

AG - GDR QCD



**Measurement of the b -jet cross section in
proton-proton collisions at $\sqrt{s} = 13.6$ TeV**

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Overview

- **Physics motivation**
- ***b*-jet tagging methods**
 1. Track Counting
 2. Boosted Decision Trees
- **2-dimensional template fitting**
- **Unfolding and corrections**
- **Systematic uncertainties**
- **Results**
- **Towards Oxygen-Oxygen collisions**

Physics Motivations

Physics motivation

Importance of heavy flavor production measurements

- Heavy quarks are produced via initial hard scatterings
- Important tests to pQCD calculations
- Baseline for heavy-ion measurements

Heavy quarks in QGP

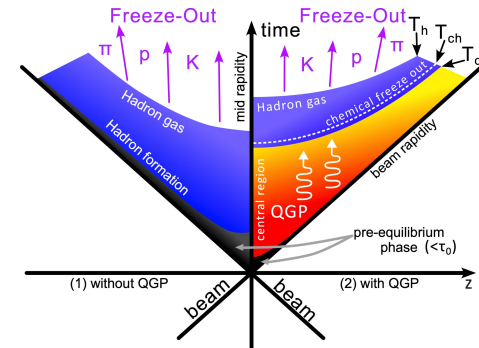
- In heavy-ion collisions, the earlier production of heavy quarks allows them to experience the entire evolution of the medium
- Understand heavy-quark energy loss mechanisms and their path length dependence

Heavy flavour jet measurements allow probing of

In pp collisions

- the dead-cone effect
- casimir effects (quark vs gluon)
- perturbative and non perturbative aspects of QCD radiation
- heavy quark hadronisation mechanisms

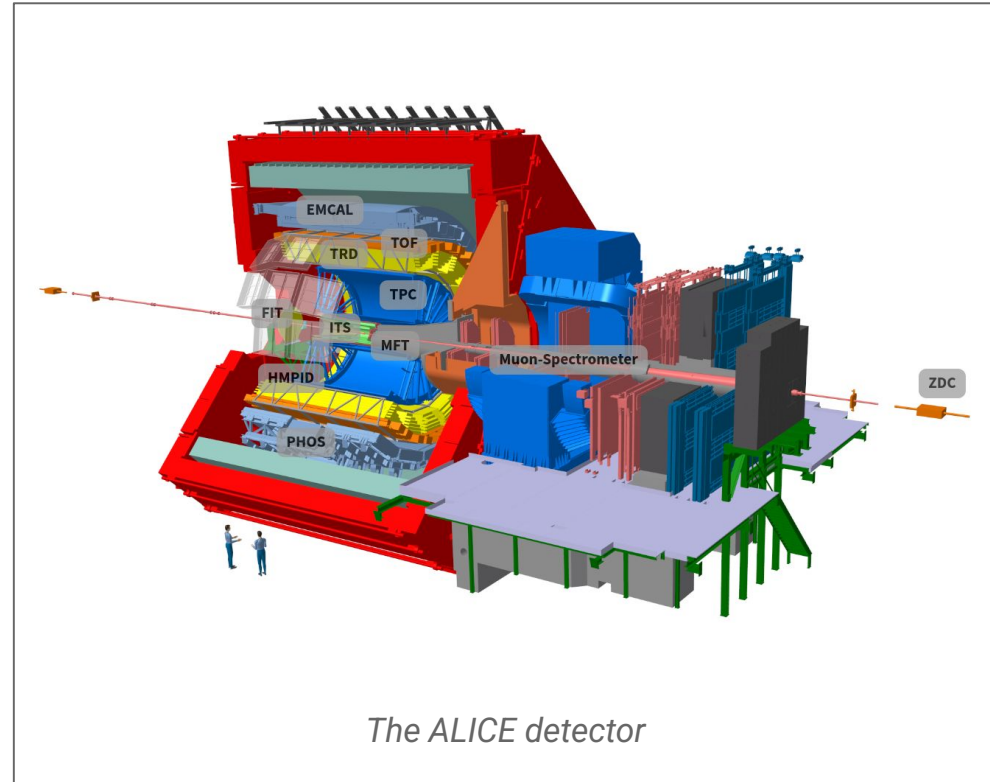
In heavy-ion collisions: measurement of heavy-flavour jets will allow the study of medium induced effects on the radiation pattern



The ALICE Apparatus

Upgraded ALICE detector in Run3

- Orders of magnitude higher statistics with respect to Run 1 and 2 – $O(3)$ and $O(2)$ for pp and PbPb respectively
- New Inner Tracking System (ITS2)
→ significant improvement of track impact parameter resolution → crucial for b -quark measurement
- Gas Electron Multipliers (GEM) based Time Projection Chamber (TPC) for continuous readout
- New Fast Interaction Trigger (FIT) for luminosity, multiplicity determination and event selection
- Detector capabilities up to very low p_T
→ ideal for R_{AA} measurements (specifically to probe HQ energy loss at low p_T)



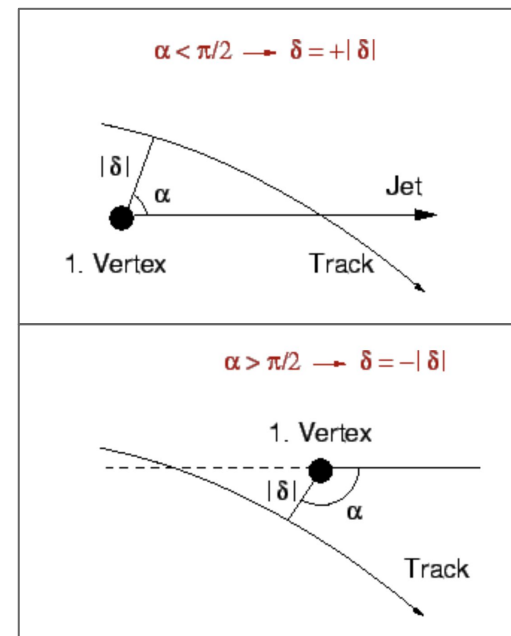
b-jet tagging methods

Two tagging methods

1. **Track Counting:** classical tagging method based on signed Impact Parameter or its significance
2. **Boosted Decision Trees:** ML based tagging – learns with “training features” like jet pT, Impact Parameter of tracks...

