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Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning



Erik Zepeda and Antonio Ortiz

Motivation Quantum Chromodynamics: the QGP





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10/09/22Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning2 / 18



10/09/22 Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning 2 / 18



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10/09/22

$$R_{\rm AA} = \frac{d^2 N_{\rm AA}/dp_{\rm T}/dy}{\langle N_{\rm coll} \rangle d^2 N_{\rm pp}/dp_{\rm T}/dy}$$

The R_{AA} behavior shows a significant energy loss of partons due the QGP

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Nagle JL. Zajc WA. 2018 Annu. Rev.
Nucl. Part. Sci. 68:211-3510/09/22Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning4 / 18





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Nagle JL. Zajc WA. 2018 Annu. Rev.

Motivation New phenomena observed in high multiplicity small systems





Nucl. Part. Sci. 68:211-3510/09/22Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning4 / 18



Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning 4 / 18

10/09/22







10/09/22 Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning 5 / 18







10/09/22 Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning 5 / 18







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Models as interactions between strings are also capable to simulate collective effects Christian Bierlich et al. Collectivity without plasma in hadronic

Christian Bierlich et al. Collectivity without plasma in hadronic collisions. Physics Letters B, 779:58–63, 2018.





h

R +

0.35

Motivation New phenomena observed in

late collective in hadronic

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Motivation

New phenomena observed in

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6 / 18

Motivation

New phenomena observed in

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We propose to extract MPI from the available ALICE pp collisions data using Machine Learning

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Based on:

Antonio Ortiz and Erik A Zepeda 2021 J. Phys. G: Nucl. Part. Phys. 48 085014

Erik Alfredo Zepeda Garcia and Antonio Ortiz, PoS LHCP2021 (2021) 347

Antonio Ortiz, Antonio Paz, José D. Romo, Sushanta Tripathy, Erik A. Zepeda, and Irais Bautista, Phys. Rev. D 102, 076014 (2020)

10/09/22Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning7 / 18

10/09/22Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning8 / 18

10/09/22Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning8 / 18

10/09/22Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning8 / 18

10/09/22

Analysis: decision trees

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Analysis: extraction of N_{mpi}

The extraction of N_{mpi} is considered a regression problem where given a set of input variables we try to minimize a loss function

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Target variable: N_{mpi}

Strategy for the extraction of $N_{\mbox{\tiny mpi}}$:

Training and Test
Monte Carlo validation
Data processing

10/09/22 Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning 9 / 18

► Training of BDT: simulated events of pp collisions at √s = 13 TeV using Pythia 8 Tune 4C

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 - We trained two BDT sets: for $|\eta| < 0.8$ and $|\eta| < 0.5$ ranges, with $p_{\tau} > 0.15$ GeV/*c*

 Training of BDT: simulated events of pp collisions at √s = 13 TeV using Pythia 8 Tune 4C

Input variables

Mid-pseudorapidity charged particle multiplicity (N_{ch})

Average transverse momentum ($\langle p_{T} \rangle$)

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Mid-pseudorapidity charged particle multiplicity (N_{ch})

Average transverse momentum ($\langle p_{\tau} \rangle$)

Based on their correlation with $\rm N_{\rm mpi}$

E. Cuautle et al. Nuclear Physics A, 956:749–752, Dec 2016

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10/09/22 Erik Zej

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Analysis: extraction of N_{mpi} Monte Carlo Validation

BDT were trained with the 2C, 4C and Monash 2013 PYTHIA 8 models, and HERWIG 7 Soft Tune

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> Aplication to simulations of pp collisions at √s = 5.02, 7 and 13 TeV using PYTHIA 8 Tune 4C


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BDT were trained with the 2C, 4C and Monash 2013 PYTHIA 8 models, and HERWIG 7 Soft Tune

> Aplication to simulations of pp collisions at √s = 5.02, 7 and 13 TeV using PYTHIA 8 Tune 4C

Validation consisted in comparing the BDT results with the information provided by PYTHIA 8 Tune 4C



Analysis: extraction of N_{mpi} Monte Carlo Validation





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10/09/22

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MC generator: C++ program inside ROOT





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3. In a particle loop the $p_{\scriptscriptstyle T}$ was randomly extracted

4. In each event the $\ {\rm \langle p_{_T} \rangle }$ was calculated



10/09/22





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Results: average number of MPI



Using the BDT, we estimated the average number of multiparton interactions $\langle N_{mpi} \rangle$ from ALICE pp collisions data at $\sqrt{s} = 7$ TeV. We found $\langle N_{mpi} \rangle = 3.98 \pm 1.01$



