



Implementation of machine learning techniques to predict impact parameter and transverse spherocity in heavy-ion collisions at the LHC

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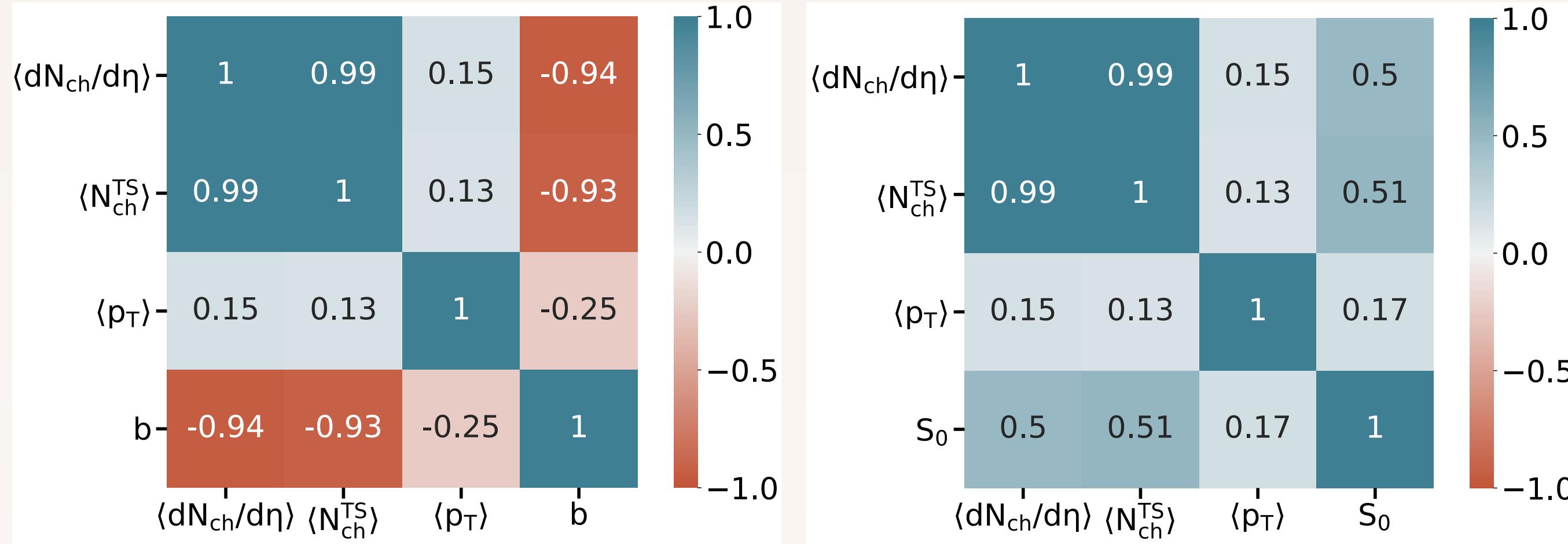
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1. Introduction

- Machine learning is being used in various classification and regression problems
- ML gives ability to the machine to predict an outcome without being explicitly programmed
- A multi-phase transport (AMPT) model is used for data generation
- Impact parameter is a crucial observable in heavy-ion collisions yet almost impossible to predict in experiments
- Transverse spherocity, an event shape observable, has recently been introduced in heavy-ion collisions to study azimuthal anisotropy [1]
- In the absence of any experimental exploration, ML could be used to estimate spherocity