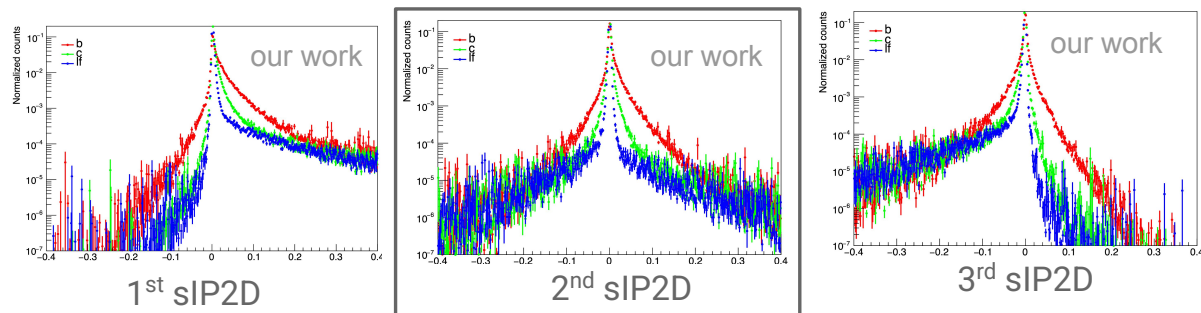
IP2D of track: distance of closest approach (DCA) of the track to the jet production vertex in the transverse plane of the detector (perpendicular to the beam). We take into account the **sign of the IP:** IP2D $\rightarrow$ sIP2D

Impact Parameter and its sign



Jet Tagging - Track counting

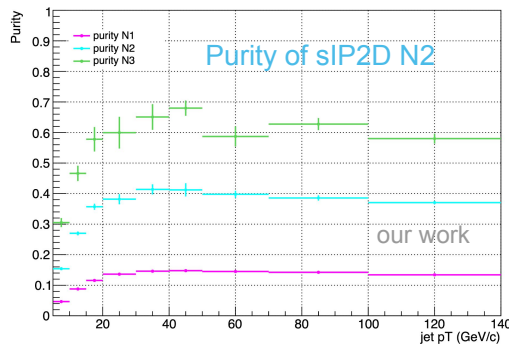
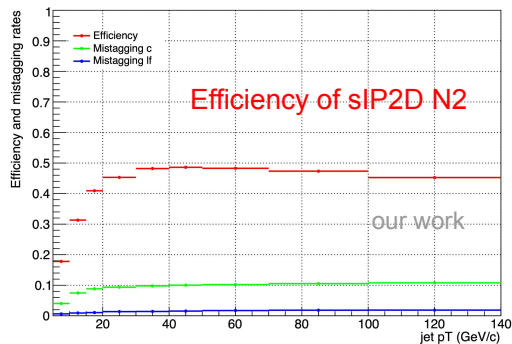
2D signed Impact Parameter distributions



sIP2D of jets : $b > c > lf$ → strong discriminating power

Arranges sIP2D of tracks in jets in **descending order** (1st, 2nd, 3rd largest sIP2D)

- Jet tagged as **b** if Nth largest sIP2D > threshold value
- 2nd largest sIP2D gives the best compromise between efficiency and purity



$$\text{Efficiency} = \frac{\text{Number of selected b-jets}}{\text{Total number of b-jets}}$$

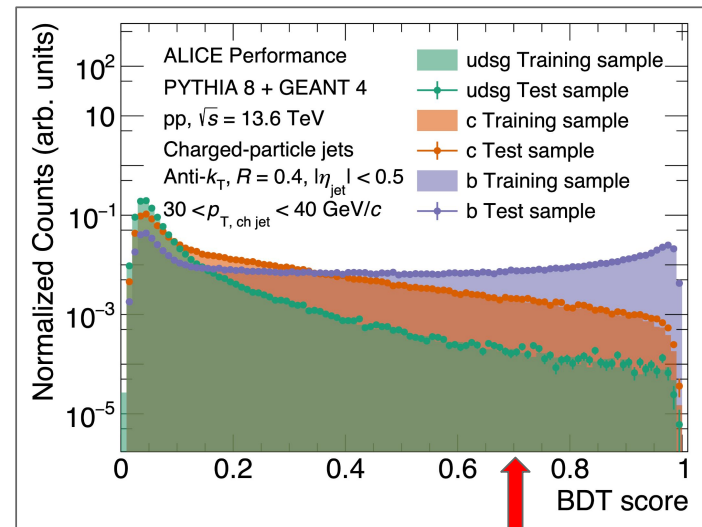
$$\text{Purity} = \frac{\text{Number of selected b-jets}}{\text{Total number of selected jets (b,c,lf)}}$$

