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ARTS AND SCIENCES

Modeling Hadronization using Machine Learning

Phenomenology 2022 Symposium

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Based on 2203.04983 with P. Ilten, T. Menzo and J. Zupan

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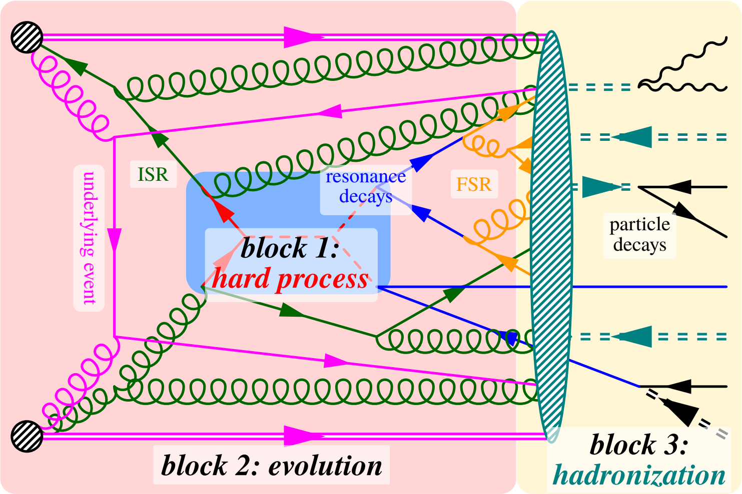
Motivation



ISR
underlying event
resonance decays
FSR
particle decays
block 1: hard process
block 2: evolution
block 3: hadronization

Motivation

- The hard process and the parton shower are perturbative in their nature

  $\Rightarrow$ Theoretical under control

- Hadronization is inherently non-perturbative

  $\Rightarrow$ Forced to use phenomenological models

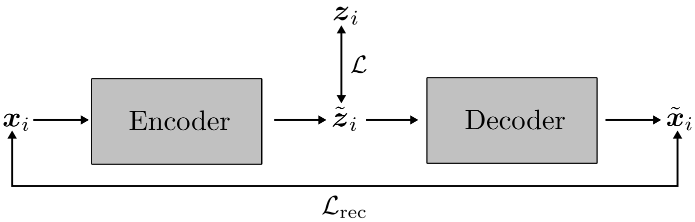
- First step: Create a Machine Learning (ML) Architecture that is able to reproduce the simplified Lund String Model

- Goal: **Train on real experimental data** and replace the Hadronization model in PYTHIA

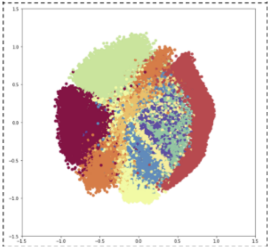
MLHAD

VAE

- VAE is a commonly used generative model:
  - $\longrightarrow$ Not flexible with the latent representation
  - $\longrightarrow$ kl-divergence limits latent distribution to a simple analytical form (e.g. Gaussian)

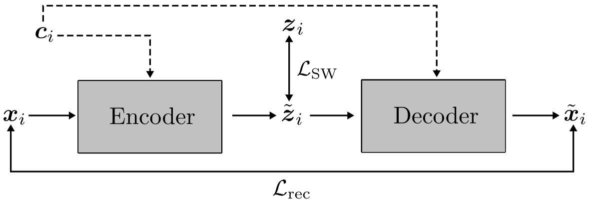


(a) Vanilla VAE
(arXiv: 1312.6114)

