
  - Stability and test of noise on training
  - Better separation of shower/hadronization