Jet Tagging - **BDTs**

Training features used in pp 13.6 TeV analysis

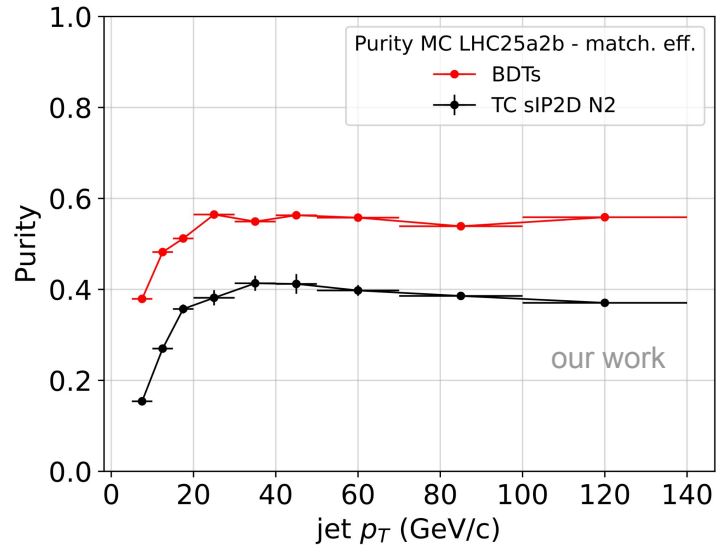
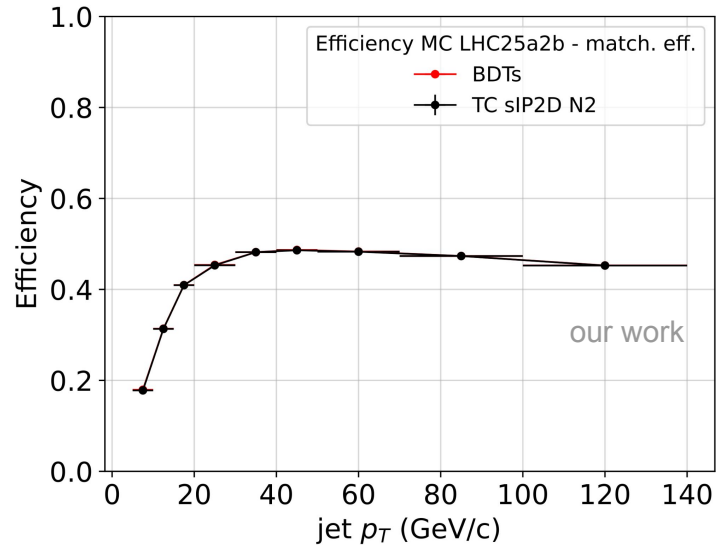
- jet p_T
- jet η
- jet ϕ
- nTracks in jet
- d_{xy} 1 to 3 (i.e. sIP2D)
- $\sigma_{d_{xy}}$ 1 to 3
- d_z 1 to 3
- σ_{d_z} 1 to 3
- track p_T 1 to 3

BDTs score distributions for each jet flavor/class
One can apply cuts on these distributions



Tagged as b above chosen score

Jet Tagging - **BDTs**



Efficiency of the BDTs matched to that of the Track Counting

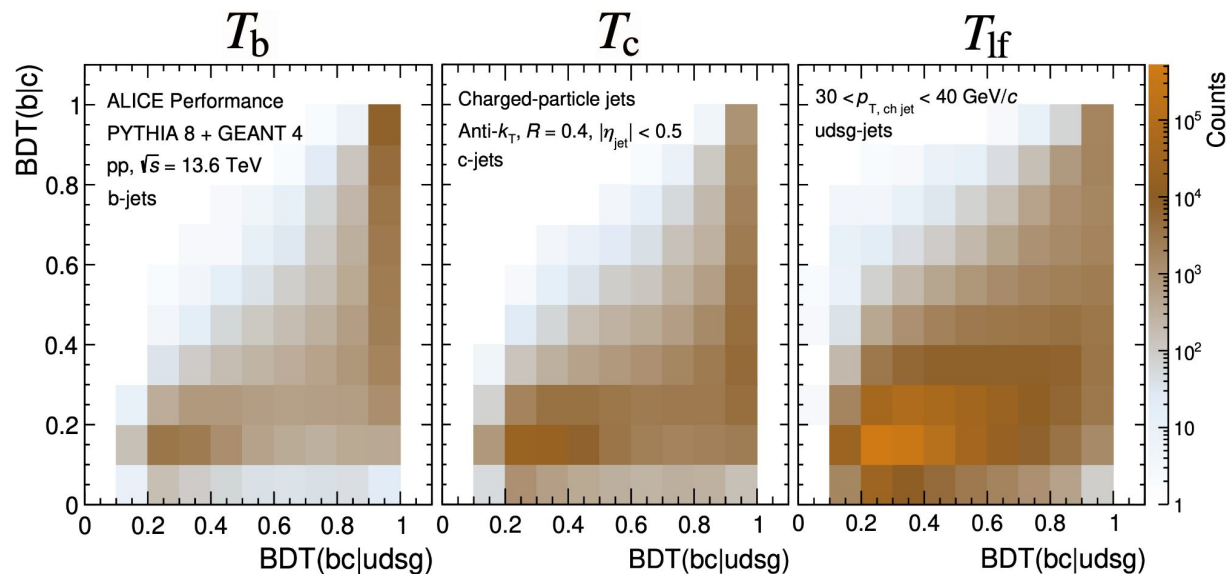
BDT based tagger provide better performance

2-dimensional template fitting

2D discriminant

$$\text{BDT}(bc|lf) = \frac{\text{BDT}(b) + \text{BDT}(c)}{\text{BDT}(b) + \text{BDT}(c) + \text{BDT}(lf)}$$