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Complements our result for $\sqrt{s} = 5.02$ and $\sqrt{s} = 13$ TeV



Results: average number of MPI





Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning 13 / 18



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Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning 13 / 18



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Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning 13 / 18



Results: multiplicity dependence of $\langle N_{mni} \rangle$



We extend our last study reported on

Antonio Ortiz, Antonio Paz, José D. Romo, Sushanta Tripathy, Erik A. Zepeda, and Irais Bautista, Phys. Rev. D 102, 076014





Data from: ALICE, PRC 99, 024906 (2019); EPJC 79 (2019) no.10, 857 Training: Pythia 8.244 tune 4C $N_{\rm ch} / \langle N_{\rm ch} \rangle$

10/09/22

Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning 14 / 18



10/09/22 Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning 14 / 18



10/09/22 Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning 14 / 18



Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning 14 / 18

10/09/22



Results: multiplicity dependence of $\langle N_{mpi} \rangle$



Our result is compared with

the ALICE collaboration analysis

B. Abelev et al. JHEP, 09:049, 2013.

In Pythia context N_{uncorrelated seeds} is defined, which provides information about the number of semipartonic interactions by event



Results: multiplicity dependence of $\langle N_{mpi} \rangle$





10/09/22Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning15 / 18



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10/09/22 Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning 15 / 18



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Completely compatible with our results!

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At higher multiplicities an increase in N_{mpi} is improbable. High multiplicity can only be reached selecting events with high multiplicity jets

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Results: multiplicity dependence of $\langle N_{mpi} \rangle$





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At higher multiplicities an increase in N_{mpi} is improbable. High multiplicity can only be reached selecting events with high multiplicity jets

This characteristic is explained as a selection bias.

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We propose to include more information in the BDT training, in order to determine if the N_{mpi} extraction improves





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We trained three BDT sets with pp collisions data at √s = 13 TeV generated with PYTHIA 8 Tune 4C ALICE Run2 Mid: Multiplicity computed in the $|\eta| < 0.8$ range

ALICE Run2 V0A+V0C: Multiplicity computed in the forward regions $2.8 < \eta < 2.5$ and $-3.6 < \eta < -1.7$ which cover the V0A and V0C arrays





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> W. Henryk. New ALICE detectors for run 3 and 4 at the CERN LHC. 958:162116, 2020

ALICE Run2 Mid: Multiplicity computed in the $|\eta| < 0.8$ range

ALICE Run2 V0A+V0C: Multiplicity computed in the forward regions $2.8 < \eta < 2.5$ and $-3.6 < \eta < -1.7$ which cover the V0A and V0C arrays

ALICE Run3 MFT+V0+: Multiplicity computed in the forward regions -3.6 < η < -2.45 and 2.2 < η < 5.1 which cover the MFT and VZERO+ detectors

10/09/22Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning16 / 18






Erik Zepeda - Extraction of Multiparton Interactions from ALICE pp collisions data using Machine Learning

10/09/22

16 / 18



Conclusions



Using the ALICE data which consist on transverse momentum spectra as a function of event multiplicity for pp collisions at $\sqrt{s} = 7$ TeV, we report $\langle N_{mpi} \rangle = 3.89 \pm 1.01$. Result being compared with $\langle N_{mpi} \rangle = 3.76 \pm 1.01$ and 4.65 ± 1.01 for $\sqrt{s} = 5.02$ and 13 TeV, which shows low energy dependence consistent with PYTHIA. This result provides experimental evidence of MPI in hadronic interactions.

▶ Using the available ALICE pp collisions data, we reported $N_{mpi} / \langle N_{mpi} \rangle$ as a function of $N_{ch} / \langle N_{ch} \rangle$ for $\sqrt{s} = 5.02$, 7 and 13 TeV. For $N_{ch} / \langle N_{ch} \rangle < 3$ we observe a linear increase, while for $N_{ch} / \langle N_{ch} \rangle > 4$ a deviation with respect to the linear trend. This result is consistent with the ALICE collaboration analysis.



Conclusions



The extraction of N_{mpi} improves considering more information in the BDT training, computing the multiplicity in the forward region. Which opens the posibility to extract the number of MPI event by event and in this way, study the particle production as a function of MPI.

Based on verifications performed with Monte Carlo event generators, and in the agreement of our results with the ALICE collaboration measurements. Our approach is robust and can be used by experiments in order to study the particle production as a function of MPI. This can help to the understanding of heavy ion-like features observed in pp collisions data.