2. Observables



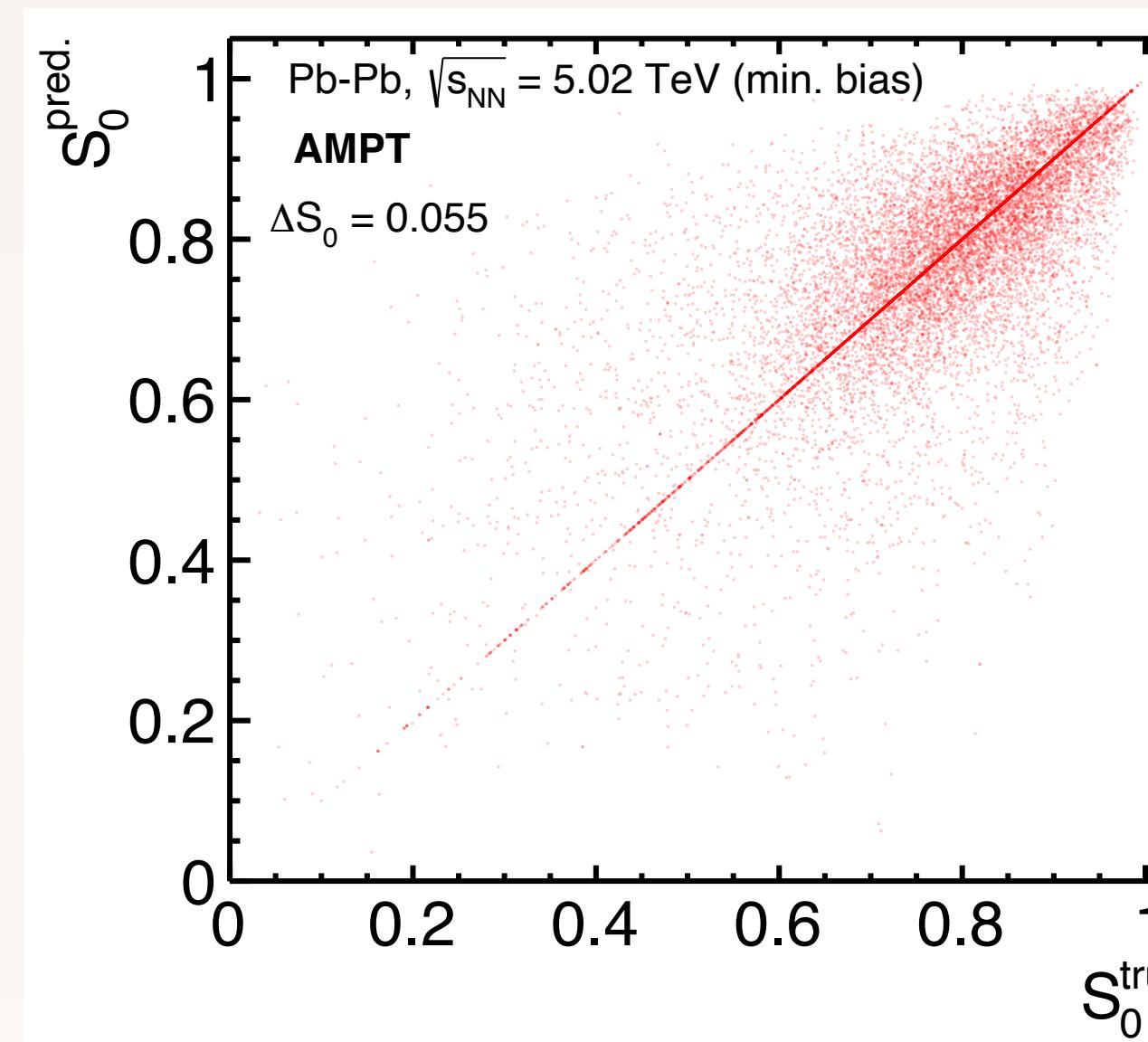
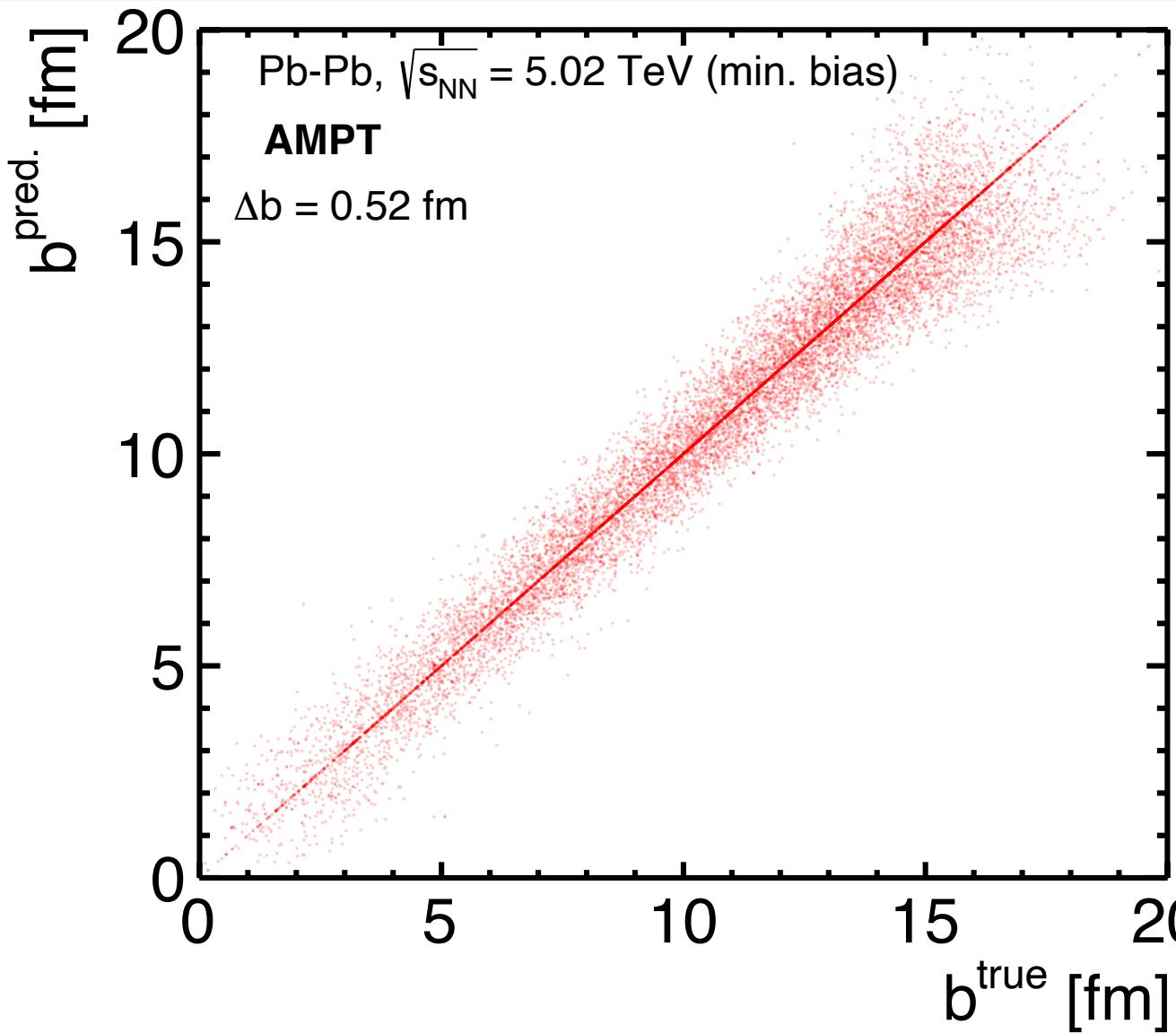
- Final state observables such as charged particle multiplicity, charged particle multiplicity in the transverse region and mean transverse momentum are chosen as the input
- Pearson correlation coefficient indicates strong linear correlation among the chosen input and target observables