$$\text{BDT}(b|c) = \frac{\text{BDT}(b)}{\text{BDT}(b) + \text{BDT}(c)}$$



Population in the templates
vary depending on the jet
flavor

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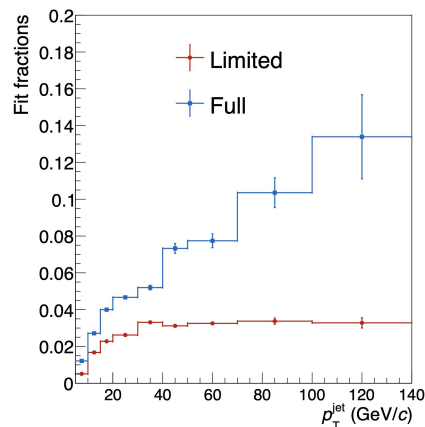
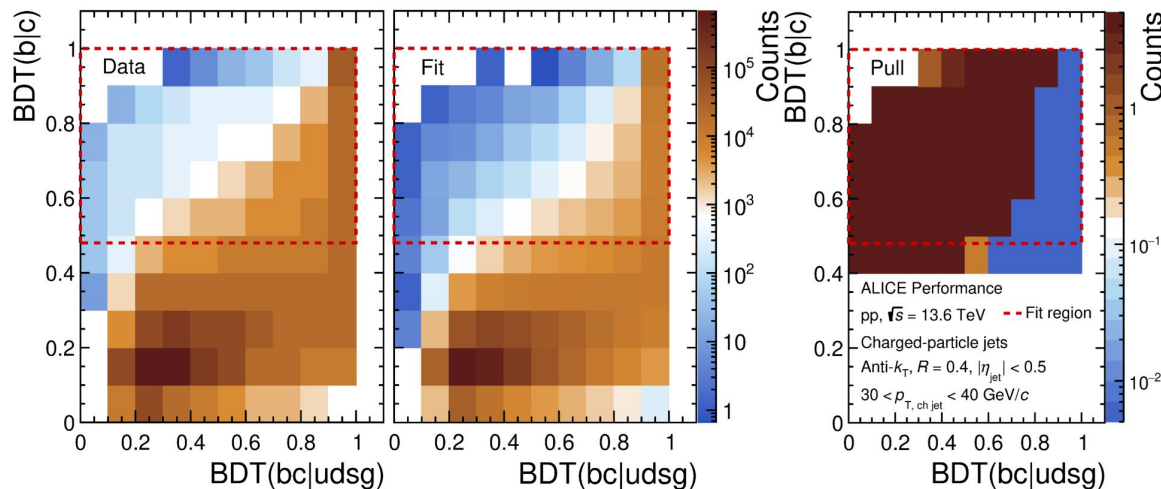
2D template fits

$$T_{\text{model}} = f_b \times T_b + f_c \times T_c + (1 - f_c - f_b) \times T_{\text{lf}}$$

$$\frac{dN_{\text{bjets}}}{dp_{\text{T, jet}}} = \frac{dN_{\text{incl}} \times f_b}{dp_{\text{T, jet}}}$$

Fit the model to the data → extract the b -fraction f_b

Limited range fits to mitigate inflation of b -fraction extraction from template mismodelling. Region chosen where $\chi^2/\text{bins} \sim 1$



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Method from LHCb [Link](#)

Unfolding and corrections

Unfolding

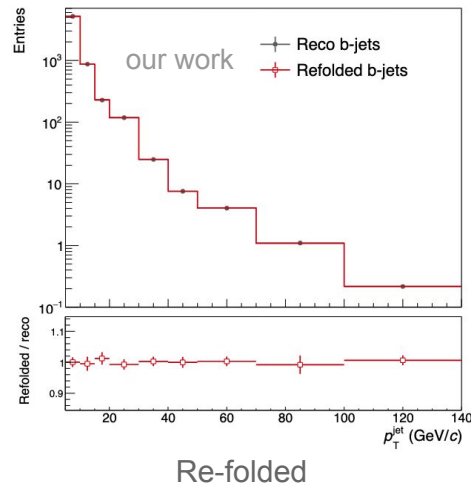
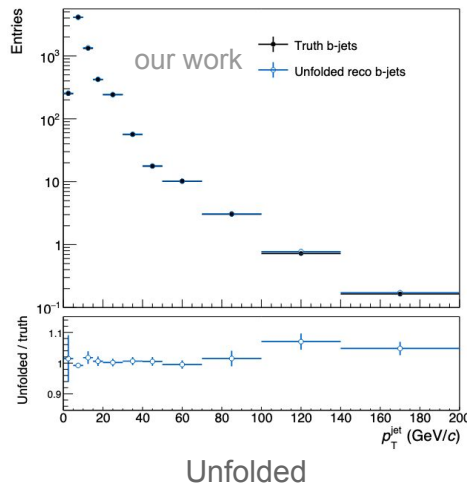
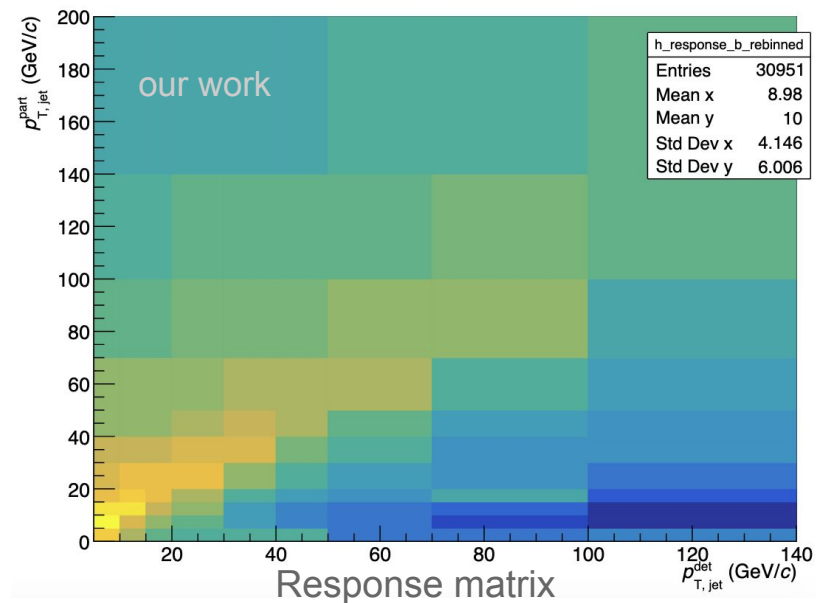
To correct for detector effects, the reconstructed spectrum is unfolded to the particle level

$$\frac{dN_{\text{bjets}}}{dp_{T, \text{jet}}} = \frac{1}{\epsilon_{\text{rec}} \epsilon_{\text{kin}}} \text{Unfold} \left(P_{\text{reco}} \frac{dN_{\text{bjets}}}{dp_{T, \text{jet}}} \right)$$

$$\epsilon_{\text{kin}} = \frac{N_{\text{b-jets}}^{\text{trunc}} |_{\text{part}}}{N_{\text{b-jets}}^{\text{un-trunc}} |_{\text{part}}}$$

$$\epsilon_{\text{reco}} = \frac{N_{\text{b-jets}}^{\text{matched}} |_{\text{part}}}{N_{\text{b-jets}}^{\text{total}} |_{\text{part}}}$$

$$P_{\text{reco}} = \frac{N_{\text{b-jets}}^{\text{matched}} |_{\text{reco}}}{N_{\text{b-jets}}^{\text{reco}} |_{\text{reco}}}$$



