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Jet tagging performance in Run 3 PbPb collisions at 5.36 TeV in CMS

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Abstract

The identification of jets initiated by heavy-flavoured particles is a crucial tool in the study of the interaction of these particles with the medium formed after a collision of heavy ions. The algorithms used in the first lead-lead (PbPb) LHC runs relied on the identification of secondary vertices, and the measurement of the displacement and other properties of the tracks in the jets. These variables were combined in a multivariate discriminator. Although adequate for the measurements performed, the performance of these algorithms was significantly worsened in more central collisions, where the impact parameter between the colliding Pb ions is small.

Recent developments on heavy-flavour identification, based on the ParticleTransformer architecture, brought significant improvements not only in the performance but also in the robustness against mis-modelling in simulation, compared to data. This has been possible thanks to the use of adversarial training approaches.

In this note it is demonstrated that with a dedicated training, taking into account the characteristics of the underlying events in PbPb collisions, it is expected to be possible to achieve a significant improvement in the performance as well as a more robust behaviour with respect to the centrality of the collisions.

Jet tagging performance in Run 3 PbPb collisions at 5.36 TeV in CMS

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The identification of jets initiated by heavy-flavoured particles is a crucial tool in the study of the interaction of these particles with the medium formed after a collision of heavy ions. The algorithms used in the first lead-lead (PbPb) LHC runs relied on the identification of secondary vertices, and the measurement of the displacement and other properties of the tracks in the jets. These variables were combined in a multivariate discriminator. Although adequate for the measurements performed, the performance of these algorithms was significantly worsened in more central collisions, where the impact parameter between the colliding Pb ions is small.

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Glossaries

- **AK4 jets**: Jets that are reconstructed by the anti-k_T algorithm [1,2] with a distance parameter of R = 0.4 using particle-flow candidates. In order to subtract the soft underlying event contribution to the jet energy in PbPb collisions, a constituent subtraction method [3] is employed.

- **Heavy-flavour jets:** Jets originating from the hadronization of bottom (b) or charm (c) hadrons.
- **Light-flavour jets:** Jets originating from the hadronization of light-flavour (uds) quarks or gluons (g).
- **Tau jets:** Jets originating from tau leptons decaying to hadrons (τ_h).

- **Secondary Vertex (SV):** The point from where the b or c hadron decays. The vertex reconstruction is performed using the adaptive vertex fitter and inclusive vertex finding (IVF) algorithm [4]. The resulting list of vertices is then subject to a cleaning procedure, rejecting SV candidates that share 70% or more of their tracks, or if the significance of the flight distance between the two secondary vertices is less than 2, one of the two secondary vertices is dropped from the collection of secondary vertices [4].

- **Adversarial Attacks (AA):** A modification of the input data causing a machine learning model to make incorrect predictions or classifications. The distortions are introduced via a penalty derived from the cost function employed by the model.

Glossaries

Jet tagging scores: the following jet tagging scores are used across this note. The term "prob(X)" denotes the probability that a jet is tagged as initiated by particle X.

Bottom (b) vs light+charm (udsgc) jet score:

$$\mathrm{b\ vs\ udsgc} = \frac{\mathrm{prob}\,(\mathrm{b})}{\mathrm{prob}\,(\mathrm{b}) + \mathrm{prob}\,(\mathrm{c}) + \mathrm{prob}\,(\mathrm{udsg})}$$

Charm (c) vs bottom (b) jet score:

$$\mathrm{c\ vs\ b} = \frac{\mathrm{prob}\,(\mathrm{c})}{\mathrm{prob}\,(\mathrm{c}) + \mathrm{prob}\,(\mathrm{b})}$$

Charm (c) vs light (udsg) jet score:

$$\mathrm{c\ vs\ udsg} = \frac{\mathrm{prob}\,(\mathrm{c})}{\mathrm{prob}\,(\mathrm{c}) + \mathrm{prob}\,(\mathrm{udsg})}$$

Tau (τ_h) vs light+heavy (udsgcb) jet score:

$$\tau_h \mathrm{\ vs\ udsgcb} = \frac{\mathrm{prob}\,(\tau_h)}{\mathrm{prob}\,(\tau_h)\ +\ \mathrm{prob}\,(\mathrm{udsgcb})}$$

