Apples to Apples in Jet Quenching

New jet quenching tools
ECT* - Trento

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LIP - Lisboa
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STRONG-2020
ECT* EUROPEAN CENTRE FOR THEORETICAL STUDIES IN NUCLEAR PHYSICS AND RELATED AREAS
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DF DEPARTMENT OF PHYSICS TÉCNICO LISBOA
LIP

Content

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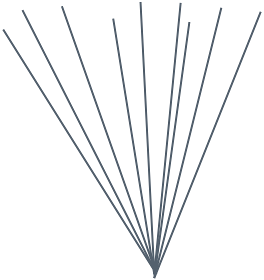
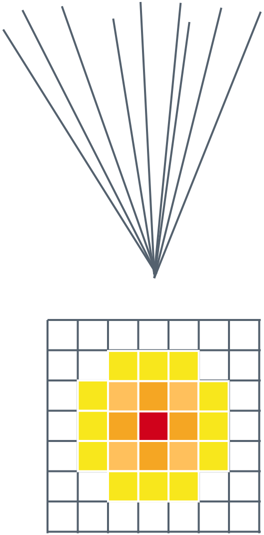
Outline

pp jet



pp jet



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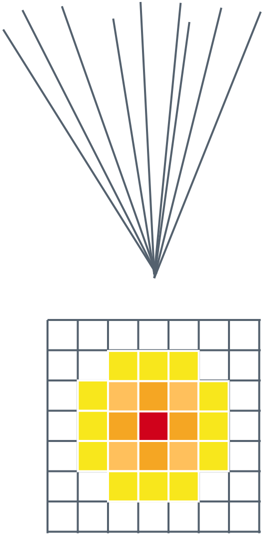
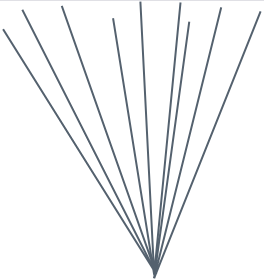
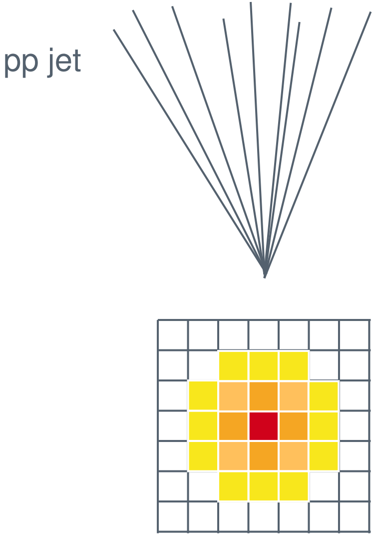


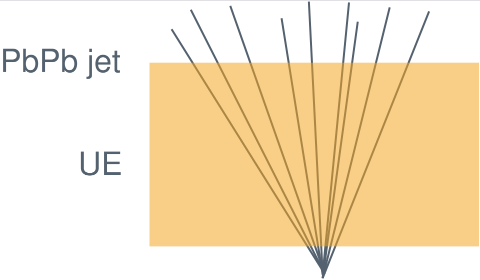
PbPb jet

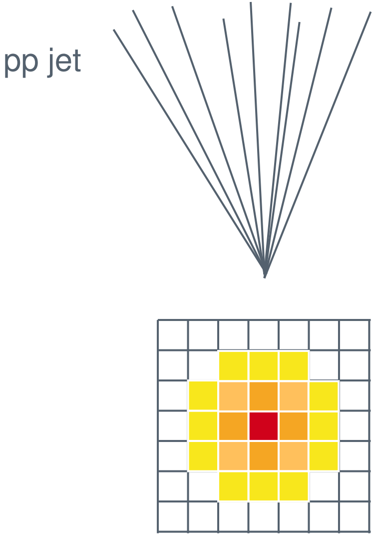


Introduction

Apples to Oranges



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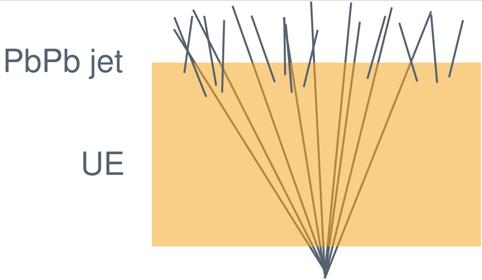
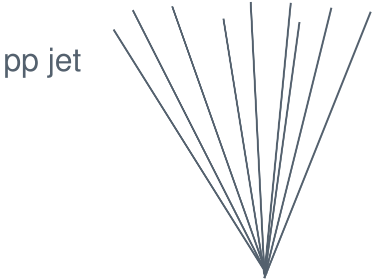
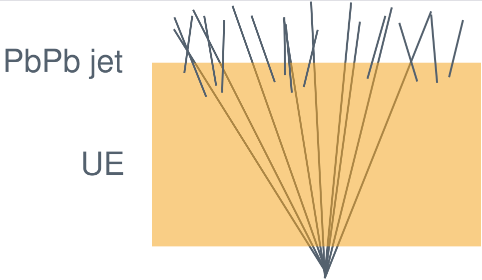
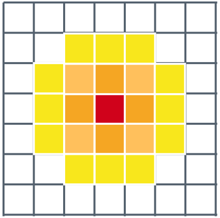

PbPb jet
UE

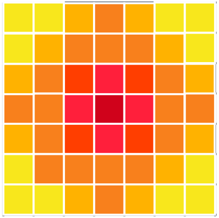


pp jet

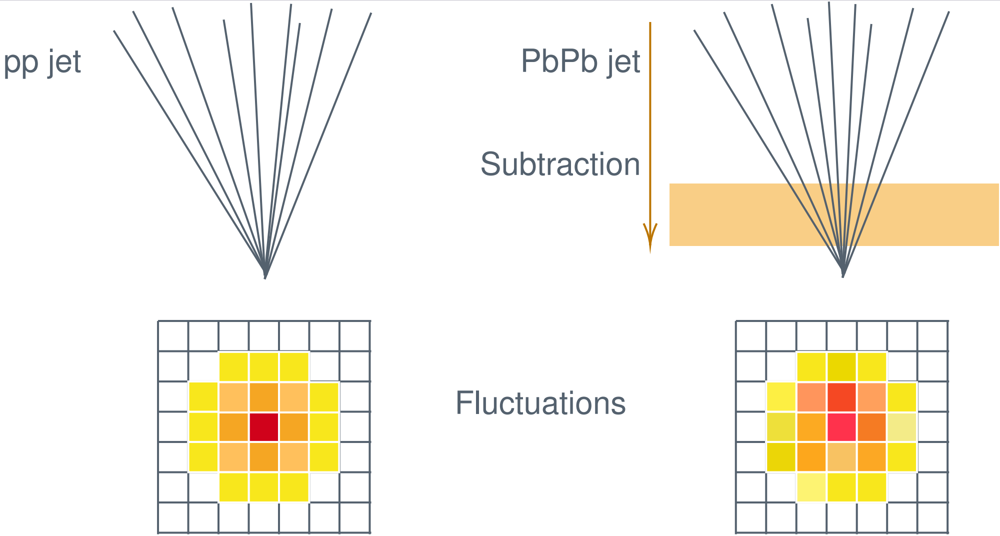


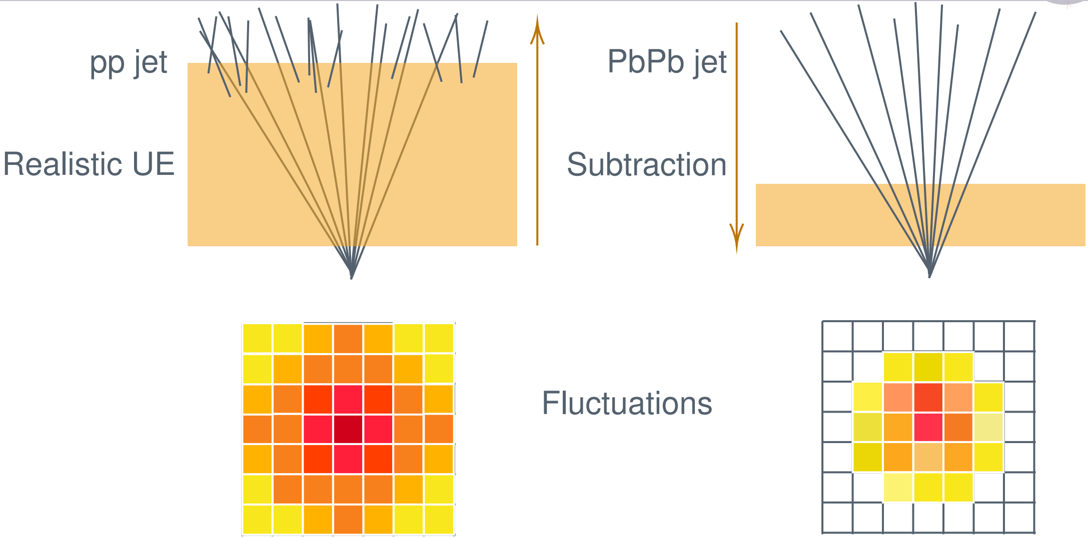
PbPb jet
UE



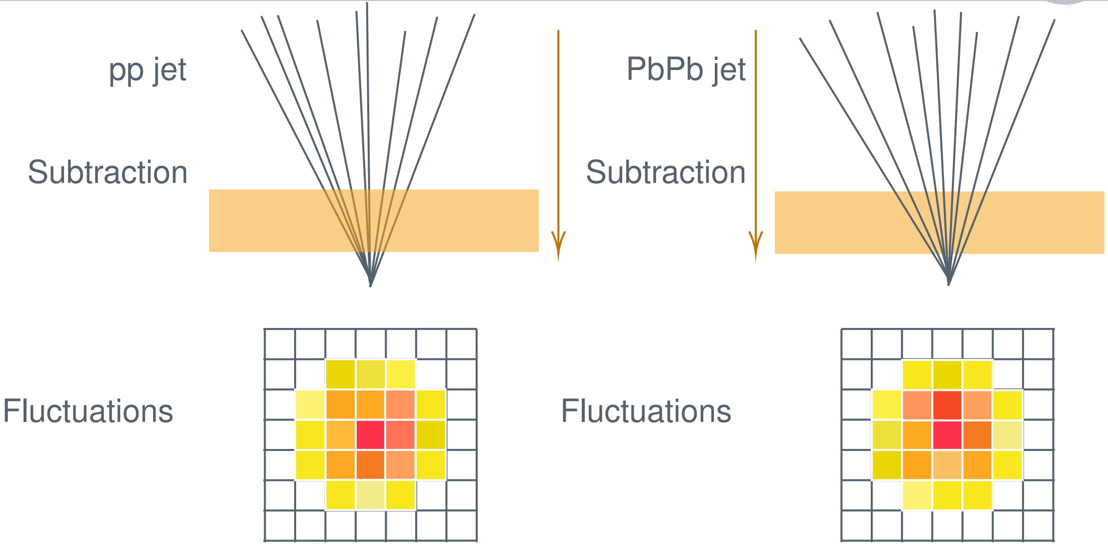


Introduction
Apples to Oranges





pp jet
Realistic UE
PbPb jet
Subtraction
Fluctuations



pp jet
Subtraction
Fluctuations
PbPb jet
Subtraction
Fluctuations

Outline

Generation Details

Process		dijets
Centrality		$[0, 10]\%$
τ_i	$=$	0.4
T_i	$=$	590 MeV
$\sqrt{s_{NN}}$	$=$	5.02 TeV
$\widehat{p}_t$	$>$	50 GeV
$\|\eta\|$	$<$	4

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Reconstruction Details		
p_t^{part}	$>$	100 MeV
$\lvert\eta^{part}\rvert$	$<$	4
Jets		0.4 anti_kt
$\lvert\eta^{jets}\rvert$	$<$	3
$\Delta\phi$	$<$	$5\pi/6$
p_t^{lead}	$>$	120 GeV
$p_t^{sublead}$	$>$	50 GeV

Experimentally motivated UE generation steps:

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1. Fit the pseudo-rapidity distribution of the UE measured experimentally from [1]. We have used a polynomial fit.

[1] Phys.Lett.B 772 (2017) 567-577, 2017.

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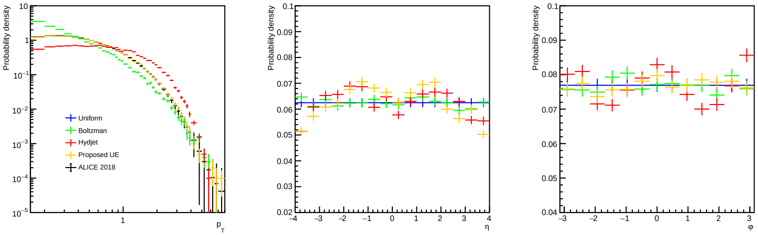
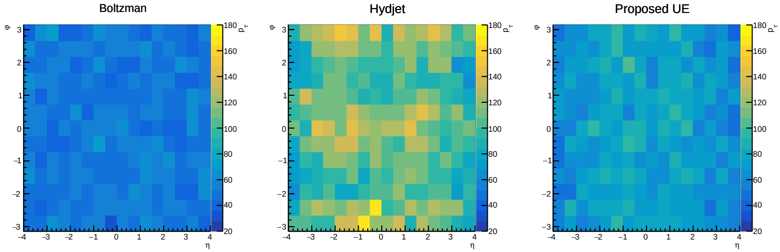
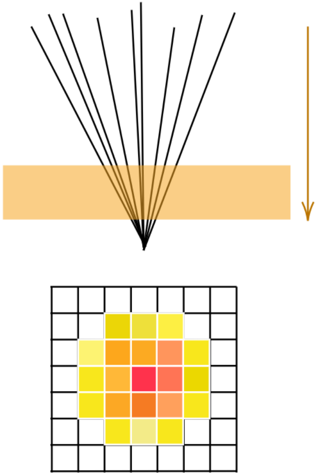
3. Take the ϕ distribution to be uniform.
4. Take the number of particles per UE to follow a Gaussian distribution of experimentally motivated average value and standard deviation.
5. For each particle to be generated, sample a value for p_T, η and ϕ from the considered distributions.
6. Considering only pions, sample randomly and uniformly one of the three species, and use its mass to complete the four-momentum of the particle.

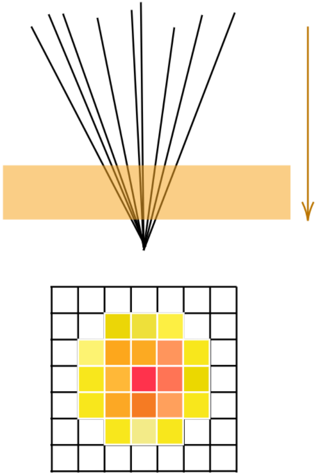
[1] Phys.Lett.B 772 (2017) 567-577, 2017.
[2] JHEP 11 (2018) 013, 2018.

Analysis Details
Underlying Event Generation Details

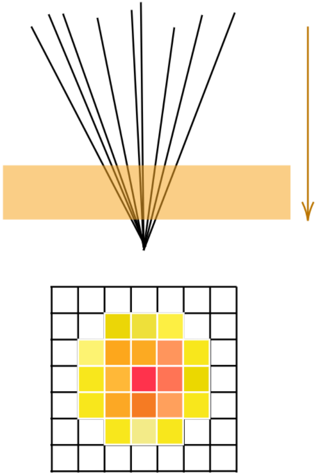








We have performed two different types of subtractions:

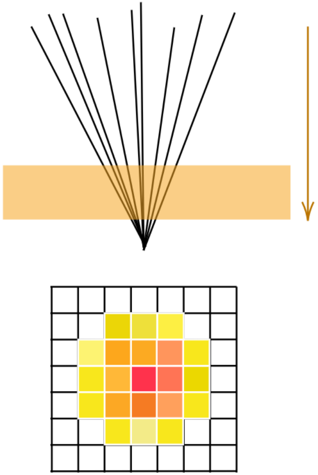


We have performed two different types of subtractions:

1. JEWEL's internal background subtraction to give physical medium response (only for PbPb and this is always performed before embedding) [3]

[3] Eur.Phys.J.C 82 (2022) 11, 1010

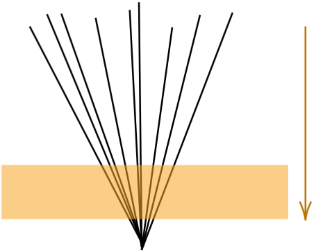
Analysis Details
Subtraction Details

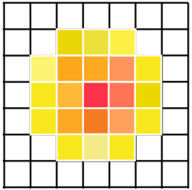


We have performed two different types of subtractions:

1. JEWEL's internal background subtraction to give physical medium response (only for PbPb and this is always performed before embedding) [3]
2. Iterative Constituent Subtraction of UE which we apply to both pp and PbPb embedded events [4]

[3] Eur.Phys.J.C 82 (2022) 11, 1010
[4] JHEP 08 (2019) 175





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1. JEWEL's internal background subtraction to give physical medium response (only for PbPb and this is always performed before embedding) [3]
2. Iterative Constituent Subtraction of UE which we apply to both pp and PbPb embedded events [4]

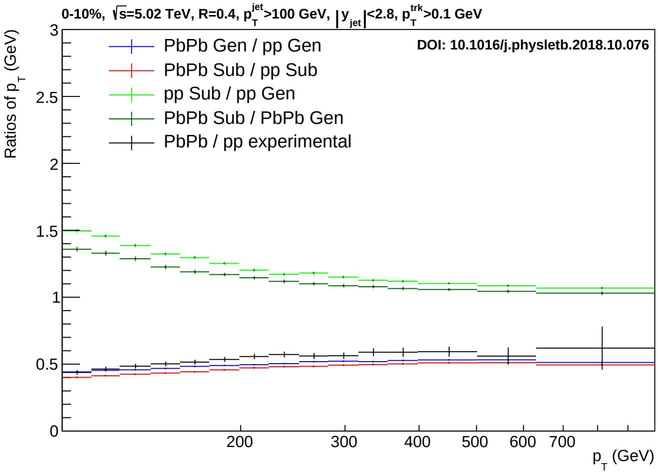
We have used the parameters suggested in [4] for 0.4 anti-kt jets.

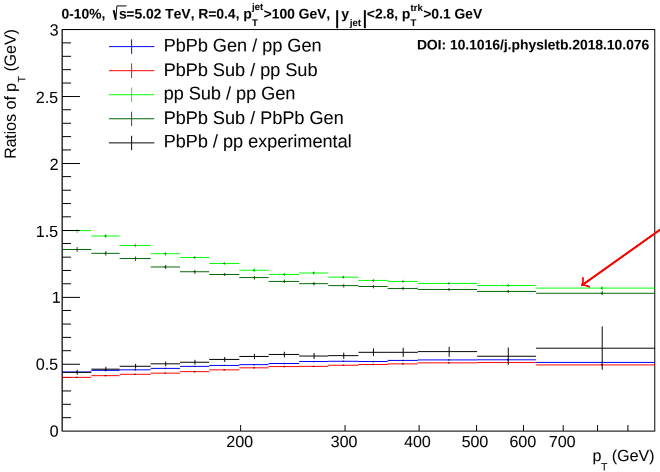
[3] Eur.Phys.J.C 82 (2022) 11, 1010
[4] JHEP 08 (2019) 175

Outline

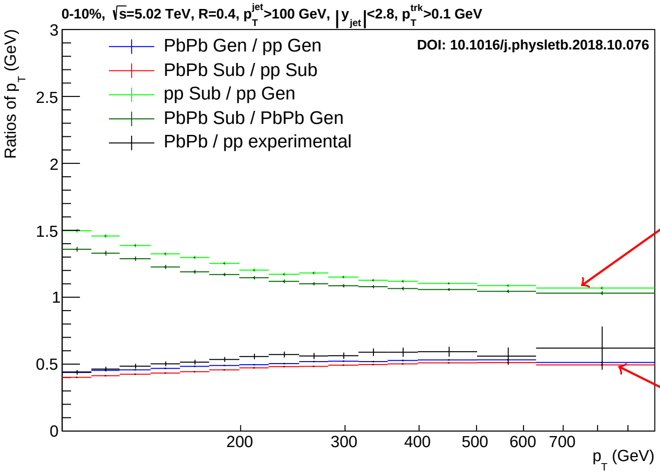
Results
Observable Robustness

Results
Observable Robustness



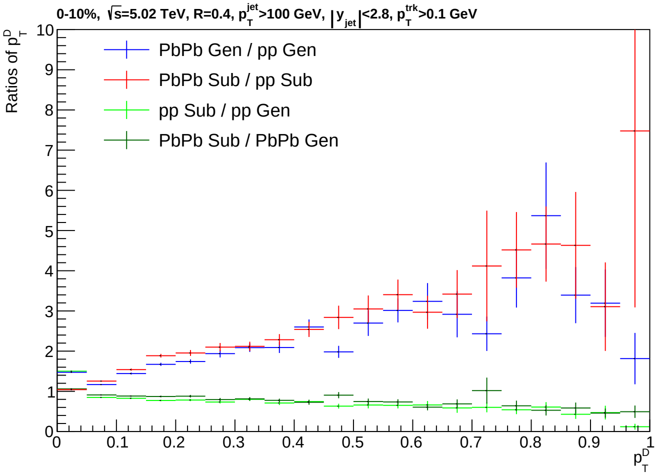


UE contamination effects for pp and PbPb



UE contamination effects for pp and PbPb

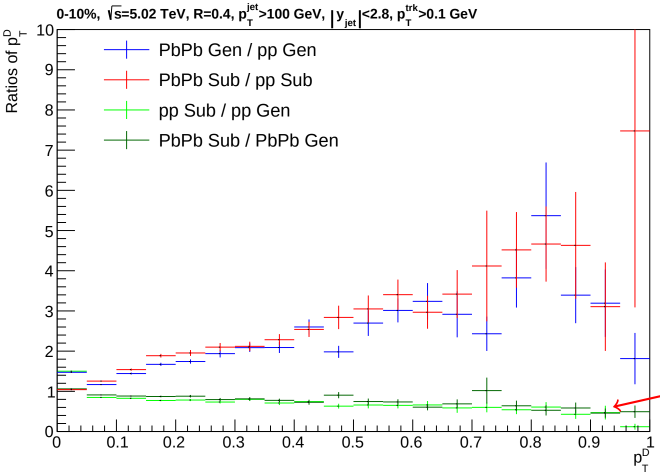
Robust to UE contamination



0-10%, $\sqrt{s}$=5.02 TeV, R=0.4, p_T^{jet}>100 GeV, $|y_{jet}|$<2.8, p_T^{trk}>0.1 GeV
Ratios of p_T^D
PbPb Gen / pp Gen
PbPb Sub / pp Sub
pp Sub / pp Gen
PbPb Sub / PbPb Gen
p_T^D
0
1
2
3
4
5
6
7
8
9
10
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9