Luminosity and corrections

$$\frac{d^2\sigma_{bjet}}{dp_{T,jet}d\eta_{jet}} = \frac{1}{\mathcal{L}_{int}} \frac{d^2N_{bjet}}{dp_{T,jet}d\eta_{jet}}$$

Measured luminosity from TVX detector:
bunch crossing / visible cross section of TVX trigger

$$\mathcal{L}_{TVX} = \frac{N^{TVX}}{\sigma^{TVX}}$$

Integrated luminosity:
Correcting TVX with visible lumi in 2023 and lumi reference in O²Physics

$$\mathcal{L}_{int} = \mathcal{L}_{TVX} \times \frac{59.4}{52.8}$$

Correction to the
selection $|z_{vtx}| < 10$ cm:

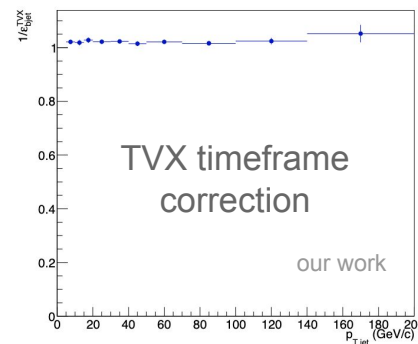
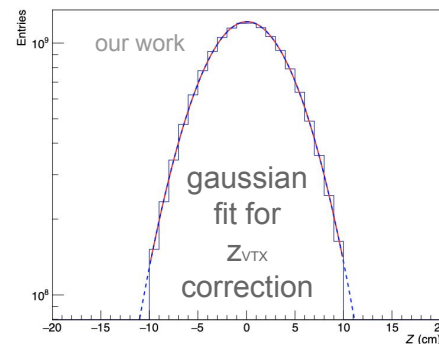
$$\epsilon_{z_{vtx}} = \frac{\int_{-10}^{+10} \text{Gaus}(z_{vtx}) dz_{vtx}}{\int_{-\infty}^{+\infty} \text{Gaus}(z_{vtx}) dz_{vtx}}$$

Correction to inefficiencies due
to readout time-frame borders
of TVX trigger:

$$\epsilon_{bjet}^{TVX} = \frac{N_{bjet}^{TVX}}{N_{bjet}^{INEL}} \Big|_{MC}$$

Corrected number of b -jets:

$$N_{bjets} \rightarrow \frac{N_{bjets}}{\epsilon_{z_{vtx}} \epsilon_{bjet}^{TVX}}$$

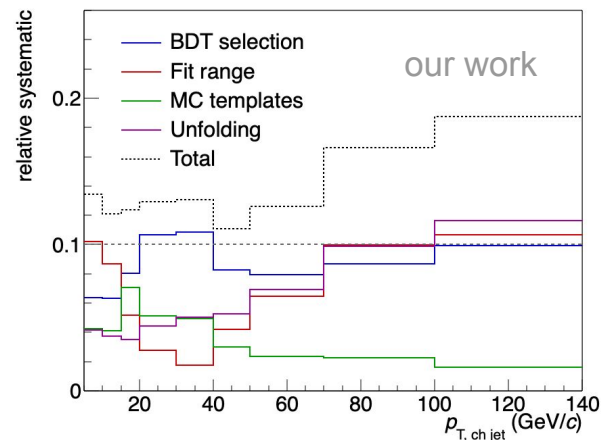


Systematic uncertainties

Systematic uncertainties

- BDT selections
 - Training seed variation
 - Hyperparameter variation
- Template Fits
 - Fit Range
 - Template shape variation
- Unfolding
 - $N_{\text{iterations}}$
 - Unfolding method
 - Closure test
 - Track reconstruction efficiency
 - Track momentum resolution
- Luminosity determination (10%)

Source	Jet p_T intervals (GeV/c)								
	5–10	10–15	15–20	20–30	30–40	40–50	50–70	70–100	100–140
BDT selection	6.35	6.34	8.03	10.67	10.86	8.27	7.95	8.68	9.95
Fit range	10.23	8.67	5.19	2.77	1.74	4.21	6.45	9.95	10.66
MC templates	4.24	4.11	7.06	5.13	4.93	3.01	2.34	2.26	1.63
N_{iter}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
SVD/Bayes	3.26	2.75	1.32	2.01	1.56	1.58	2.57	3.02	3.54
Closure	1.26	1.04	0.86	0.49	0.46	0.55	0.83	2.98	4.24
Tracking efficiency	0.90	1.33	2.70	3.77	4.53	4.80	6.00	7.70	8.55
p_T smearing	0.45	0.50	0.57	0.77	0.97	0.90	1.50	3.13	4.50
Total unfolding	4.18	3.76	3.50	4.42	5.01	5.27	6.95	9.88	11.64
Total	13.43	12.10	12.39	12.94	13.06	11.08	12.59	16.64	18.73



Results

b -jet cross section

$$\frac{d^2\sigma_{bjet}}{dp_{T,jet}d\eta_{jet}} = \frac{1}{\mathcal{L}_{int}} \frac{d^2N_{bjet}}{dp_{T,jet}d\eta_{jet}}$$