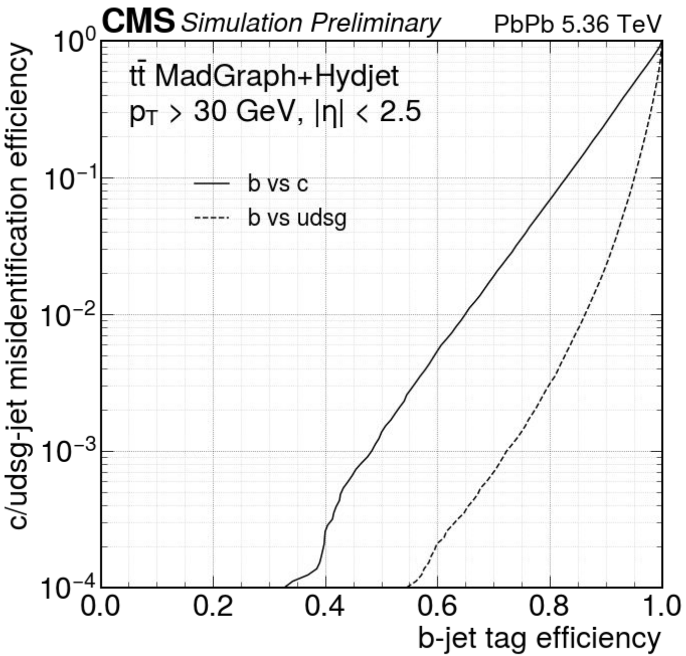
Glossaries

- **UParT:** A ParticleTransformer [5] model designed for AK4 jet tasks, performing in an inclusive way both heavy flavour and τ_h identification, combined with a flavour-aware jet energy regression and jet energy resolution estimation. It introduces pairwise "interaction" features between jet constituents (charged and neutral particles) and secondary vertices, enhancing internal jet relations. UParT utilizes a novel Adversarial Training (AT) paradigm based on the Rectified Normed Gradient Method (R-NGM) [6] maintaining the Particle Cloud representation, allowing the model to learn from input feature distortions and improve robustness against Monte-Carlo (MC) simulation mismodeling. Additionally, it preserves the feature importance mapping from AA gradient, highlighting critical features for jet classification and ensuring high performance and robustness in heavy-flavour tagging. More details on UParT are documented in [7].

- **PbPb run:** The Run 3 PbPb data taking period covered in this note took place in October of 2023. In order to train the jet taggers and assess their performance, a MC sample of top pair production derived using the MadGraph generator [8] and embedded in PbPb HYDJET underlying events [9] was used. The MC sample included a realistic simulation of the CMS detector using GEANT4 [10] and the data taking conditions of the 2023 PbPb run. This includes, among others, the emulation of dead areas in the barrel pixel detector [11].

- **PbPb centrality:** the collision centrality in PbPb events represents the degree of overlap or impact parameter of the two colliding nuclei, and is determined by the total transverse energy deposit in both Hadron Forward calorimeters [12].

