Prediction for impact parameter and transverse spherocity in heavy-ion collisions at the LHC

Workshop on Application of AI and ML

10th Nov 2022

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Based on:

N. Mallick, S. Tripathy, A. N. Mishra, S. Deb, and R. Sahoo, Phys. Rev. D103, 094031 (2021)

Outline

- Quark-gluon plasma
- Heavy-ion collisions
- Machine learning in HEP
- Inversion problem
- Decision Trees
- Results
- Summary

Quark-gluon plasma

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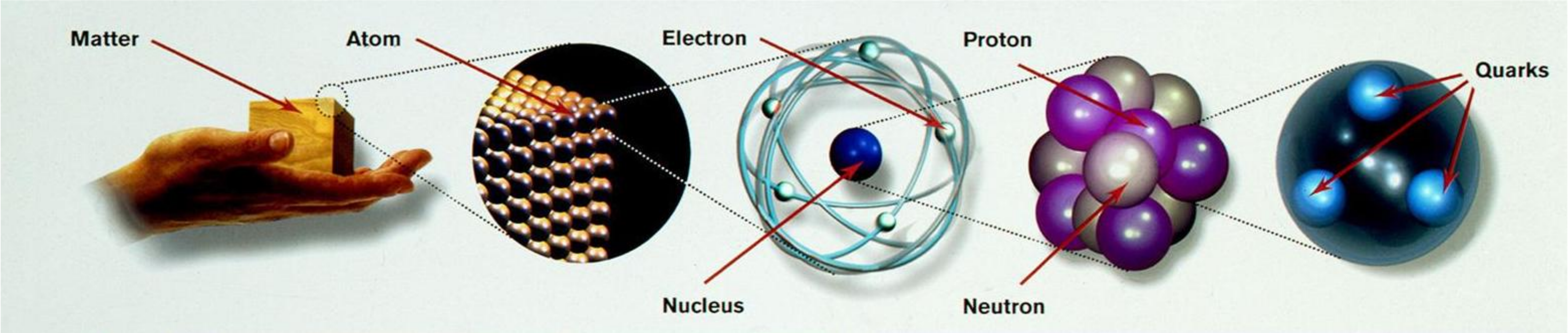

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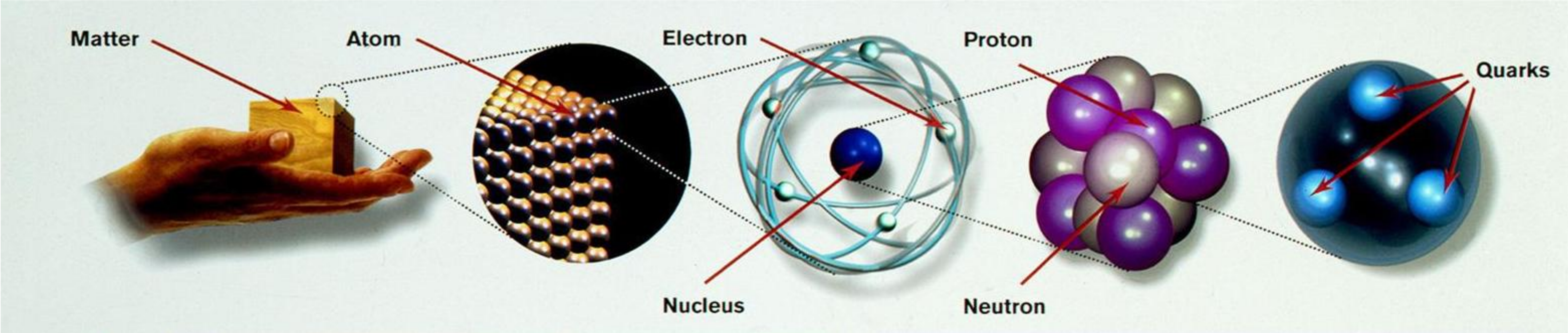
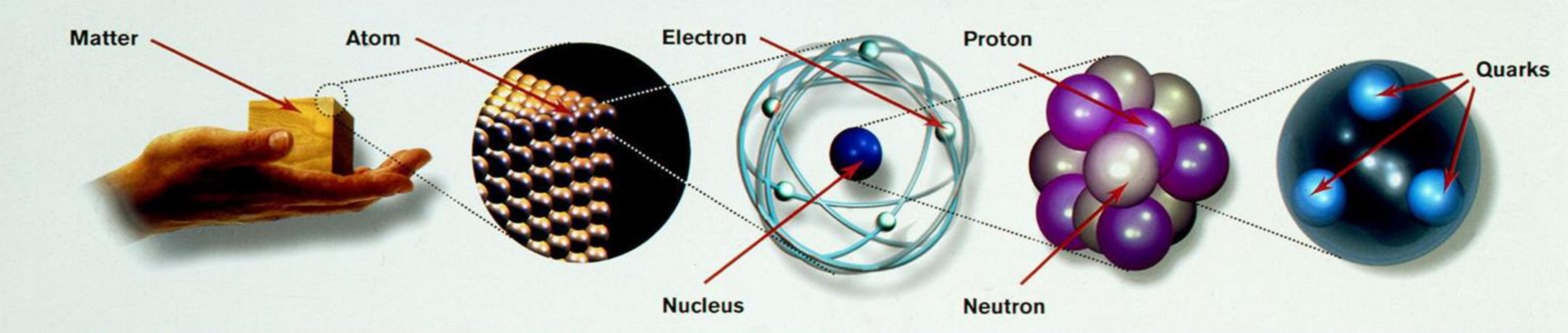


- Quarks: the fundamental bits of matter
- Gluons: carrier of strong force
- Theory of strong force: Quantum Chromodynamics (QCD)
- Color confinement: quarks and gluons can not be isolated
- Asymptotic freedom: weaker interaction at higher energy
- Heavy-ions: Pb, Au, Xe nucleus
- Quark-gluon plasma: Thermalised hot and dense state of deconfined partons

Quark-gluon plasma



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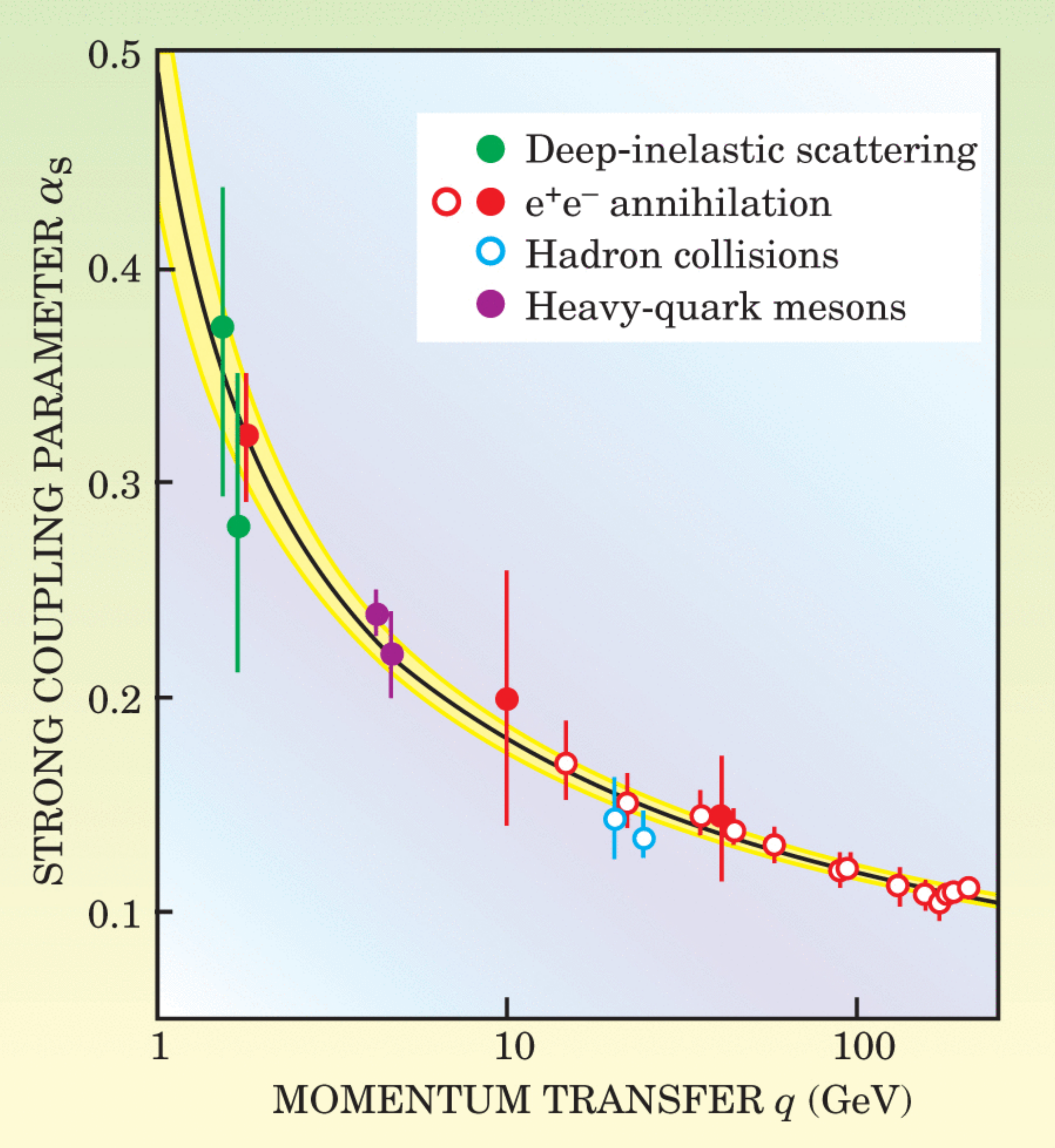
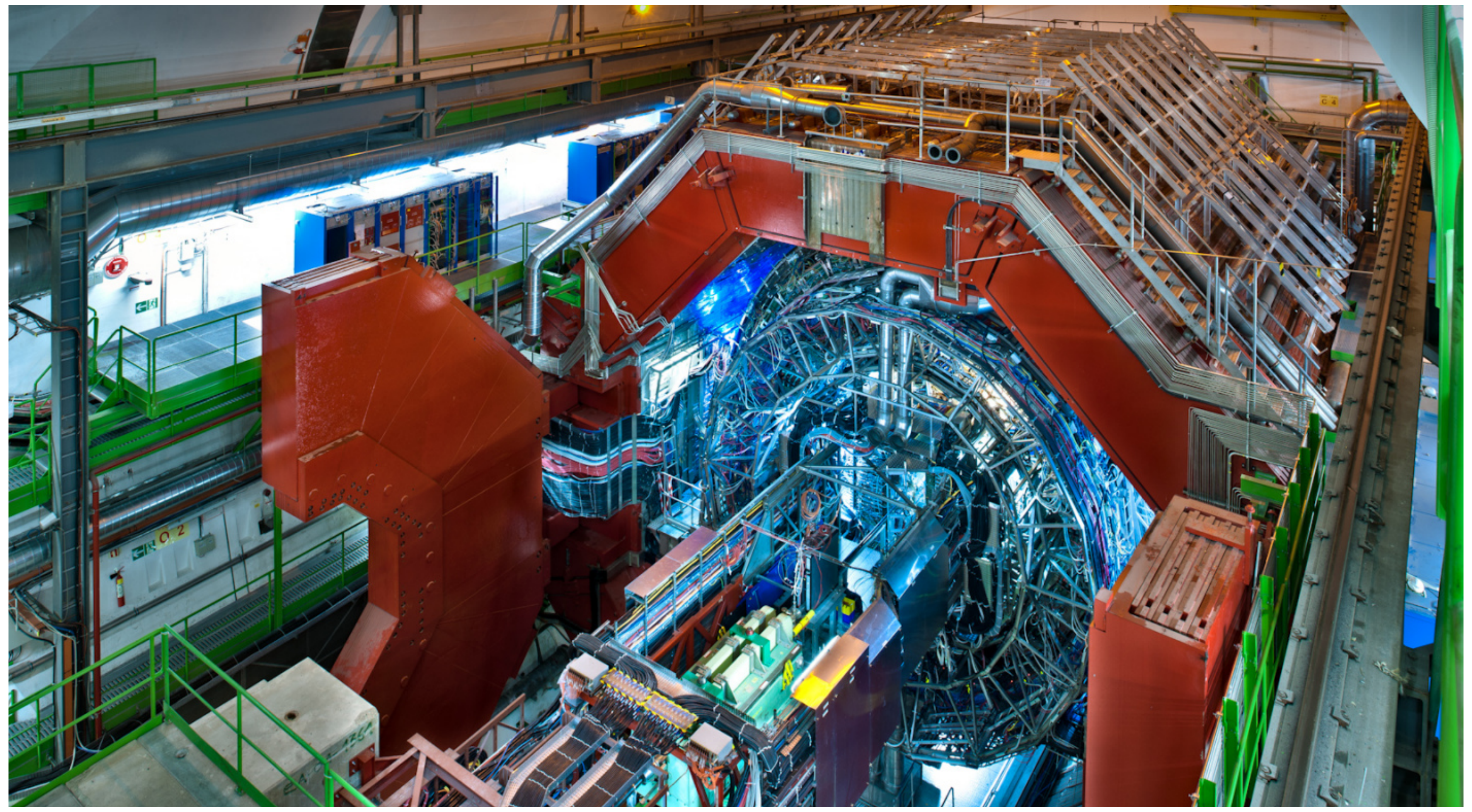


Heavy-ion collisions



ALICE Detector, LHC, CERN

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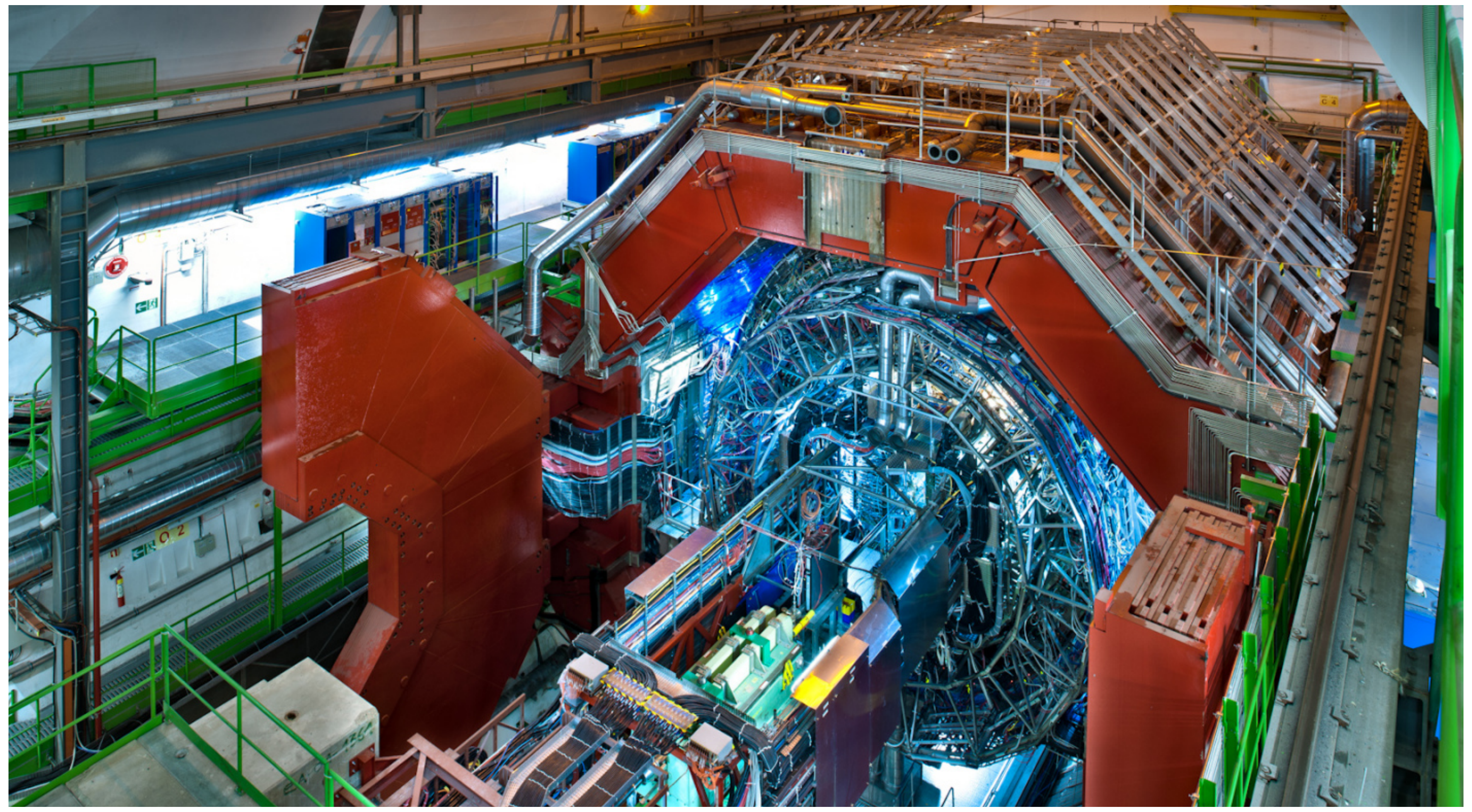