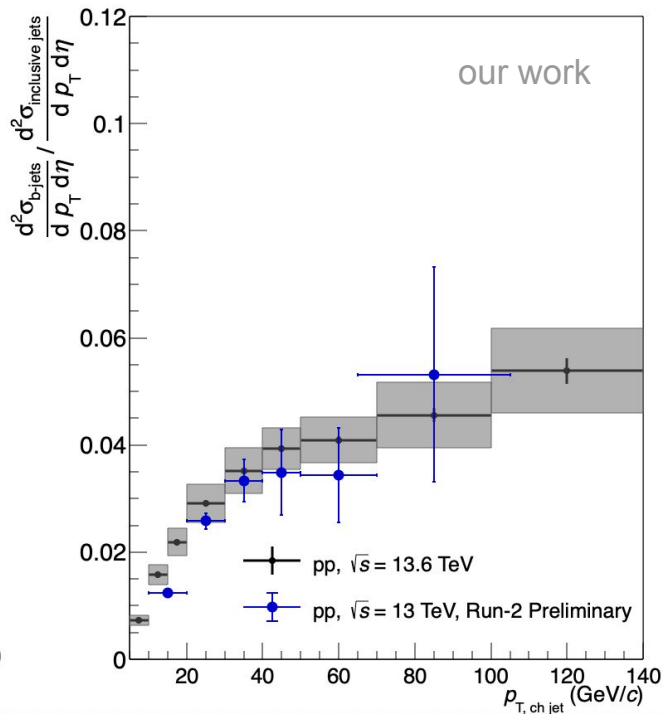
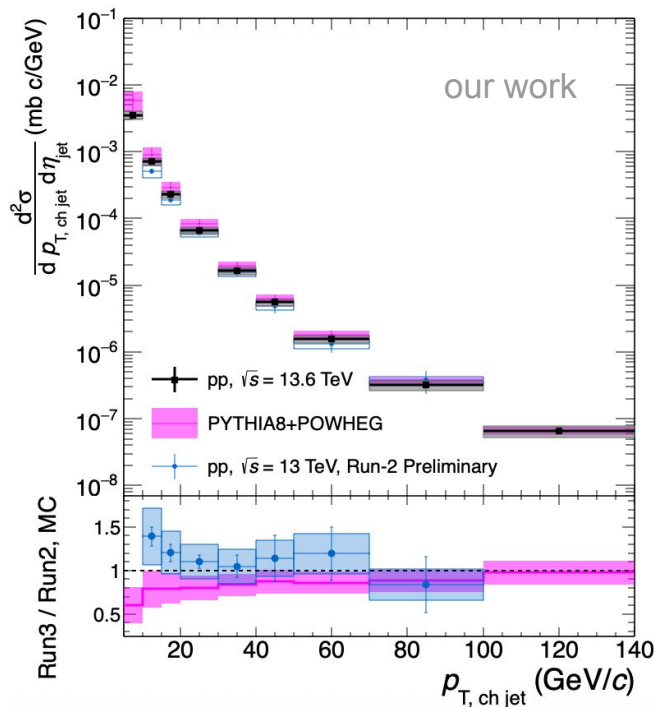
with

$$\frac{dN_{bjets}}{dp_{T,jet}} = \frac{dN_{incl} \times f_b}{dp_{T,jet}}$$

Underestimation at low p_T with Run 2 preliminary results (up to 40%).

Overestimation at low p_T with model calculations (up to 40%)

Ratio of b -jet cross section over inclusive jet cross section (ALICE 2024 Preliminary)

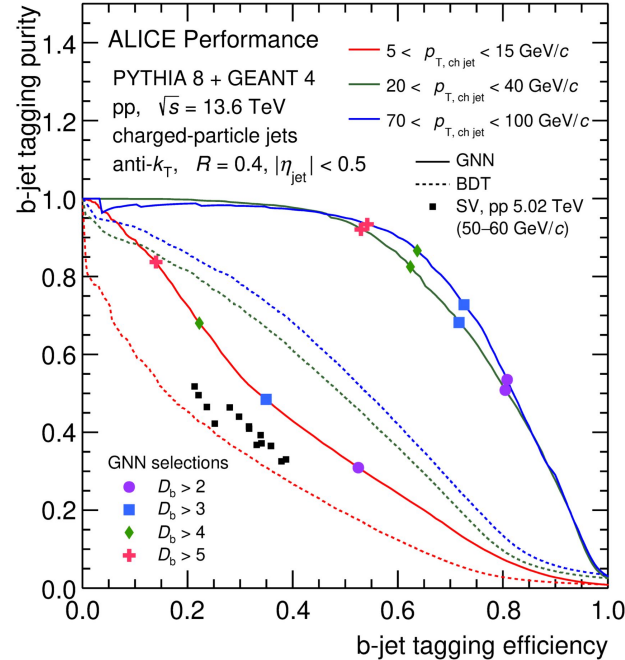


Comparison with other methods

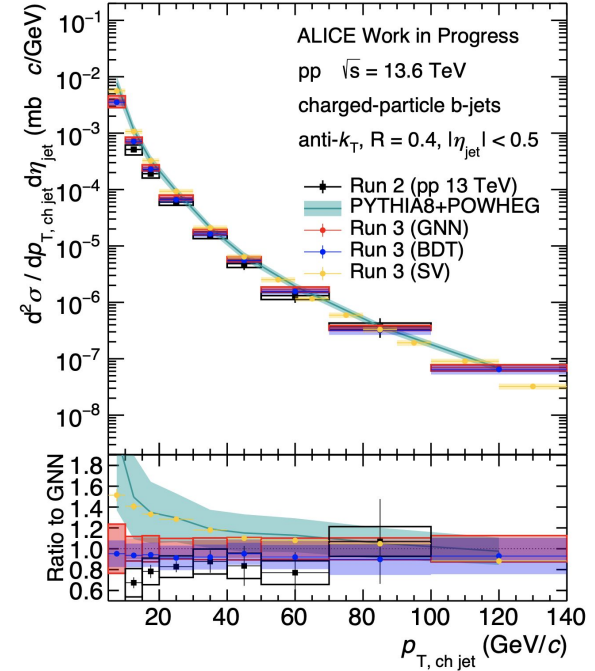
Multiple b -jet tagging approaches were studied:
Graph Neural Networks, BDTs and Secondary Vertex.