b-tagging performance



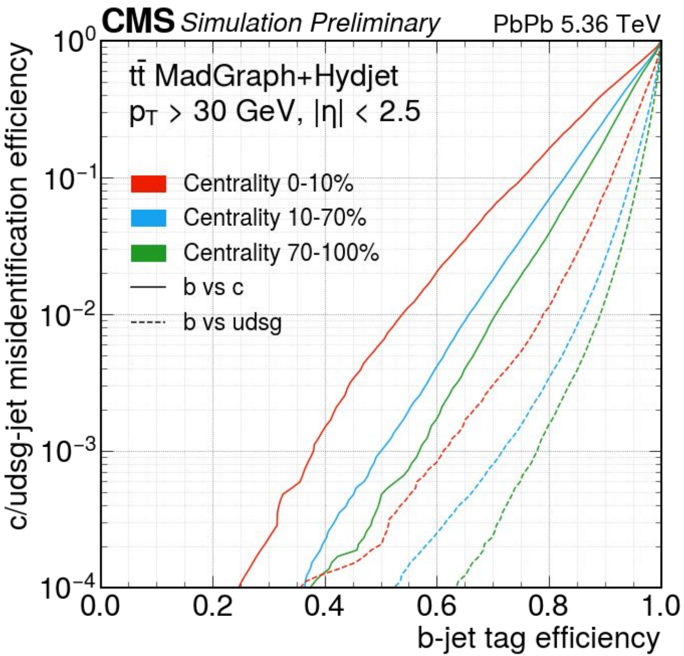
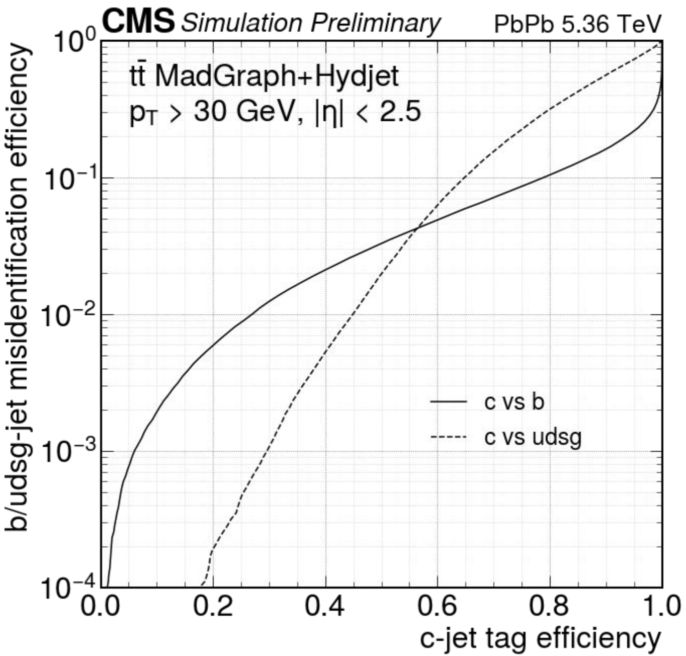


Figure 1 - UParT b-tagging ROC curves derived in a scenario where the PbPb centrality is uniformly distributed (left) and in different categories of PbPb centrality (right). The UParT performance is shown for both c-jet (solid line) and light-jet (dash line) rejection. The b vs udsgc score is used for both b vs c and b vs udsg discrimination.

c-tagging performance



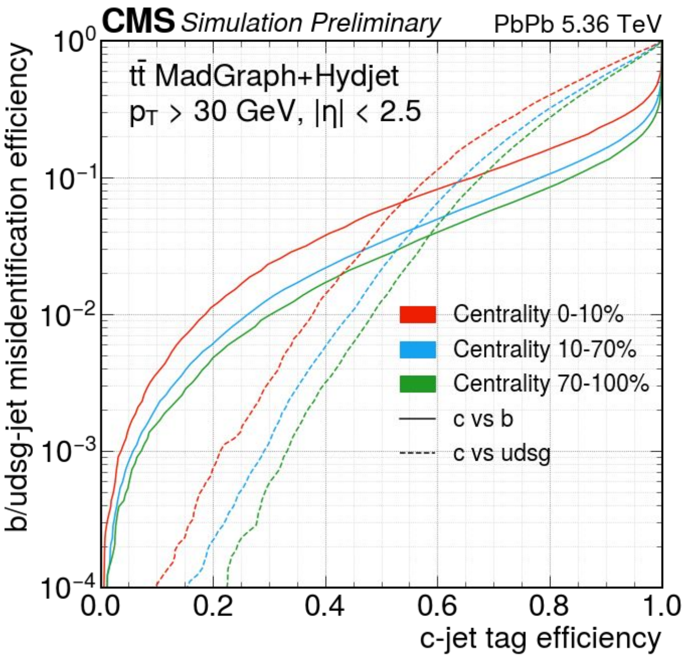


Figure 2 - UParT c-tagging ROC curves derived in a scenario where the PbPb centrality is uniformly distributed (left) and in different categories of PbPb centrality (right). The UParT performance is shown for both b-jet (solid line) and light-jet (dash line) rejection. The c vs b (c vs udsg) score is used for c vs b (c vs udsg) discrimination. Charm jet tagging is trained on PbPb events for the first time in Run 3.