2. Method

- Gradient boosting decision trees (GBDTs) for regression [2,3]
- Loss function: Least squares, Least absolute deviation and Huber function
- Maximum number of trees: 100
- Learning rate: 0.1, Maximum depth: 40
- Training sample size: 60,000 events
- The least difference in Δb and ΔS_0 among the different

loss functions are taken as the systematic uncertainty

$$\Delta b = \frac{1}{N_{\text{events}}} \sum_{n=1}^{N_{\text{events}}} |b_n^{\text{true}} - b_n^{\text{pred.}}|$$

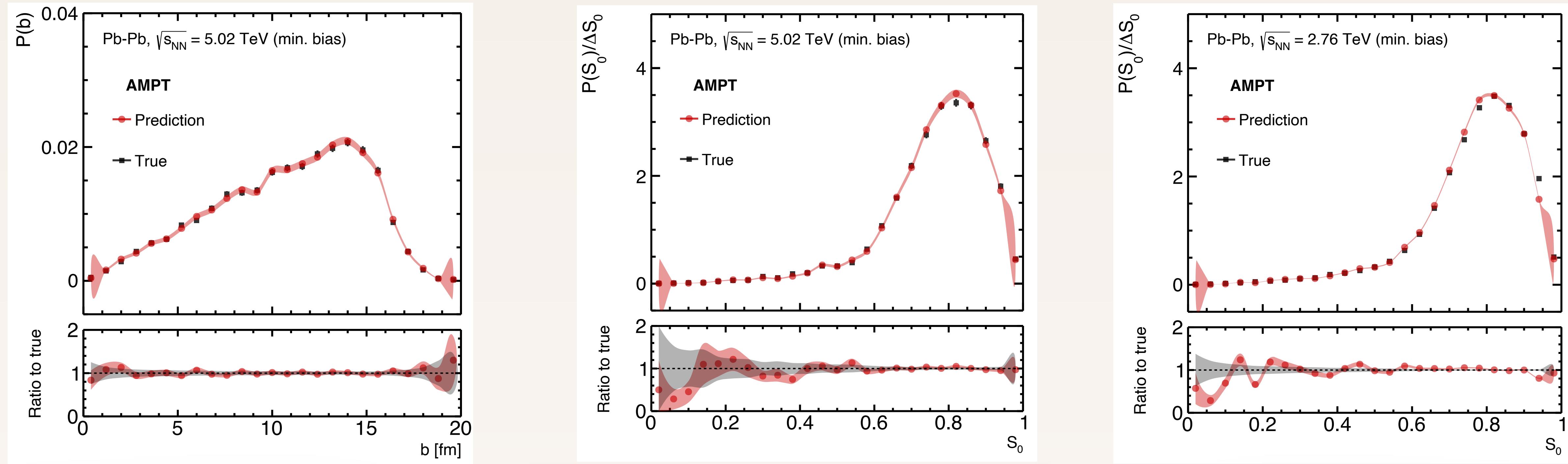


- Least squares loss function gives minimum Δb and ΔS_0
- Training error saturates at 60K events
- Prediction error for $\Delta b = 0.52 \text{ fm}$ and $\Delta S_0 = 0.055$
- Prediction vs. true plot shows a straight line with slope = 1