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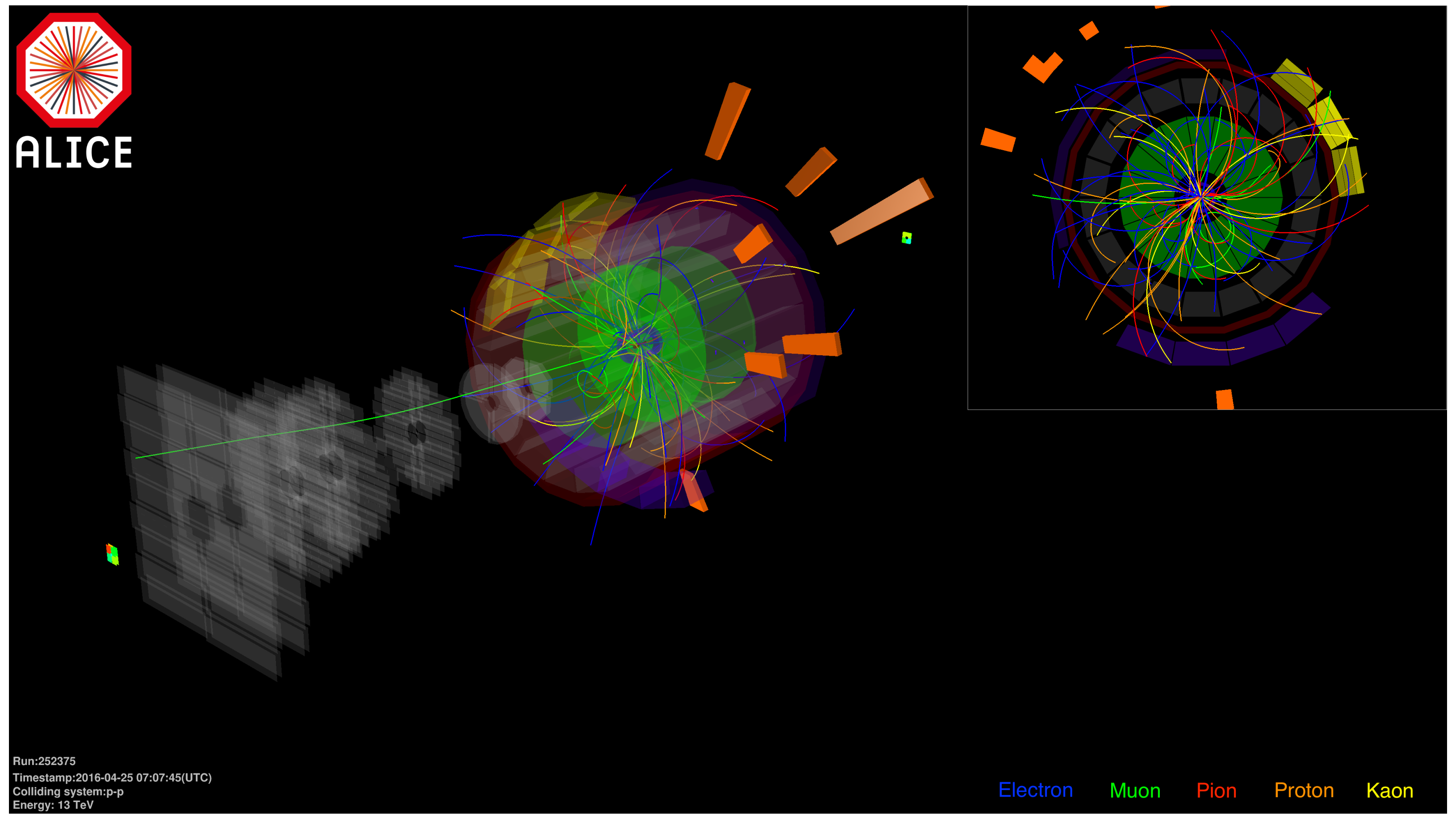
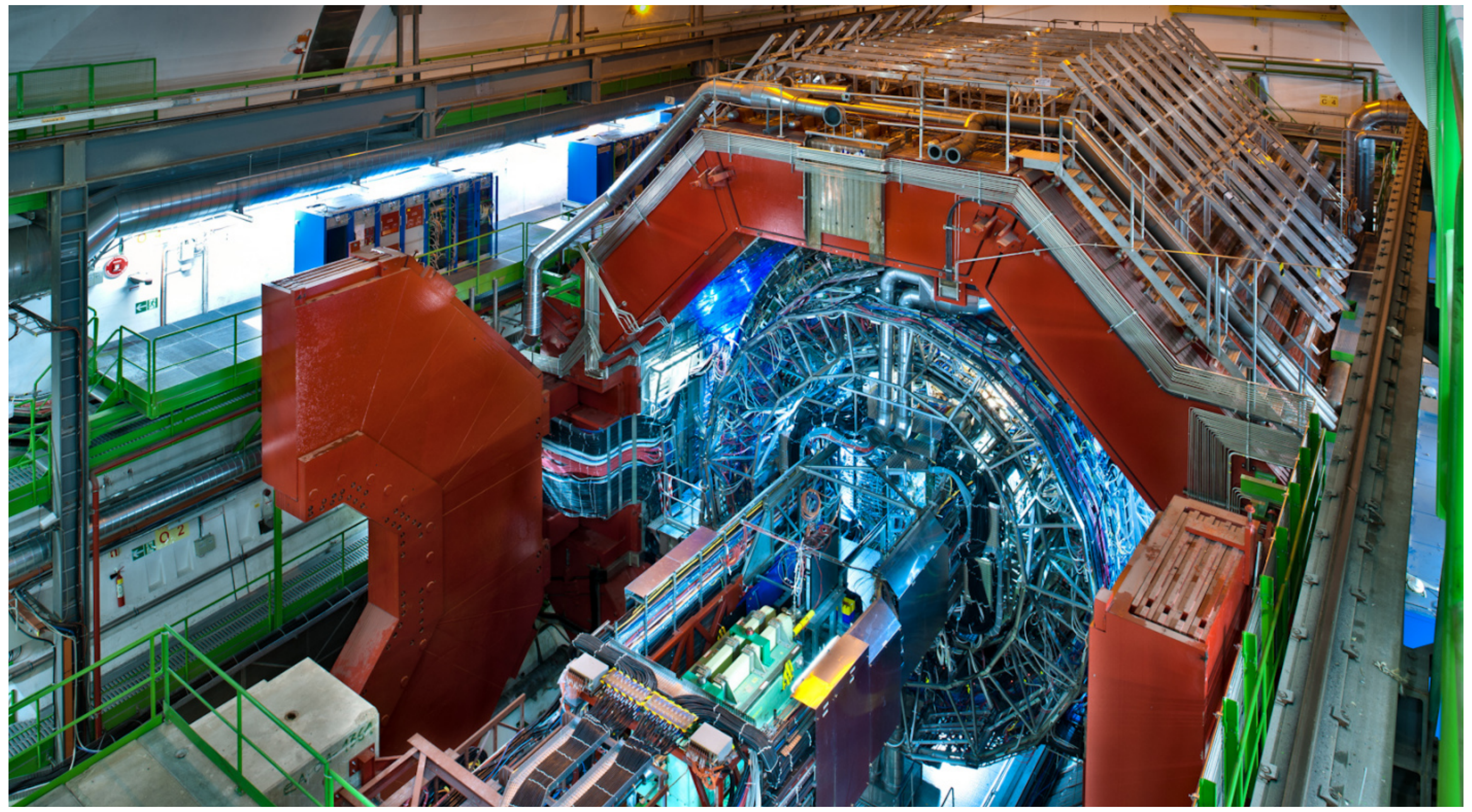
proton-proton collisions, $\sqrt{s} = 13$ TeV



https://cds.cern.ch/record/2149032

Heavy-ion collisions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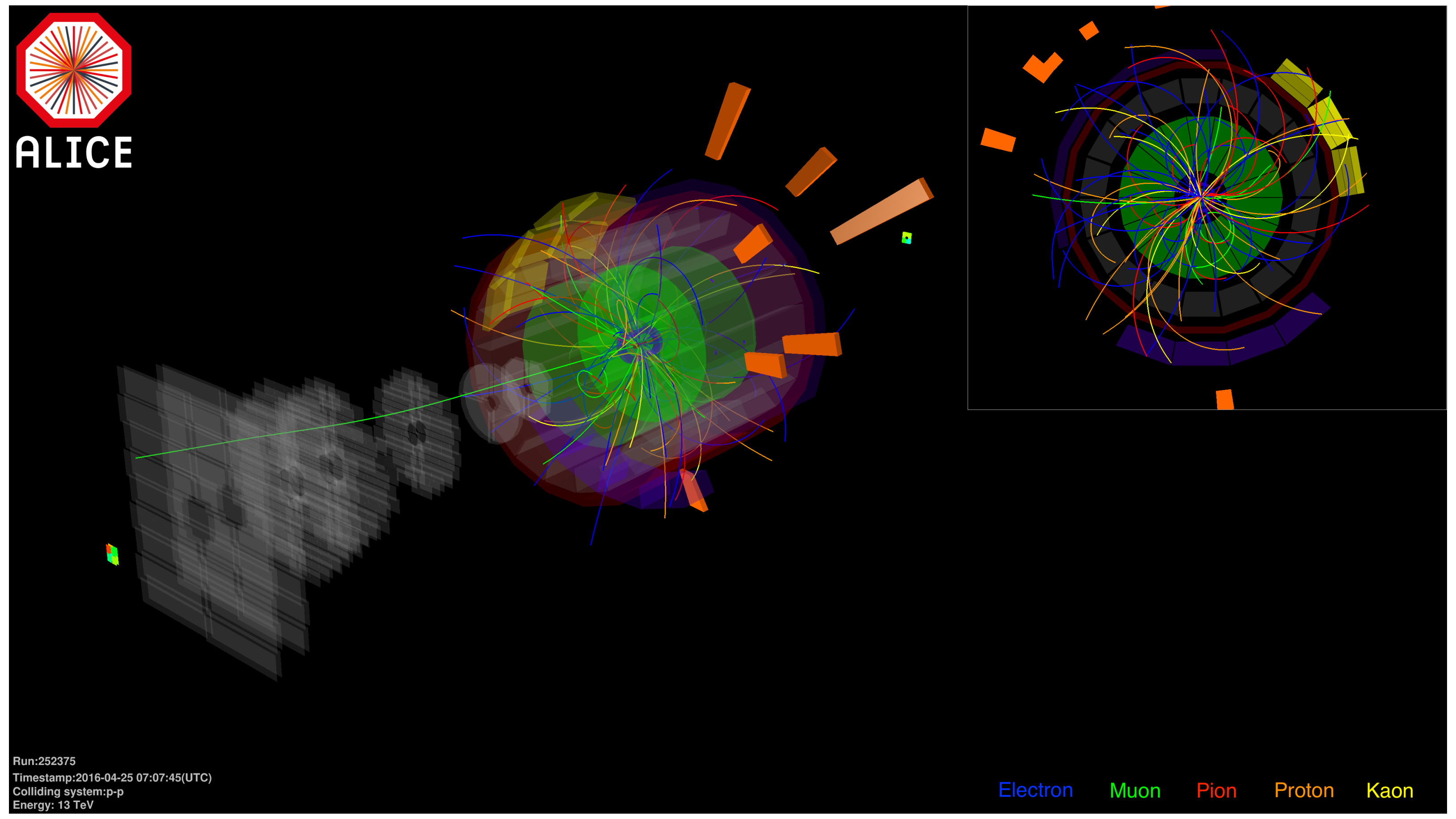

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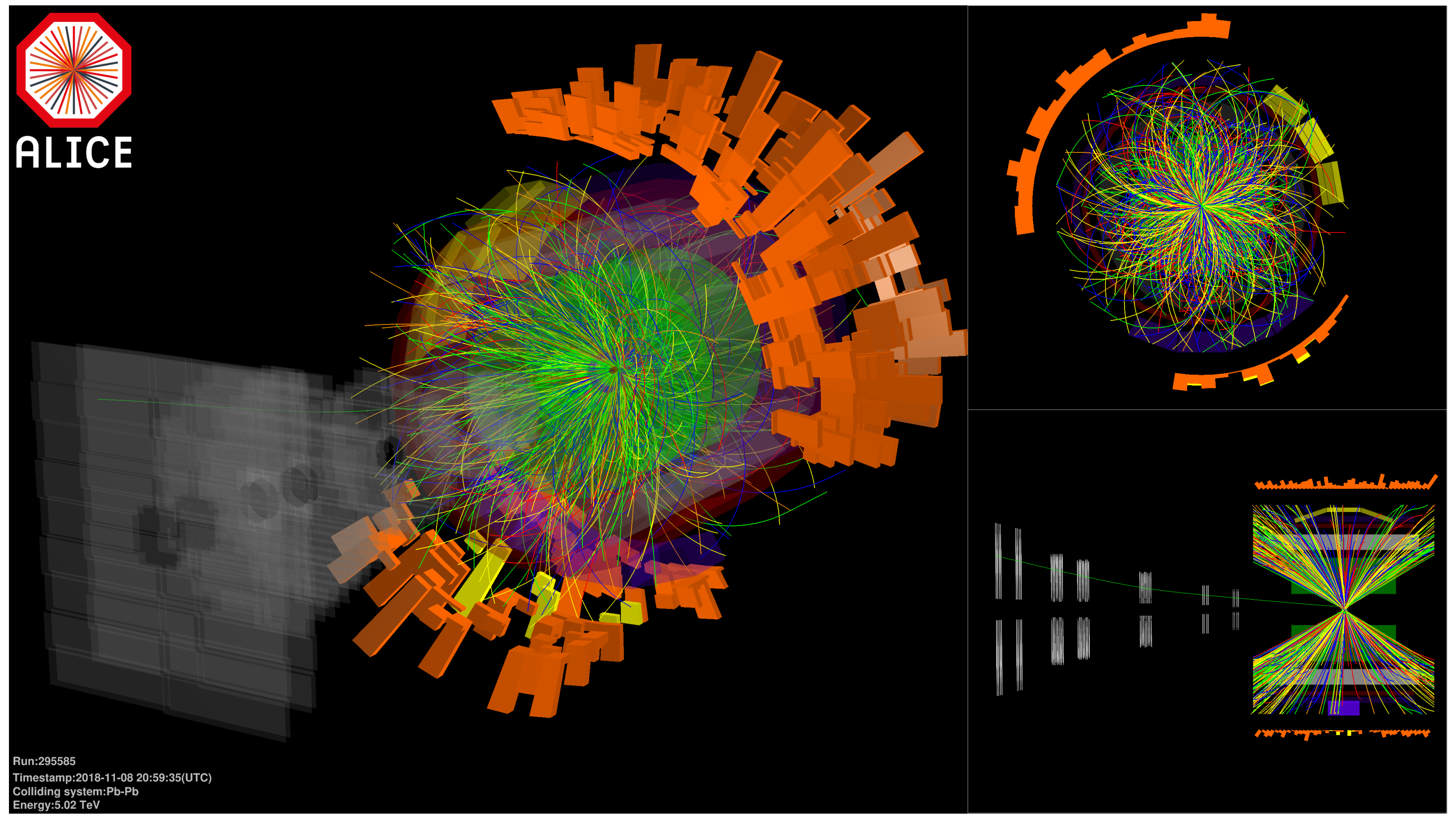
Pb-Pb collisions, $\sqrt{s_{\mathrm{NN}}} = 5.02$ TeV



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Heavy-ion collisions

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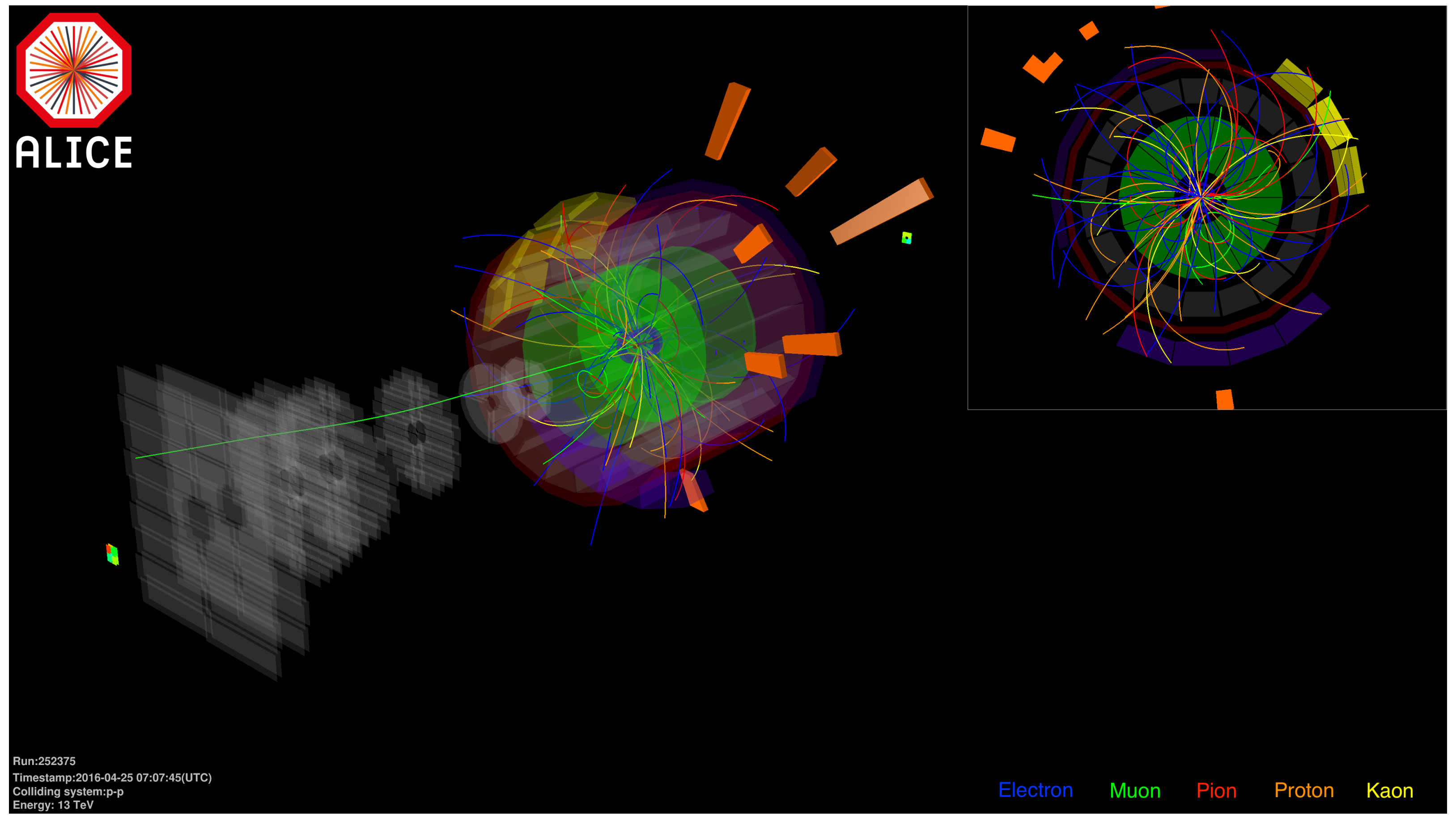

