Universal Monte Carlo Event Generator

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The big picture

hadrons as **emergent phenomena** of QCD

quarks and gluons
The big picture

hadrons as emergent phenomena of QCD

nucleon structure

quarks and gluons
The big picture

hadrons as emergent phenomena of QCD

nucleon structure  quarks and gluons  hadronization
From detectors to partons
From detectors to partons

Detector response

QED effects

QCD effects
From detectors to partons

\[ \sigma_{\text{EXP}} = w_{\text{DR}} \otimes w_{\text{QED}} \otimes \sigma_{\text{QCD}} \]
The goals

Build a theory-free MCEG
Map out particles correlations without biases from approximated theory
MCEG as a data storage utility
The goals

- Build a **theory-free** MCEG
The goals

- Build a theory-free MCEG
- Map out particles correlations without biases from approximated theory
The goals

- Build a **theory-free** MCEG
- Map out particles correlations without biases from **approximated theory**
- MCEG as a **data storage utility**
Nature

Events: vertex level

[Bar chart showing data distribution]
Nature

Events: vertex level

Experimental detector

Events: detector level

distortion
Nature

Events: vertex level

Experimental detector

Events: detector level

Inverse problem
Nature

AI

distortion

Events: vertex level

Experimental detector

Events: detector level
Nature

AI

Experimental detector

Detector simulator

neural net detector

Likelihood
Nature

AI

data compression

Experimental detector

Detector simulator

neural net detector

Likelihood

Events: vertex level

Events: detector level

distortion

distortion
Our strategy
Our strategy

- Replace Nature → Pythia for validation
Our strategy

- Replace **Nature** $\rightarrow$ **Pythia** for validation

- Ignore **detector effects** to start
Our strategy

- Replace **Nature** $\rightarrow$ **Pythia** for validation

- Ignore **detector effects** to start

- Find a suitable “**image**” representation for the events
Pythia

Events: vertex level

AI

data compression

Likelihood

Events: vertex level
Pythia

Events: vertex level

AI

Events: vertex level

Likelihood

Generator

FC NN

FC NN

FC NN

Pythia

$l + p \rightarrow l' + X$

Discriminator

FC NN

FC NN

FC NN

MMD

$z \in N(0, 1)$

Features Transform

$p_i \rightarrow k_i$

Features Extension

$k_x, k_y, k_z, k_{T}, k_{0}, k_{00}, k_{000}/k_x$

Wasserstein Loss

MMD Loss

$z \in N(0, 1)$
Error bands generated with bootstrapped samples
Isocontours are in agreement

\( x_{\text{bj}}, Q^2 \) correlation is learned without adding \( x_{\text{bj}} \cdot Q^2 \) feature
Challenges

- Find optimal data representation
  → what is the **image of an event**?
Challenges

- Find optimal data representation
  → what is the image of an event?

- How to make the GAN to learn the features of the event? → CNN
Challenges

- Find optimal data representation
  → what is the image of an event?

- How to make the GAN to learn the features of the event? → CNN

- How to escalate from low to higher multiplicities?
Summary and outlook

It is possible to train a GAN at the event level to build a MCEG
Summary and outlook

- It is possible to train a GAN at the event level to build a MCEG.

- The current design provides a blueprint for a generator with higher multiplicity.
Summary and outlook

- More work is needed, but the results are encouraging
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- A fully trained UMCEG will be a complementary tool to theory-based MCEGs such as Pythia.