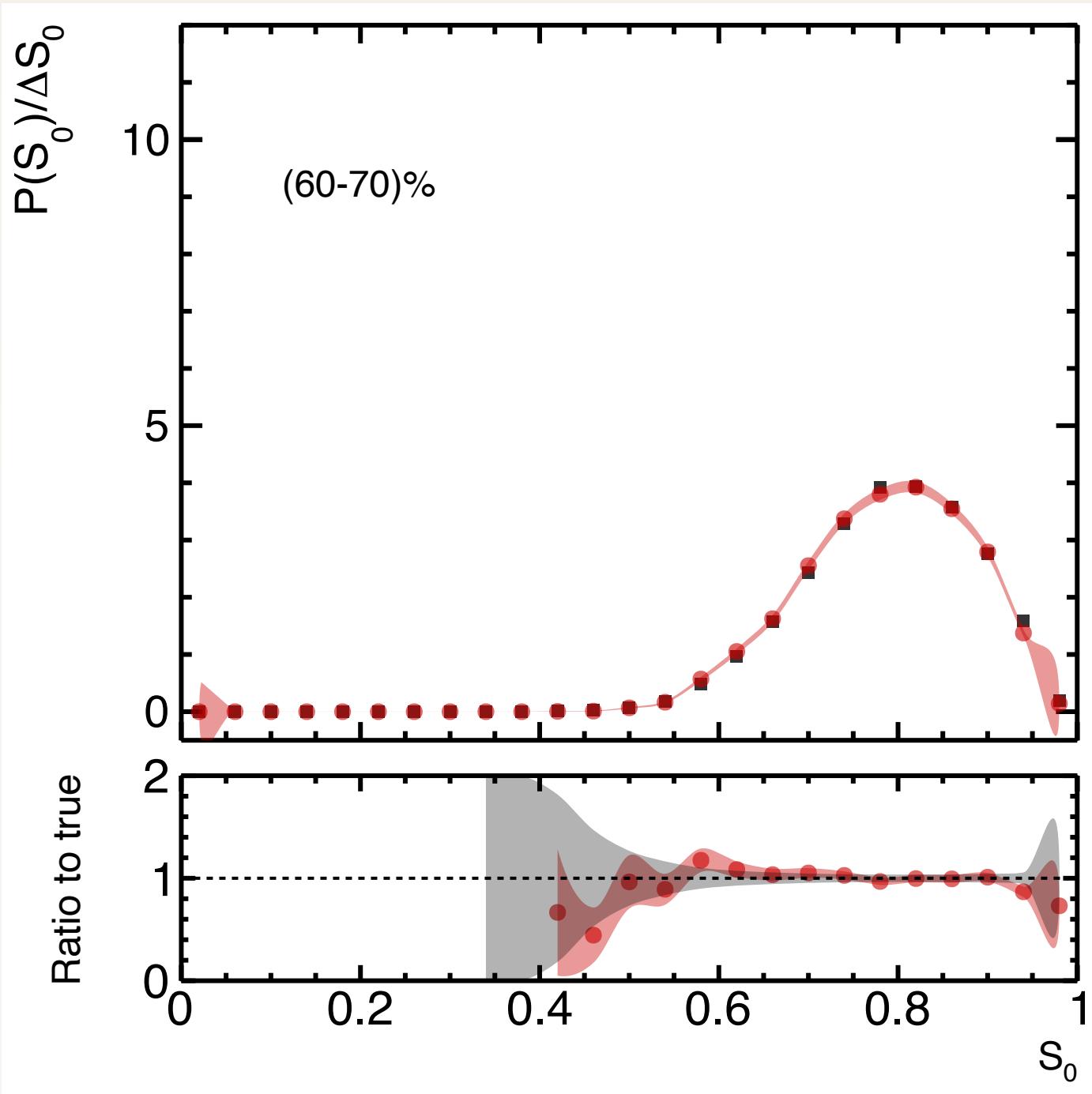
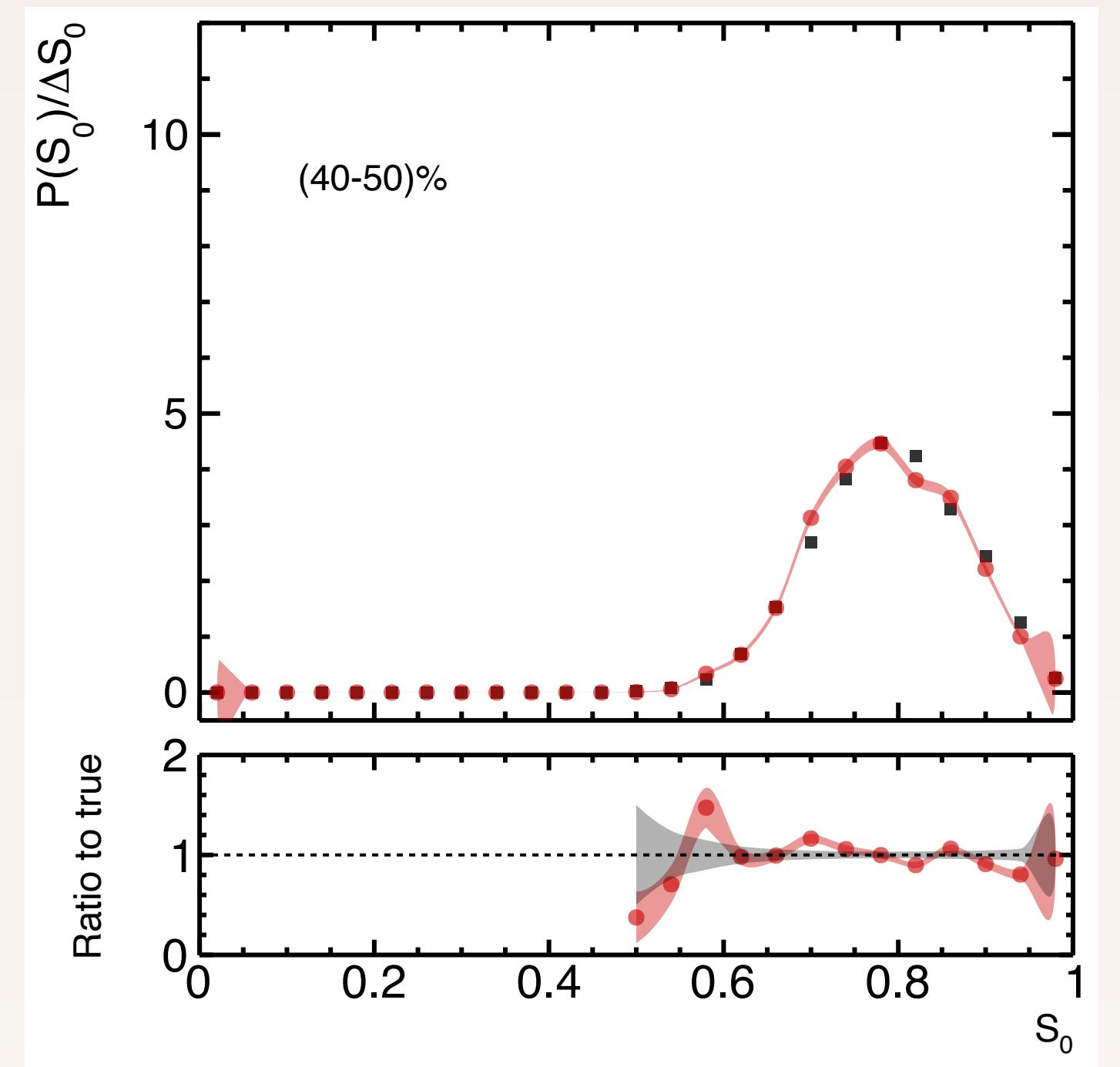