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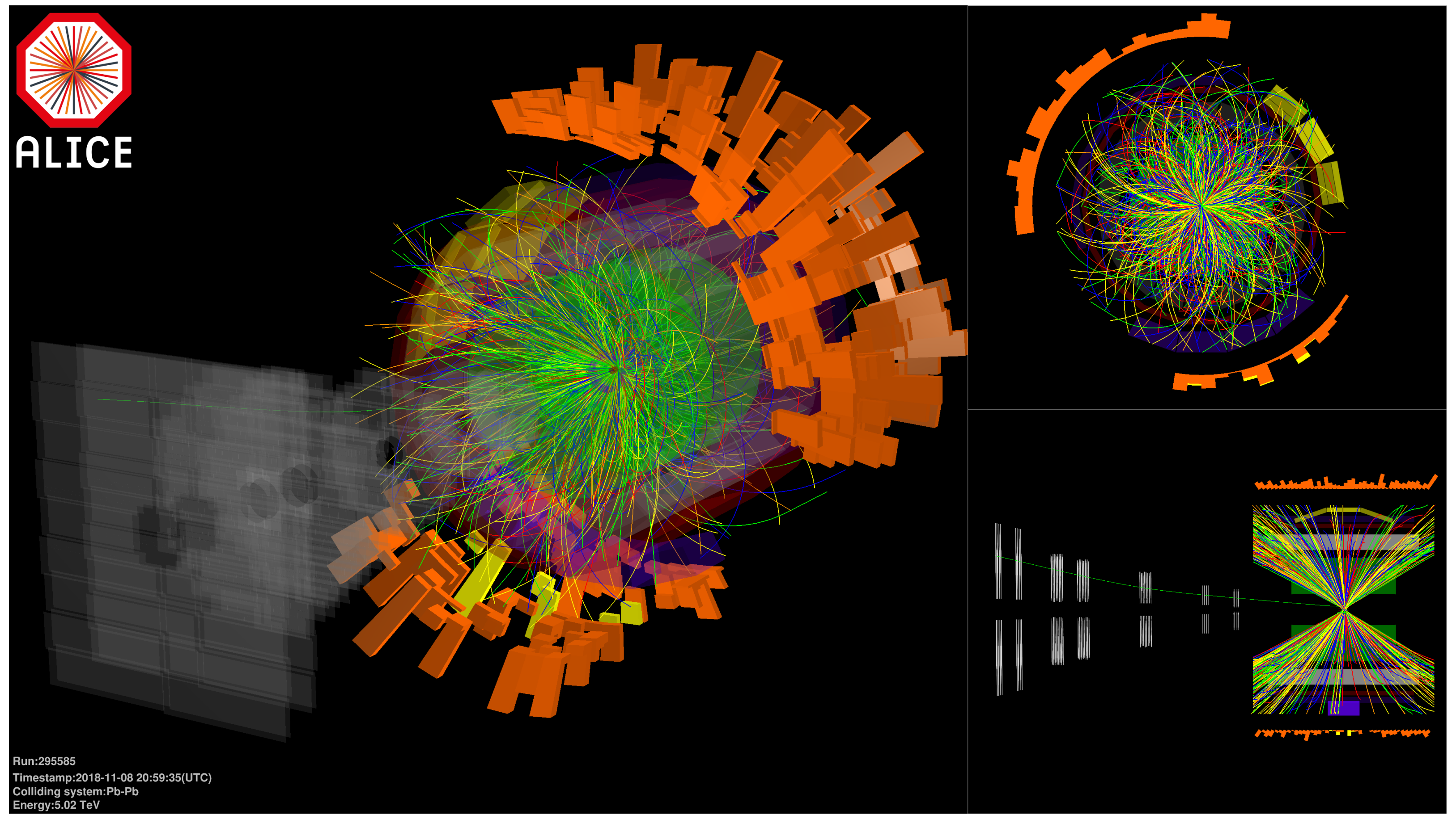

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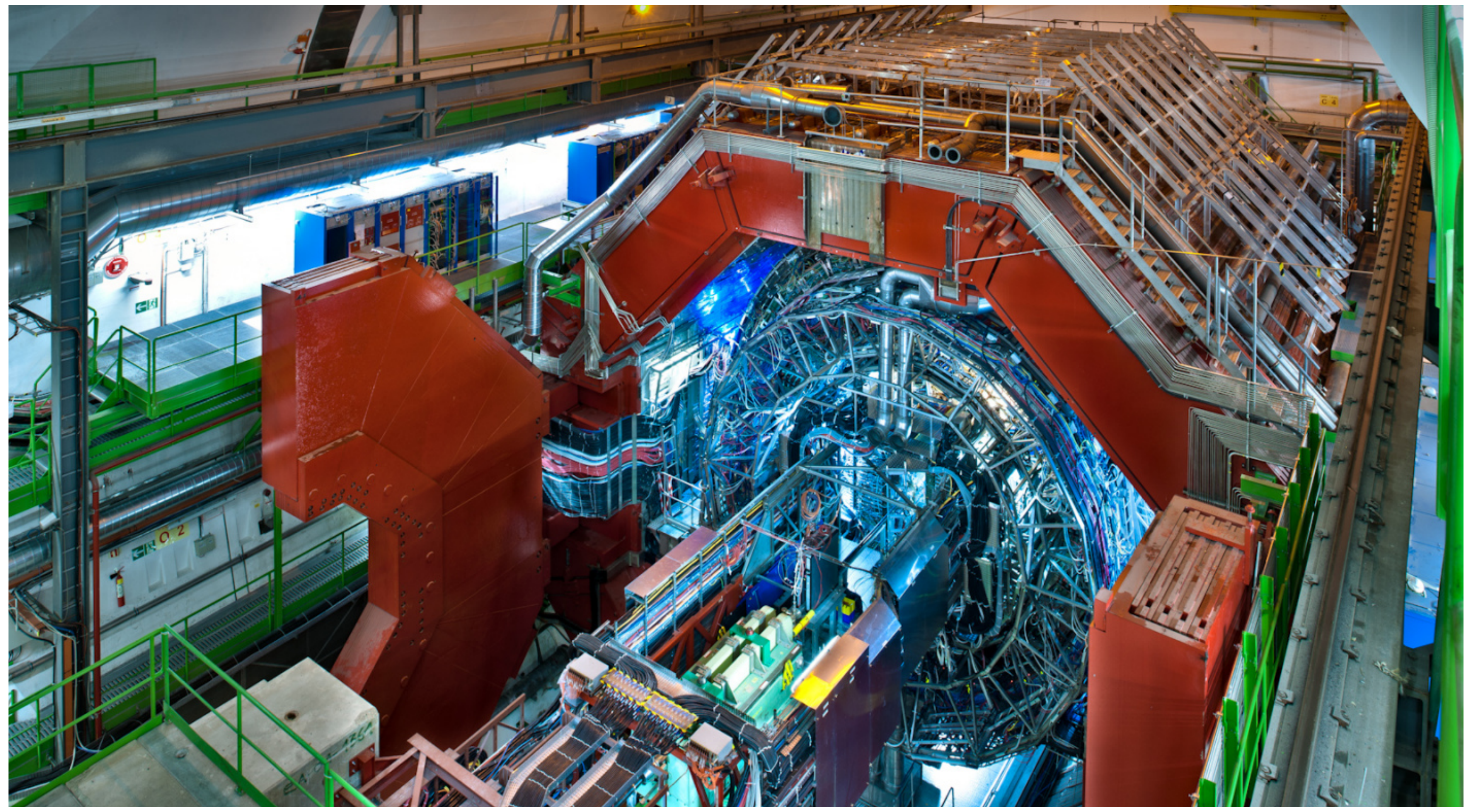
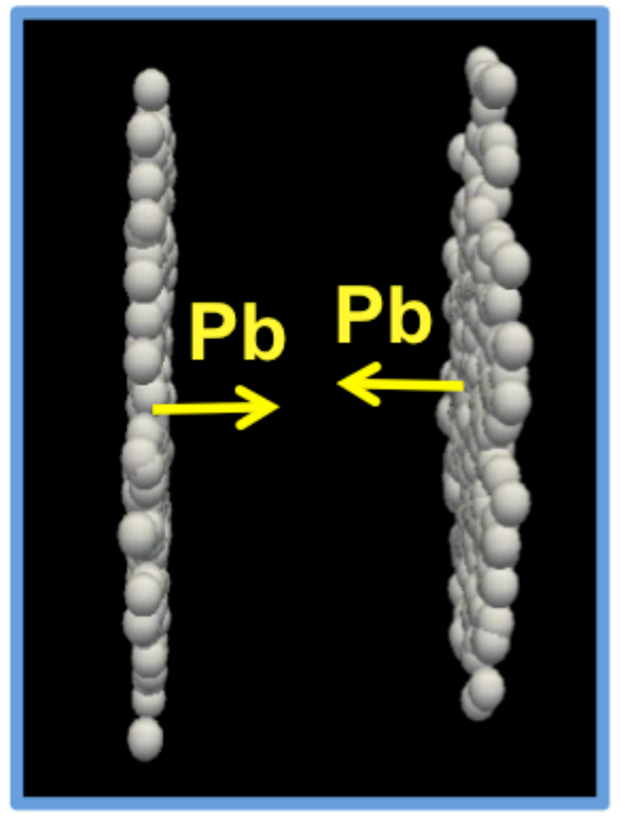


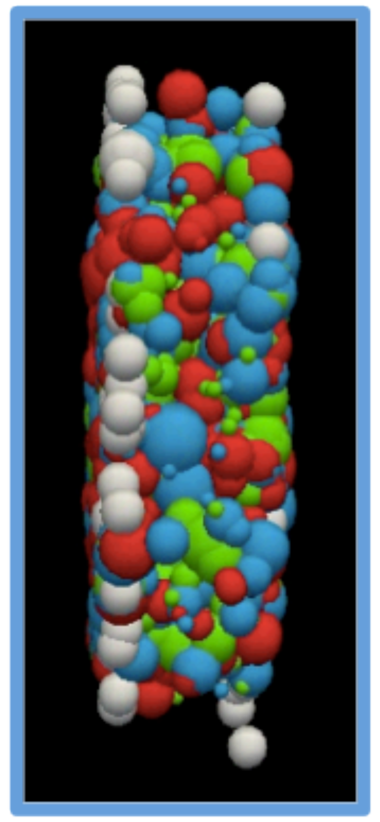
ALICE Detector, LHC, CERN

time

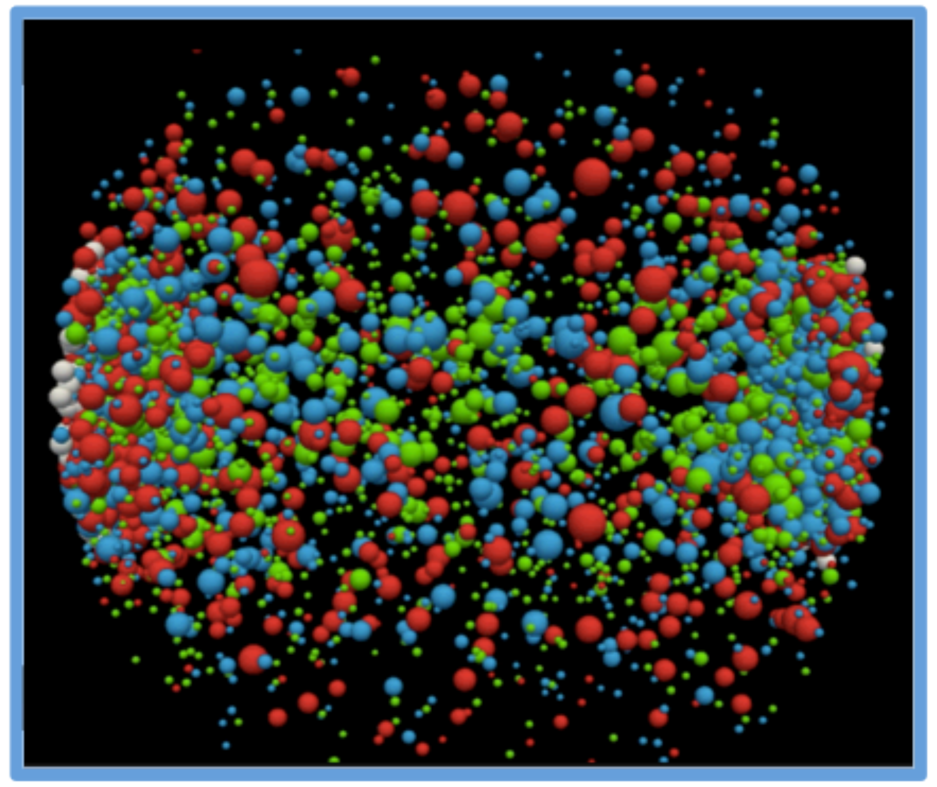
Pre-reaction



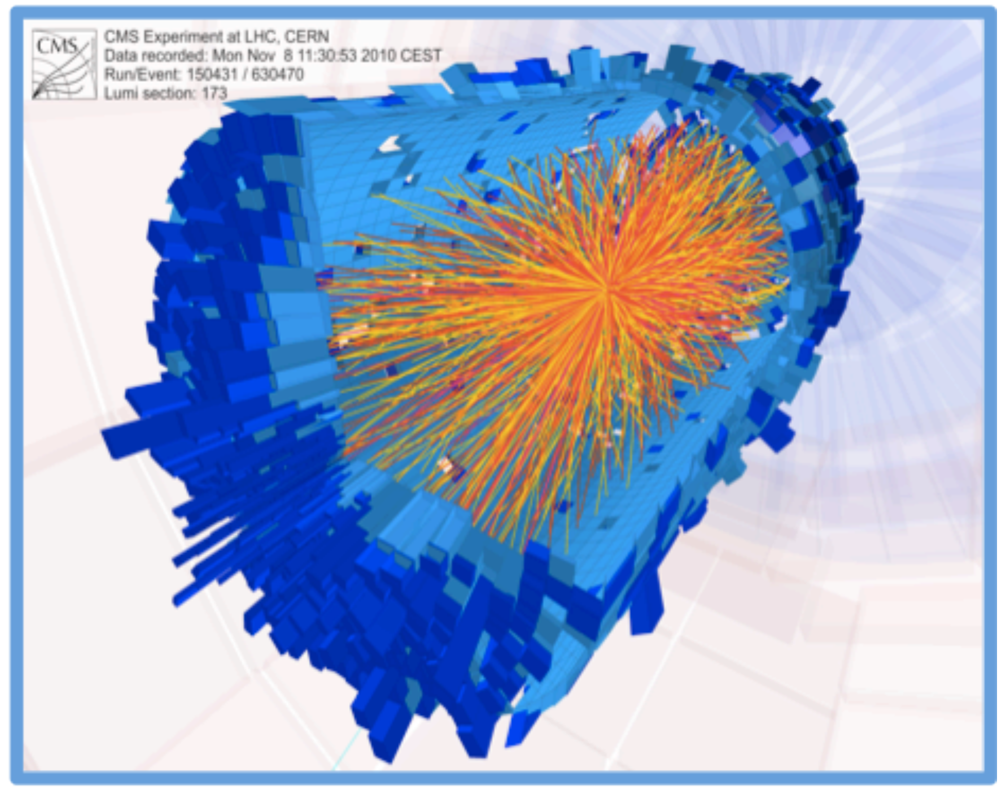
QGP



Hadronization



Detection



Machine learning in HEP

https://iml-wg.github.io/HEPML-LivingReview/

Machine learning in HEP

- Particle Identification
- Track reconstruction
- Triggering
- Fast Simulation
- Data Quality Monitoring
- Unfolding Techniques
- Signal and background classification
- Jet identification and tagging
- Beyond standard model physics
- **Heavy-ion physics and QGP phenomenology**

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https://root.cern/
https://root.cern/manual/tmva/
Scikit-learn: Machine Learning in Python, Pedregosa et al., JMLR 12, pp. 2825-2830, 2011
https://keras.io/
https://www.tensorflow.org/

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- Transverse distance between the centres of colliding nuclei
- Initial geometry affects the final state particle production
- Order of a few fermi (10^{-15}m)

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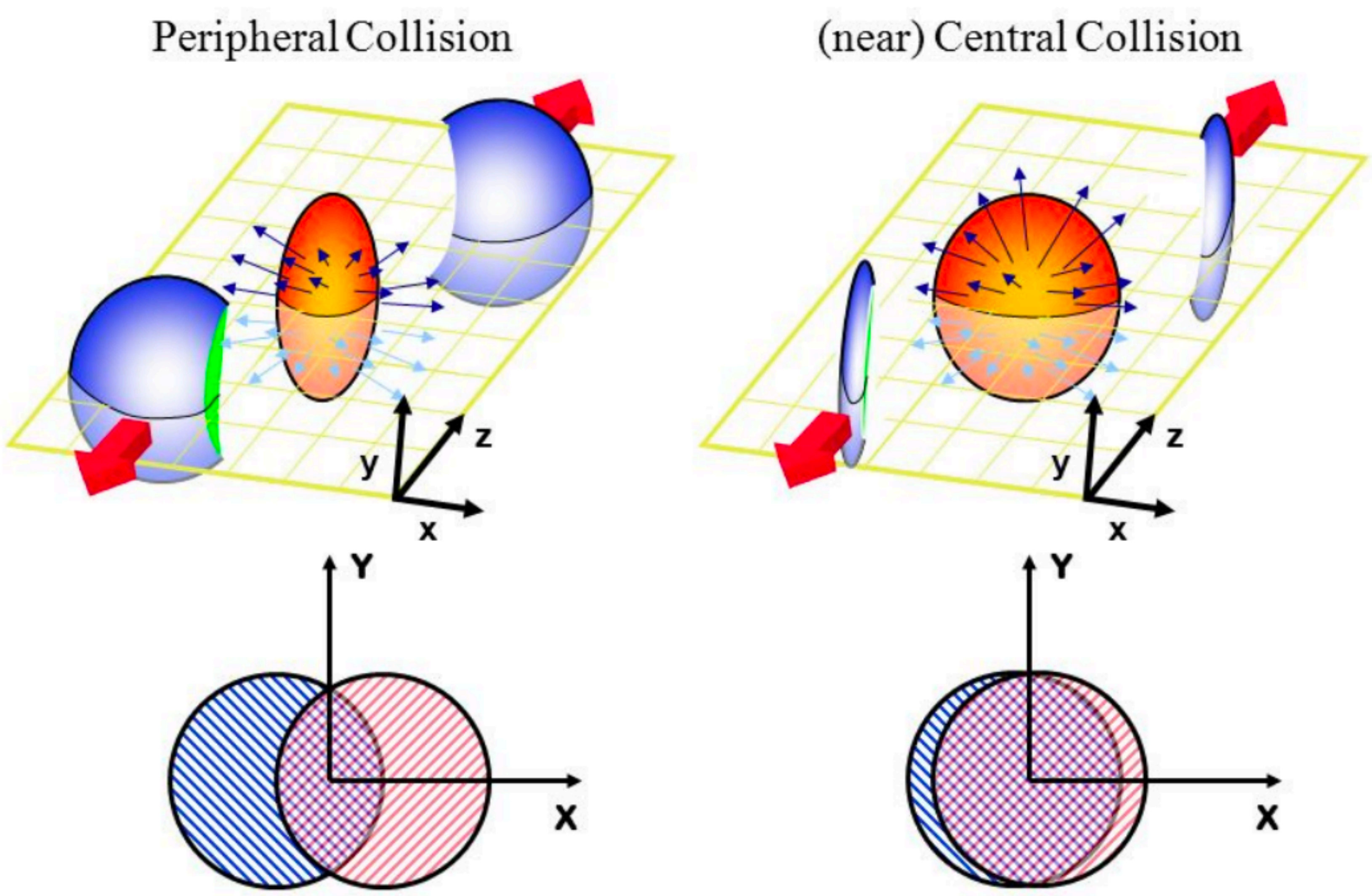