τ_h-tagging performance

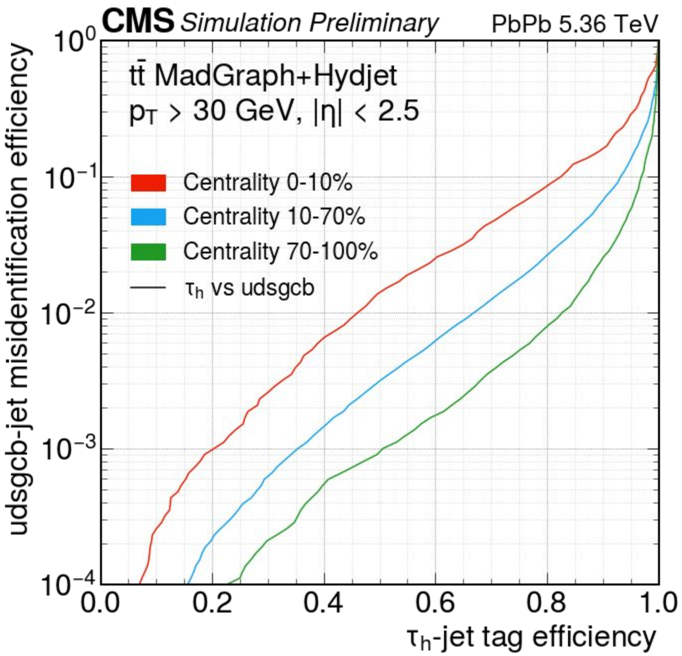
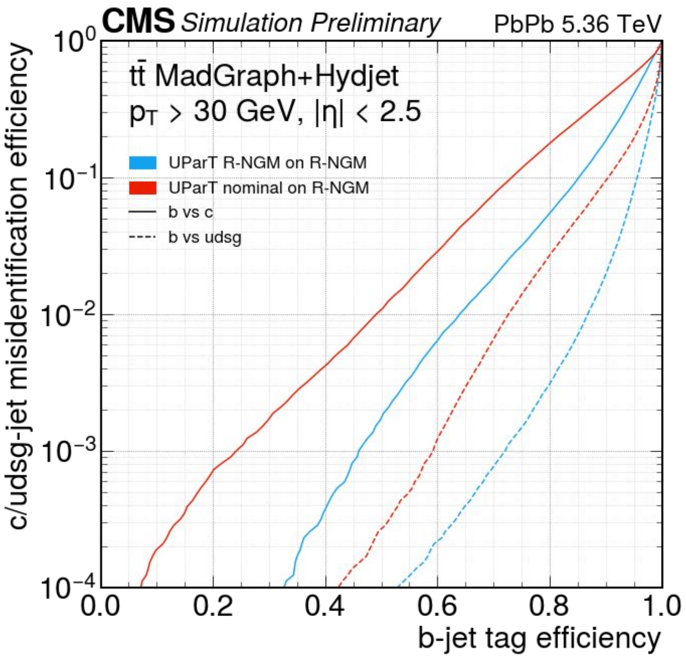


Figure 3 - UParT τ_h-tagging ROC curves derived in different categories of PbPb centrality. The UParT performance is shown for all (light and heavy) jet rejection. The τ_h vs udsgcb score is used. Tau jet tagging is trained on PbPb events for the first time in Run 3.