Results

Observable Robustness



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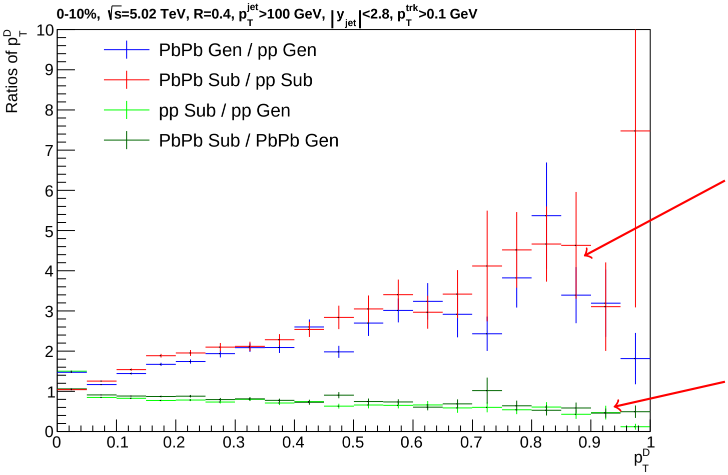
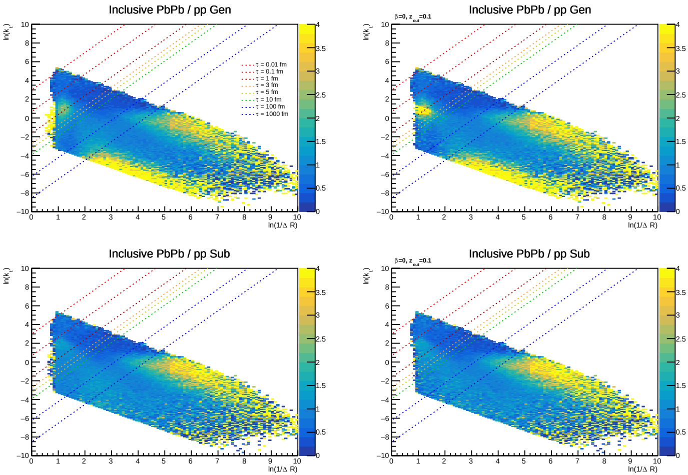


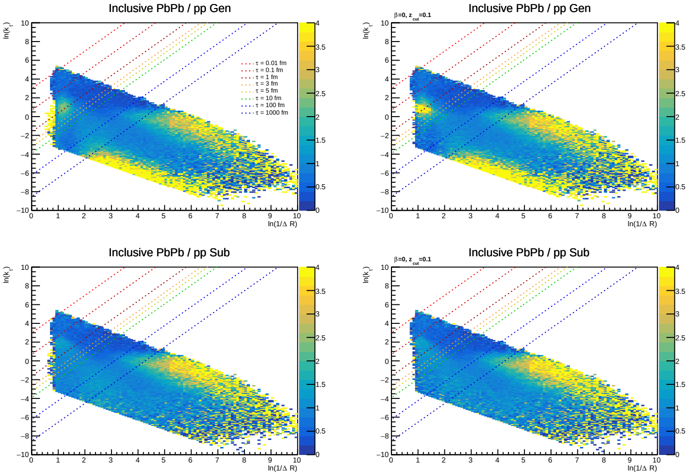
Robust to UE contamination

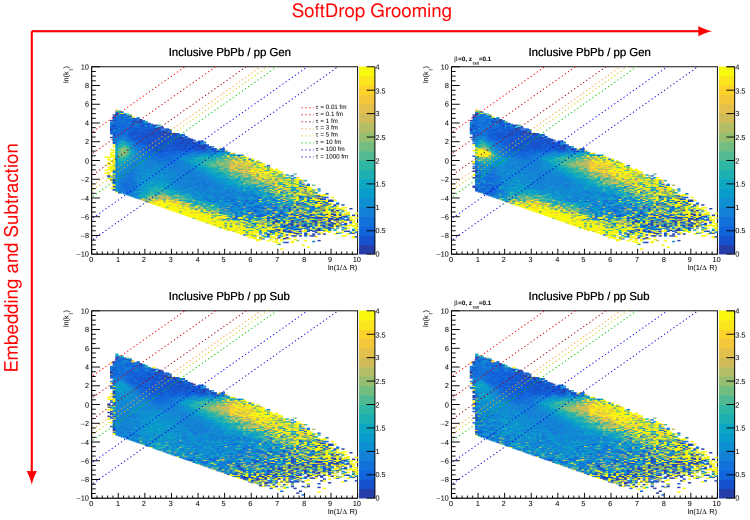
UE contamination effects for pp and PbPb

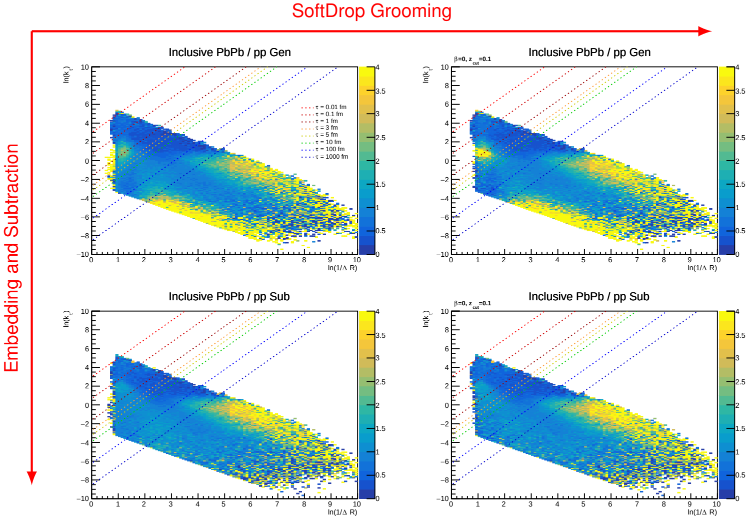


Inclusive PbPb / pp Gen
Inclusive PbPb / pp Gen
β=0, z_cut=0.1
Inclusive PbPb / pp Sub
Inclusive PbPb / pp Sub
β=0, z_cut=0.1
ln(k_t)
ln(1/Δ R)
τ = 0.01 fm
τ = 0.1 fm
τ = 1 fm
τ = 3 fm
τ = 5 fm
τ = 10 fm
τ = 100 fm
τ = 1000 fm

SoftDrop Grooming




SoftDrop Grooming
Embedding and Subtraction
Inclusive PbPb / pp Gen
Inclusive PbPb / pp Sub
β=0, z_cut=0.1
ln(k_t)
ln(1/Δ R)
τ = 0.01 fm
τ = 0.1 fm
τ = 1 fm
τ = 3 fm
τ = 5 fm
τ = 10 fm
τ = 100 fm
τ = 1000 fm



Grooming seems to increase the signal in the medium time window, but the subtraction always depletes the signal in this region.

We now turn to the effects of UE contamination in a ML analysis.

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We reproduced the results presented by Ankita on Monday for the PCA, AE and BDT analysis on the gen level, [5], and after UE embedding and subtraction (our work).

[5] 10.48550/arXiv.2304.07196

Observable	Type
y_{SD} ϕ_{SD} $\Delta p_{T,SD} = p_{T,jet} - p_{T,jet_{SD}}$ m_{SD} $n_{\text{const,SD}}$	Jet Momenta and Constituent Multiplicity
$\bar{r}_{SD} = \frac{1}{n_{\text{const,SD}}} \lambda^0_{1,SD}$ $\bar{r}^2_{SD} = \frac{1}{n_{\text{const,SD}}} \lambda^0_{2,SD}$ $rz_{SD} = \lambda^1_{1,SD}$ $r^2 z_{SD} = \lambda^1_{2,SD}$ $\bar{z}^2_{SD} = \frac{1}{n_{\text{const,SD}}} \lambda^2_{0,SD}$ $p_T D_{SD} = \sqrt{\sum_{i \in jet_{SD}} p^2_{T,i}} / p_{T,jet,SD}$	Angularities
$\tau_{2,SD}$, $\tau_{3,SD}$ $\tau_{1,2,SD}$, $\tau_{2,3,SD}$	N-subjettiness
$\lvert Q^{0.3}_{SD}\rvert$, $\lvert Q^{0.5}_{SD}\rvert$, $\lvert Q^{0.7}_{SD}\rvert$, $\lvert Q^{1.0}_{SD}\rvert$,	Jet-Charges
R_g, z_g, n_{SD}	SoftDrop Grooming Intrinsic
$R_{g,A}$, $z_{g,A}$, κ_A with $A \in \{TD, ktD, zD\}$	Dynamical Grooming Intrinsic

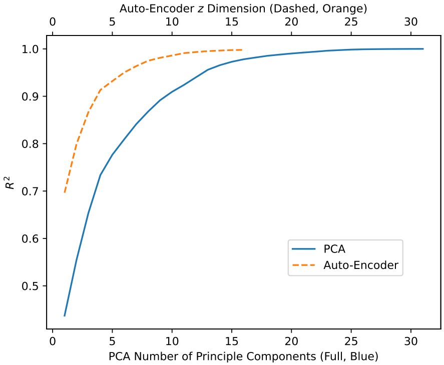
Ankita's talk on Monday

[5] 10.48550/arXiv.2304.07196

Results

ML Robustness

No UE



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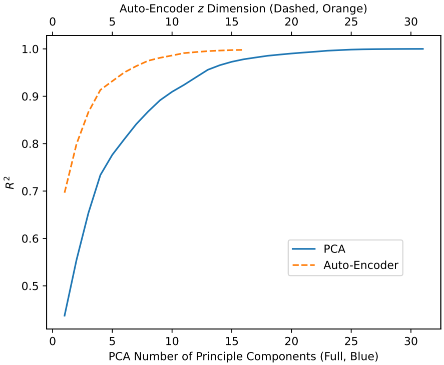
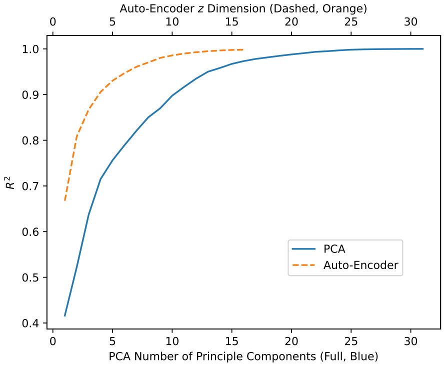
No UE



With subtracted UE



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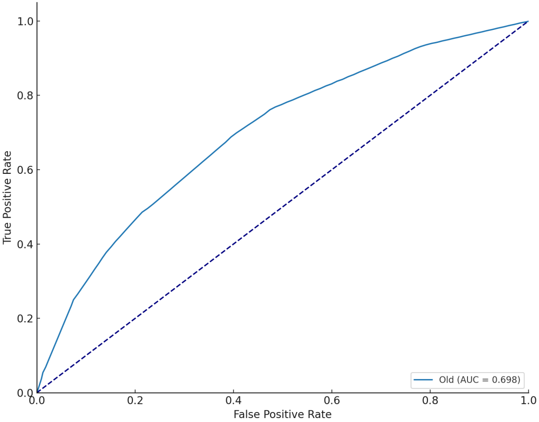
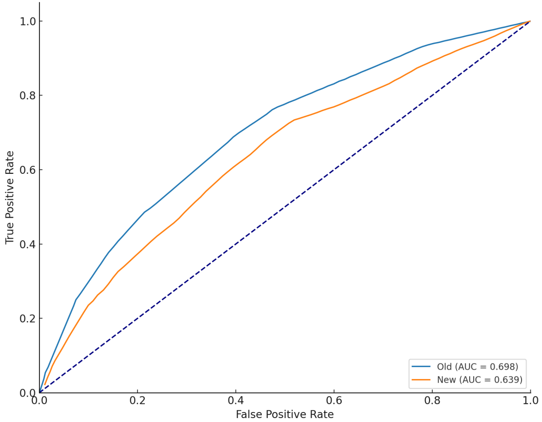
BDT using the same variables



[5] 10.48550/arXiv.2304.07196

BDT using the same variables



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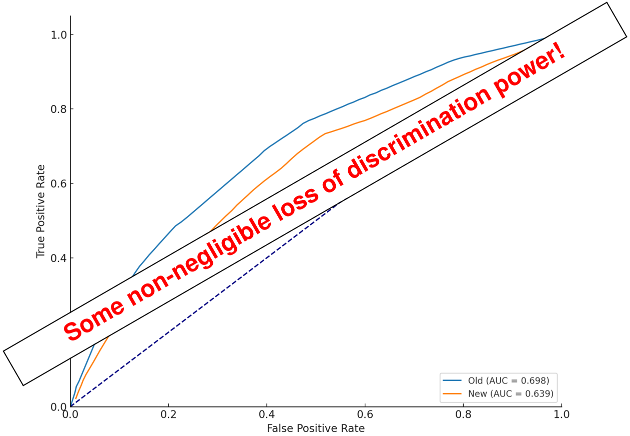
BDT using the same variables



[5] 10.48550/arXiv.2304.07196

But...

But... are there better choices of observables?

Results

A note on EFPs

Results
A note on EFPs

"These observables are multiparticle energy correlators with specific angular structures which directly result from IRC safety."

[6] doi.org/10.1007/JHEP04(2018)013

"These observables are multiparticle energy correlators with specific angular structures which directly result from IRC safety."

"EFPs can be viewed as a discrete set of C-correlators"

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"EFPs can be viewed as a discrete set of C-correlators"

"EFPs form a linear basis of all IRC-safe observables, making them suitable for a wide variety of jet substructure contexts where linear methods are applicable"

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"EFPs form a linear basis of all IRC-safe observables, making them suitable for a wide variety of jet substructure contexts where linear methods are applicable"

"There is a one-to-one correspondence between EFPs and loopless multigraphs, which helps to visualize and calculate the EFPs"

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"EFPs form a linear basis of all IRC-safe observables, making them suitable for a wide variety of jet substructure contexts where linear methods are applicable"

"There is a one-to-one correspondence between EFPs and loopless multigraphs, which helps to visualize and calculate the EFPs"

"(...) we usually truncate by restricting to the set of all multigraphs with at most d edges (...) this truncation results in a finite number of EFPs at each order of truncation, which is not true for truncation by the number of vertices."

[6] doi.org/10.1007/JHEP04(2018)013

$$\text{EFP}_G = \sum_{i_1=1}^{M} \cdots \sum_{i_N=1}^{M} z_{i_1} \cdots z_{i_N} \prod_{(k,\ell)\in G} \theta_{i_k i_\ell},$$

[6] doi.org/10.1007/JHEP04(2018)013

Results
A note on EFPs

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$$\bullet_j \iff \sum_{i_j=1}^{M} z_{i_j}$$

[6] doi.org/10.1007/JHEP04(2018)013

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[6] doi.org/10.1007/JHEP04(2018)013

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$$k \;\text{———}\; \ell \iff \theta_{i_k i_\ell}$$

[6] doi.org/10.1007/JHEP04(2018)013

$$\text{EFP}_G = \sum_{i_1=1}^{M} \cdots \sum_{i_N=1}^{M} z_{i_1} \cdots z_{i_N} \prod_{(k,\ell)\in G} \theta_{i_k i_\ell}; \qquad \bullet_j \iff \sum_{i_j=1}^{M} z_{i_j} \qquad k \text{ ——— } \ell \iff \theta_{i_k i_\ell}$$

$$= \sum_{i_1=1}^{M}\sum_{i_2=1}^{M}\sum_{i_3=1}^{M}\sum_{i_4=1}^{M}\sum_{i_5=1}^{M} z_{i_1} z_{i_2} z_{i_3} z_{i_4} z_{i_5} \theta_{i_1 i_2} \theta_{i_2 i_3} \theta_{i_1 i_3} \theta_{i_1 i_4} \theta_{i_1 i_5} \theta_{i_4 i_5}^2$$

[6] doi.org/10.1007/JHEP04(2018)013

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 $j \iff \sum_{i_j=1}^{M} z_{i_j}$

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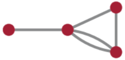

$$= \sum_{i_1=1}^{M}\sum_{i_2=1}^{M}\sum_{i_3=1}^{M}\sum_{i_4=1}^{M} z_{i_1} z_{i_2} z_{i_3} z_{i_4} \theta_{i_1 i_2}\theta_{i_2 i_3}\theta^2_{i_2 i_4}\theta_{i_3 i_4}$$

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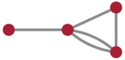 $= \sum_{i_1=1}^{M}\sum_{i_2=1}^{M}\sum_{i_3=1}^{M}\sum_{i_4=1}^{M} z_{i_1} z_{i_2} z_{i_3} z_{i_4} \theta_{i_1 i_2}\theta_{i_2 i_3}\theta_{i_2 i_4}^2\theta_{i_3 i_4}$

$$\frac{m_J^2}{p_{TJ}^2} = \sum_{i_1=1}^{M}\sum_{i_2=1}^{M} z_{i_1} z_{i_2} (\cosh(\Delta y_{i_1 i_2}) - \cos(\Delta\phi_{i_1 i_2})) = \frac{1}{2} \times$$  $+ \cdots$

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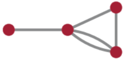
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$$+ \cdots$$

$$\lambda^{(2)} = \frac{1}{2}\sum_{i\in J}\sum_{j\in J} z_i z_j \theta_{ij}^2 = \frac{1}{2} \times$$

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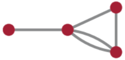 $= \sum_{i_1=1}^{M}\sum_{i_2=1}^{M}\sum_{i_3=1}^{M}\sum_{i_4=1}^{M} z_{i_1} z_{i_2} z_{i_3} z_{i_4} \theta_{i_1 i_2}\theta_{i_2 i_3}\theta^2_{i_2 i_4}\theta_{i_3 i_4}$

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$\lambda^{(4)} =$  $- \frac{3}{4} \times$ 

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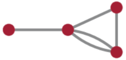 $= \sum_{i_1=1}^{M}\sum_{i_2=1}^{M}\sum_{i_3=1}^{M}\sum_{i_4=1}^{M} z_{i_1} z_{i_2} z_{i_3} z_{i_4} \theta_{i_1 i_2}\theta_{i_2 i_3}\theta^2_{i_2 i_4}\theta_{i_3 i_4}$

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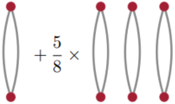
$\lambda^{(6)} =$  $- \frac{3}{2} \times$  $+ \frac{5}{8} \times$ 

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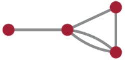
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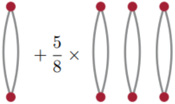
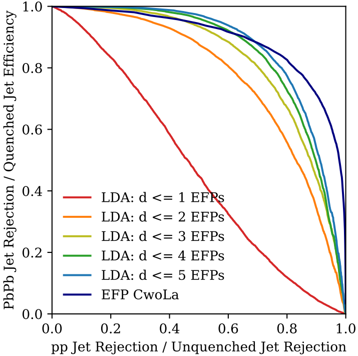
$\lambda^{(6)} =$  $- \frac{3}{2} \times$  $+ \frac{5}{8} \times$ 

Take home: EFPs are interesting.

[6] doi.org/10.1007/JHEP04(2018)013

On the next analysis we focus on Linear Discriminant Analysis (LDA) with these observables and medium response.

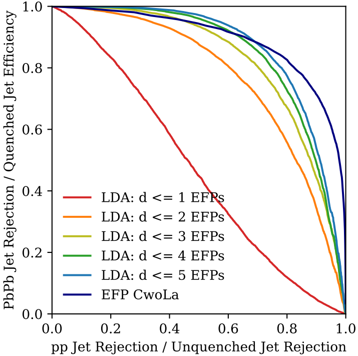
No UE



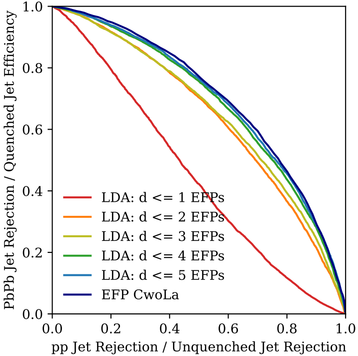
[6] doi.org/10.1007/JHEP04(2018)013

Results
ML Robustness

No UE

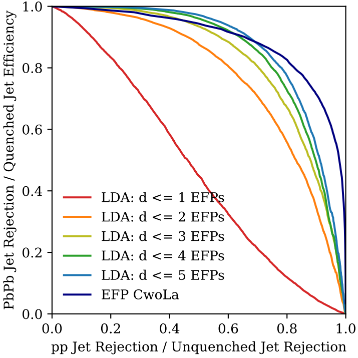


With subtracted UE

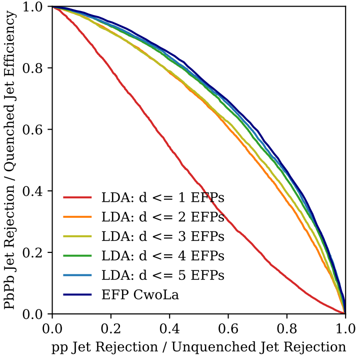


[6] doi.org/10.1007/JHEP04(2018)013

No UE



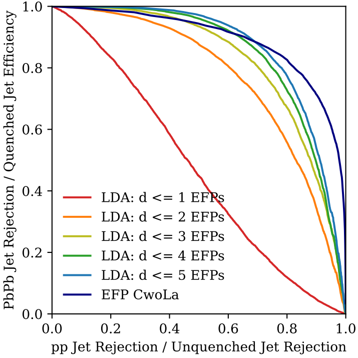
With subtracted UE



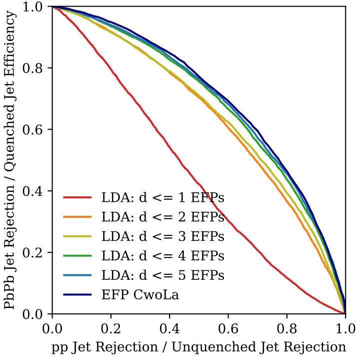
Classification on gen level, picks up on the medium response and the model performs very well.

[6] doi.org/10.1007/JHEP04(2018)013

No UE



With subtracted UE



Classification on gen level, picks up on the medium response and the model performs very well. Applying the procedure greatly reduces the discrimination power (AUC from .85 to .7).

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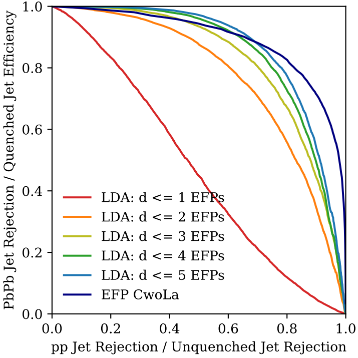
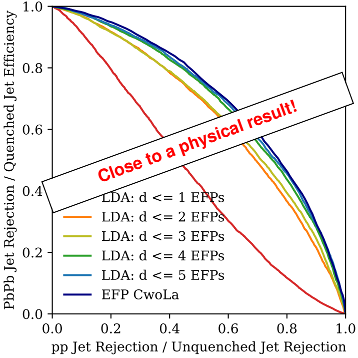
No UE



With subtracted UE



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But..