$$0 \leq b \leq 2R$$

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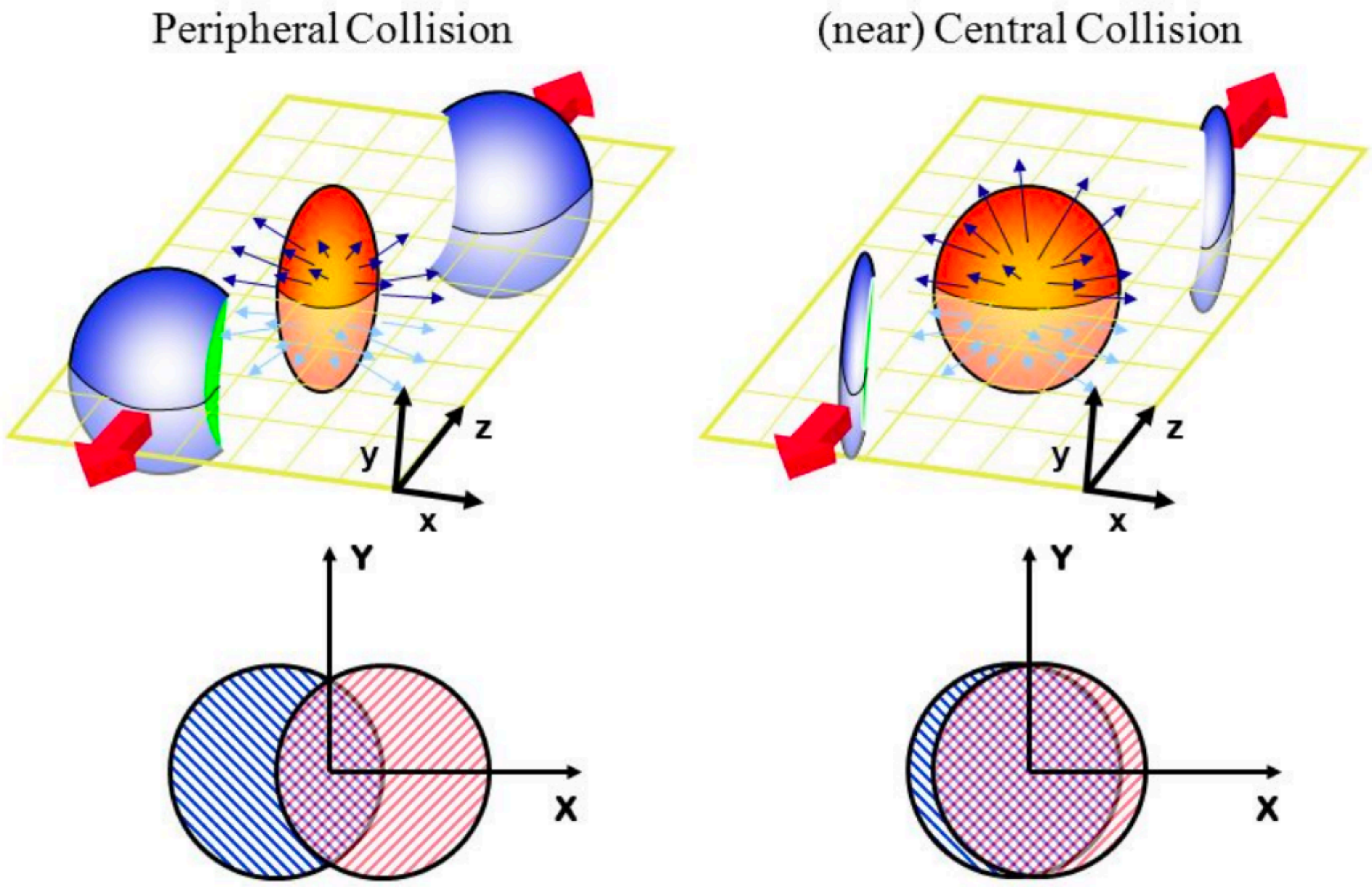

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Transverse Spherocity (S_0)

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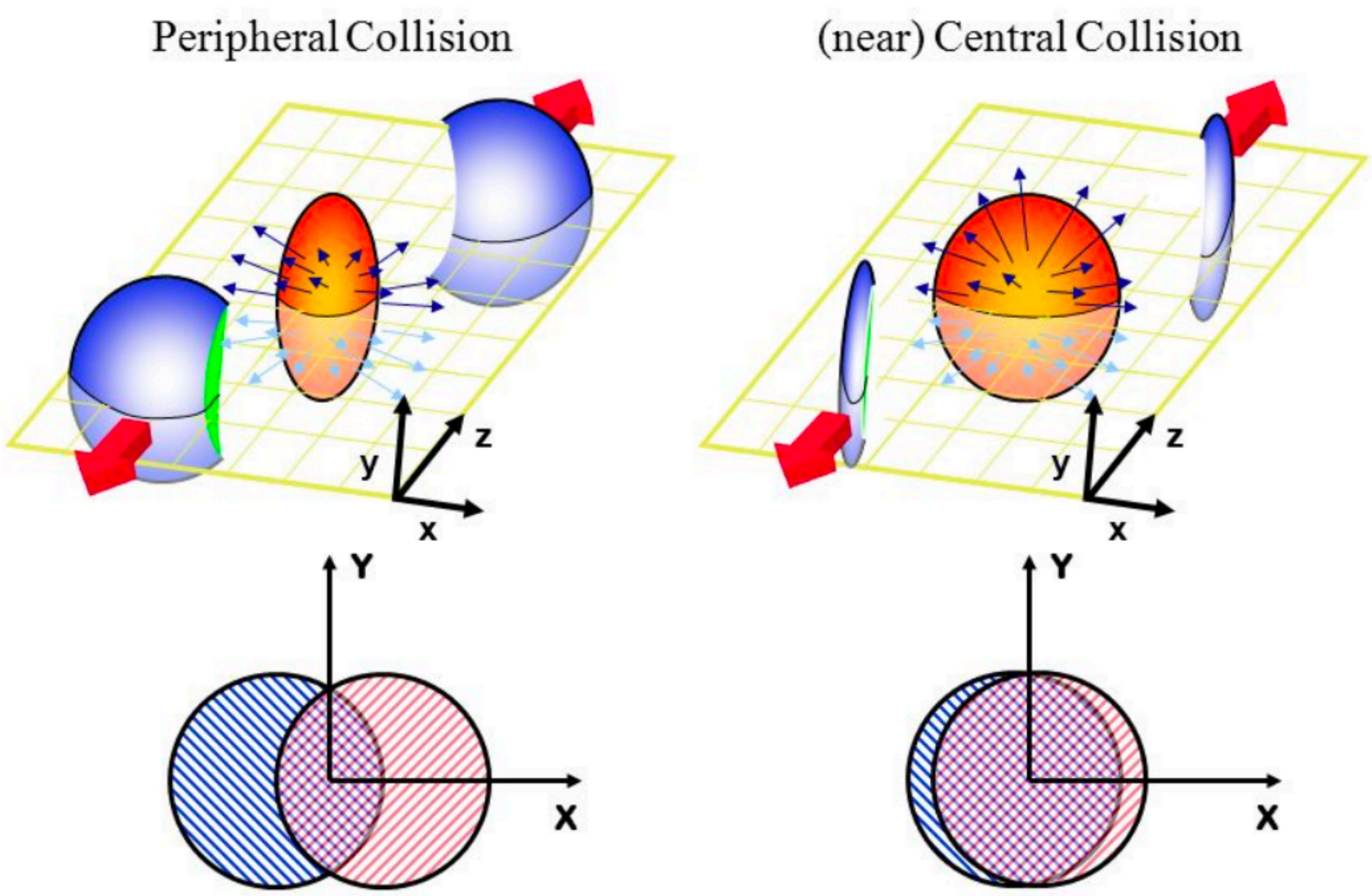

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Transverse Spherocity (S_0)

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  1. Jetty: Back-to-back structure, indication of hard-QCD
  2. Isotropic: soft-QCD process
- Dominance of isotropic events in high multiplicity pp collisions

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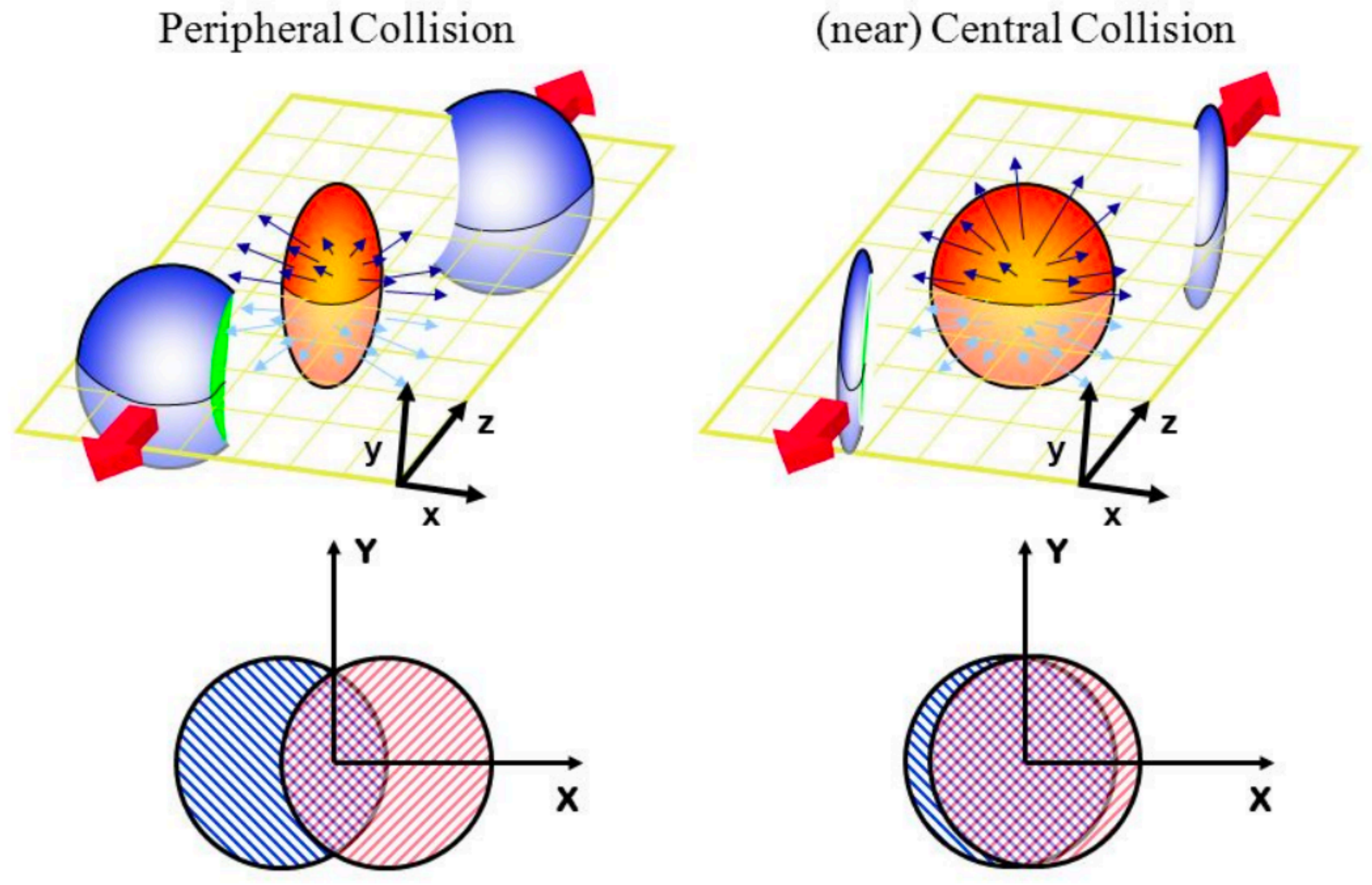

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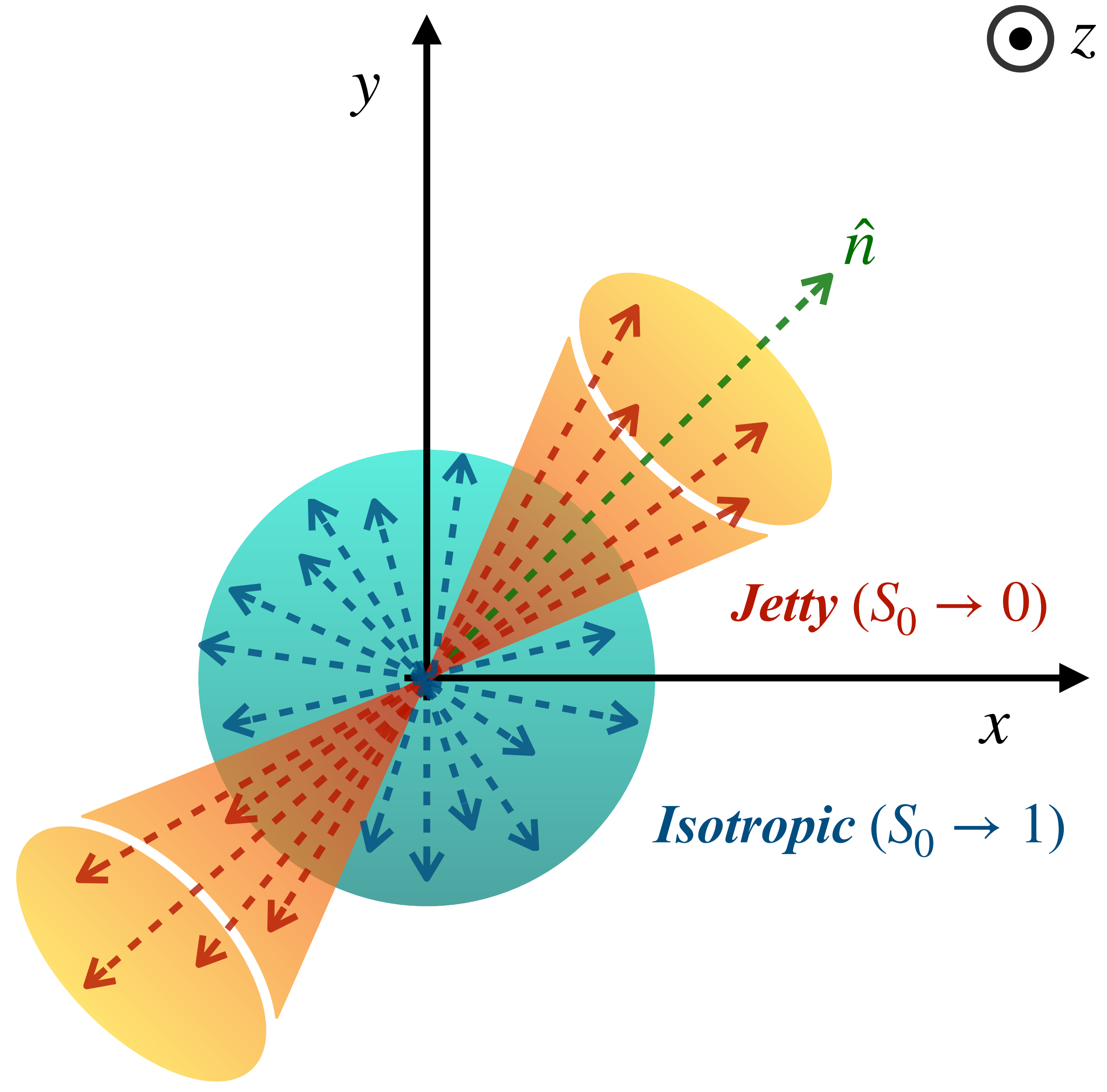

Schematic picture showing possible **jetty** and **isotropic** event formations in the transverse plane

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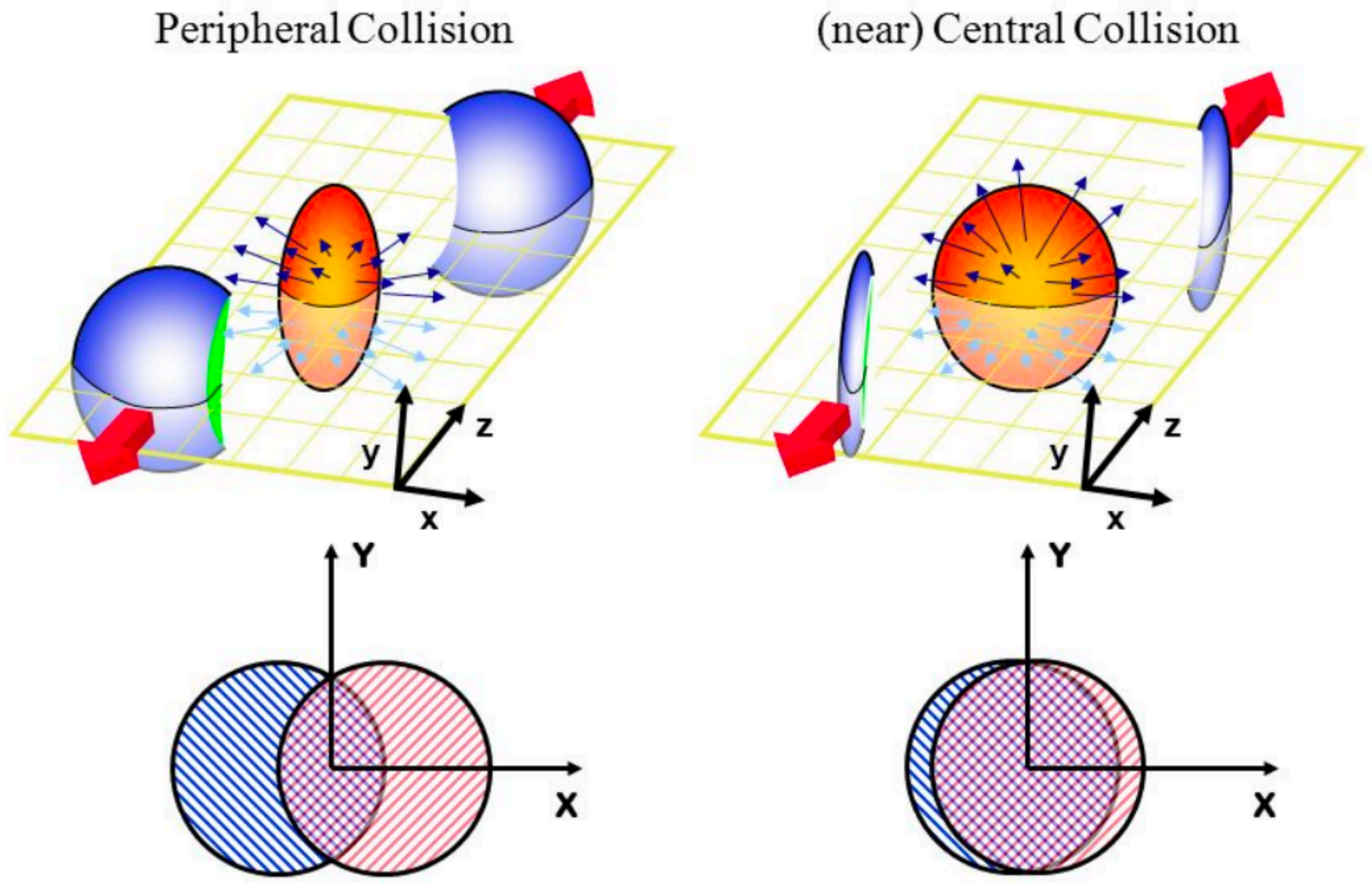