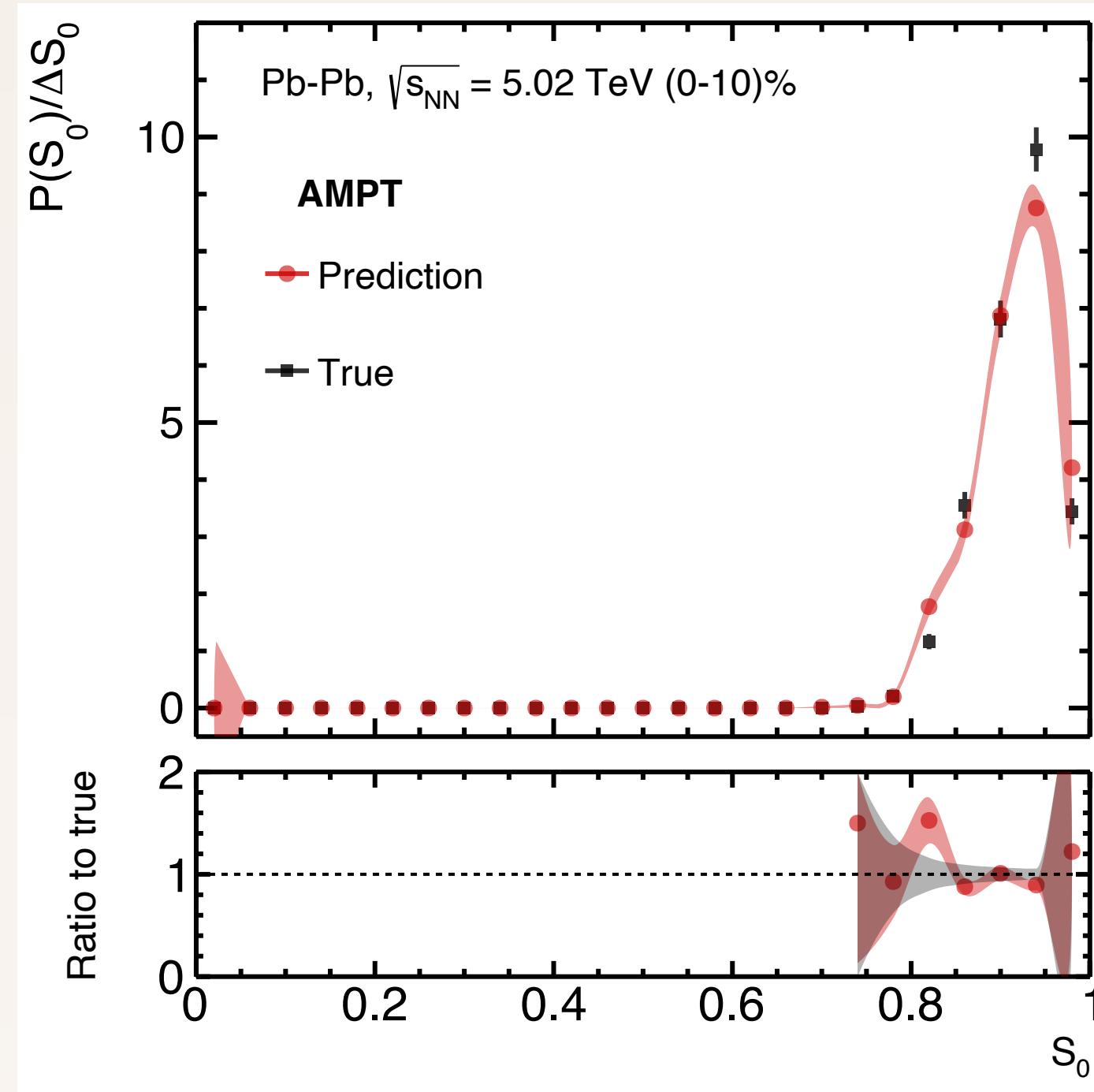
2. J. H. Friedman, [Ann. Stat. 29, 1189 \(2001\)](#).