But.. We have trained on a weighted sample but without the weights (sklearn's **Linear** Discriminant Analysis (LDA) model, does not handle weights)

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Is it stable? Can we train on weighted (MC), test on unweighted (Data)?

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Results

A note on EFPs

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Is the model robust to this?

We are going to perform a test now without medium response.

Results
A note on EFPs

Results
A note on EFPs

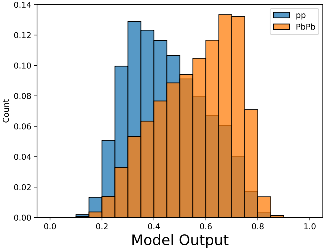
Tested on / Trained on	Weighted	Unweighted
Weighted		
Unweighted		

Results

A note on EFPs

Tested on: Weighted | Unweighted

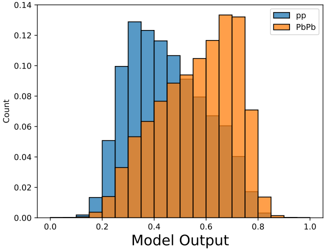
Trained on: Weighted | Unweighted

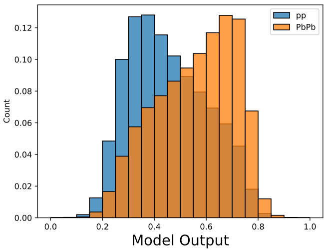


Tested on | Weighted | Unweighted

Trained on

Weighted



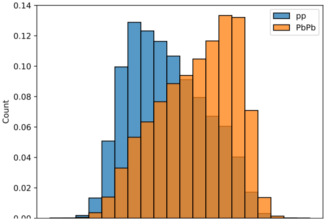


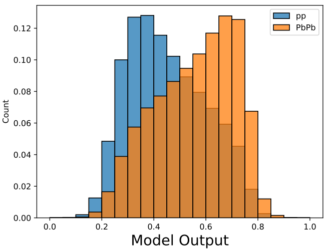
Unweighted

Results
A note on EFPs

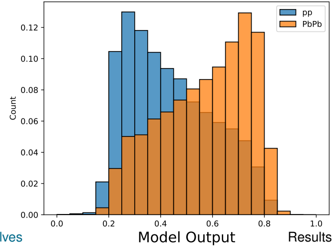
Tested on: Weighted | Unweighted

Trained on: Weighted



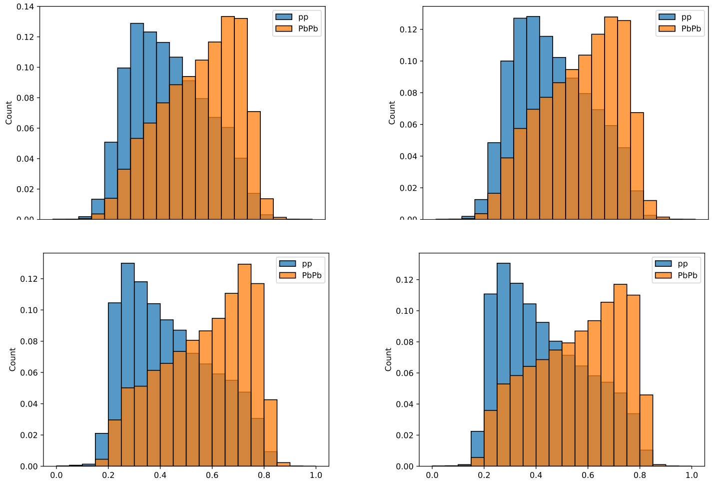


Trained on: Unweighted

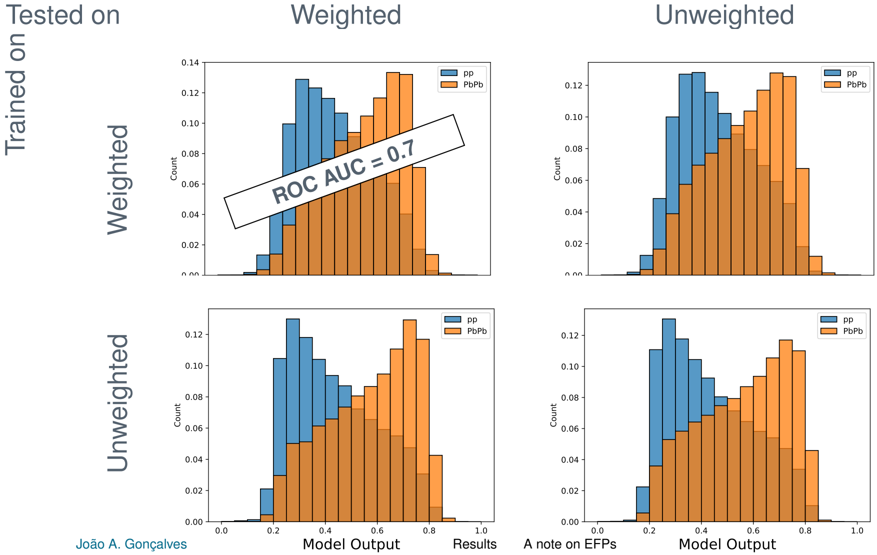


Tested on: Weighted | Unweighted

Trained on: Weighted | Unweighted



Results
A note on EFPs

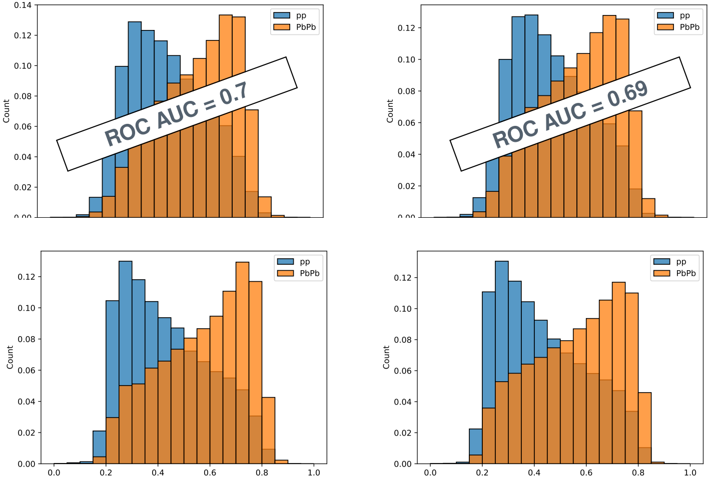


Tested on | Weighted | Unweighted

Trained on

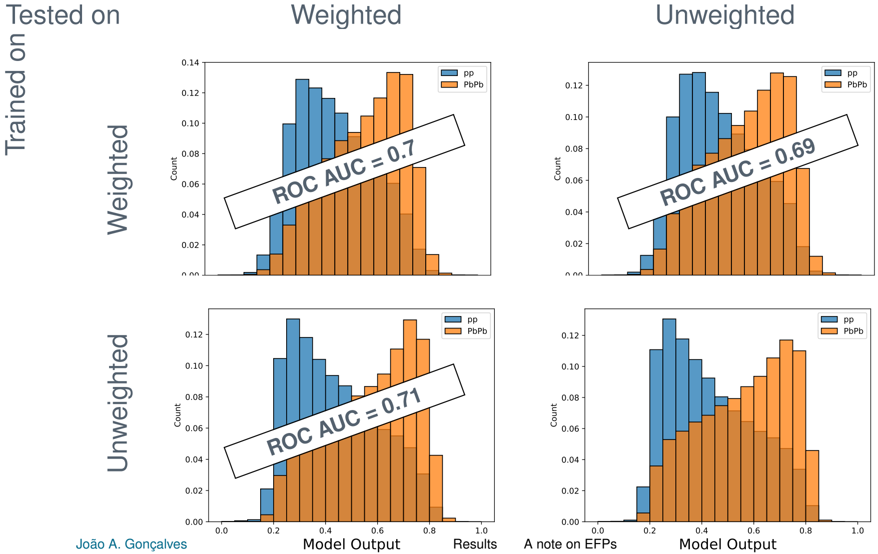
Weighted

Unweighted



Results

A note on EFPs

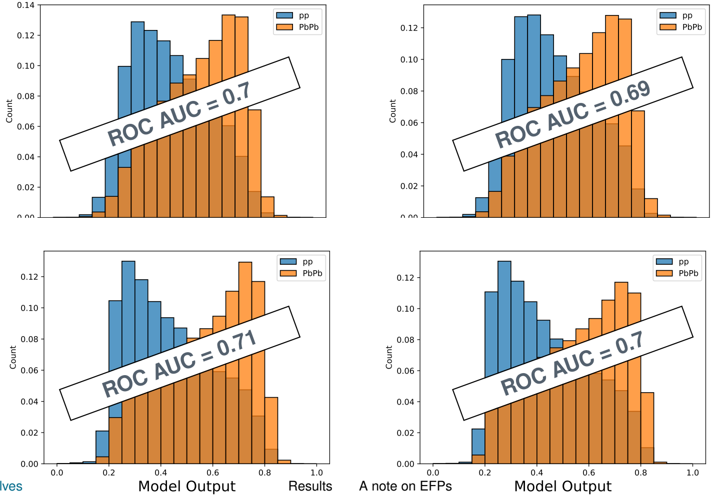


Tested on | Weighted | Unweighted

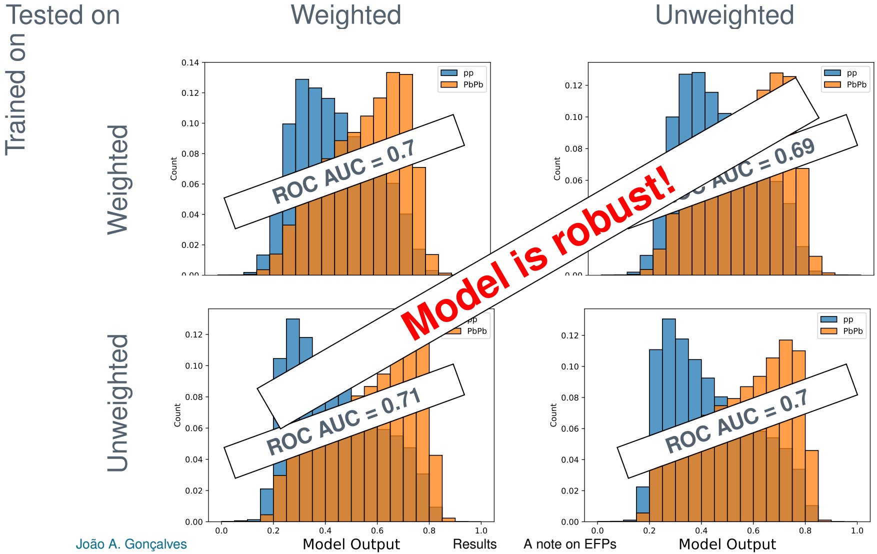
Trained on

Weighted

Unweighted



Results
A note on EFPs



Outline

Conclusions

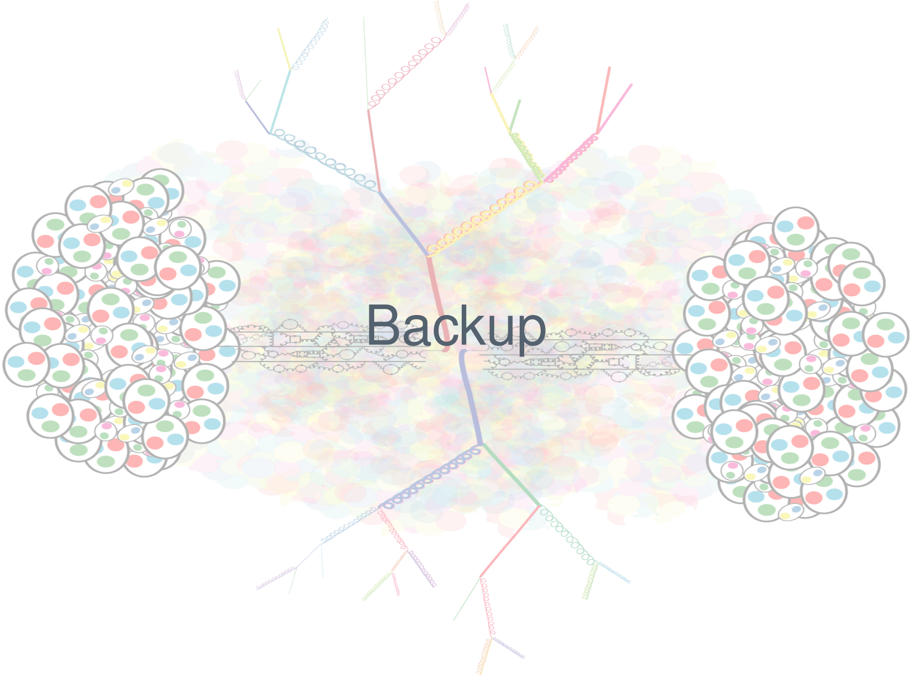
1. In order to compare apples to apples, such that our algorithms hunt the physics not procedural fluctuations, one needs to embed the pp jets in a "as similar as possible" UE, uncorrelated with the hard scattering, and perform the same procedure as in PbPb jets.
2. The way we model this "fake" UE is crucial for our final results, but more crucial even for the possibility of a fair usable jet-by-jet quenching tagger in experiment, theory and phenomenology.
3. Modelling this UE directly through data seems to be our best option.
4. The modifications and discriminant information left after the procedure is the only one we can access in experiment and so is the only one we can take as physical.
5. Only the effects present after a similar procedure, can be taken as true PbPb modifications against a pp baseline.

Future Work

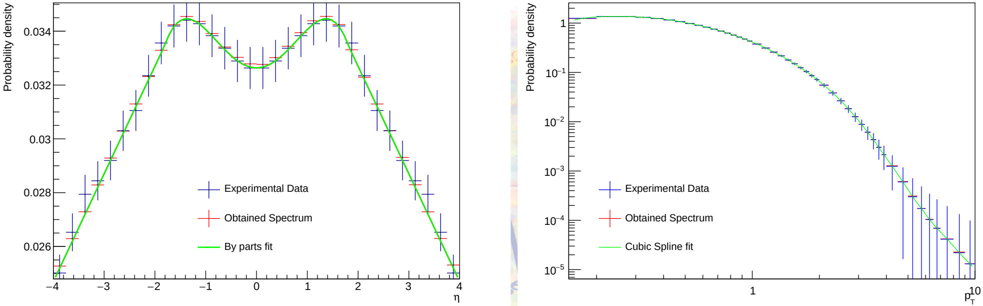
1. We intend to take this work further and study the impact of this procedure on different Neural Networks architectures, through supervised, unsupervised and semi-supervised learning. (many already done)
2. The inclusion of some data-driven modelling for ϕ would make the comparison between pp and PbPb jets fairer.
3. The inclusion of other particle species other then pions according to their measured abundance in experiment, would make the comparison even fairer.

Thank you for your attention!

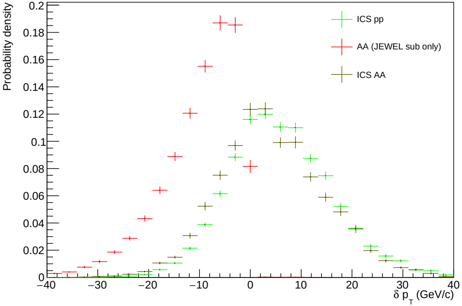
Backup

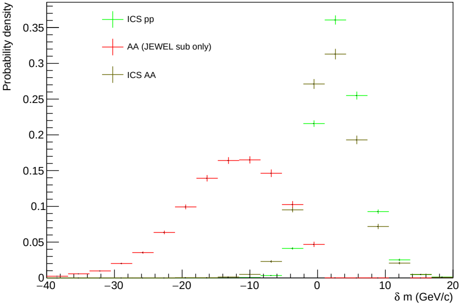


Underlying Event Fits


Probability density
0.034
0.032
0.03
0.028
0.026
−4
−3
−2
−1
0
1
2
3
4
η
Experimental Data
Obtained Spectrum
By parts fit
Probability density
1
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
1
10
p_T
Experimental Data
Obtained Spectrum
Cubic Spline fit

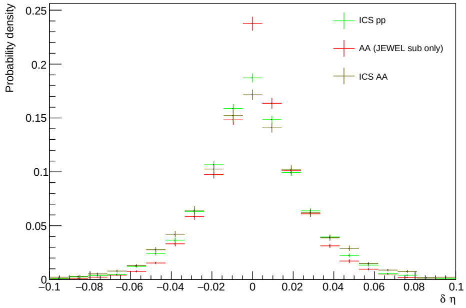
Subtraction Quality Plots

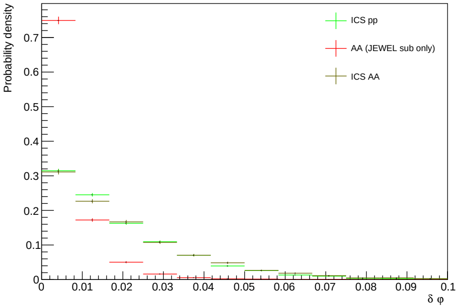




$$\delta p_T = p_T^{sub} - p_T^{gen}$$

$$\delta m = m^{sub} - m^{gen}$$

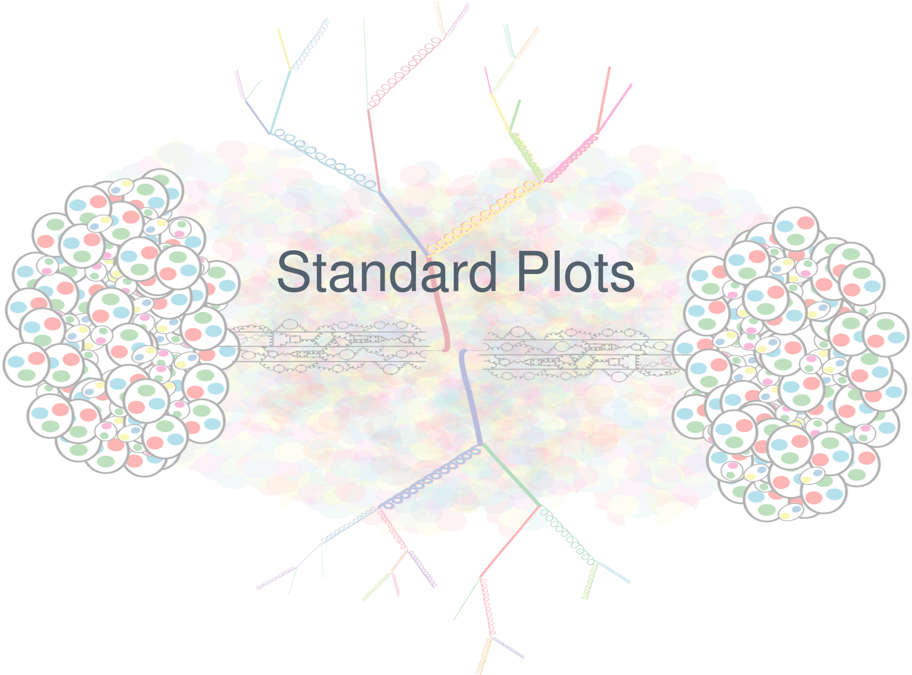


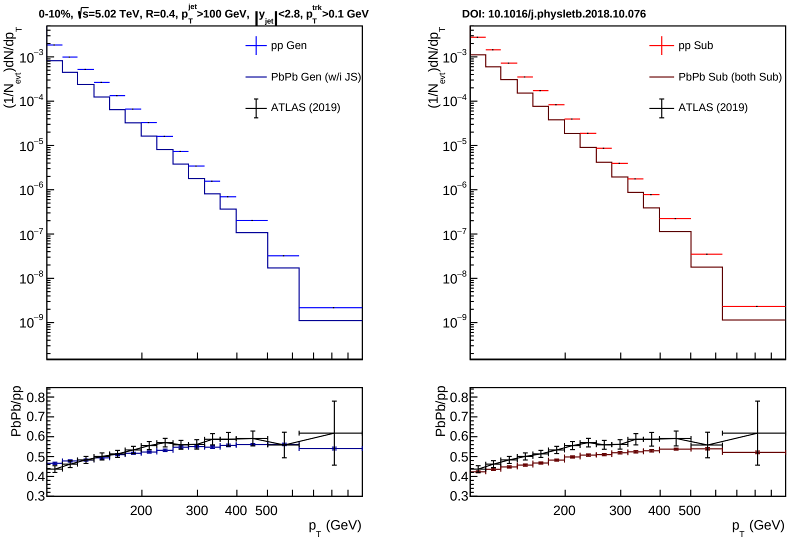


$$\delta\eta = \eta^{sub} - \eta^{gen}$$

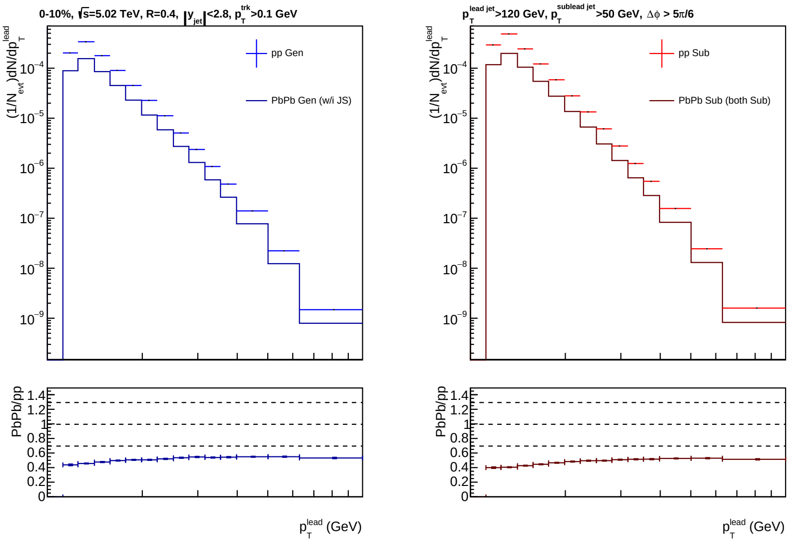
$$\delta\phi = \phi^{sub} - \phi^{gen}$$