b and c-tagging robustness



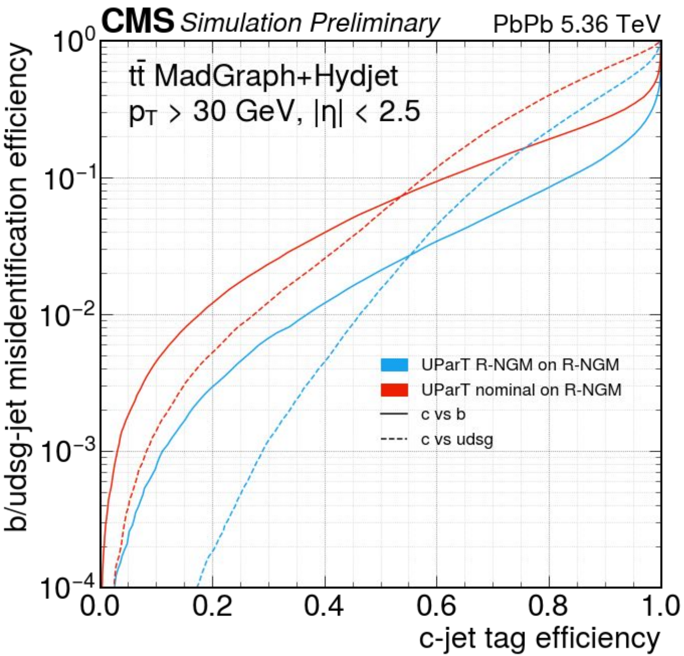
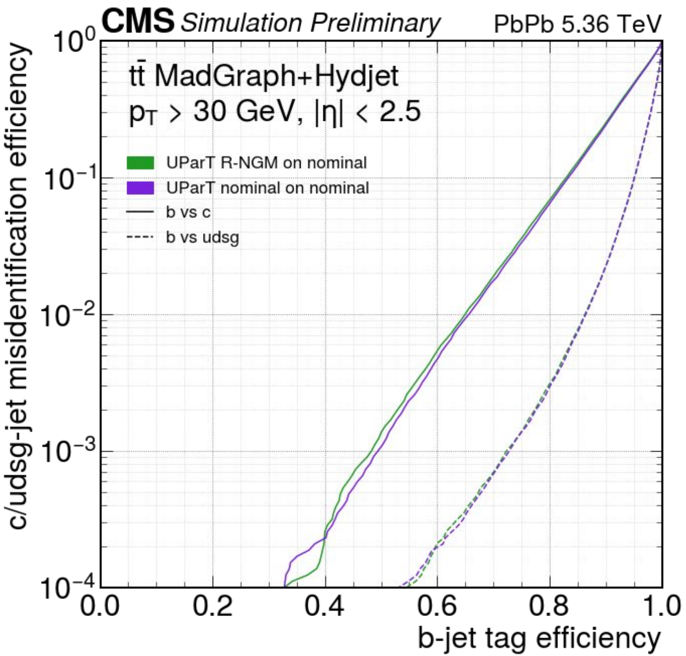


Figure 4 - UParT b (left) and c (right)-tagging adversarial ROC curves. The UParT performance is shown for both heavy (solid line) and light (dash line) jet rejection. The R-NGM adversarial strategy (blue) shows a substantial adversarial robustness compared to the nominal training (red) when applied on a sample with adversarial attacks. The b vs udsgc score is used in the left plot, while the c vs b and c vs udsg scores have been used in the right plot.

b and c-tagging robustness



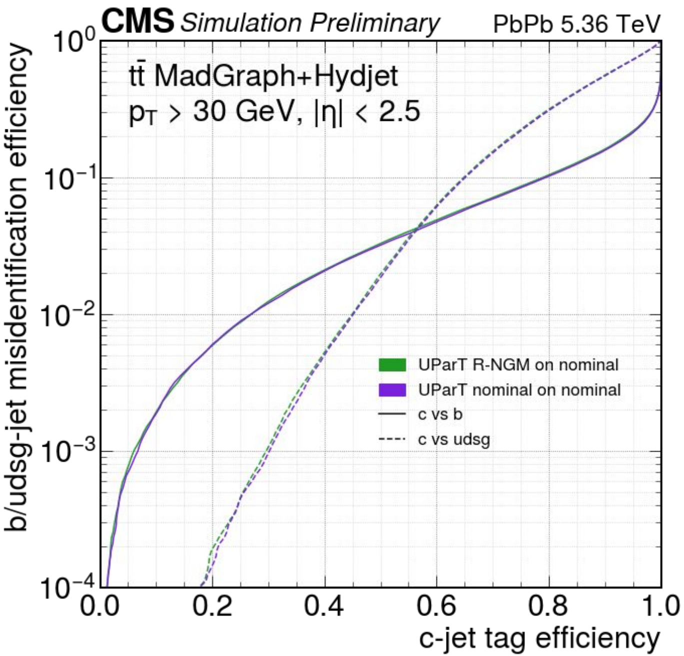


Figure 5 - UParT b (left) and c (right)-tagging adversarial ROC curves. The UParT performance is shown for both heavy (solid line) and light (dash line) jet rejection. The R-NGM adversarial strategy (green) shows a similar performance compared to the nominal training (violet) when applied on a nominal sample. The b vs udsgc score is used in the left plot, while the c vs b and c vs udsg scores have been used in the right plot.