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  1. Jetty: Back-to-back structure, indication of hard-QCD
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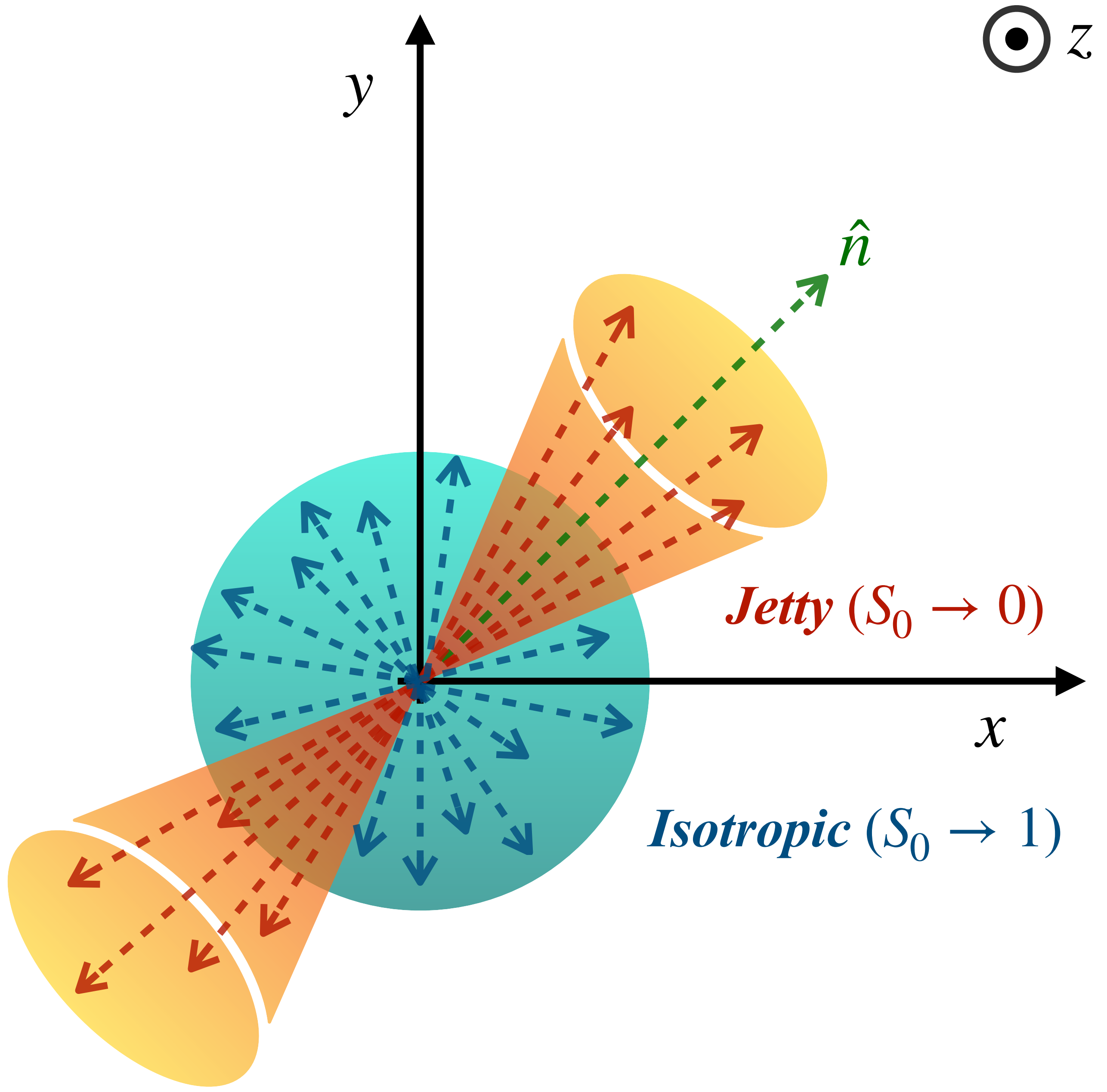
$$S_0 = \frac{\pi^2}{4} \times \min_{\hat{n}=(n_x,n_y,0)} \left(\frac{\Sigma_i \, |\vec{p}_{T_i} \times \hat{n}|}{\Sigma_i \, \vec{p}_{T_i}} \right)^2$$

$$p_{\mathrm{T}} = \sqrt{p_x^2 + p_y^2}$$

A. Khuntia et al., J. Phys. G48, 035102 (2021)

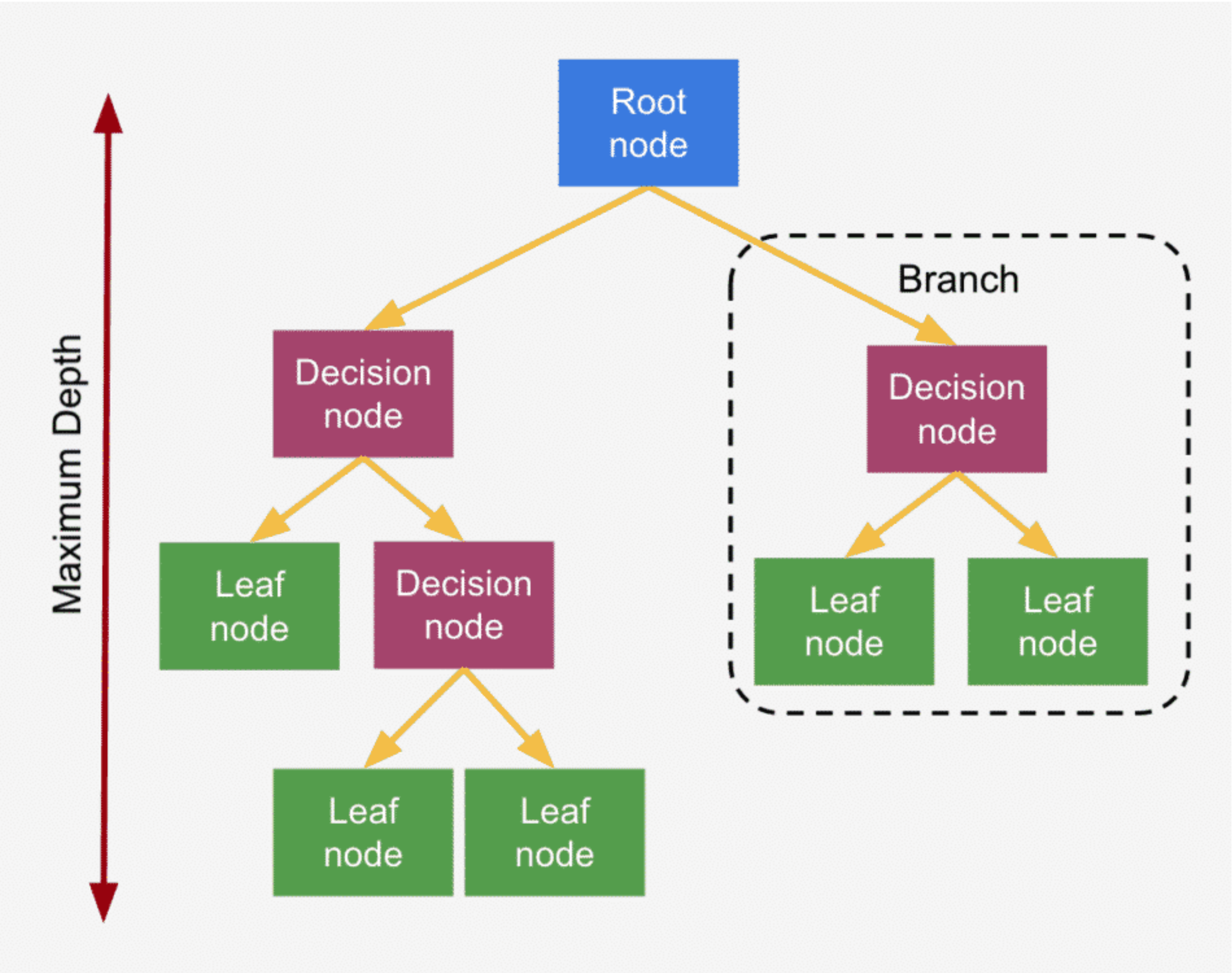
S. Prasad, N. Mallick, D. Behera, R. Sahoo, and S. Tripathy, Sci.Rep. 12, 3917 (2022)



Schematic picture showing possible jetty and isotropic event formations in the transverse plane

Boosted Decision Trees

- Trees are structures that takes recursive decisions
- Built in a top-down approach
- Root node: The starting point
  Internal nodes: further decision points
  Leaf nodes: End points (target class or values)
- Criteria of splitting:
  Classification: Minimise the node impurity
  Regression: Minimise the MSE, MAE
- Splitting continues till a preset (max_depth)
- Boosting: Building an additive forward staged model by combining the outcomes of all previous ones
- Boosting compensates the shortcomings
- Shortcomings are identified as the gradient



Input observables and correlation

- Pearsons correlation coefficient:

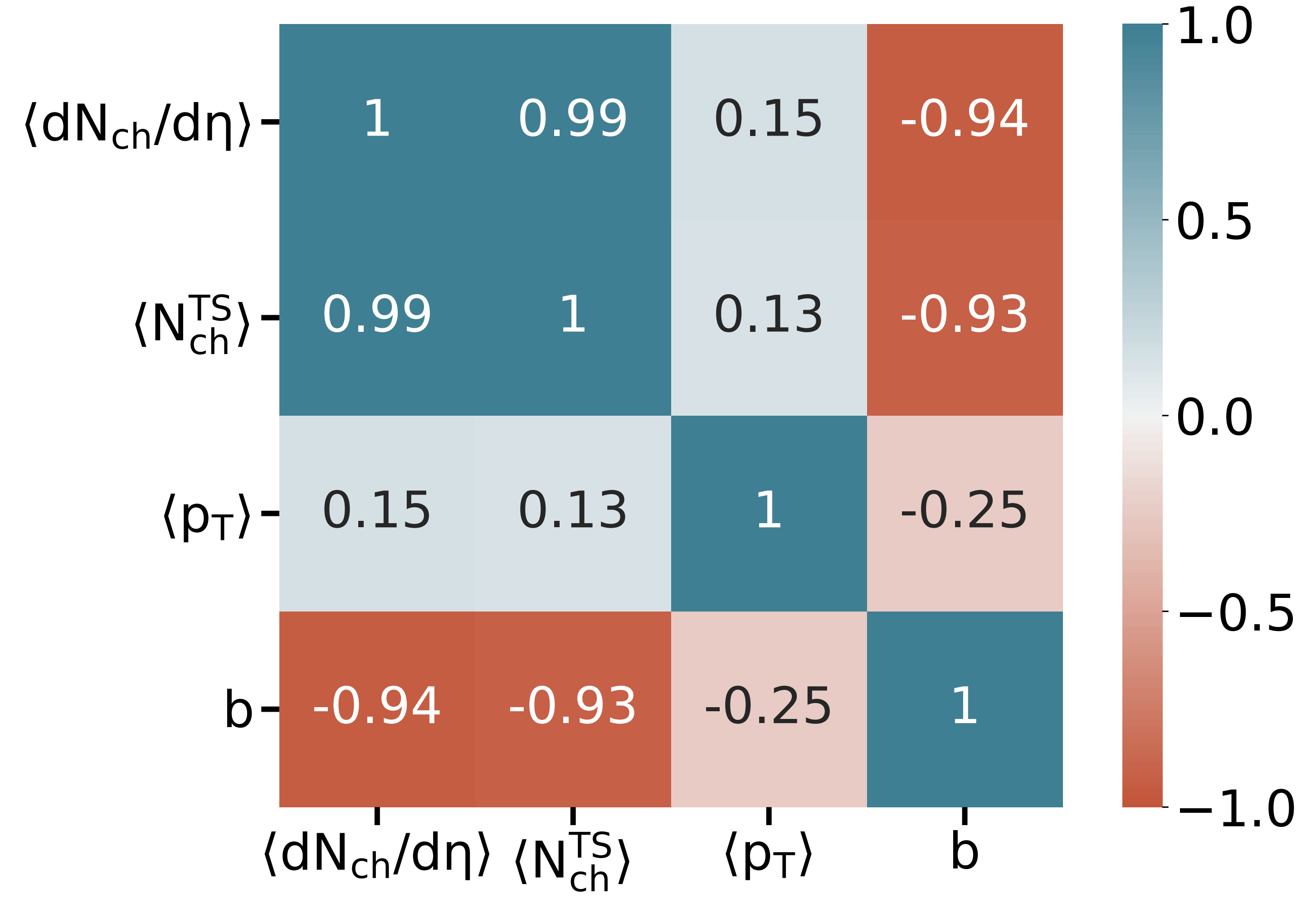
$$\rho = \frac{\mathrm{cov}(x, y)}{\sigma_x \sigma_y}$$

  Input variables: $\langle dN_{ch}/d\eta \rangle$, $\langle N_{ch}^{TS} \rangle$ and $\langle p_T \rangle$

  Output variable: b and S_0

- Good correlation is seen among chosen input and output variables
- The algorithm tries to understand the correlation and exploit the features to arrive on a conclusion (a number)

Impact parameter (b)



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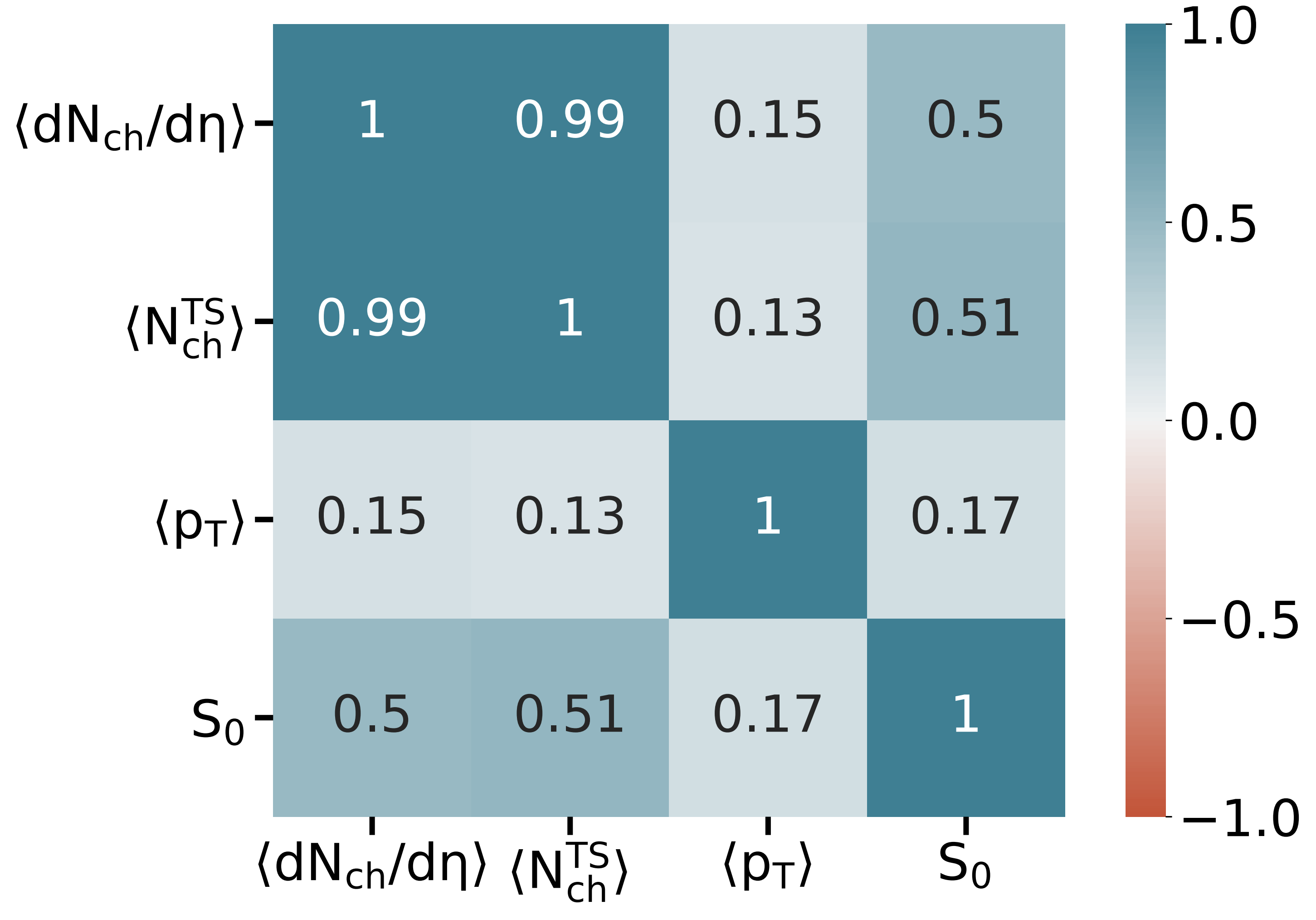

N. Mallick, S. Tripathy, A. N. Mishra, S. Deb, and R. Sahoo, Phys. Rev. D103, 094031 (2021)

Parameters and training

- Loss Function: Least Square Loss
- Small learning rate = 0.1
- Number of trees = 100
- Training Size: 60,000 events (min. bias)

$$\text{Least Sqare loss}: l(y_i, F(\mathbf{x_i})) = \frac{1}{2}(y_i - F(\mathbf{x_i}))^2$$

$$\Delta S_0 = \frac{1}{N_{\text{events}}} \sum_{n=1}^{N_{\text{events}}} |S_{0_n}^{true} - S_{0_n}^{pred.}|$$

Size of training data		2K	10K	20K	40K	50K	60K
Δb [fm]	(Impact parameter)	0.71	0.62	0.58	0.53	0.52	0.52
ΔS_0	(Spherocity)	0.079	0.068	0.062	0.058	0.056	0.055

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J. H. Friedman, Ann. Stat. 29, 1189 (2001).