Standard Plots

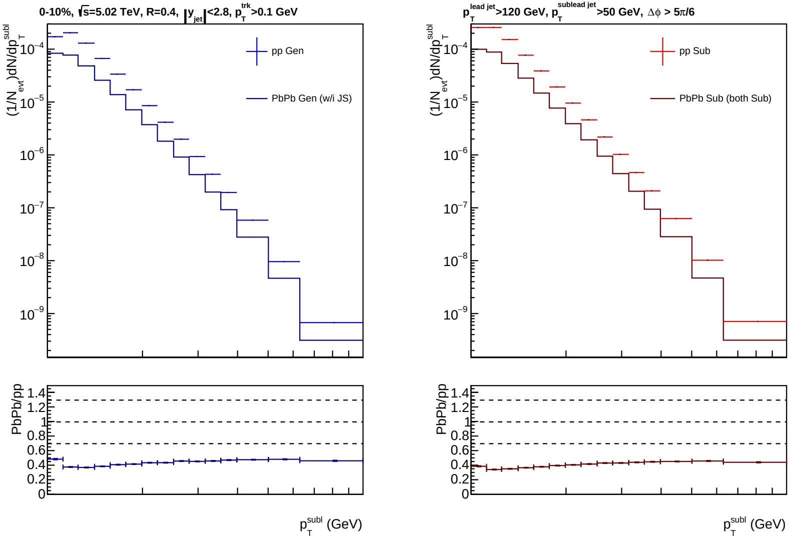




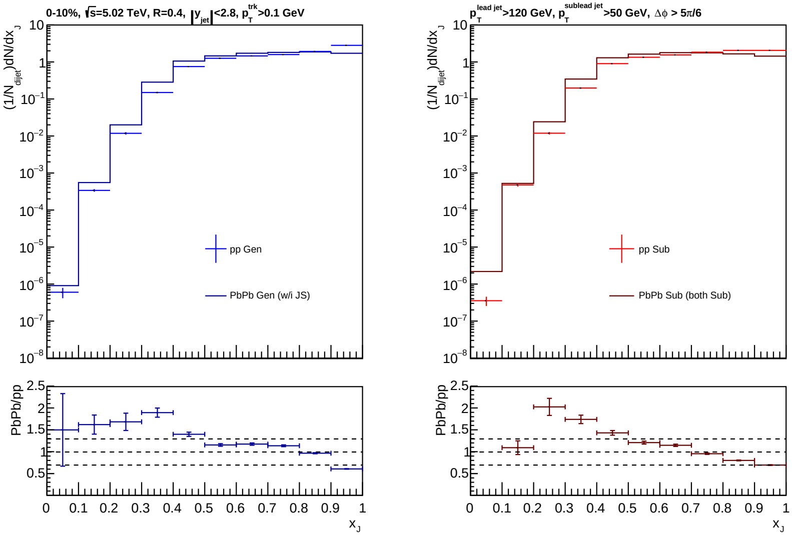
0-10%, √s=5.02 TeV, R=0.4, p_T^jet>100 GeV, |y_jet|<2.8, p_T^trk>0.1 GeV
DOI: 10.1016/j.physletb.2018.10.076
(1/N_evt)dN/dp_T
pp Gen
PbPb Gen (w/i JS)
ATLAS (2019)
pp Sub
PbPb Sub (both Sub)
PbPb/pp
200
300
400
500
p_T (GeV)



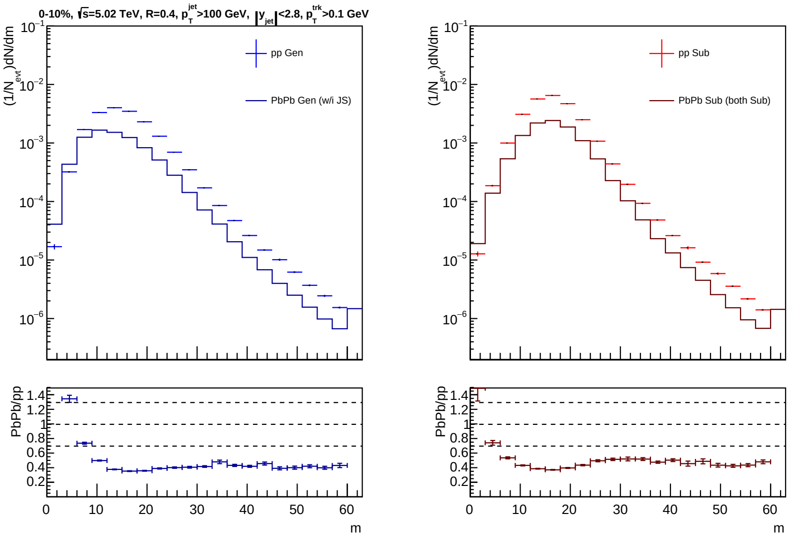
0-10%, √s=5.02 TeV, R=0.4, |y_jet|<2.8, p_T^trk>0.1 GeV
p_T^lead jet>120 GeV, p_T^sublead jet>50 GeV, Δφ > 5π/6
(1/N_evt)dN/dp_T^lead
pp Gen
PbPb Gen (w/i JS)
pp Sub
PbPb Sub (both Sub)
PbPb/pp
p_T^lead (GeV)



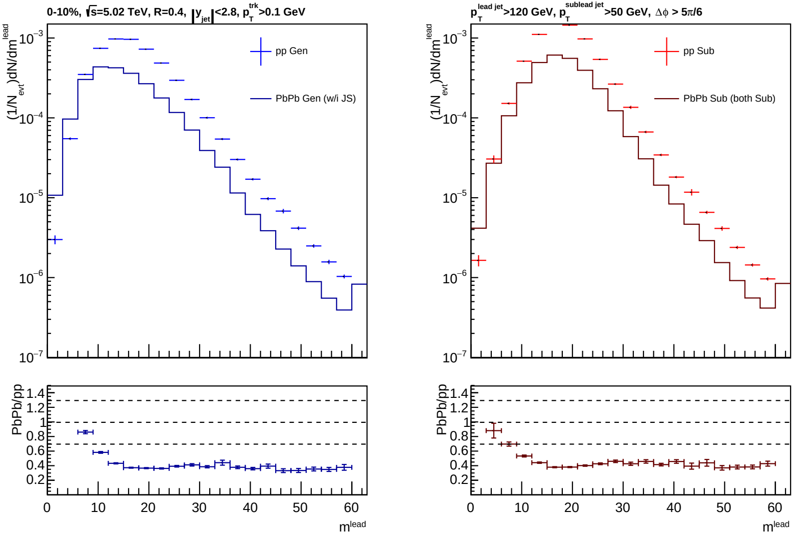
0-10%, √s=5.02 TeV, R=0.4, |y_jet|<2.8, p_T^trk>0.1 GeV
p_T^lead jet>120 GeV, p_T^sublead jet>50 GeV, Δφ > 5π/6
(1/N_evt)dN/dp_T^subl
10^-4
10^-5
10^-6
10^-7
10^-8
10^-9
pp Gen
PbPb Gen (w/i JS)
pp Sub
PbPb Sub (both Sub)
PbPb/pp
1.4
1.2
1
0.8
0.6
0.4
0.2
0
p_T^subl (GeV)



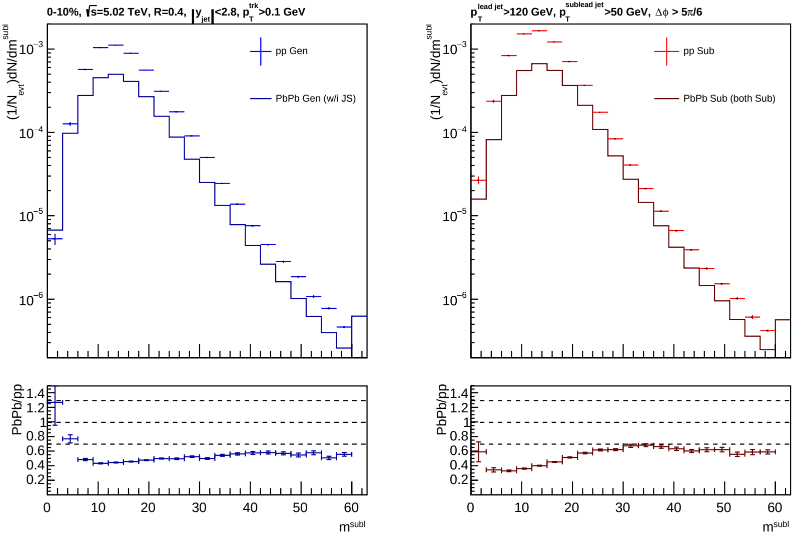
$$x_j = p_T^{sublead} / p_T^{lead}$$



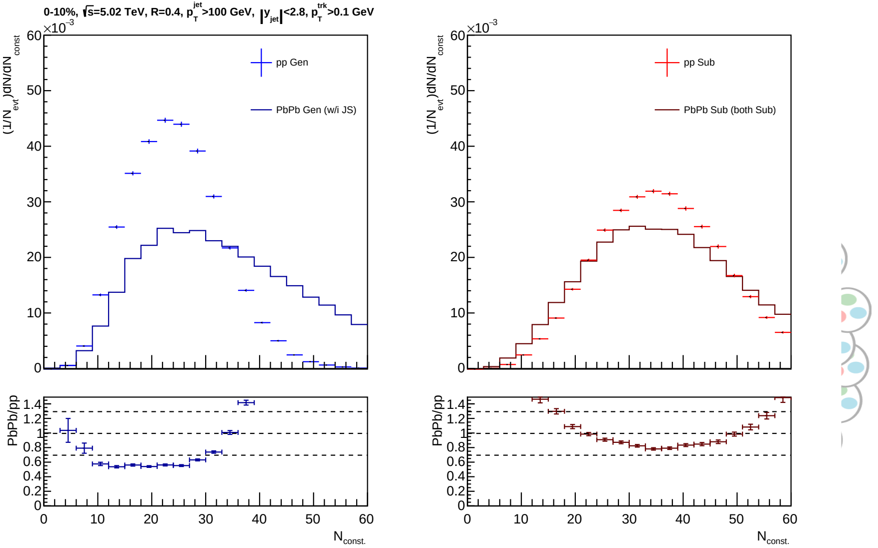
0-10%, $\sqrt{s}$=5.02 TeV, R=0.4, p_T^{jet}>100 GeV, $|y_{jet}|$<2.8, p_T^{trk}>0.1 GeV
pp Gen
PbPb Gen (w/i JS)
$(1/N_{evt})dN/dm$
PbPb/pp
m
pp Sub
PbPb Sub (both Sub)
$(1/N_{evt})dN/dm$
PbPb/pp
m



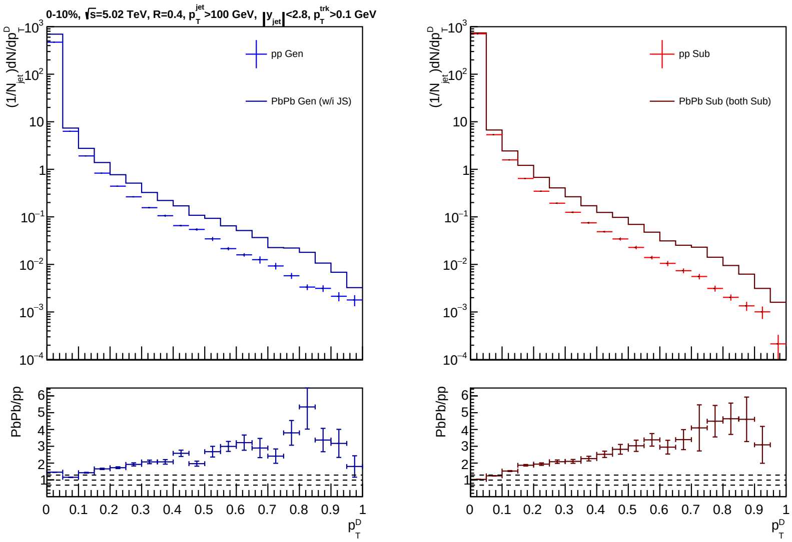
0-10%, √s=5.02 TeV, R=0.4, |y_jet|<2.8, p_T^trk>0.1 GeV
p_T^lead jet>120 GeV, p_T^sublead jet>50 GeV, Δϕ > 5π/6
(1/N_evt)dN/dm^lead
pp Gen
PbPb Gen (w/i JS)
pp Sub
PbPb Sub (both Sub)
PbPb/pp
m^lead



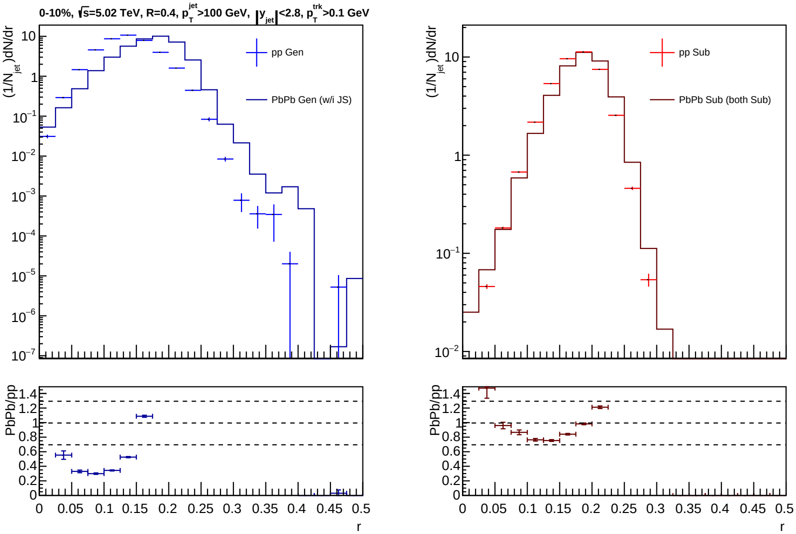
0-10%, √s=5.02 TeV, R=0.4, |y_jet|<2.8, p_T^trk>0.1 GeV
p_T^lead jet>120 GeV, p_T^sublead jet>50 GeV, Δϕ > 5π/6
(1/N_evt)dN/dm^subl
pp Gen
PbPb Gen (w/i JS)
pp Sub
PbPb Sub (both Sub)
PbPb/pp
m^subl



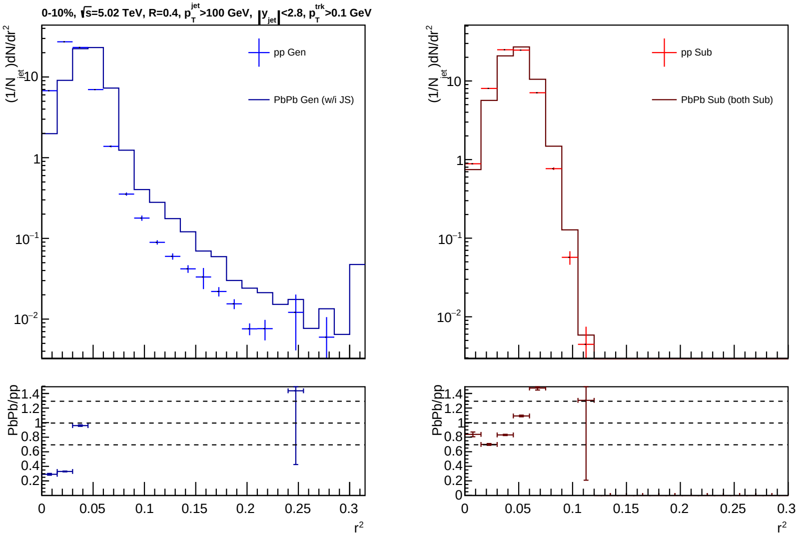
$$N_{cts} = \sum_{consts} 1$$



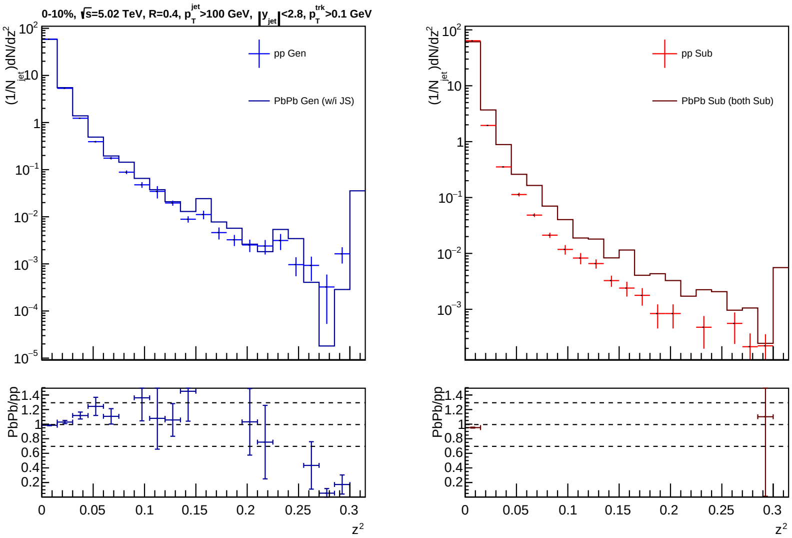
$$p_T^D = \left(\frac{p_T^i}{p_T^{jet}}\right)^2 cos^2(r);\, r = \sqrt{(\phi_i - \phi_{jet})^2 + (\eta_i - \eta_{jet})^2}$$



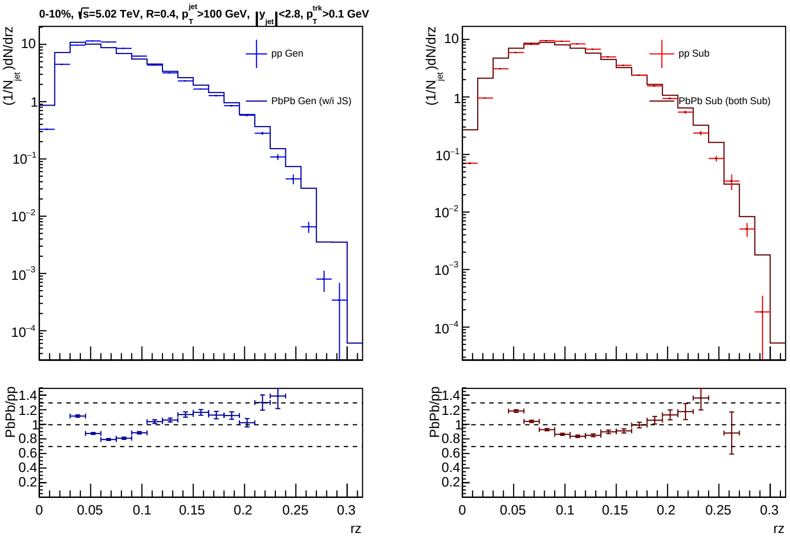
$$r = \sum_{consts} \frac{1}{N_{consts}} \sqrt{(\phi_i - \phi_{jet})^2 + (\eta_i - \eta_{jet})^2}$$



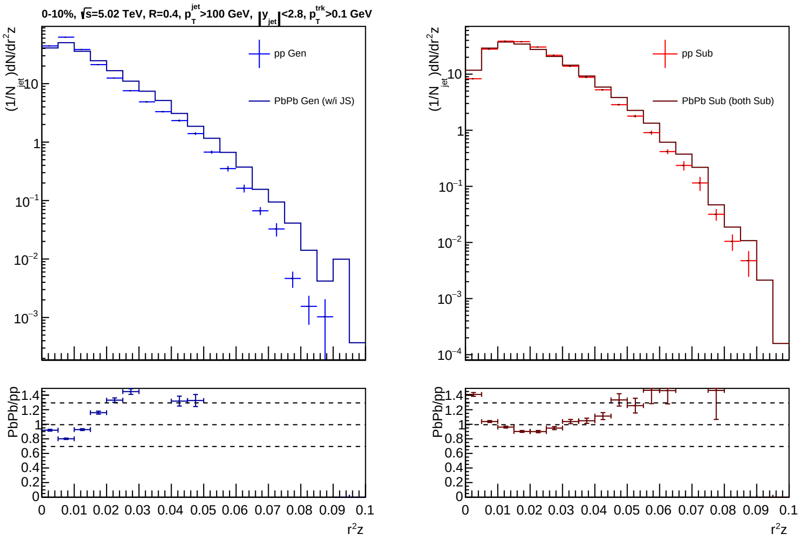
$$r^2 = \sum_{consts} \frac{1}{N_{consts}} \left| (\phi_i - \phi_{jet})^2 + (\eta_i - \eta_{jet})^2 \right|$$



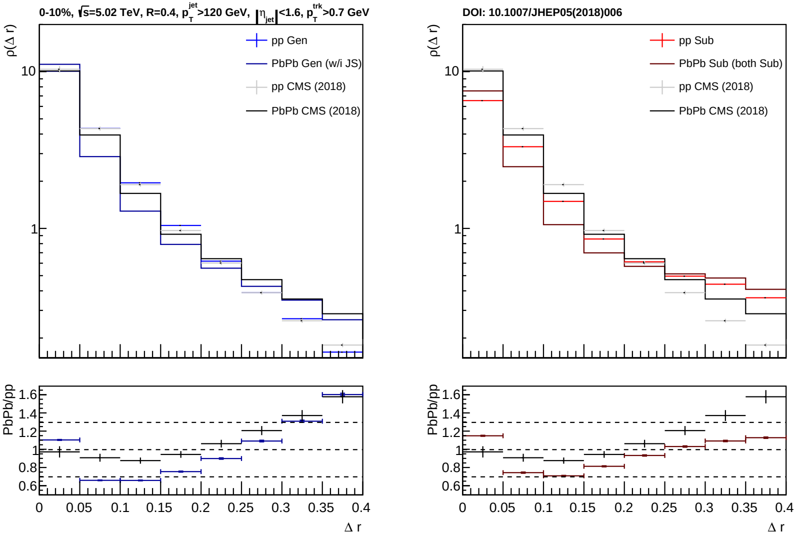
$$z^2 = \sum_{consts} \frac{1}{N_{consts}} \left(\frac{p_T^i}{p_T^{jet}} \right)^2$$



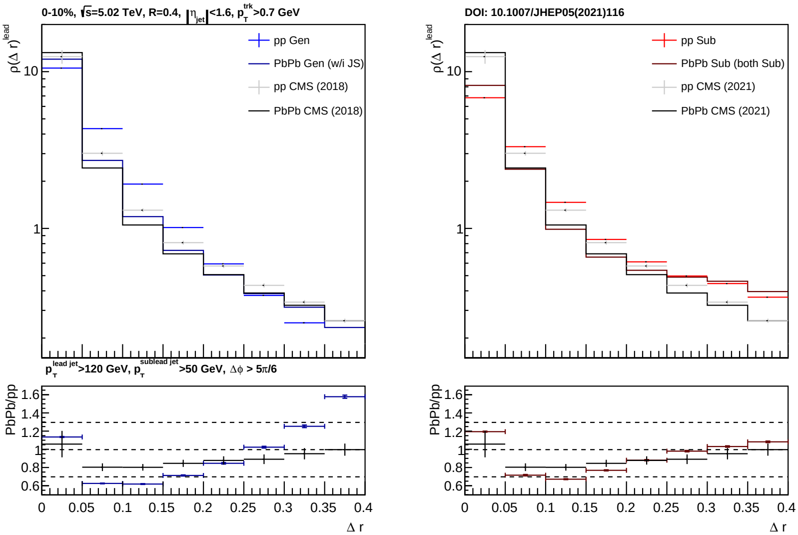
$$rz = \sum_{consts} \frac{1}{N_{consts}} \left(\frac{p_T^i}{p_T^{jet}} \right) \sqrt{(\phi_i - \phi_{jet})^2 + (\eta_i - \eta_{jet})^2}$$