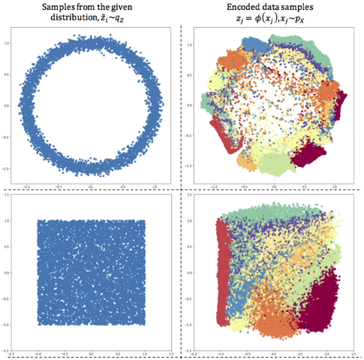


(b) VAE latent space

cSWAE



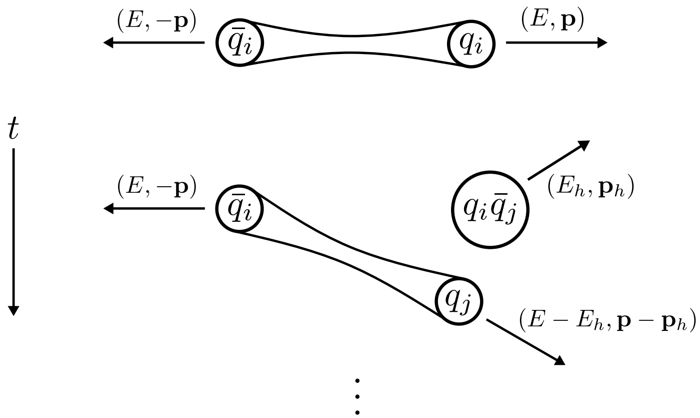
(a) cSWAE architecture



(b) SWAE latent space
(arXiv: 1804.01947)

Total loss: $\mathcal{L} = \mathcal{L}_{rec} + \mathcal{L}_{SWD}$

Lund-String model



Lund-String model

- Selection of the flavor and hadron kinematics are independent until the final stages
- Final stages of hadronization: String energy is close to the nonperturbative scale $\longrightarrow$ the flavor and kinematic selection become interwined

  $\Longrightarrow$ CM string energy cutoff $E_{\text{cut}} = 5$ GeV
- Coordinate system is oriented such the z-axis and the initial string direction are aligned

$$p_x = p_T \cos\varphi \qquad p_y = p_T \sin\varphi \qquad p_T = \sqrt{p_x^2 + p_y^2}$$

- String breaking and hadron emission are axial symmetric in PYTHIA

  $\Longrightarrow$ Reduces to a 2 variable problem: p_z and p_T
- Input data $\mathbf{x_i} \in \left[p_z^{(i)}, p_T^{(i)}\right]$; conditioned on the initial string energy E_i
- Limit the training on light quark flavors and only pions as final state hadrons