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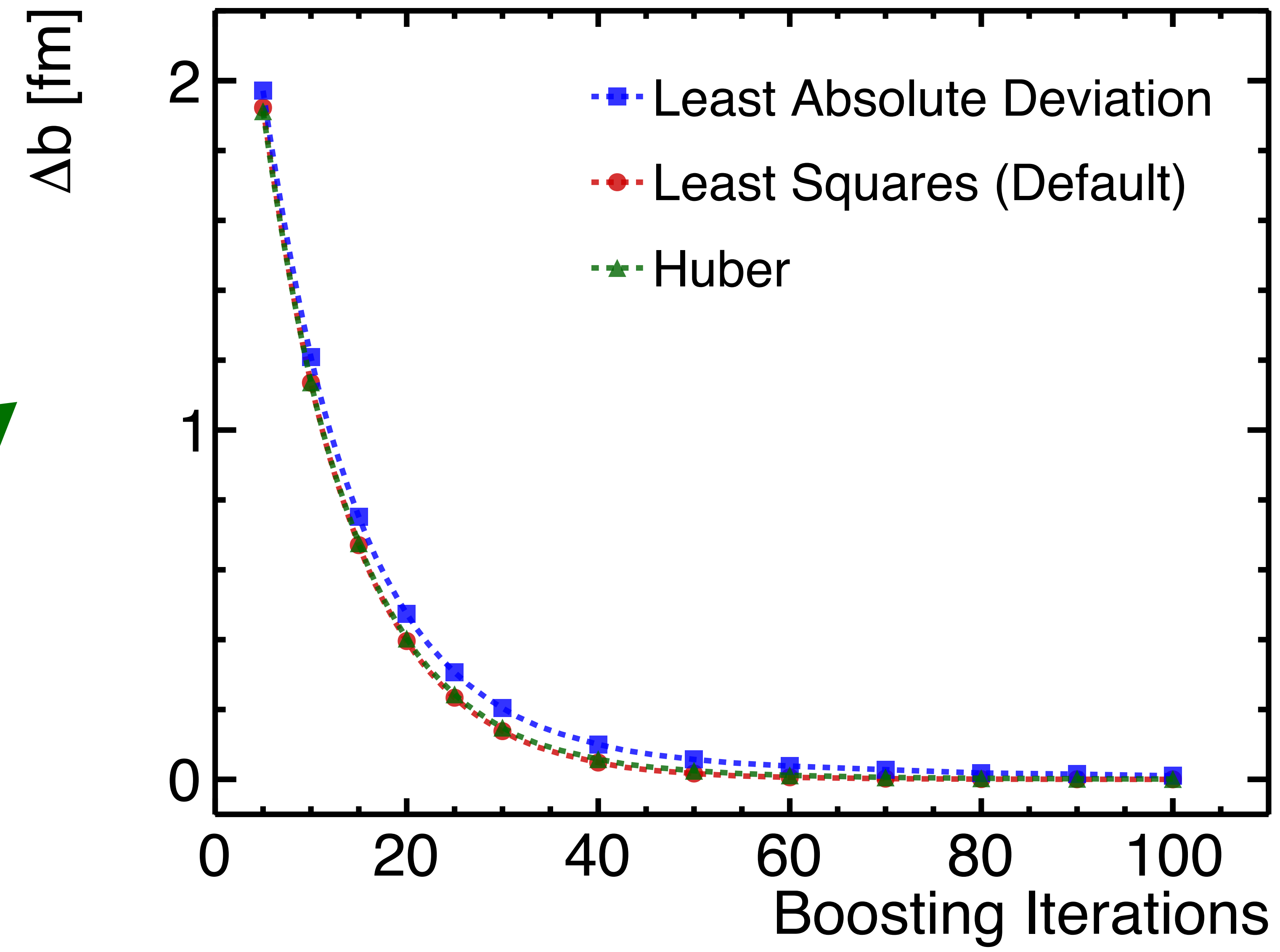

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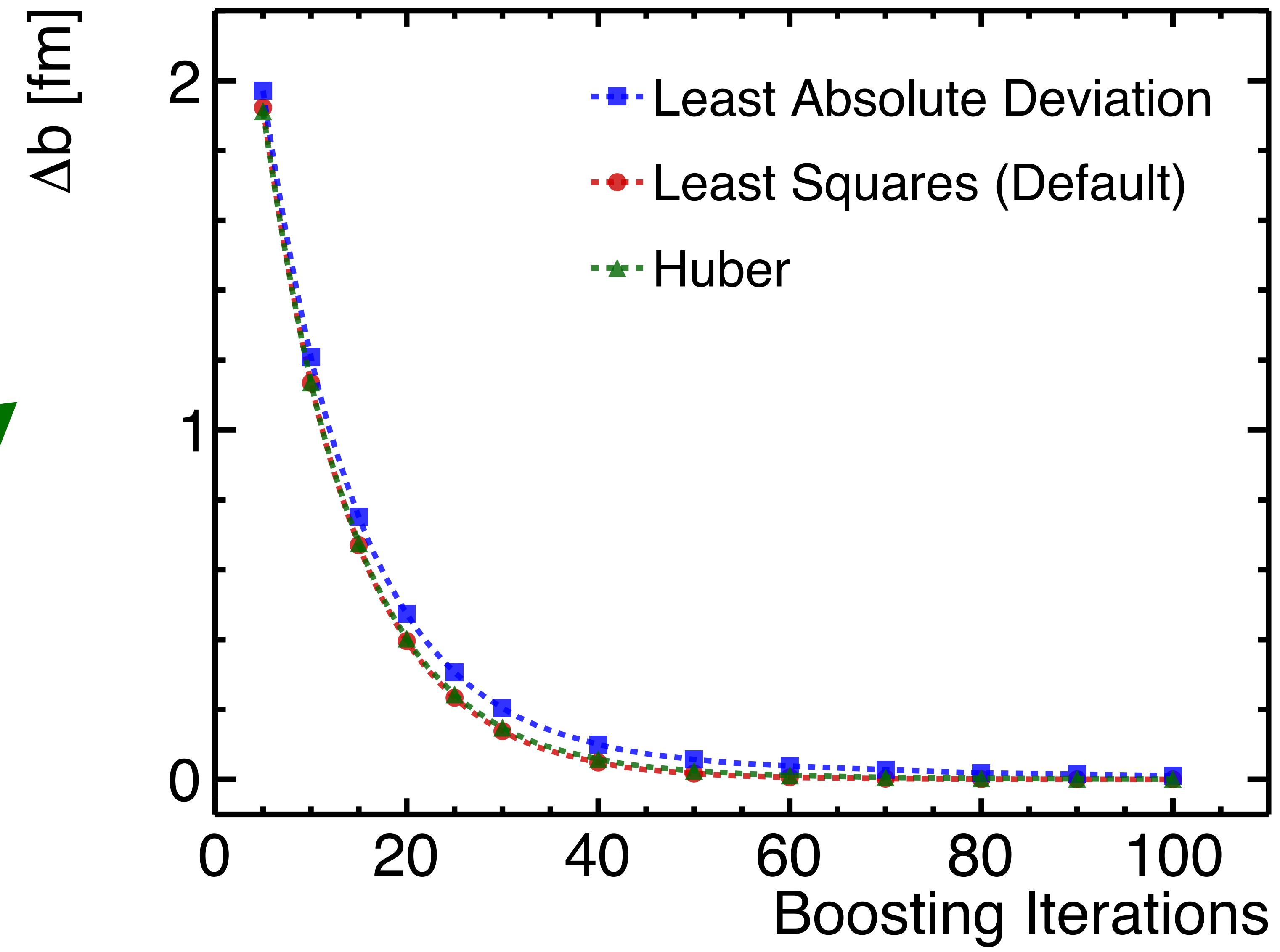

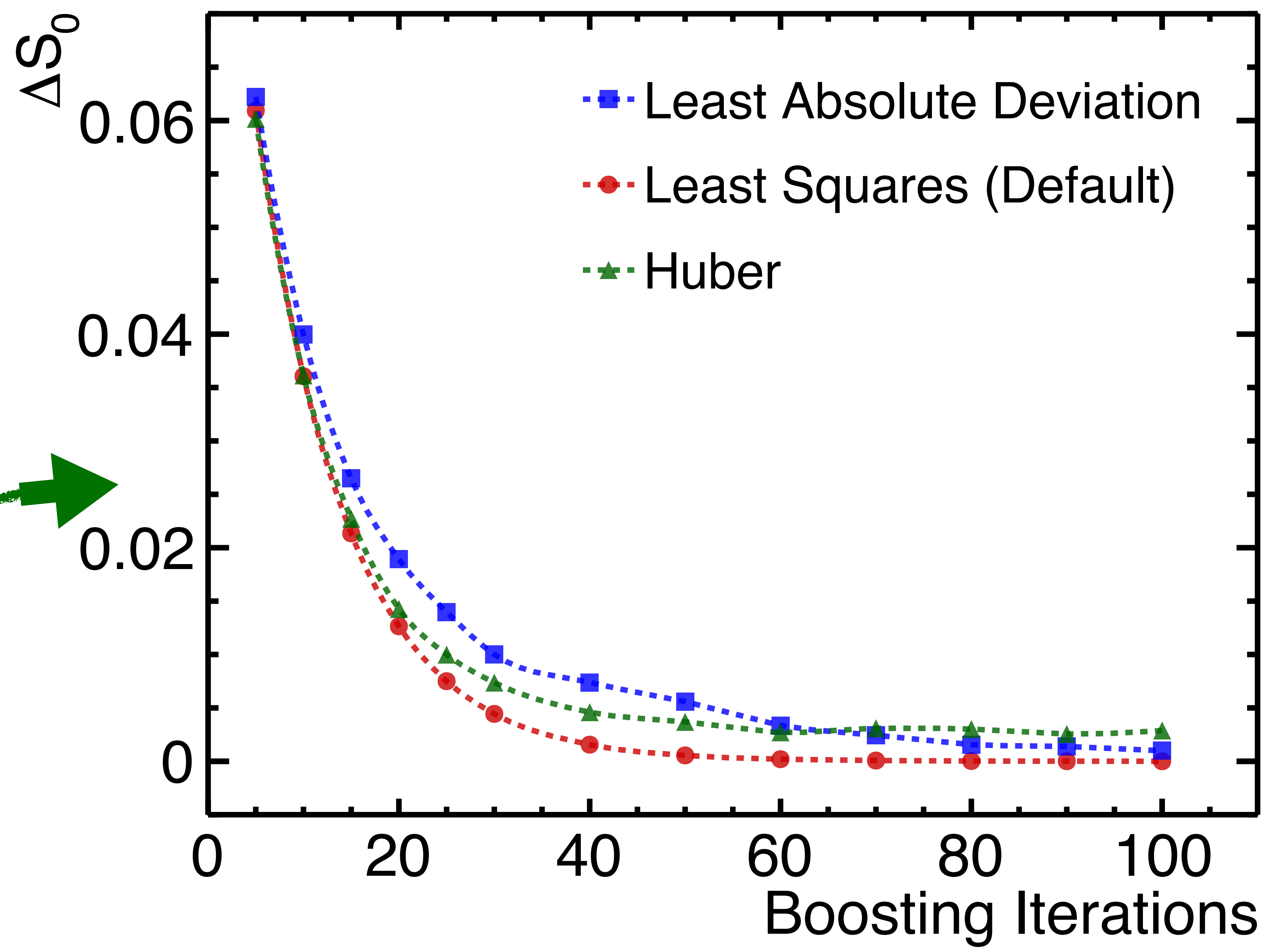

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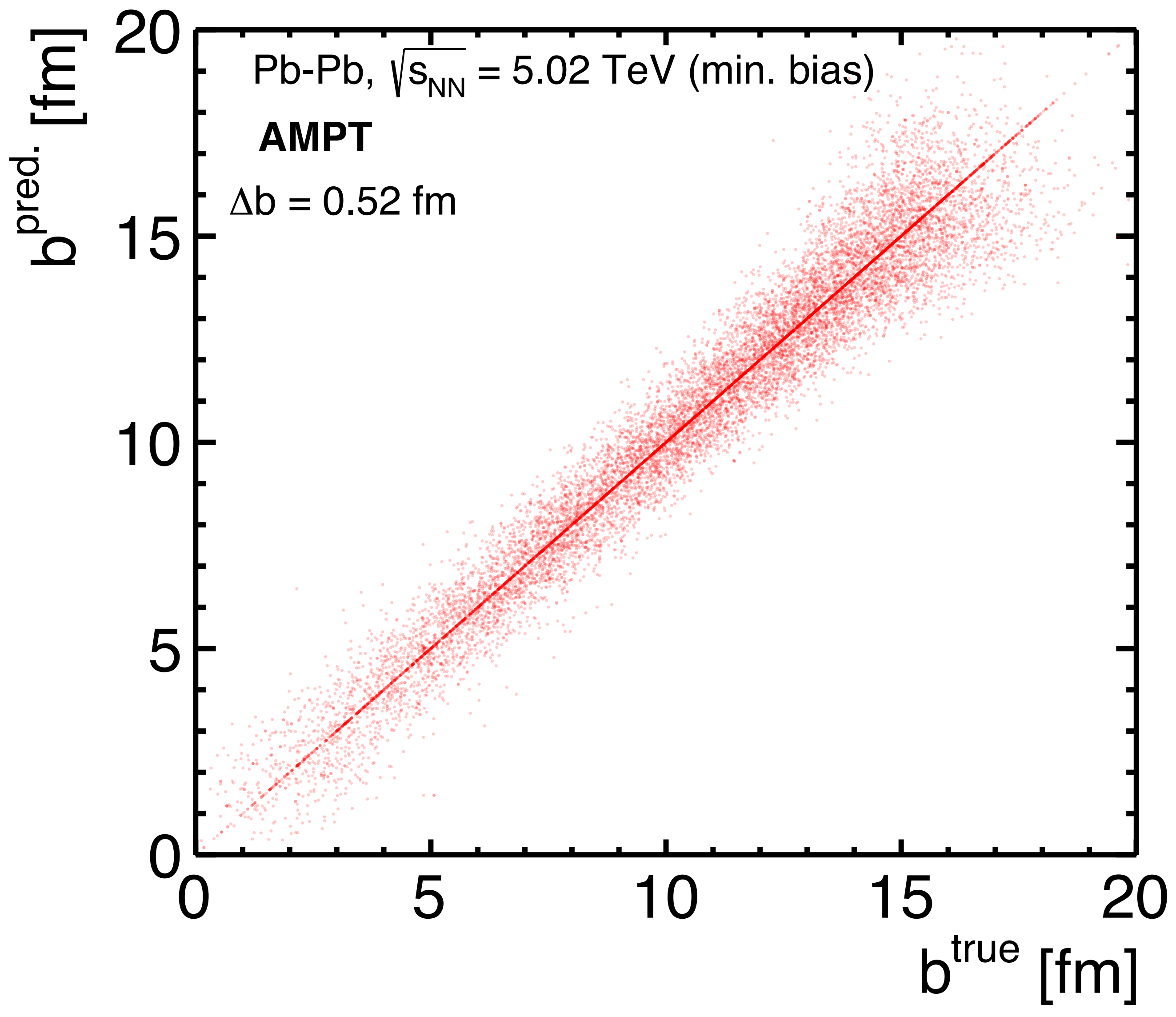

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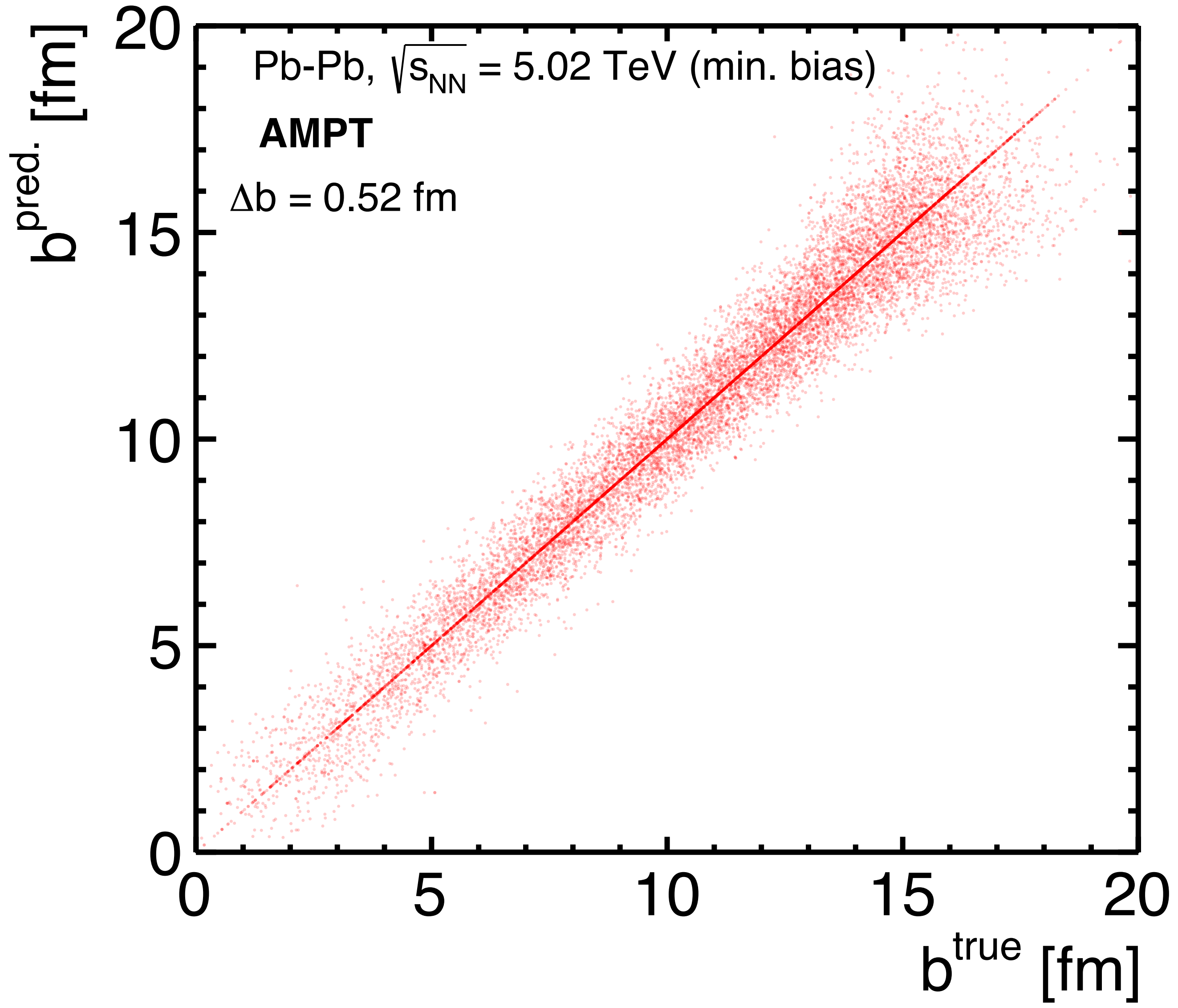