GNNs yield the best performance.

BDTs and GNNs are compatible



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Towards Oxygen-Oxygen collisions

Training features

Old set of training features (3 tracks)

- jet p_T
- jet η
- jet ϕ
- nTracks in jet
- d_{xy} 1 to 3
- $\sigma_{d_{xy}}$ 1 to 3
- d_z 1 to 3
- σ_{d_z} 1 to 3
- track p_T 1 to 3

New set of training features (10 tracks + track eta)

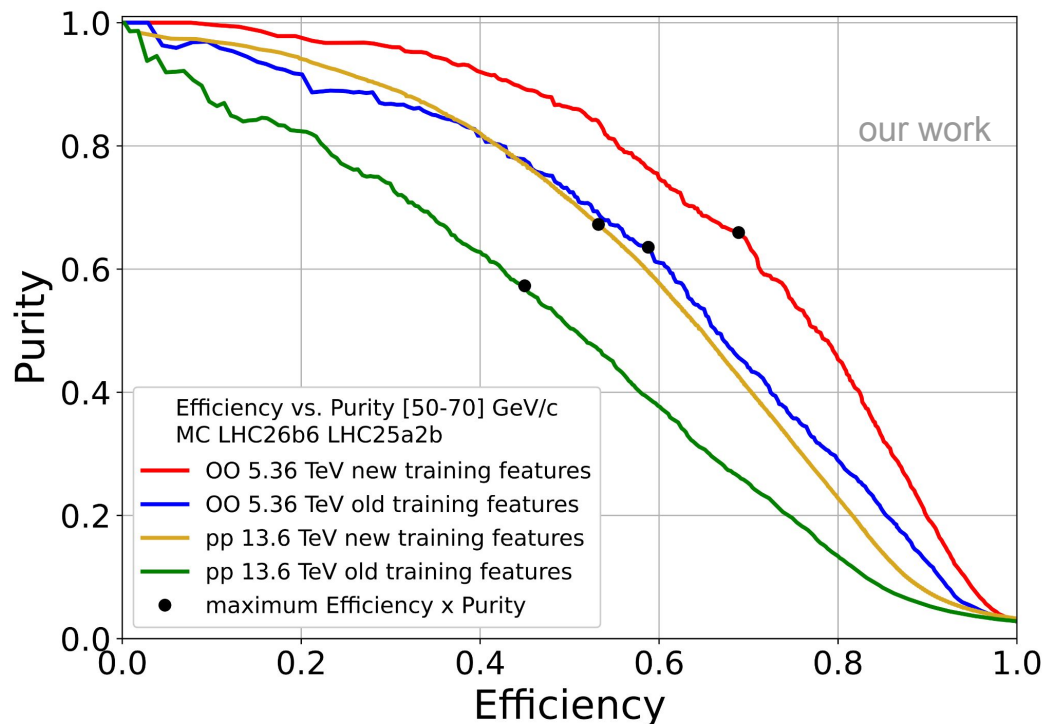
- jet p_T
- jet η
- jet ϕ
- nTracks in jet
- d_{xy} 1 to 10
- $\sigma_{d_{xy}}$ 1 to 10
- d_z 1 to 10
- σ_{d_z} 1 to 10
- track p_T 1 to 10
- track η 1 to 10

Performance: proton-proton 13.6 TeV and O-O 5.36 TeV

Efficiency vs. Purity:

Improved performance of BDTs with new training features in pp@13.6 TeV and OO@5.36 TeV

Better performance on O-O 5.36 TeV than on pp 13.6 TeV when the same training features are used
→ under investigation



Conclusion and outlook

Measurement of b -jet cross section observed for the first time with Machine and Deep learning methods in ALICE → benchmark for pQCD studies with beauty and baseline for heavy-ion measurements

Measurement to be moved to 2026 data for the publication

Study of b -jet production in OO collisions at $\sqrt{s_{\text{NN}}} = 5.36$ TeV is ongoing – Towards a b -jet R_{OO} measurement

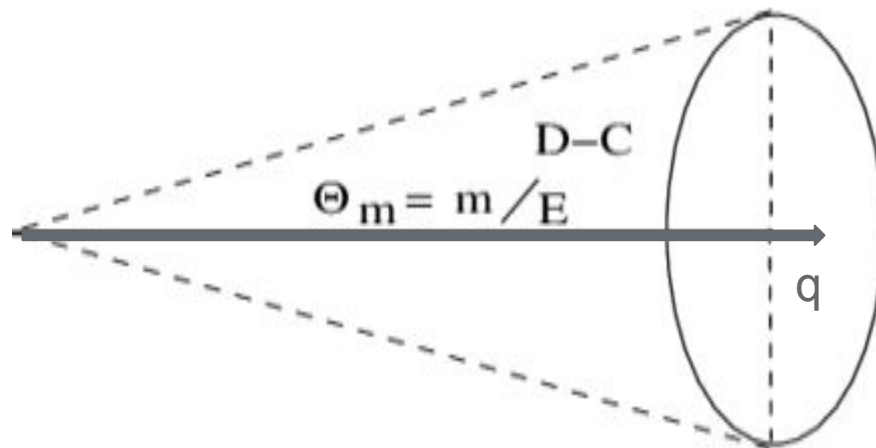
Thank you for listening

BACK UP

Dead Cone effect

Radiative energy loss
suppressed in the “Dead Cone”