MLHAD overview

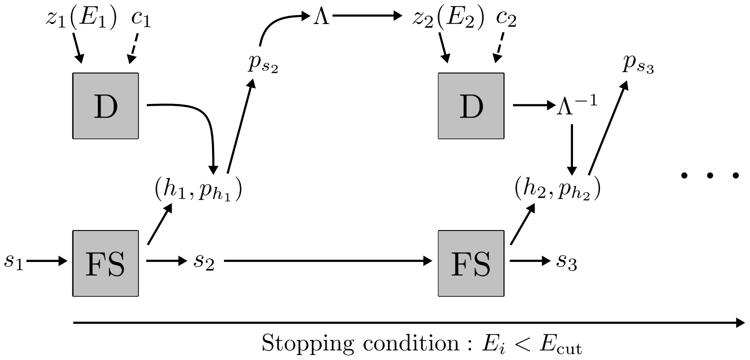


Illustration of the conditional generation

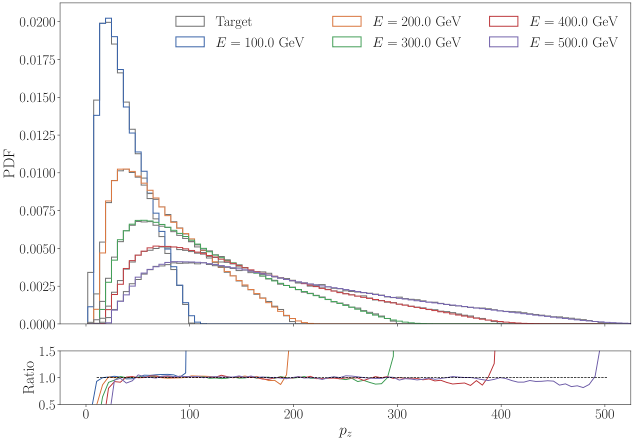
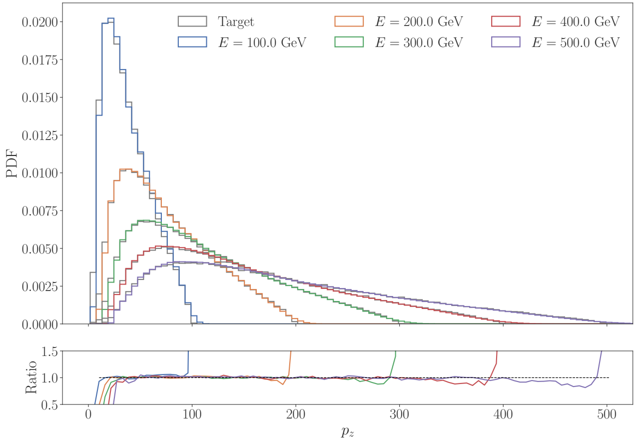
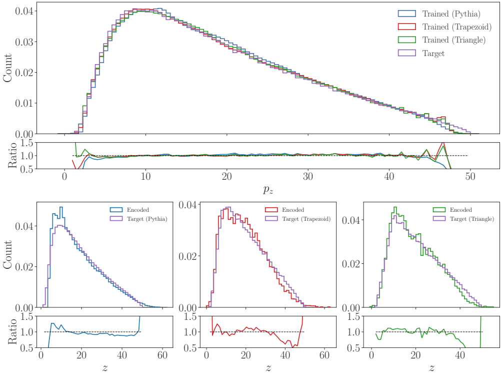


Illustration of the conditional generation

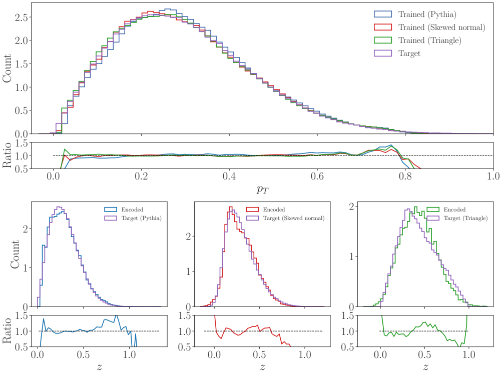


$\Longrightarrow$ **Fixed initial string energy:** $E_i = 50$ GeV

Results

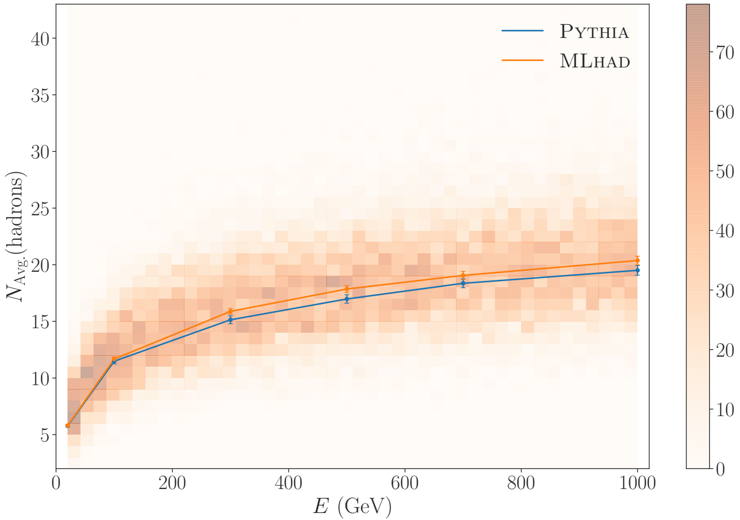


(a) MLHAD generated p_z and latent distribution



(b) MLHAD generated p_T and latent distribution

Results



Pythia
MLhad
$N_{\text{Avg.}}$ (hadrons)
E (GeV)
0
200
400
600
800
1000
5
10
15
20
25
30
35
40
0
10
20
30
40
50
60
70