3. L. Breiman, J. H. Friedman, R. A. Olshen, and C. J. Stone, Classification and Regression Trees (Wadsworth & Brooks/Cole Advanced Books & Software, Monterey, CA, 1984), p. 358,
<https://doi.org/10.1002/cyto.990080516>.

3. Results and discussions



- Training for impact parameter and transverse spherocity is done on Pb-Pb collisions, $\sqrt{s_{NN}} = 5.02$ TeV (min. bias) data from AMPT
- Black band denotes **statistical uncertainty** in simulated (true) values
- Red band denotes the **quadratic sum of statistical and systematic uncertainty** in the predicted values from the ML-model
- The predictions for impact parameter and transverse spherocity in Pb-Pb collisions, $\sqrt{s_{NN}} = 5.02$ TeV (min. bias) are in **good agreement with the true values**
- ML-model trained on Pb-Pb collisions, $\sqrt{s_{NN}} = 5.02$ TeV (min. bias) data **successfully predicts** transverse spherocity distribution for Pb-Pb collisions, $\sqrt{s_{NN}} = 2.76$ TeV (min. bias)



- Training for transverse spherocity is done on **Pb-Pb collisions, $\sqrt{s_{NN}} = 5.02$ TeV (min. bias)** data from AMPT
- Black band denotes **statistical uncertainty** in simulated (true) values
- Red band denotes the **quadratic sum of statistical and systematic uncertainty** in the predicted values from the ML-model
- ML-model trained on **Pb-Pb collisions, $\sqrt{s_{NN}} = 5.02$ TeV (min. bias)** data **successfully predicts** the transverse spherocity distributions at various centralities such as (0-10)%, (40-50)% and (60-70)%