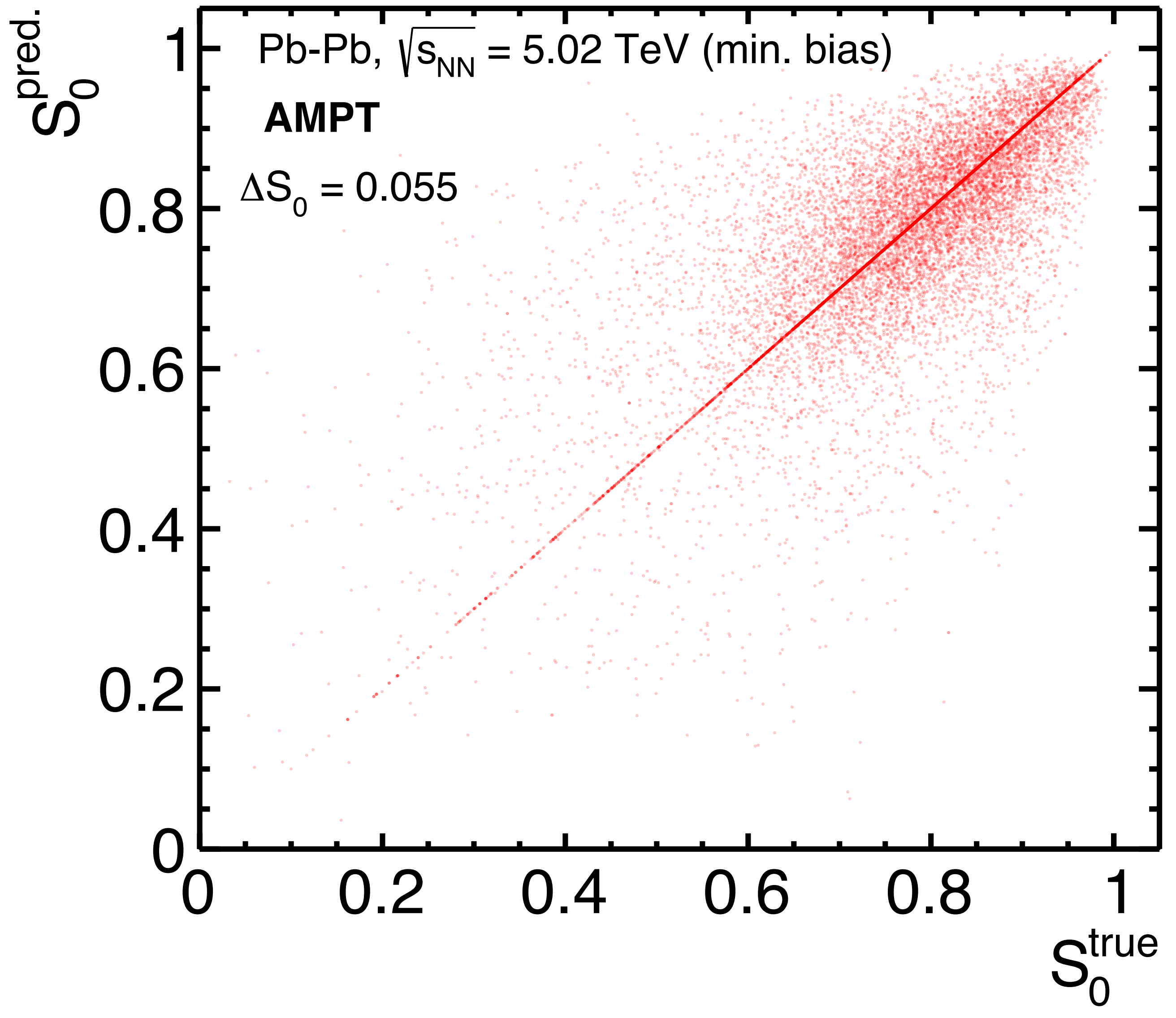

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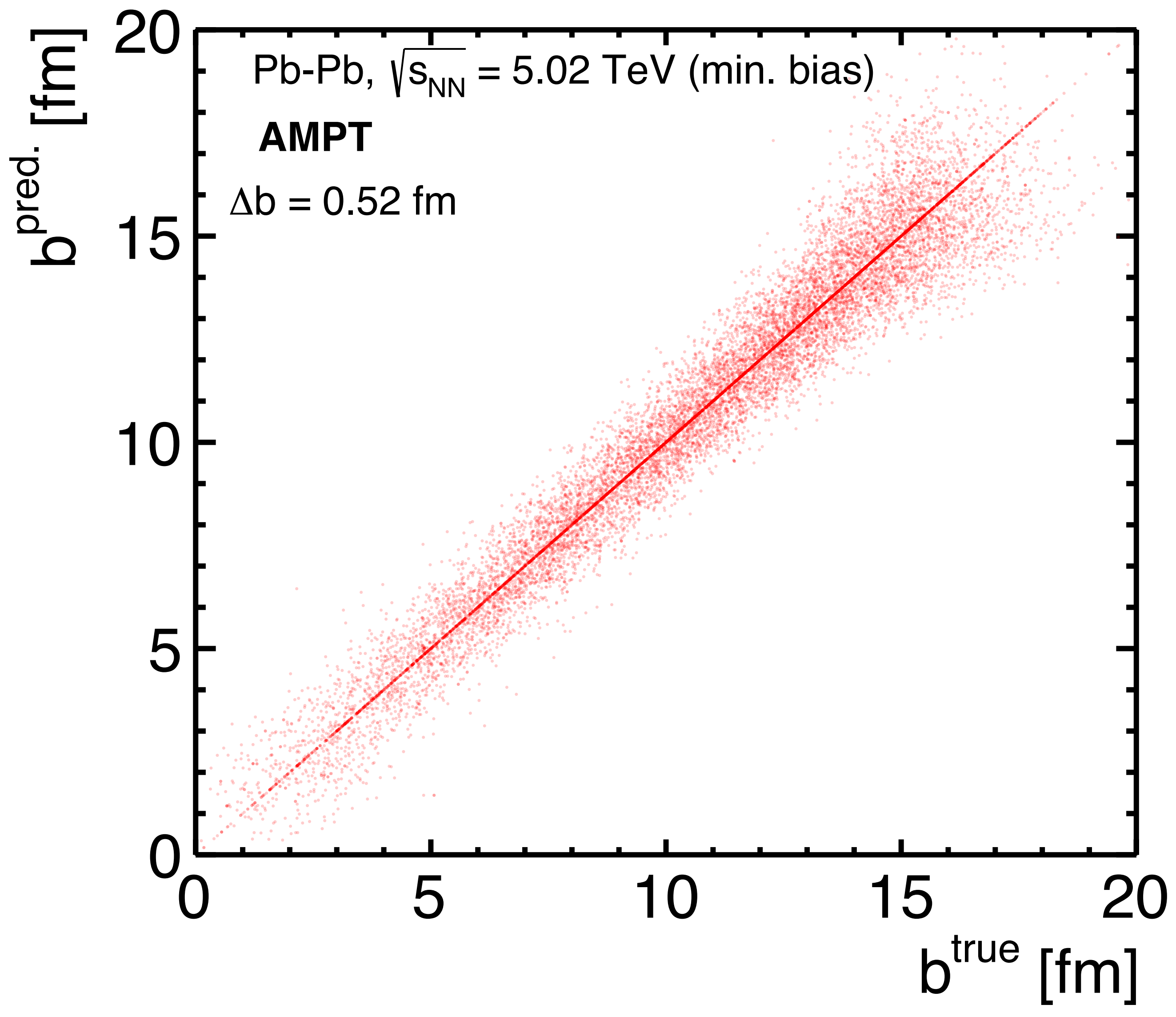

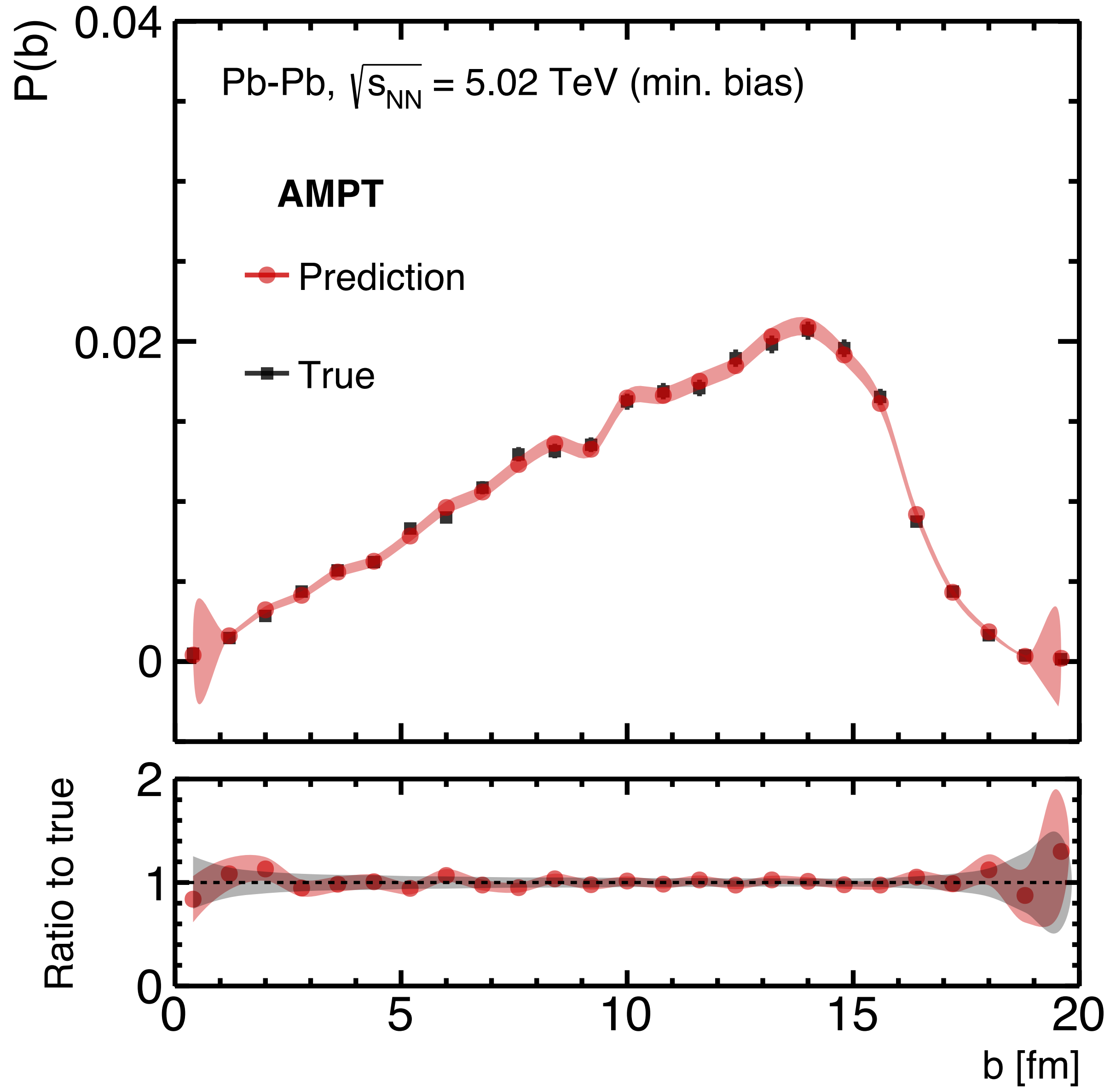

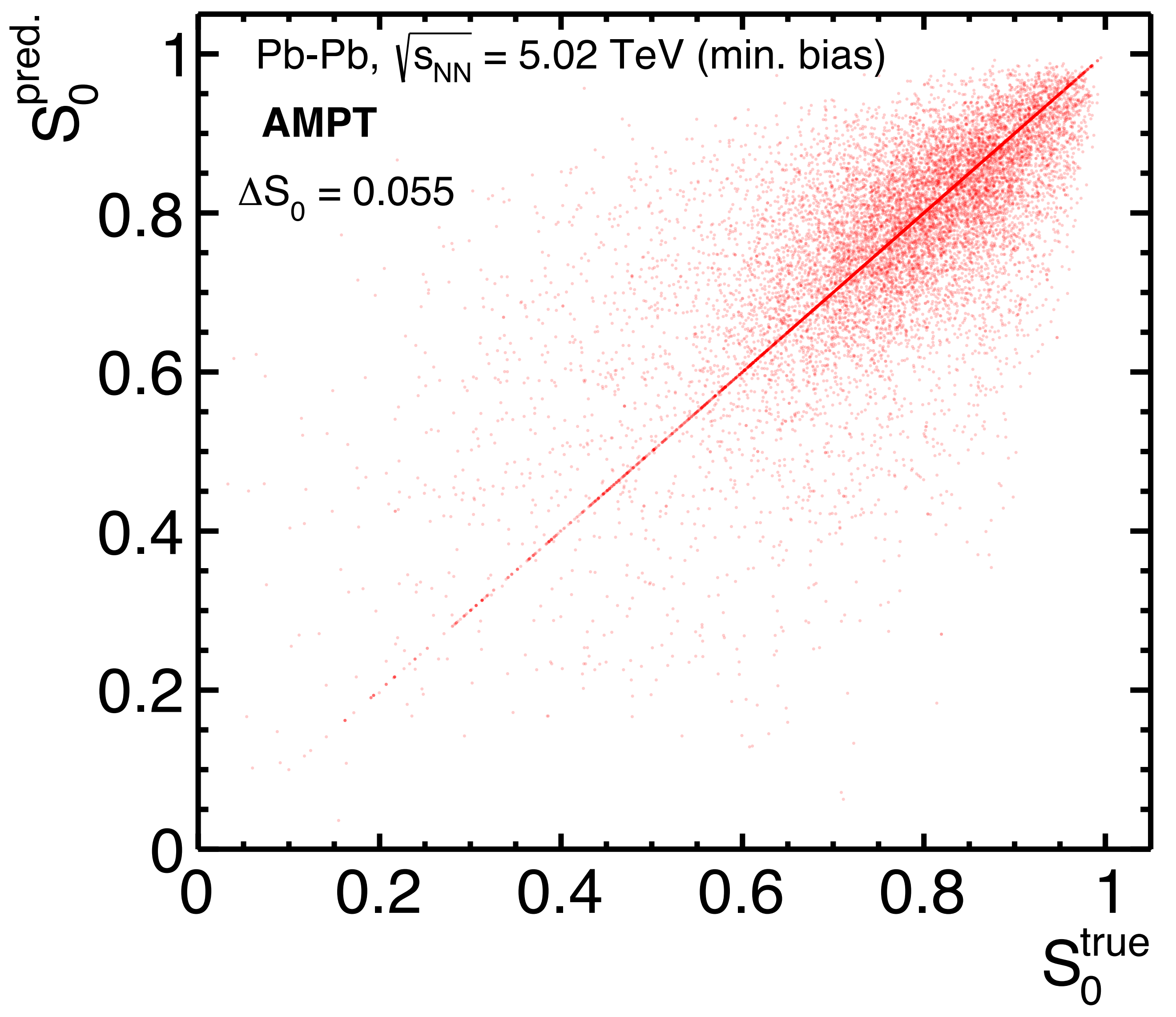

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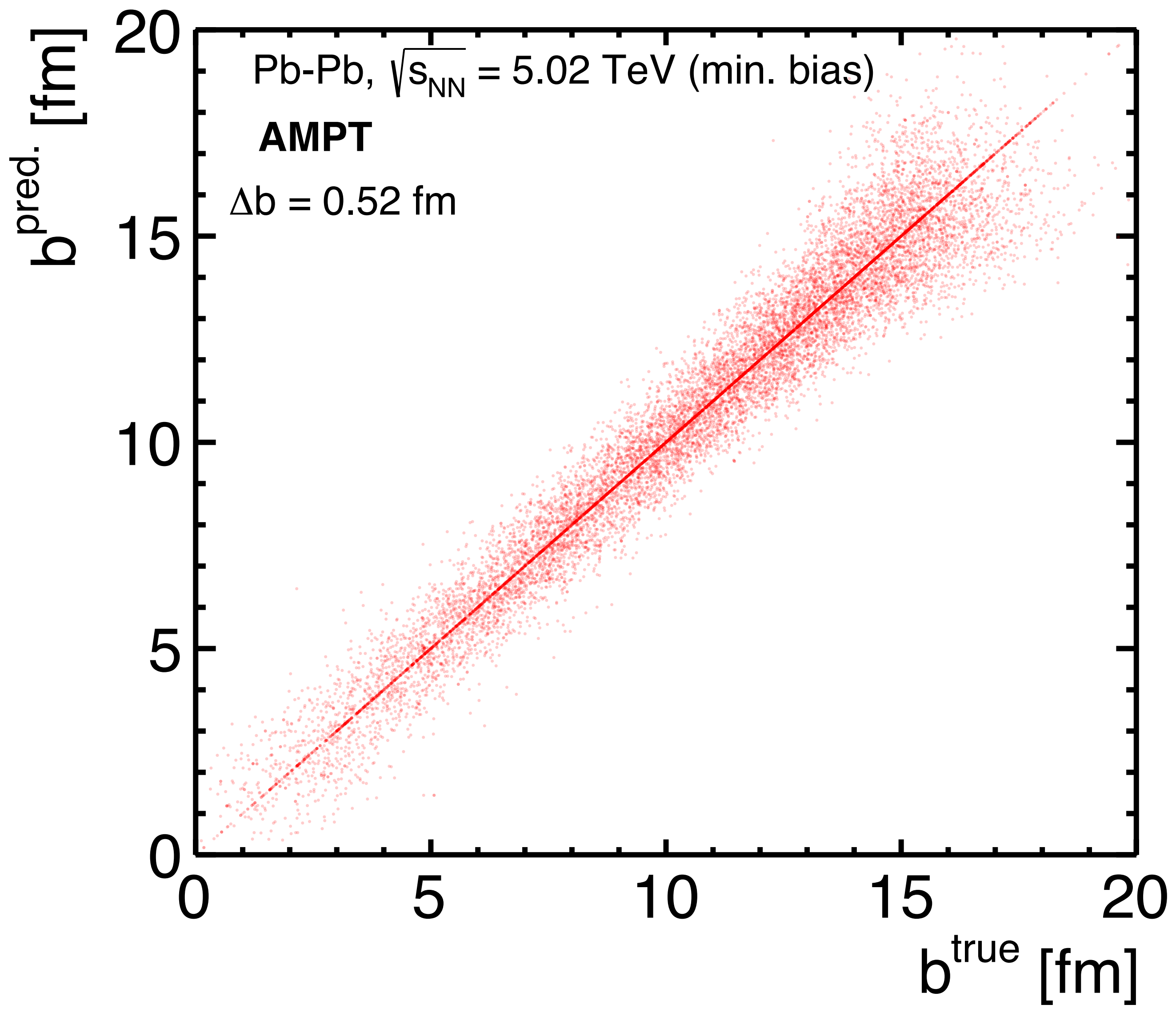