Conclusion and Outlook

- MLHAD based on the cSWAE architecture was succesfully trained on a simplified PYTHIA Hadronization model
  - $\Rightarrow$ limited to light quark flavor endings of the string and only pions as final state hadrons
  - $\Rightarrow$ MLHAD is extendable to handle all possible string flavors and kinematics
- Flexibility in the choice of the latent space distribution (does not need to have an analytical form)
- Public code available: `https://gitlab.com/uchep/mlhad`

Work in progress [1]

- Performing training on physically accessible observables to train MLHAD on **real experimental data**
- Extending MLHAD e.g. additional conditional labels allow:
  - $\rightarrow$ Additional conditional labels allow to generate hadron flavors with kinematic dependence
  - $\rightarrow$ Replacing PYTHIA's FS by a ML architecture
  - $\rightarrow$ Interpolating to different string energies
- Exploring different architectures (e.g. based on normalizing flows and RNNs)

[1] In collaberation with P. Ilten, T. Menzo, J. Zupan, M. Szewc and S. Mrenna

Back up

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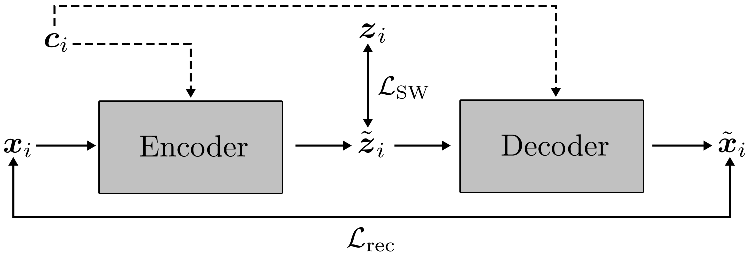
cSWAE Training-process

- conditioned on initial string energy $E_i \rightarrow c_i = (\bar{c}_i, 1 - \bar{c}_i)$:

$$E_i = E_{min}\bar{c}_i + E_{max}(1 - \bar{c}_i) \quad \Rightarrow \quad \bar{c}_i = \frac{E_{max} - E_i}{E_{max} - E_{min}}$$

- Encoder ϕ:
  - Input data $\mathbf{x_i}$ is a $N_e = 100$ dimensional vector, where $\mathbf{x_i} \in [p_{z,k}^{(i)}, p_{T,k}^{(i)}]$
  - p_z and p_T are uncorrelated and treated seperately
  - Takes as input x_i and c_i; returns the latent space vector $\bar{z}_i = \phi(x_i, c_i)$
- Decoder ψ:
  - Takes as input $\bar{z}_i$ and returns $\bar{x}_i = \psi(\phi(x_i, c_i))$
- Limit the training on light quark flavors and only pions as final state hadrons

cSWAE architecture



$$\mathcal{L}_{\mathrm{rec}} = \frac{1}{N_{\mathrm{tr}}} \sum_{i=1}^{N_{\mathrm{tr}}} \left[\frac{1}{Q} d_2^2(\boldsymbol{x}_i, \psi(\phi(\boldsymbol{x}_i, \boldsymbol{c}_i))) + d_1(\boldsymbol{x}_i, \psi(\phi(\boldsymbol{x}_i, \boldsymbol{c}_i))) \right],$$

$$\mathcal{L}_{\mathrm{SW}} = \frac{\lambda}{L N_{\mathrm{tr}}} \sum_{\ell=1}^{L} \sum_{i=1}^{N_{\mathrm{tr}}} d_{\mathrm{SW}}(\boldsymbol{\theta}_\ell \cdot \boldsymbol{z}_{[i]_\ell}, \boldsymbol{\theta}_\ell \cdot \phi(\boldsymbol{x}_{[i]_\ell}, \boldsymbol{c}_i)),$$

cSWAE architecture