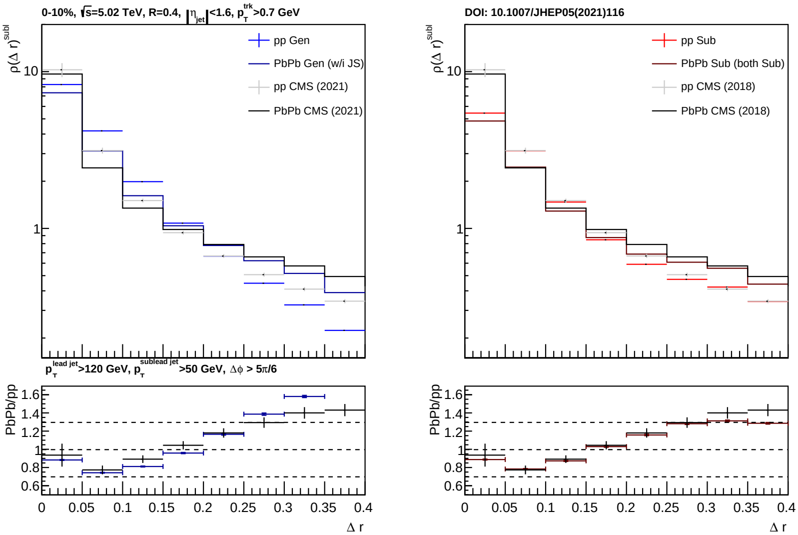
$$r^2 z = \sum_{consts} \frac{1}{N_{consts}} \left(\frac{p_T^i}{p_T^{jet}} \right) \left| (\phi_i - \phi_{jet})^2 + (\eta_i - \eta_{jet})^2 \right|$$



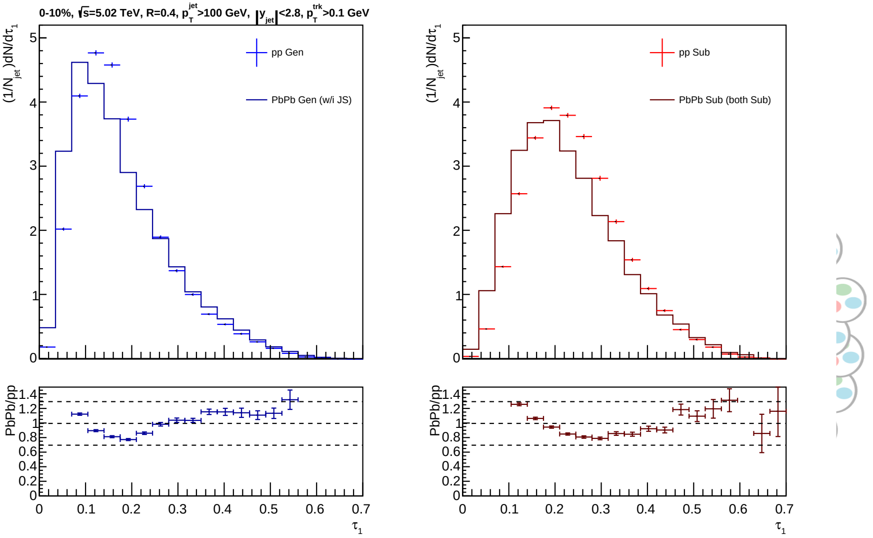
$$\rho(\Delta r) = \frac{1}{\delta r}\frac{1}{N_{jets}}\sum_{consts\in\Delta r} p_T^{const}$$



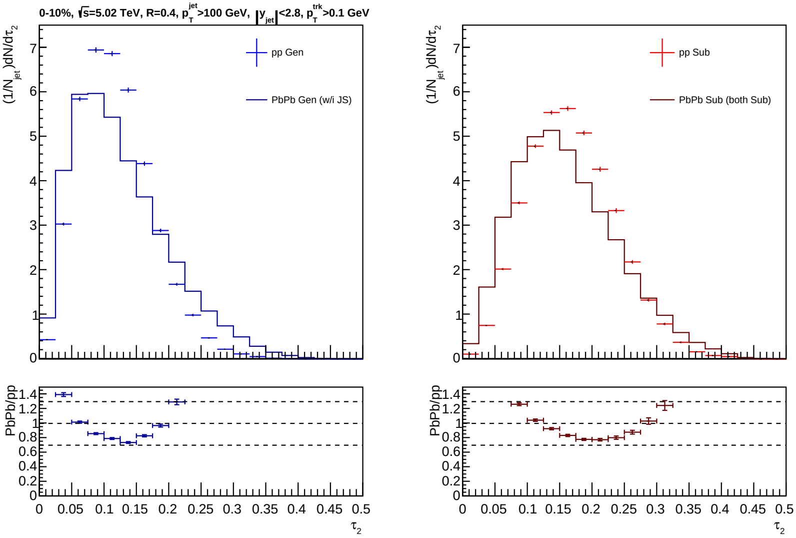
$$\rho(\Delta r) = \frac{1}{\delta r}\frac{1}{N_{jets}} \sum_{consts \in \Delta r} p_T^{const}$$



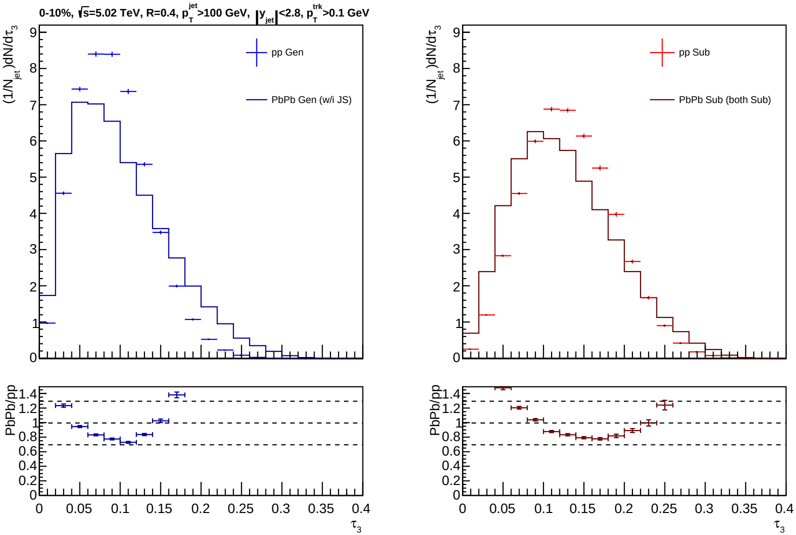
$$\rho(\Delta r) = \frac{1}{\delta r}\frac{1}{N_{jets}} \sum_{consts \in \Delta r} p_T^{const}$$



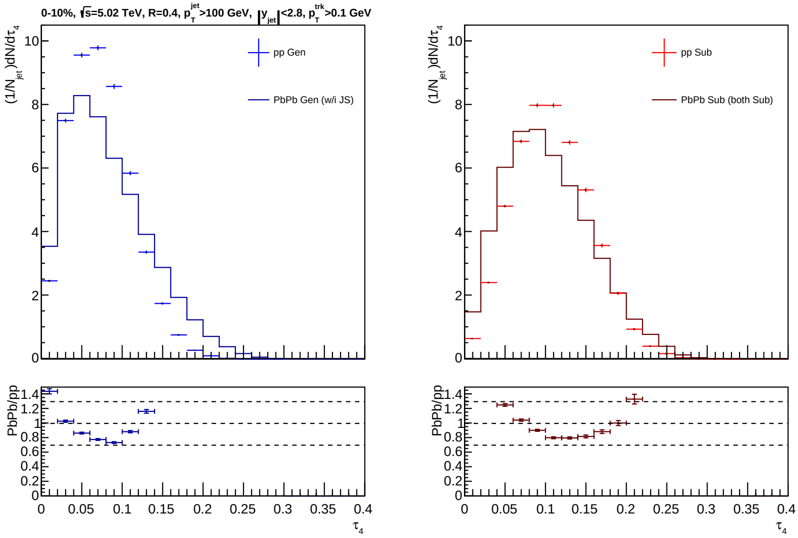
$$\tau_1 = \sum_{consts} p_T^{const} \Delta R_{subjet1,const}$$



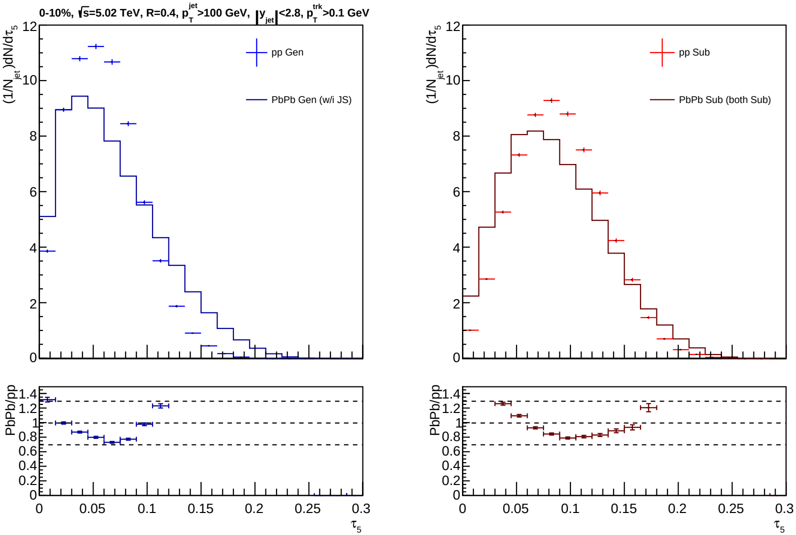
$$\tau_2 = \sum_{consts} p_T^{const}\, min(\Delta R_{subjet1,const}, \Delta R_{subjet2,const})$$



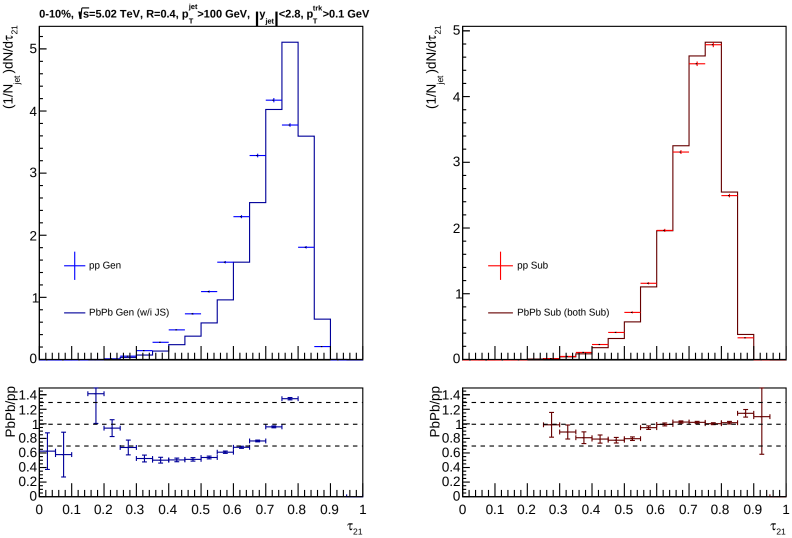
$$\tau_3 = \sum_{consts} p_T^{const} min(\Delta R_{subjet1,const}, \Delta R_{subjet2,const}, \Delta R_{subjet3,const})$$



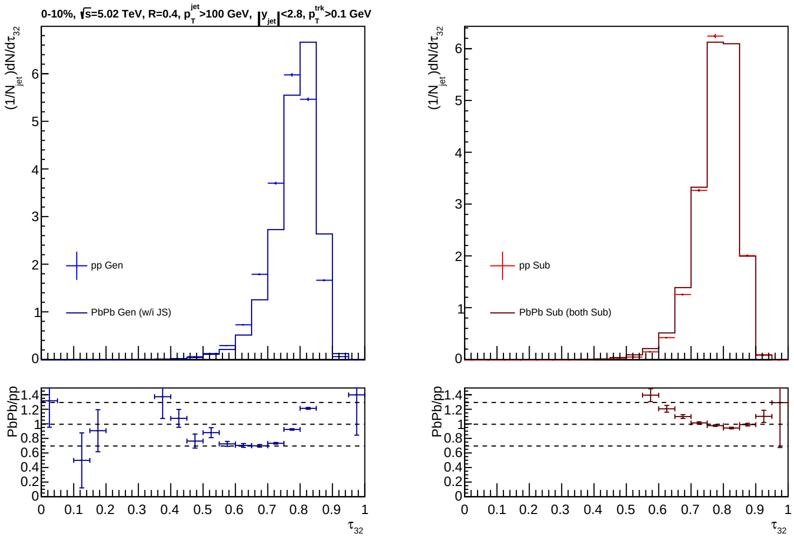
$$\tau_4 = \sum_{consts} p_T^{const} min(\Delta R_{subjet1,const}, \Delta R_{subjet2,const}, \Delta R_{subjet3,const}, \Delta R_{subjet4,const})$$



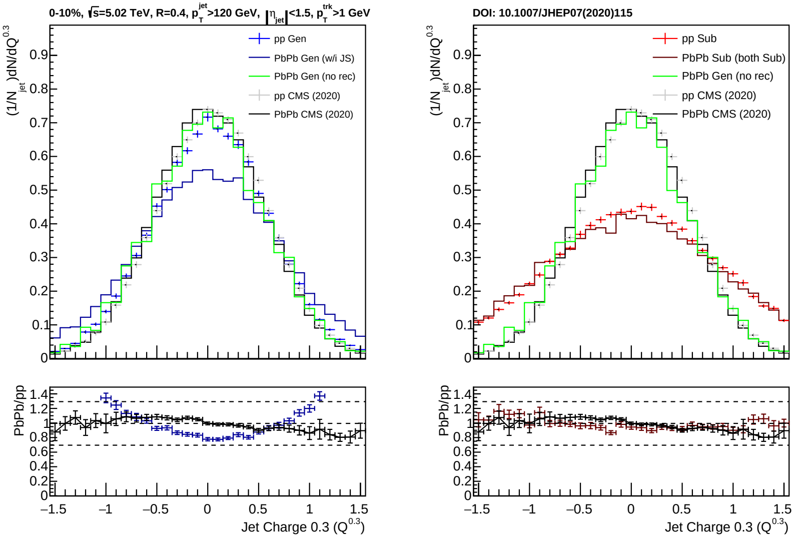
$$\tau_5 = \sum_{consts} p_T^{const} min(\Delta R_{subjet1,const}, \Delta R_{subjet2,const}, \Delta R_{subjet3,const}, \dots, \Delta R_{subjet5,const})$$



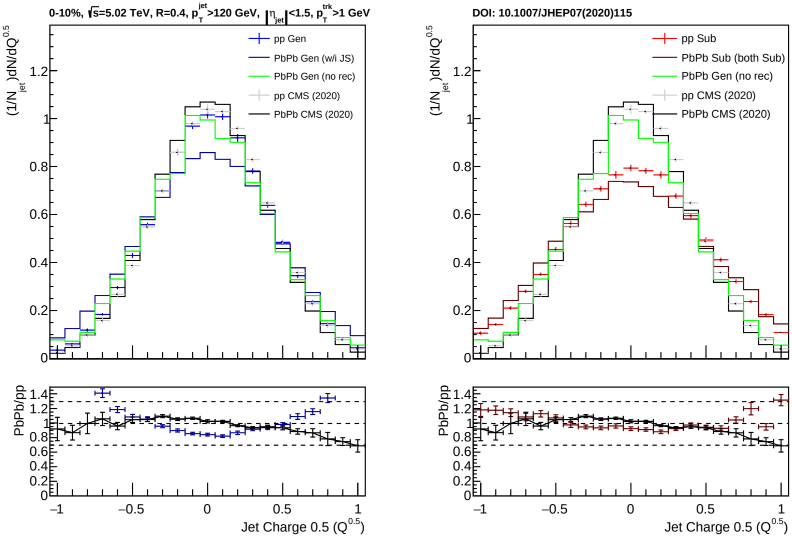
$$\tau_{21} = \frac{\tau_2}{\tau_1}$$



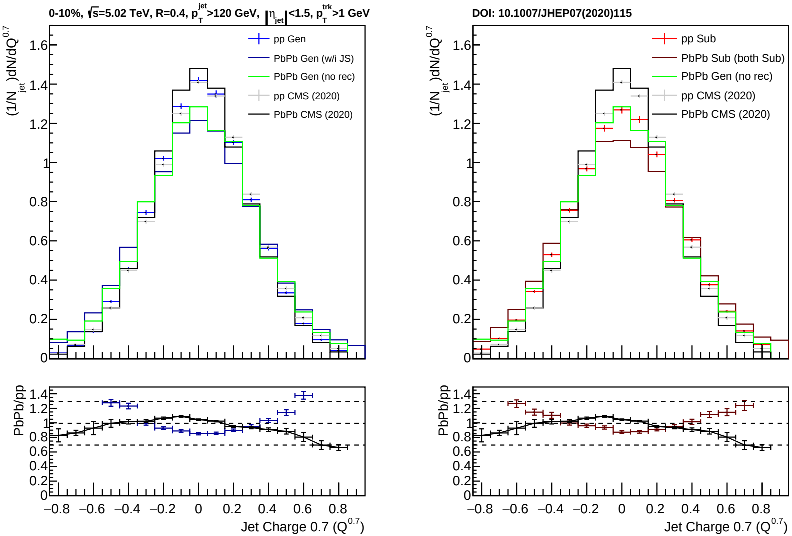
$$\tau_{21} = \frac{\tau_3}{\tau_2}$$



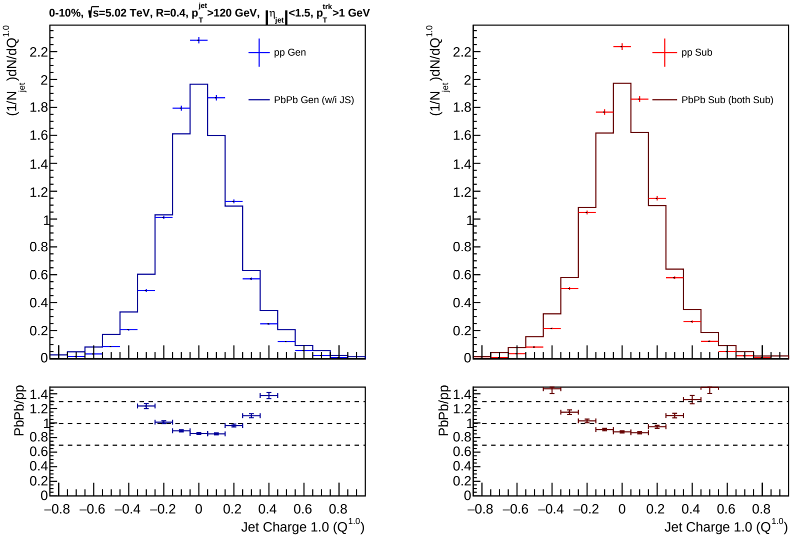
$$Q^{0.3} = \frac{1}{(p_T^{jet})^{0.3}} \sum_{consts} q^{const} (p_T^{const})^{0.3}$$



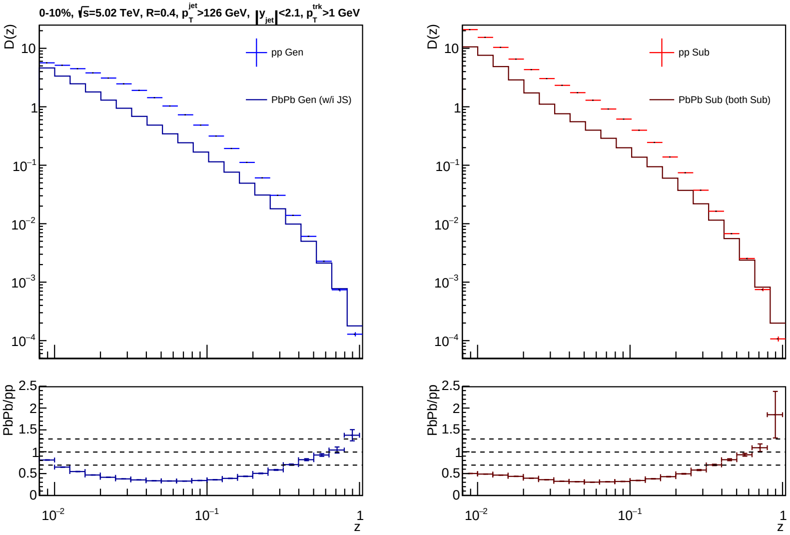
$$Q^{0.5} = \frac{1}{(p_T^{jet})^{0.5}} \sum_{consts} q^{const} (p_T^{const})^{0.5}$$



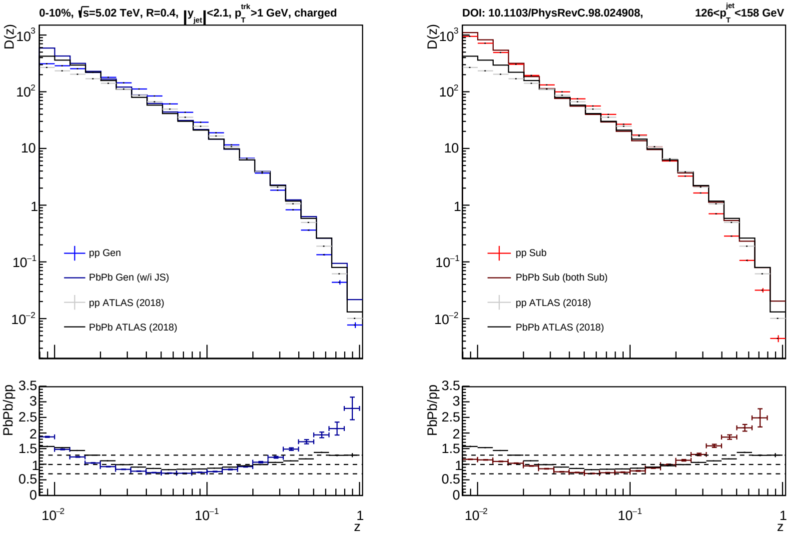
$$Q^{0.7} = \frac{1}{(p_T^{jet})^{0.7}} \sum_{consts} q^{const} (p_T^{const})^{0.7}$$