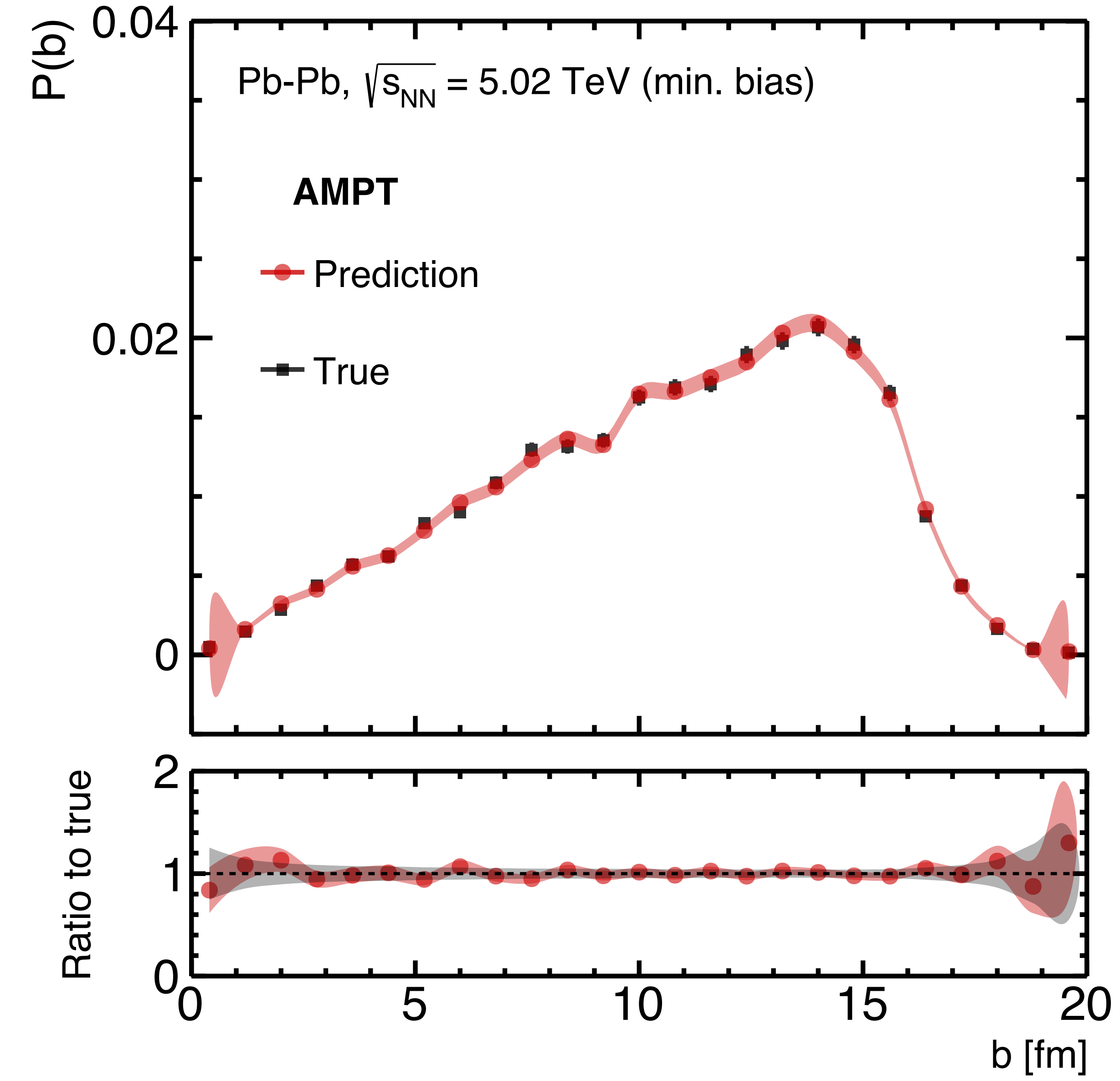

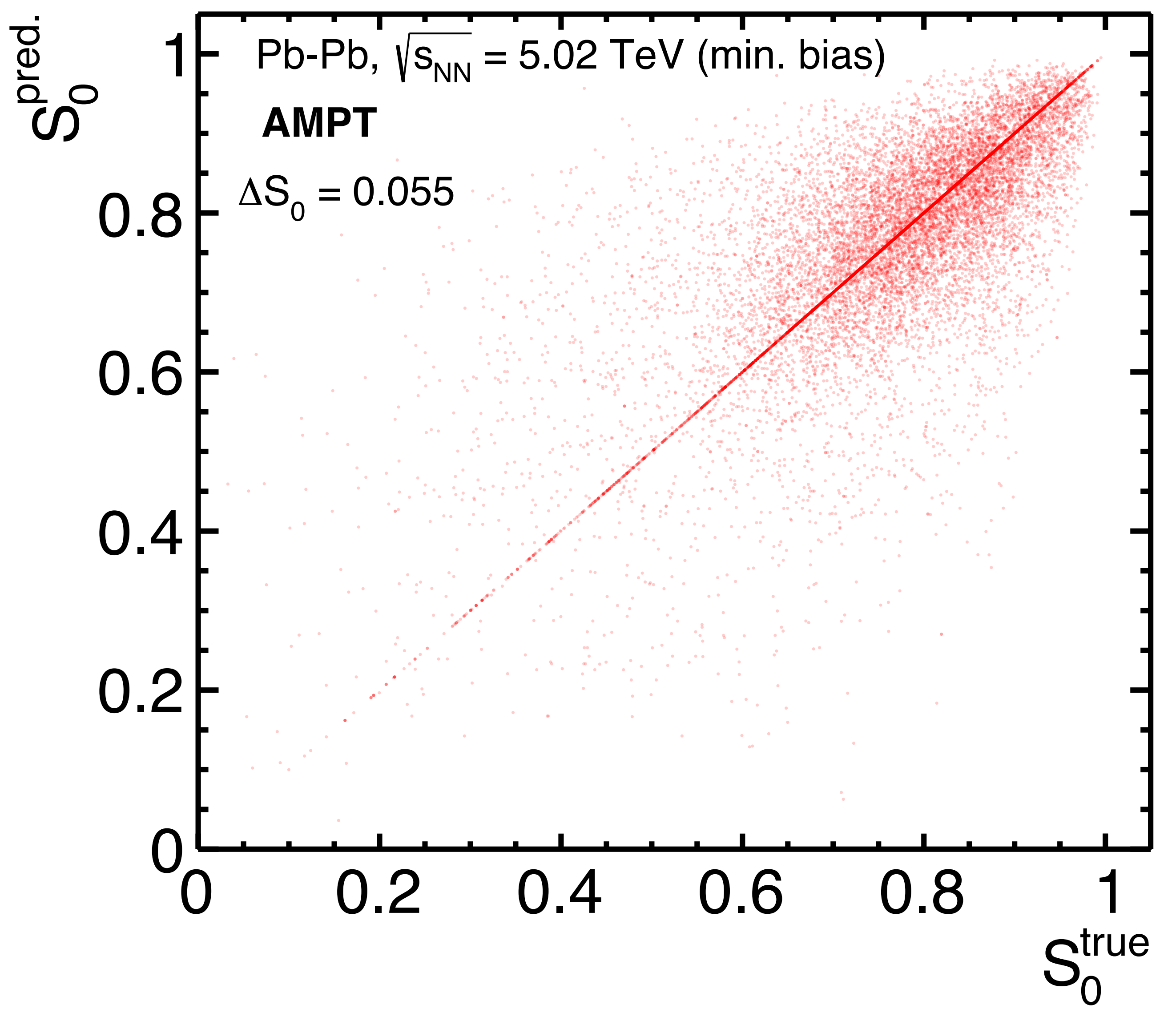

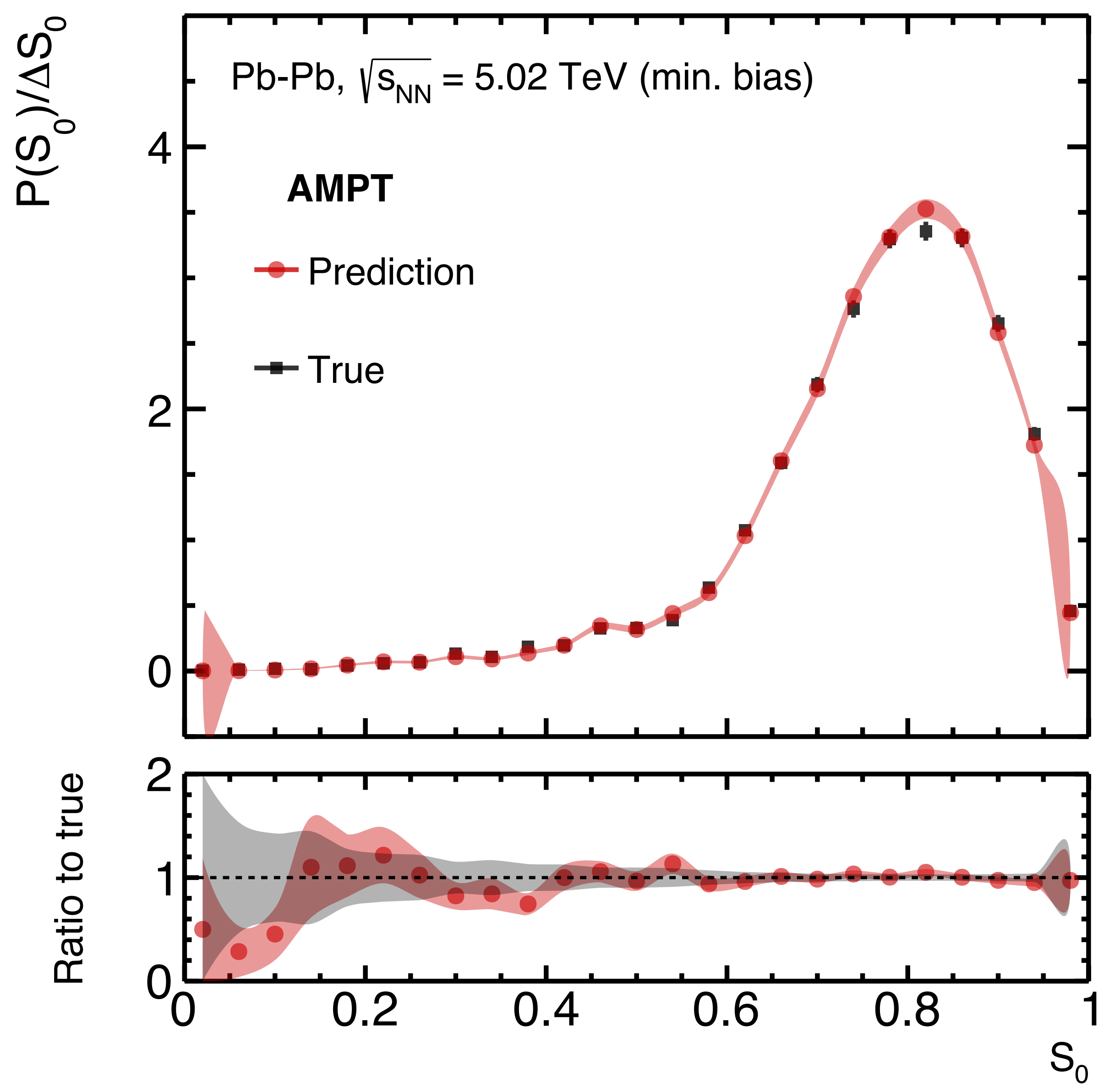

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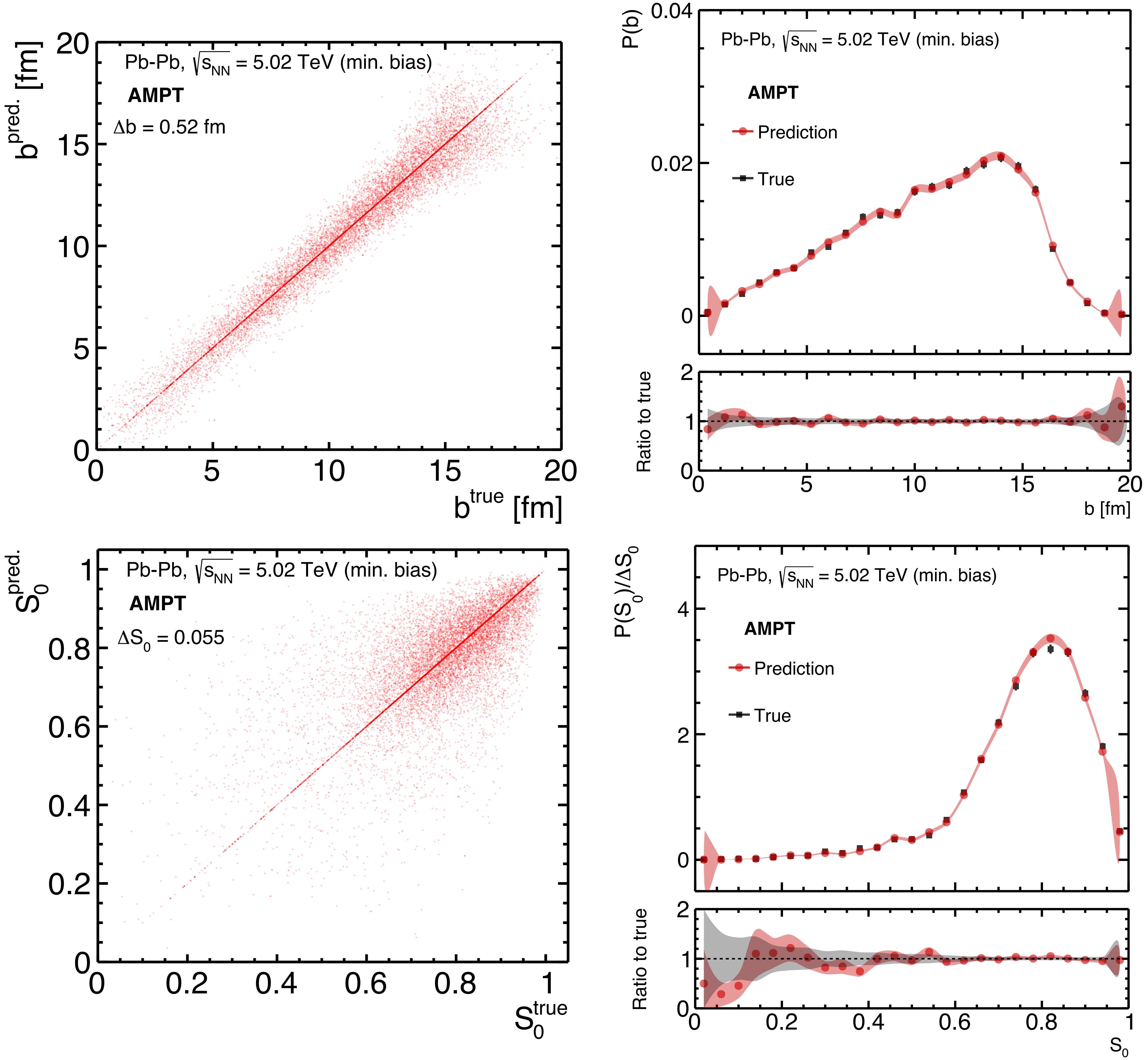

- The ML model trained with 5.02 TeV minimum bias simulated data
- Most of the points populate $y = x$
- The predictions for both impact parameter and spherocity distributions are in good agreement with the simulated data

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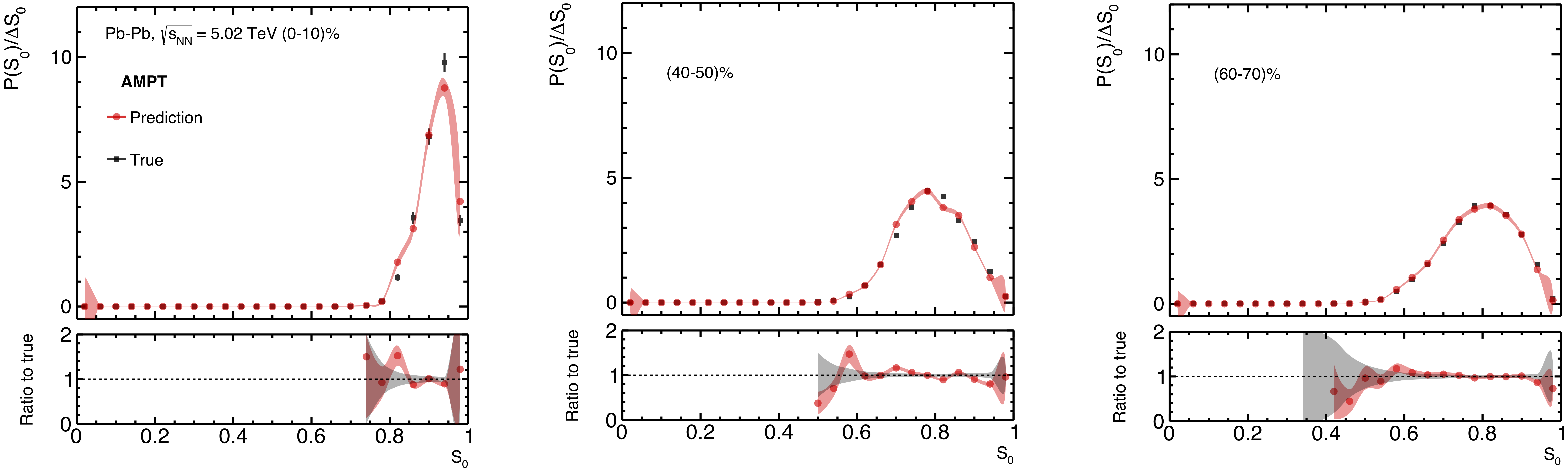

- Centrality-wise spherocity distributions
- Training is done using minimum bias simulated data
- **BDT preserves the centrality (or multiplicity) dependence**

N. Mallick, S. Tripathy, A. N. Mishra, S. Deb, and R. Sahoo, Phys. Rev. D103, 094031 (2021)

Summary

Summary

- Report the first implementation of ML tools for the estimation of impact parameter and transverse spherocity in heavy-ion collisions at the LHC
- BDT preserves the centrality and energy dependence of particle production
- Final state particle information is used
- Training is resource hungry → application is faster and economic
- A learning process → Scope for improvements

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- Report the first implementation of ML tools for the estimation of impact parameter and transverse spherocity in heavy-ion collisions at the LHC
- BDT preserves the centrality and energy dependence of particle production
- Final state particle information is used
- Training is resource hungry → application is faster and economic
- A learning process → Scope for improvements

Thank you!