b-tagging performance in Run 2 vs Run 3

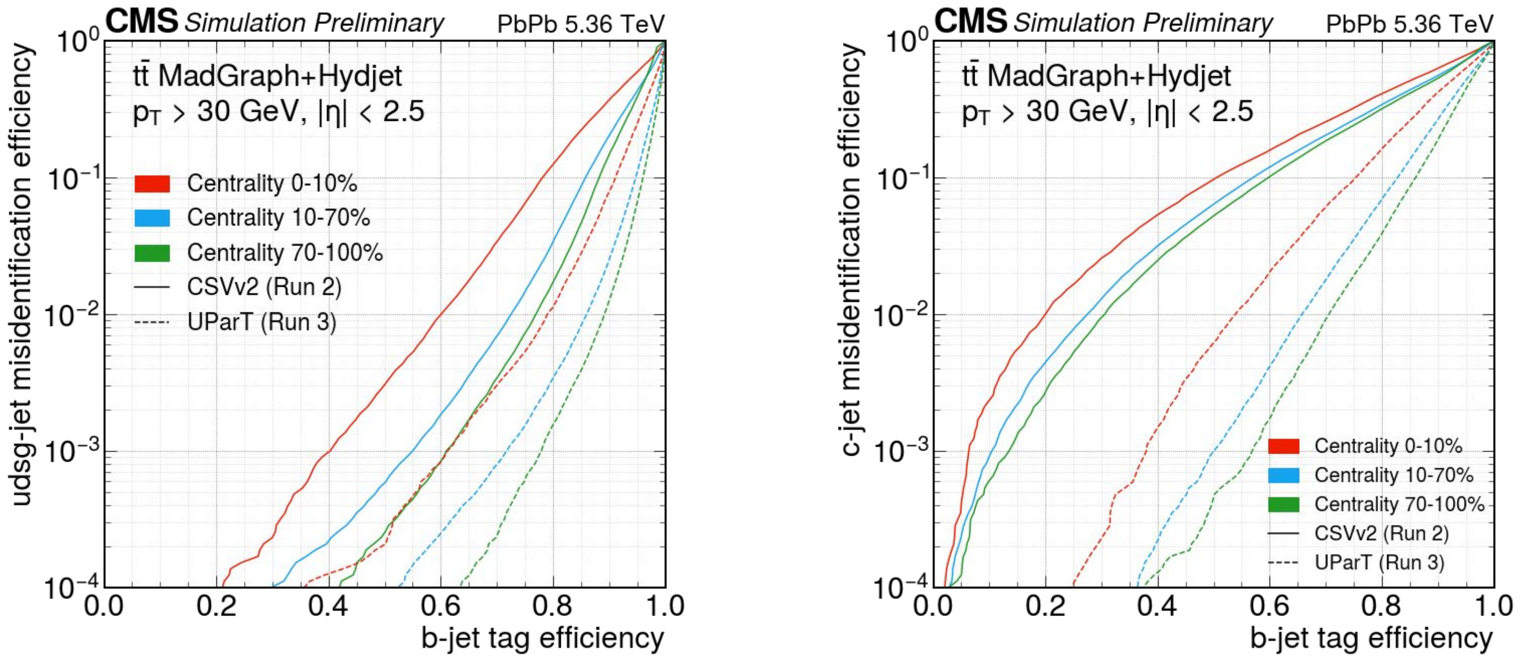


Figure 6 - b-tagging ROC curves in different categories of PbPb centrality. The Combined Secondary Vertex (CSV) v2 model shown is a multivariate tagger trained on Run 2 PbPb simulations and used in Run 2 PbPb analyses [13]. The CSVv2 (solid line) and UParT (dash line) performance is shown for both light-jet (left) and c-jet (right) rejection. The b vs udsgc score is used on both plots.

Summary

- Recent developments in machine learning algorithms have enabled a unified approach to jet tagging based on a ParticleTransformer model named UParT.
- The UParT model allows the identification of light- and heavy-flavour jets with outstanding performance in heavy-ion collisions across different PbPb centralities.
- This approach incorporates in addition a novel adversarial training technique achieving excellent robustness and minimizing the impact of mismodeling.
- Comparisons between Run 2 and Run 3 taggers used in PbPb analyses show an improvement in the light-jet rejection by a factor of 10 and c-jet rejection by a factor of 4 in PbPb collisions.

References

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