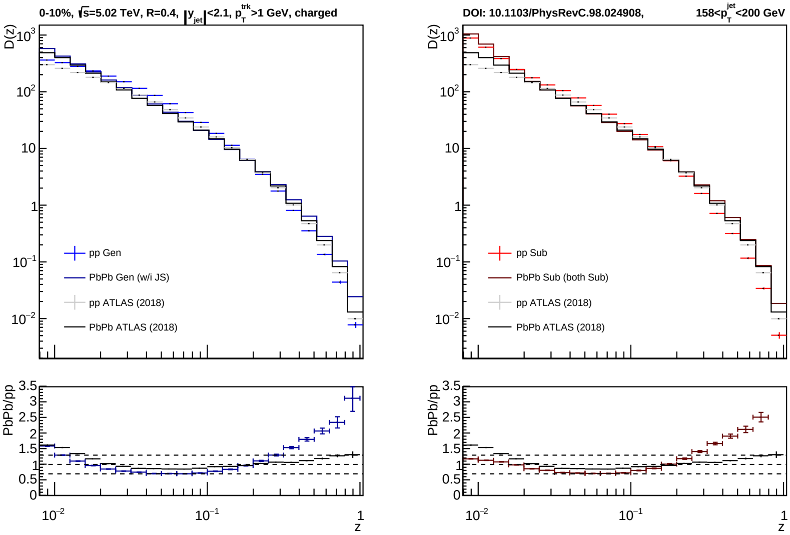
$$Q^{1} = \frac{1}{p_T^{jet}} \sum_{consts} q^{const} p_T^{const}$$



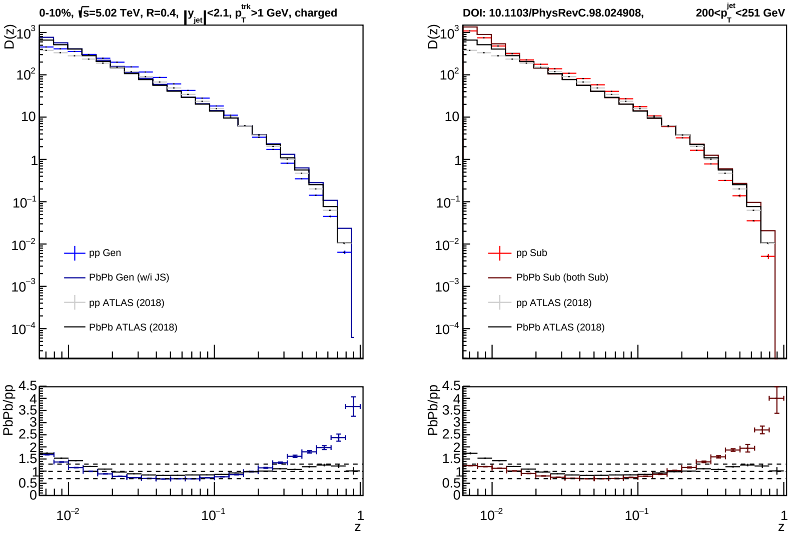
$$D(z) = \frac{1}{N_{jet}} \frac{dN_{chg}}{dz}; \; z = \frac{p_T^{const} \cos(\Delta R)}{p_T^{jet}}$$



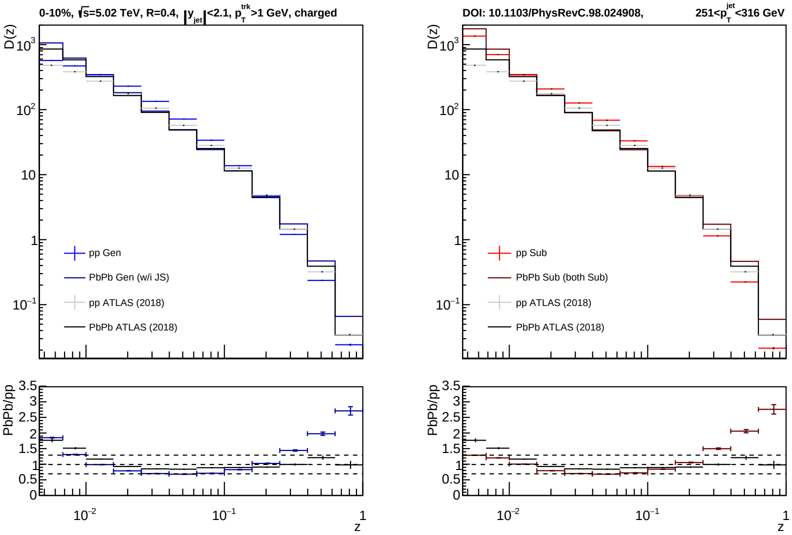
$$D(z) = \frac{1}{N_{jet}} \frac{dN_{chg}}{dz};\; z = \frac{p_T^{const} \cos(\Delta R)}{p_T^{jet}}$$



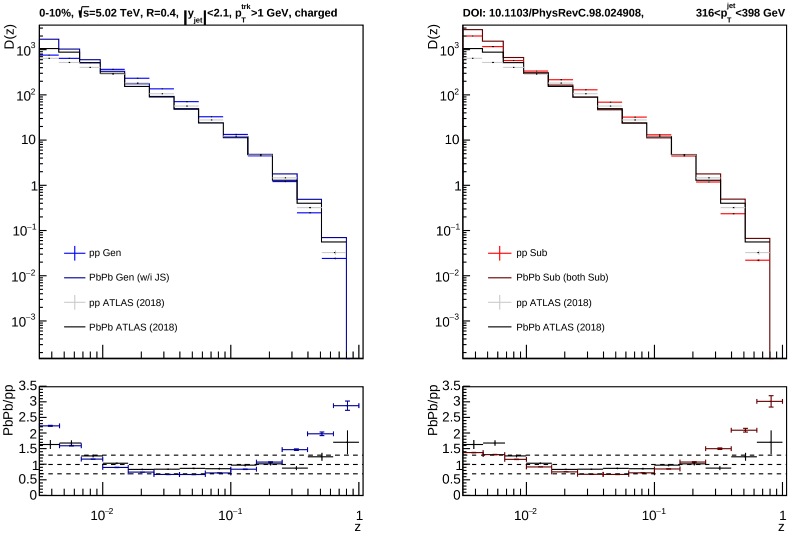
$$D(z) = \frac{1}{N_{jet}} \frac{dN_{chg}}{dz}; z = \frac{p_T^{const} \cos(\Delta R)}{p_T^{jet}}$$



$$D(z) = \frac{1}{N_{jet}} \frac{dN_{chg}}{dz};\ z = \frac{p_T^{const} \cos(\Delta R)}{p_T^{jet}}$$

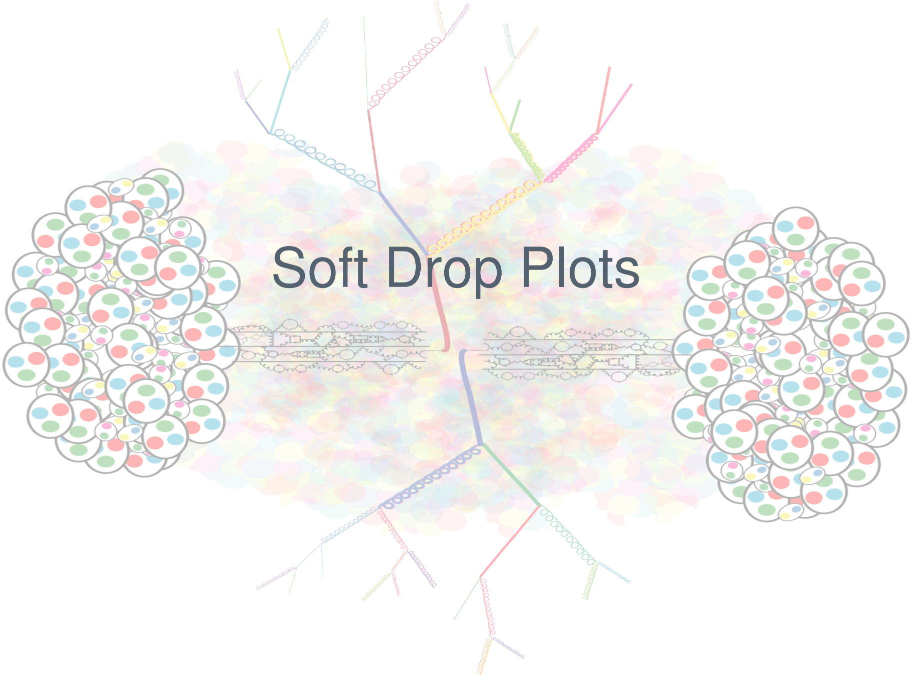


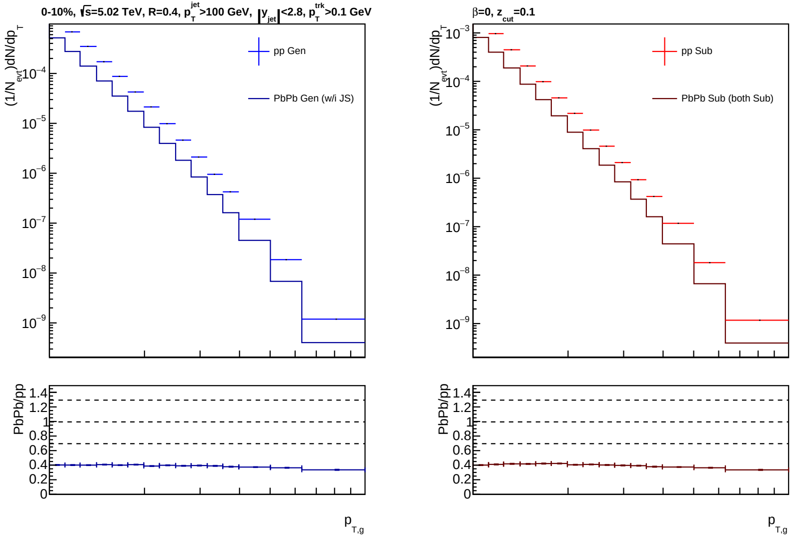
$$D(z) = \frac{1}{N_{jet}} \frac{dN_{chg}}{dz}; z = \frac{p_T^{const} \cos(\Delta R)}{p_T^{jet}}$$



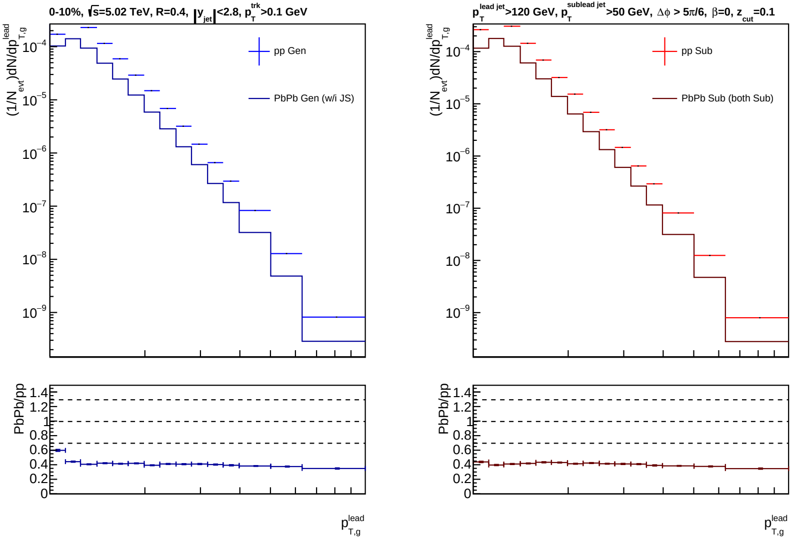
$$D(z) = \frac{1}{N_{jet}} \frac{dN_{chg}}{dz}; \; z = \frac{p_T^{const} \cos(\Delta R)}{p_T^{jet}}$$

Soft Drop Plots

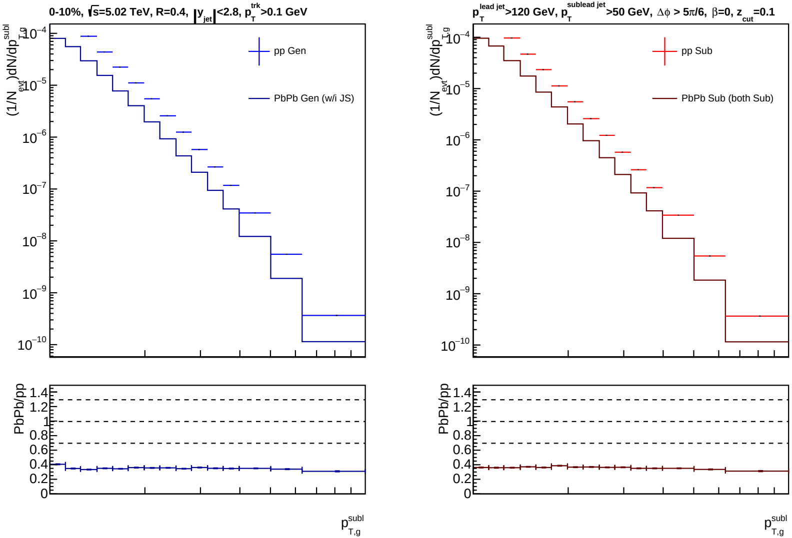




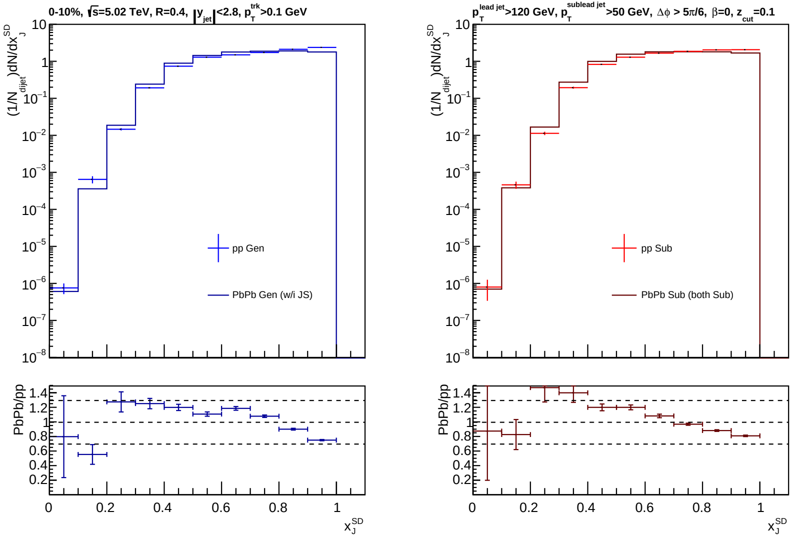
0-10%, √s=5.02 TeV, R=0.4, p_T^jet>100 GeV, |y_jet|<2.8, p_T^trk>0.1 GeV
β=0, z_cut=0.1
(1/N_evt)dN/dp_T
pp Gen
PbPb Gen (w/i JS)
pp Sub
PbPb Sub (both Sub)
PbPb/pp
p_T,g



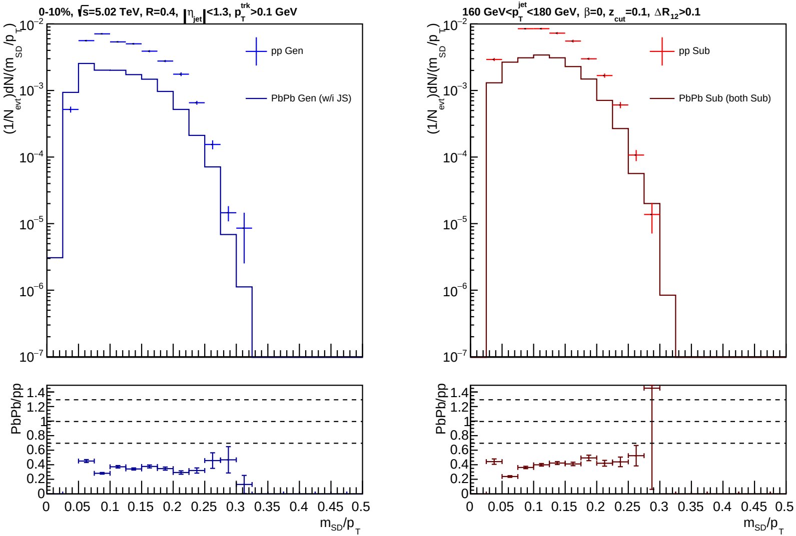
0-10%, $\sqrt{s}$=5.02 TeV, R=0.4, $|y_{jet}|$<2.8, p_T^{trk}>0.1 GeV
$p_T^{lead\ jet}$>120 GeV, $p_T^{sublead\ jet}$>50 GeV, $\Delta\phi$ > 5π/6, β=0, z_{cut}=0.1
$(1/N_{evt})dN/dp_{T,g}^{lead}$
pp Gen
PbPb Gen (w/i JS)
pp Sub
PbPb Sub (both Sub)
PbPb/pp
$p_{T,g}^{lead}$



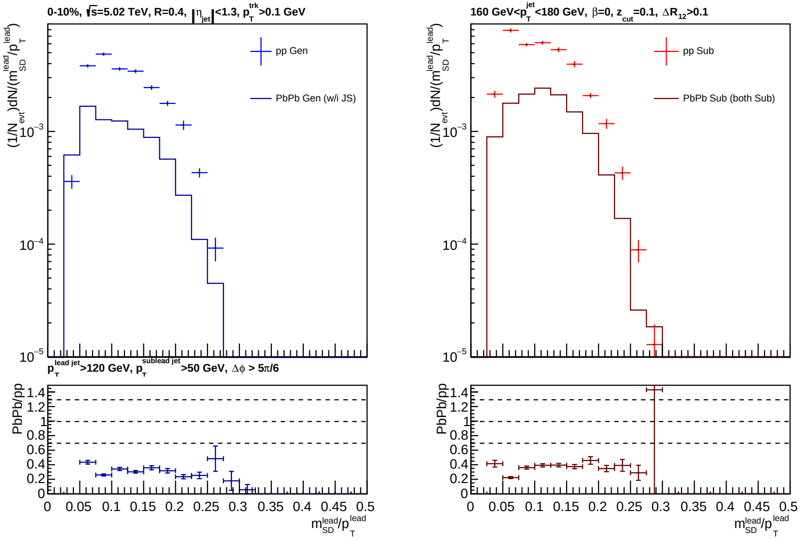
0-10%, √s=5.02 TeV, R=0.4, |y_jet|<2.8, p_T^trk>0.1 GeV
p_T^lead jet>120 GeV, p_T^sublead jet>50 GeV, Δφ > 5π/6, β=0, z_cut=0.1
(1/N_evt)dN/dp_T,g^subl
pp Gen
PbPb Gen (w/i JS)
pp Sub
PbPb Sub (both Sub)
PbPb/pp
p_T,g^subl



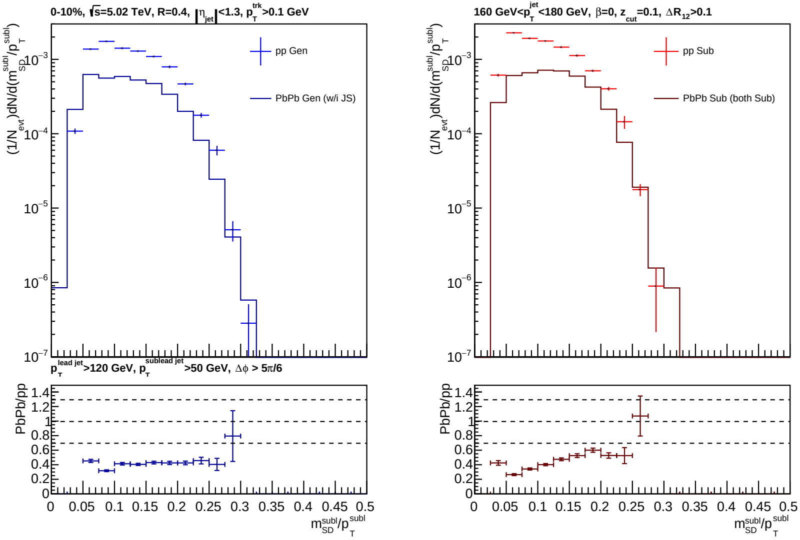
$$x_j^{SD} = p_{T,g} T^{sublead} / p_{T,g}^{lead}$$



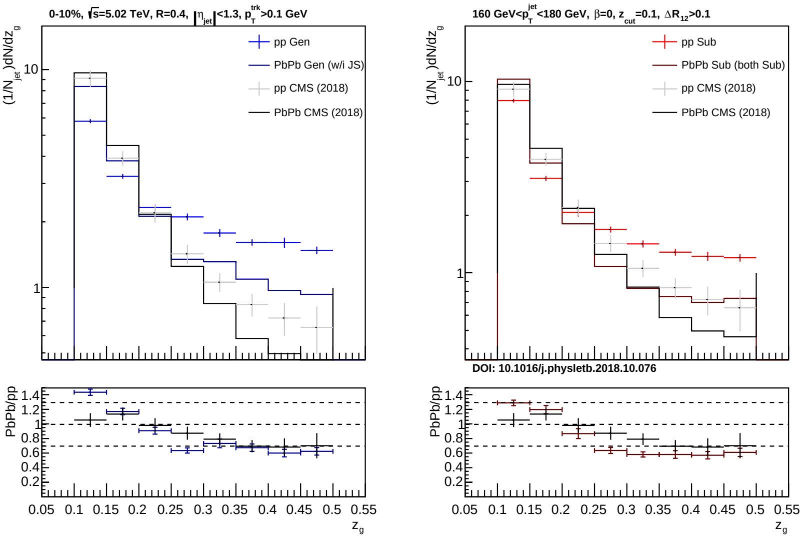
0-10%, √s=5.02 TeV, R=0.4, |η_jet|<1.3, p_T^trk>0.1 GeV
160 GeV<p_T^jet<180 GeV, β=0, z_cut=0.1, ΔR_12>0.1
(1/N_evt)dN/(m_SD/p_T)
pp Gen
PbPb Gen (w/i JS)
pp Sub
PbPb Sub (both Sub)
PbPb/pp
m_SD/p_T



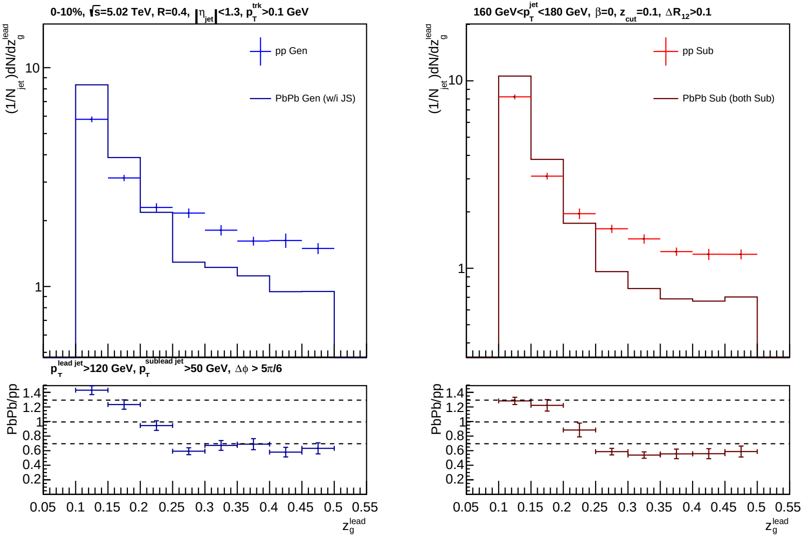
0-10%, √s=5.02 TeV, R=0.4, |η_jet|<1.3, p_T^trk>0.1 GeV
160 GeV<p_T^jet<180 GeV, β=0, z_cut=0.1, ΔR_12>0.1
pp Gen
PbPb Gen (w/i JS)
pp Sub
PbPb Sub (both Sub)
p_T^lead jet>120 GeV, p_T^sublead jet>50 GeV, Δϕ > 5π/6
(1/N_evt)dN/(m_SD^lead/p_T^lead)
PbPb/pp
m_SD^lead/p_T^lead



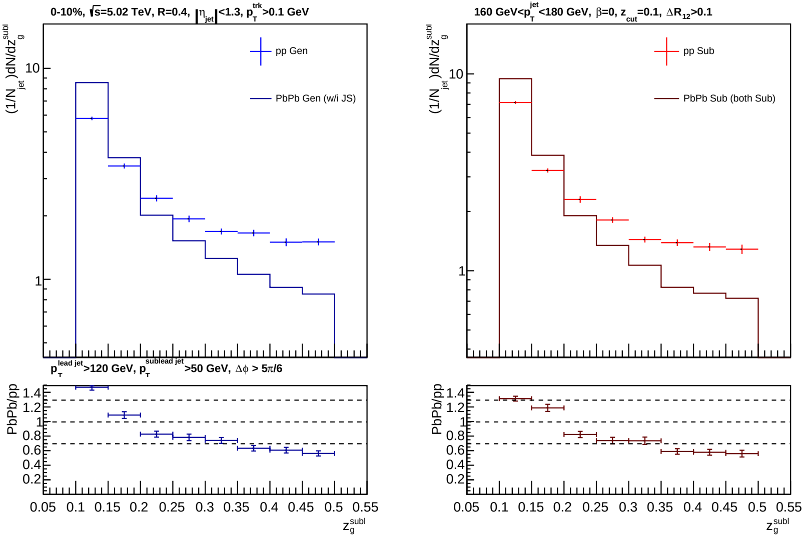
0-10%, √s=5.02 TeV, R=0.4, |η_jet|<1.3, p_T^trk>0.1 GeV
160 GeV<p_T^jet<180 GeV, β=0, z_cut=0.1, ΔR_12>0.1
p_T^lead jet>120 GeV, p_T^sublead jet>50 GeV, Δφ > 5π/6
pp Gen
PbPb Gen (w/i JS)
pp Sub
PbPb Sub (both Sub)
(1/N_evt)dN/d(m_SD^subl/p_T^subl)
PbPb/pp
m_SD^subl/p_T^subl



0-10%, √s=5.02 TeV, R=0.4, |η_jet|<1.3, p_T^trk>0.1 GeV
160 GeV<p_T^jet<180 GeV, β=0, z_cut=0.1, ΔR_12>0.1
pp Gen
PbPb Gen (w/i JS)
pp CMS (2018)
PbPb CMS (2018)
pp Sub
PbPb Sub (both Sub)
(1/N_jet)dN/dz_g
PbPb/pp
z_g
DOI: 10.1016/j.physletb.2018.10.076



0-10%, √s=5.02 TeV, R=0.4, |η_jet|<1.3, p_T^trk>0.1 GeV
160 GeV<p_T^jet<180 GeV, β=0, z_cut=0.1, ΔR_12>0.1
p_T^lead jet>120 GeV, p_T^sublead jet>50 GeV, Δφ > 5π/6
(1/N_jet)dN/dz_g^lead
pp Gen
PbPb Gen (w/i JS)
pp Sub
PbPb Sub (both Sub)
PbPb/pp
z_g^lead



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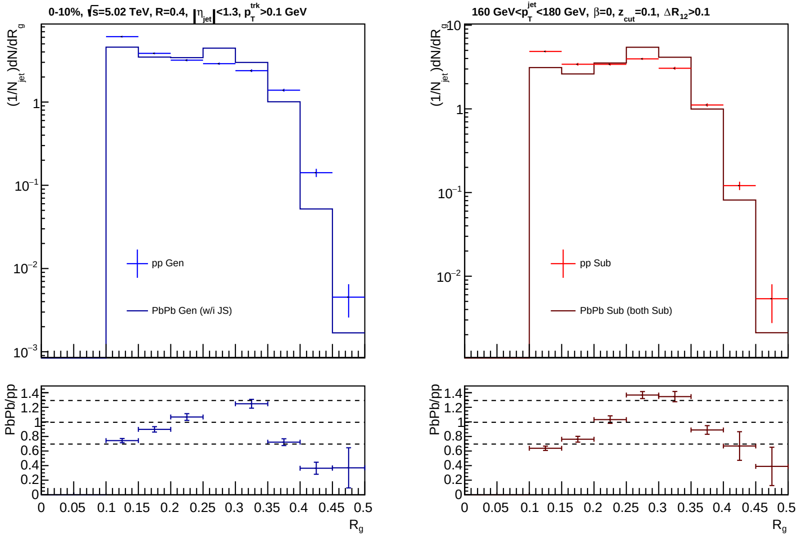
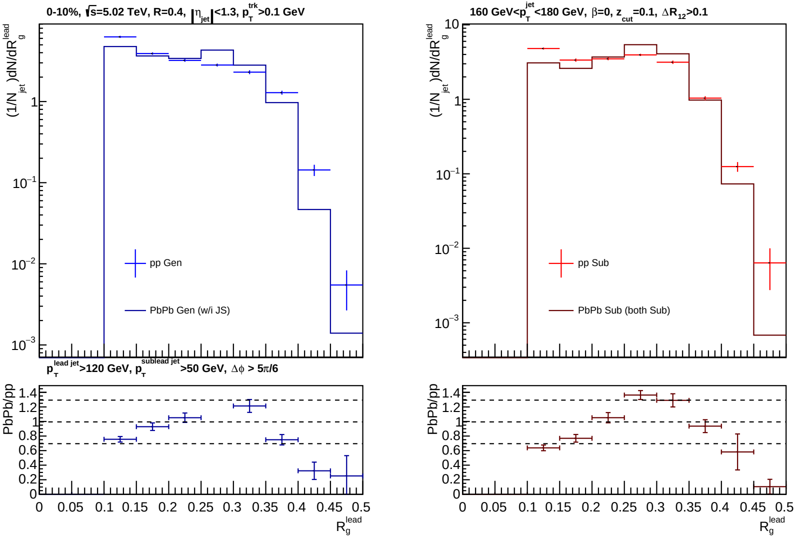
160 GeV<p_T^jet<180 GeV, β=0, z_cut=0.1, ΔR_12>0.1
pp Gen
PbPb Gen (w/i JS)
pp Sub
PbPb Sub (both Sub)
(1/N_jet)dN/dz_g^subl
PbPb/pp
p_T^lead jet>120 GeV, p_T^sublead jet>50 GeV, Δφ > 5π/6
z_g^subl



0-10%, √s=5.02 TeV, R=0.4, |η_jet|<1.3, p_T^trk>0.1 GeV
160 GeV<p_T^jet<180 GeV, β=0, z_cut=0.1, ΔR_12>0.1
(1/N_jet)dN/dR_g
pp Gen
PbPb Gen (w/i JS)
pp Sub
PbPb Sub (both Sub)
PbPb/pp
R_g



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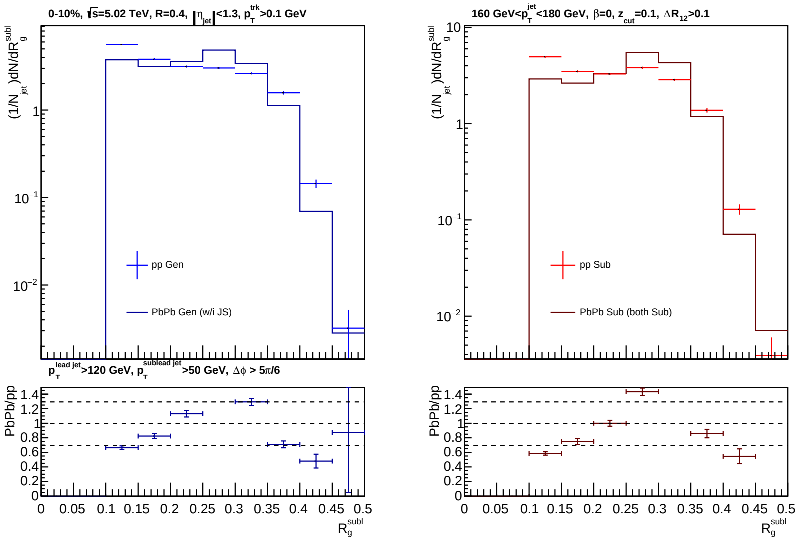
160 GeV<p_T^jet<180 GeV, β=0, z_cut=0.1, ΔR_12>0.1
p_T^lead jet>120 GeV, p_T^sublead jet>50 GeV, Δφ > 5π/6
(1/N_jet)dN/dR_g^lead
pp Gen
PbPb Gen (w/i JS)
pp Sub
PbPb Sub (both Sub)
PbPb/pp
R_g^lead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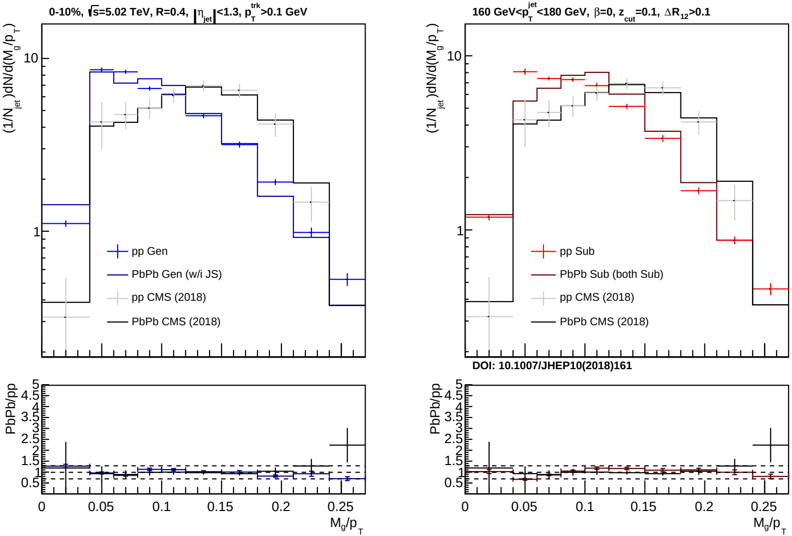
160 GeV<p_T^jet<180 GeV, β=0, z_cut=0.1, ΔR_12>0.1
p_T^lead jet>120 GeV, p_T^sublead jet>50 GeV, Δϕ > 5π/6
(1/N_jet)dN/dR_g^subl
PbPb/pp
R_g^subl
pp Gen
PbPb Gen (w/i JS)
pp Sub
PbPb Sub (both Sub)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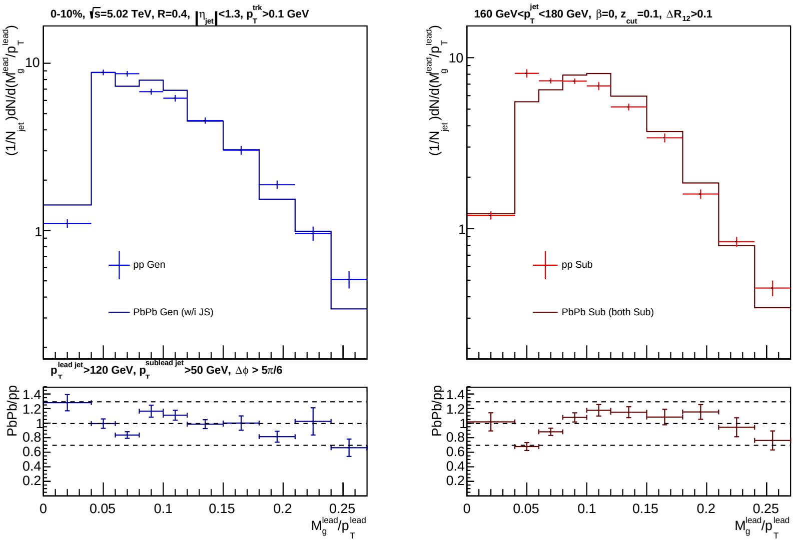
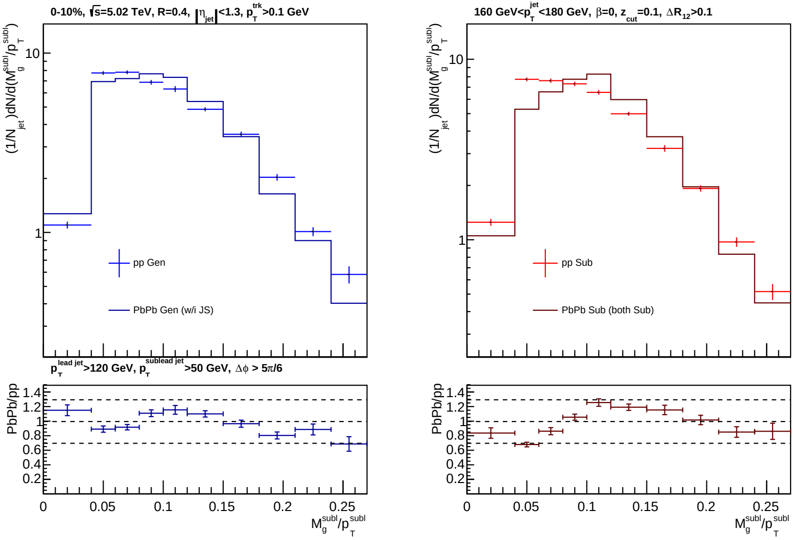
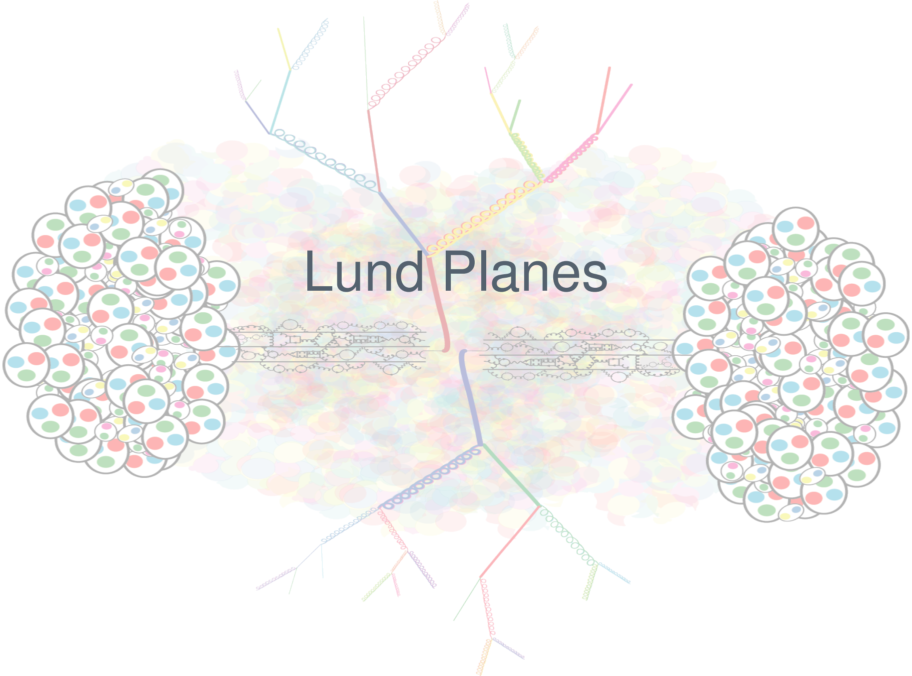
160 GeV<p_T^jet<180 GeV, β=0, z_cut=0.1, ΔR_12>0.1
(1/N_jet)dN/d(M_g/p_T)
pp Gen
PbPb Gen (w/i JS)
pp CMS (2018)
PbPb CMS (2018)
pp Sub
PbPb Sub (both Sub)
DOI: 10.1007/JHEP10(2018)161
PbPb/pp
M_g/p_T



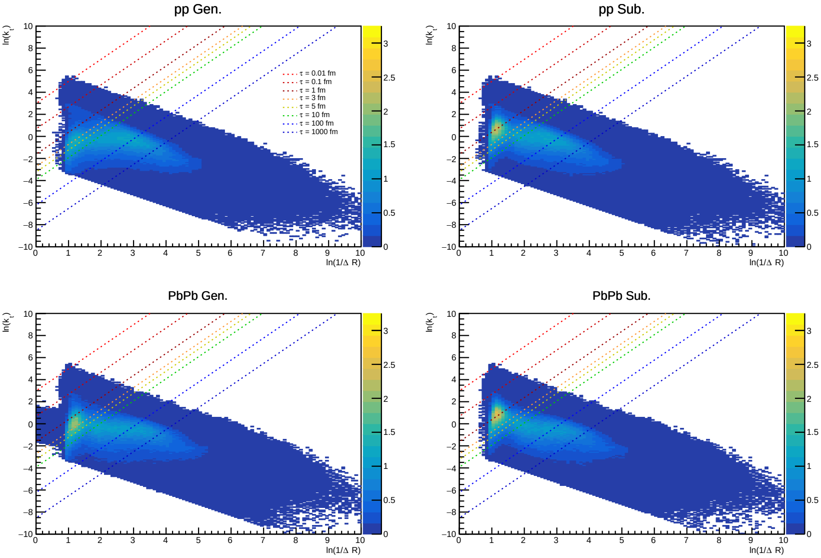
0-10%, √s=5.02 TeV, R=0.4, |η_jet|<1.3, p_T^trk>0.1 GeV
160 GeV<p_T^jet<180 GeV, β=0, z_cut=0.1, ΔR_12>0.1
(1/N_jet)dN/d(M_g^lead/p_T^lead)
pp Gen
PbPb Gen (w/i JS)
pp Sub
PbPb Sub (both Sub)
p_T^lead jet>120 GeV, p_T^sublead jet>50 GeV, Δϕ > 5π/6
PbPb/pp
M_g^lead/p_T^lead


0-10%, √s=5.02 TeV, R=0.4, |η_jet|<1.3, p_T^trk>0.1 GeV
160 GeV<p_T^jet<180 GeV, β=0, z_cut=0.1, ΔR_12>0.1
p_T^lead jet>120 GeV, p_T^sublead jet>50 GeV, Δφ > 5π/6
(1/N_jet)dN/d(M_g^subl/p_T^subl)
pp Gen
PbPb Gen (w/i JS)
pp Sub
PbPb Sub (both Sub)
PbPb/pp
M_g^subl/p_T^subl

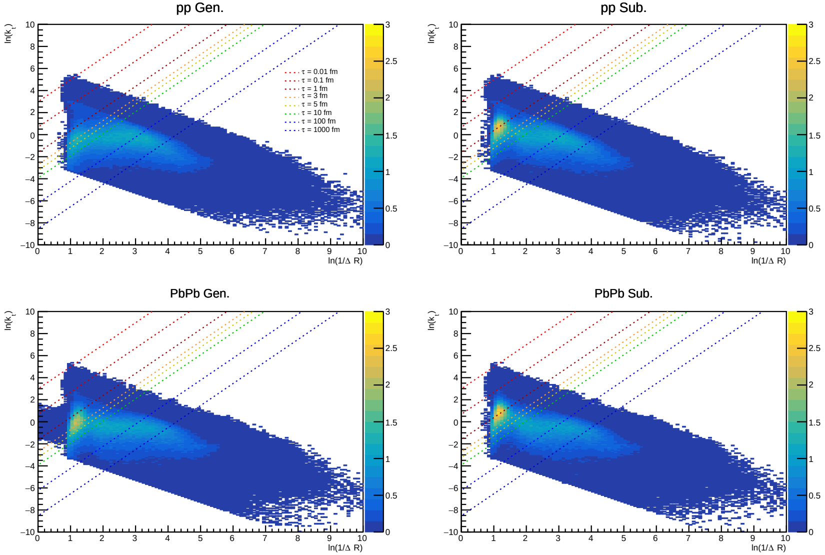
Lund Planes



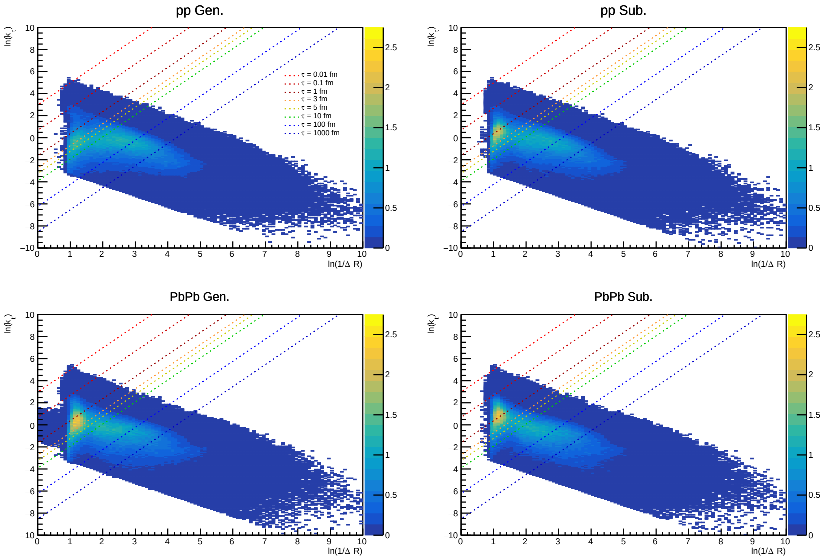
Lund Planes - Full Inclusive



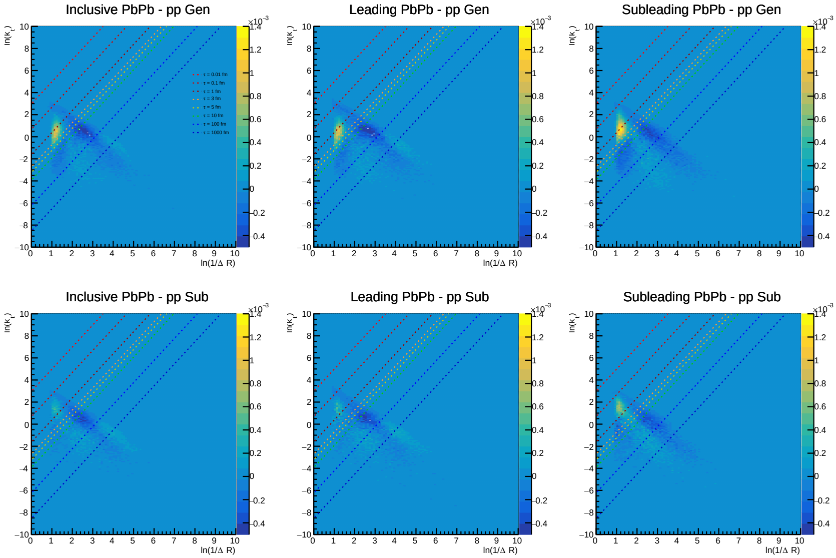
Lund Planes - Full Leading



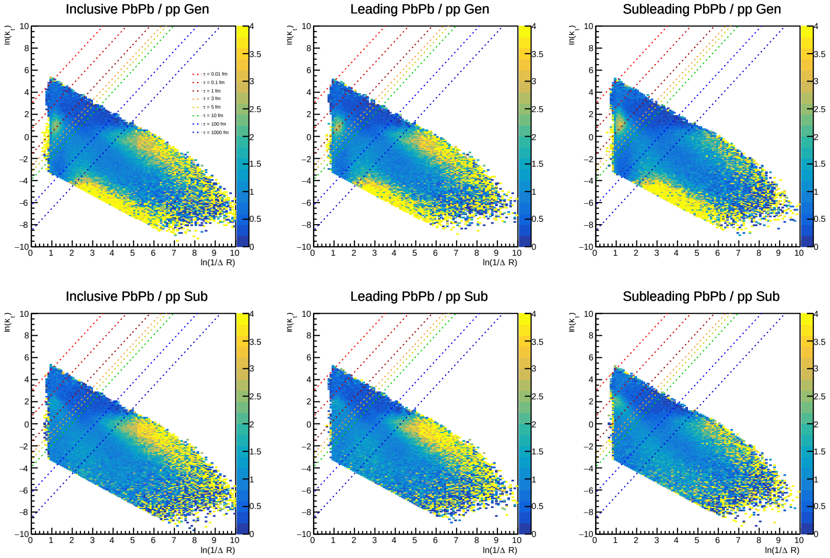
Lund Planes - Full Subleading



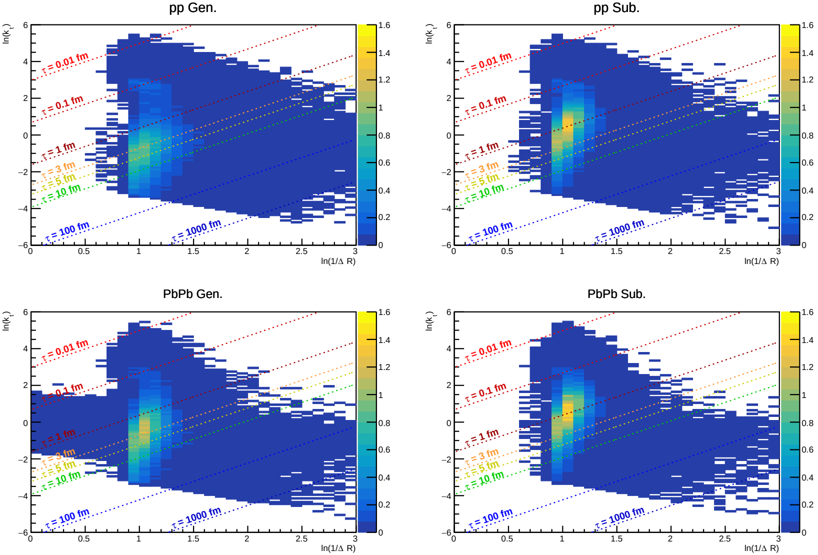
Lund Planes - Full Difference



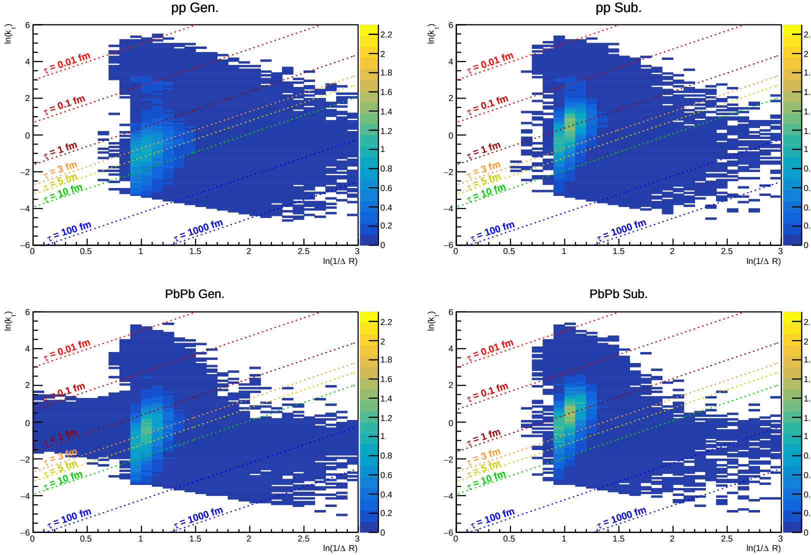
Lund Planes - Full Ratio



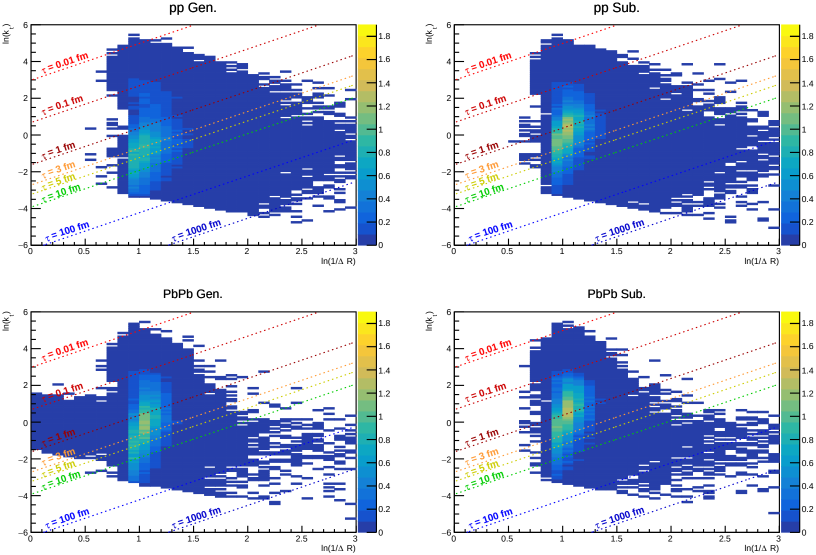
Lund Planes - First Splitting Inclusive



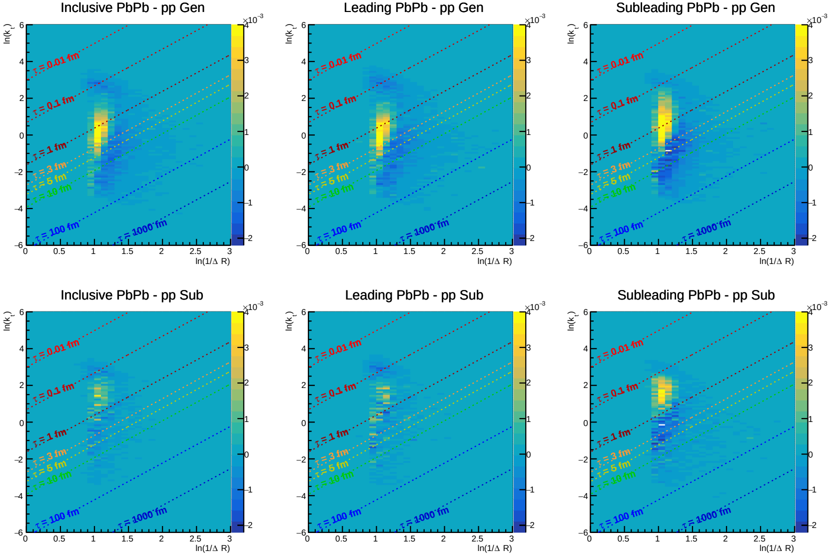
Lund Planes - First Splitting Leading



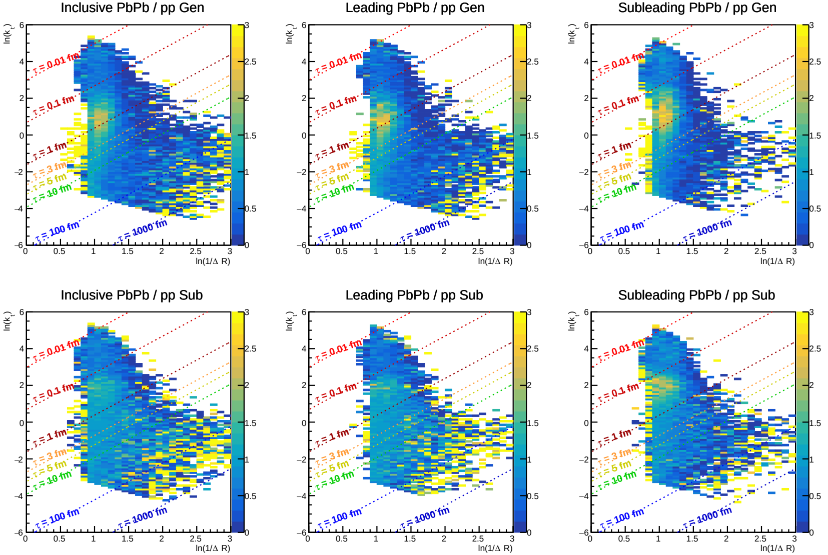
Lund Planes - First Splitting Subleading



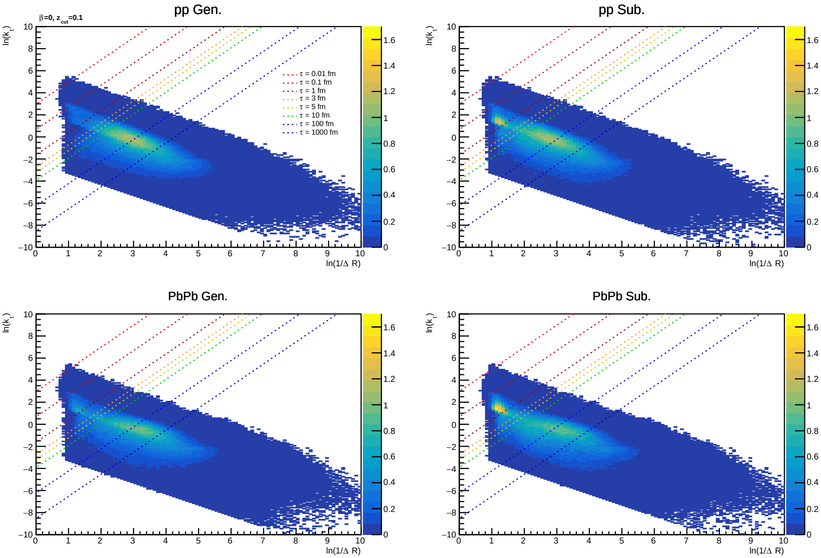
Lund Planes - First Splitting difference



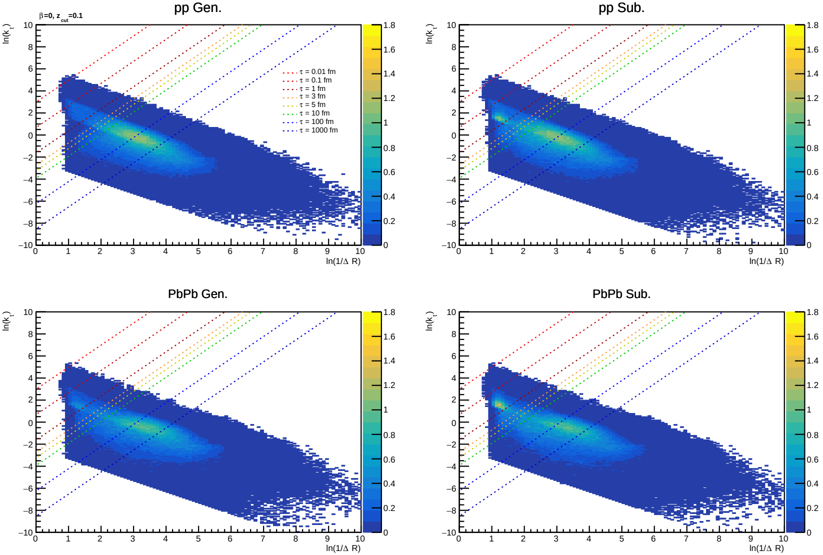
Lund Planes - First Splitting Ratio



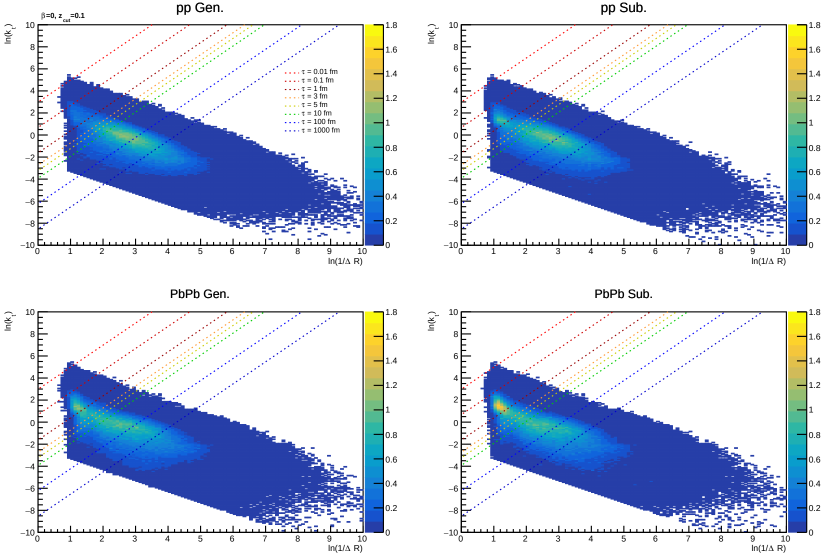
Lund Planes SD - Full Inclusive



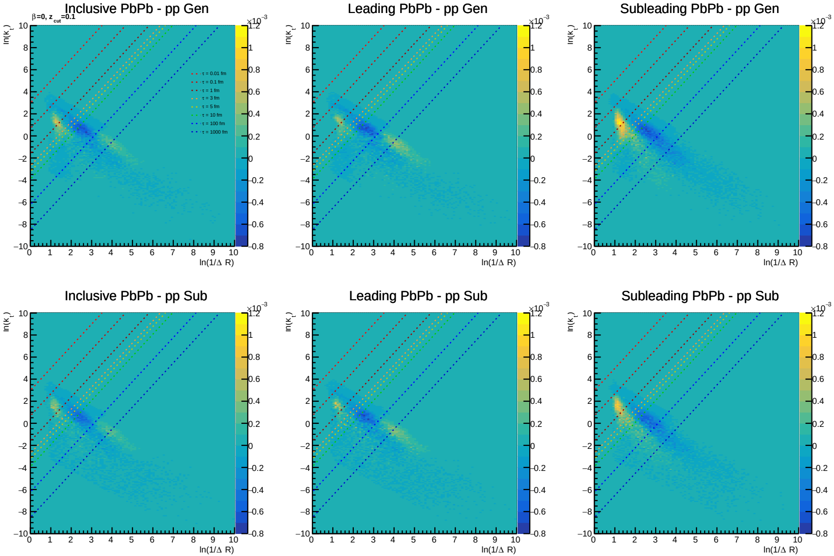
Lund Planes SD - Full Leading



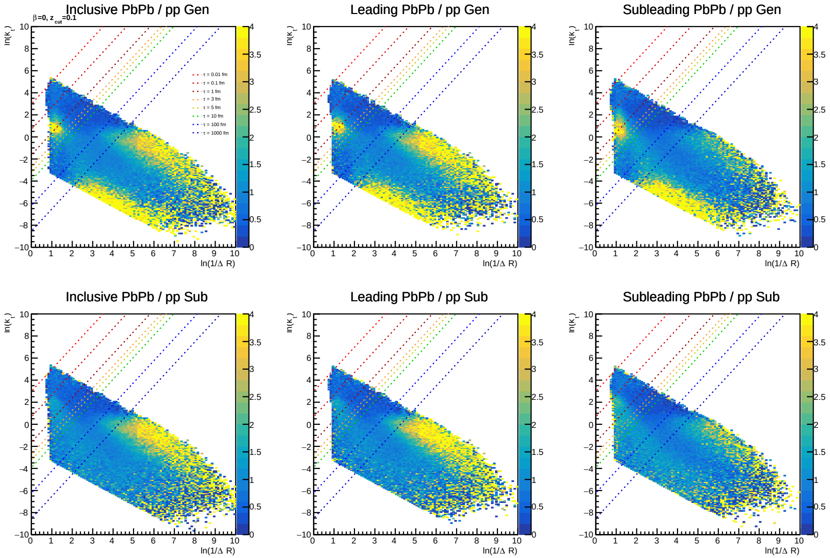
Lund Planes SD - Full Subleading



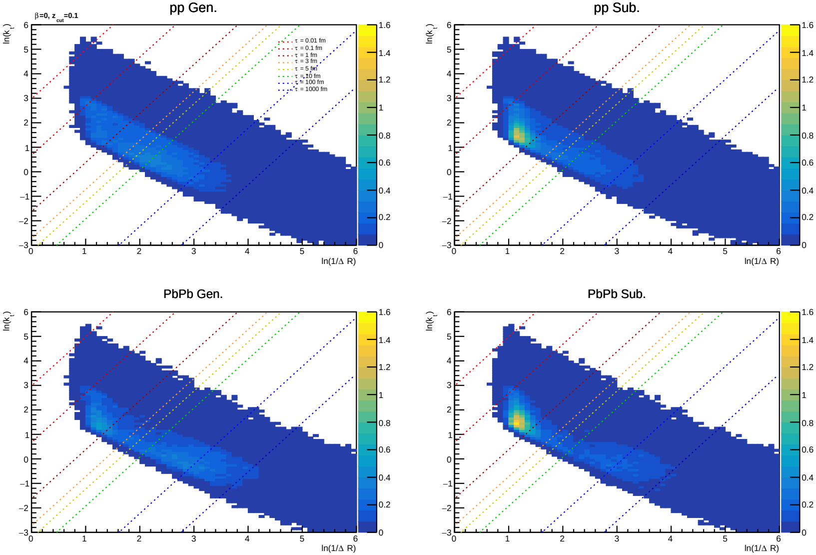
Lund Planes SD - Full Difference



Lund Planes SD - Full Ratio



Lund Planes SD - First Splitting Inclusive



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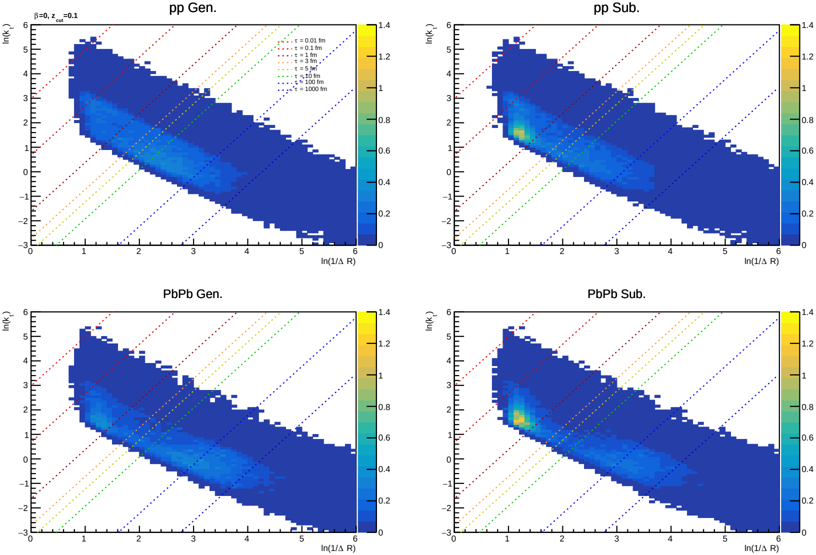

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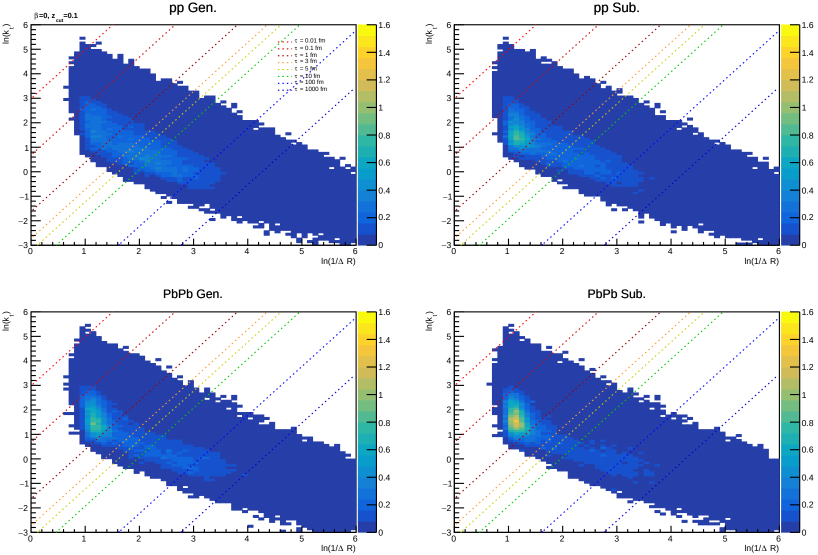
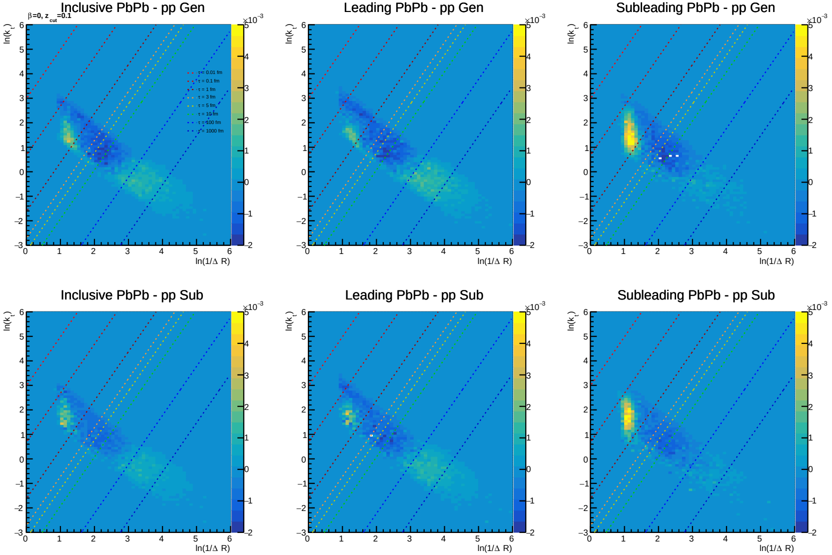


Lund Planes SD - First Splitting difference



Lund Planes SD - First Splitting Ratio