Stronger with b quarks than
with c quarks because of larger
mass



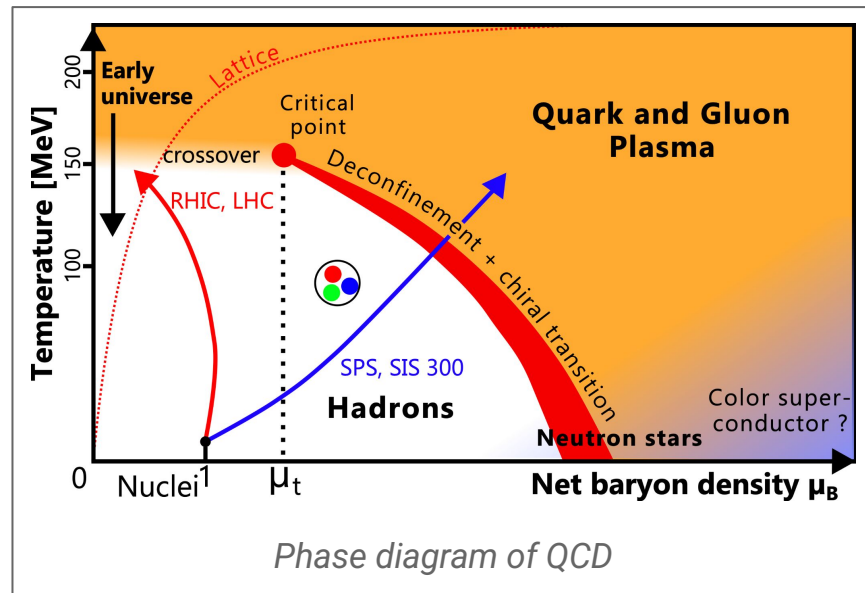
Probing QGP with heavy-flavour (HF) quarks

HF quarks produced in hard scatterings at initial collision stages, before the formation of QGP
→ experience the entire QGP evolution

« Brownian motion » inside QGP
→ Collective and **energy-loss effects** resulting from interaction with QGP constituents

Advantages of *b*-quarks over *c*-quarks due to higher mass:

- Much less thermalized → more sensitive probe of HF transport in QGP
- Better theory control in transport modelling
- Disentangle collisional and radiative energy loss, radiative energy loss suppression due to more sizable dead-cone effect



PhD subject - quick explanation

Measurement of b -jet production in pp and Pb-Pb collisions with Run3 data
→ **Nuclear modification in Pb-Pb or O-O with respect to pp reference**

Advantage of studying **b -jet production** :

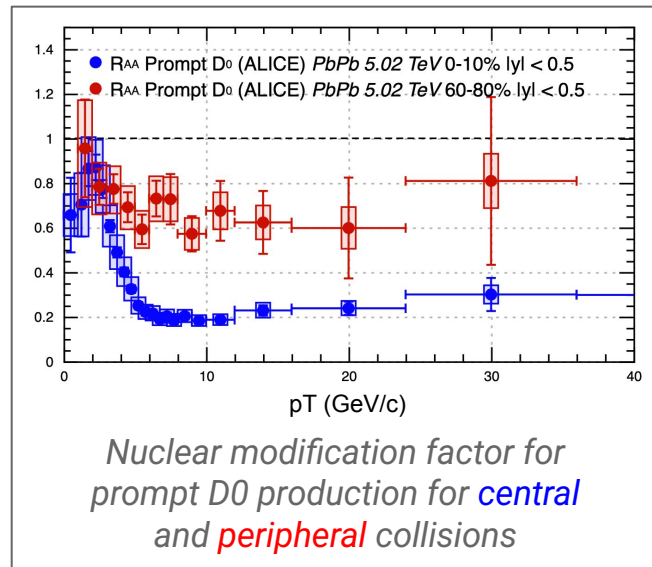
- Jet p_T directly related to b quark p_T
- Jet substructure provides unique insight into the energy loss mechanisms

Measurement of b -jets consists of :

1. Jet reconstruction
2. b -jet tagging/identification (separation from charm and light-flavour jets)
3. Proper treatment of huge background in Pb-Pb, especially at lower jet p_T

Upgraded ALICE detector in Run3 :

- Orders of magnitude higher statistics for b physics with respect to Run 1-2
- New Inner Tracking System → significant improvement of track impact parameter resolution → crucial for b -quark measurement

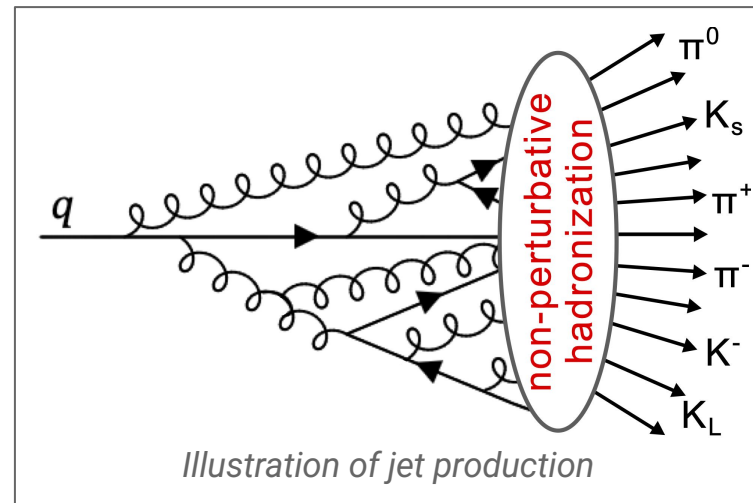


Jet algorithms

Jet reconstruction algorithms are either “sequential clustering algorithm” (SCA) or “Cone Algorithms”

IRC safe: InfraRed and Collinear - guarantees that the measured jet can be linked to a theoretical observable

Used anti-kT algorithm to reconstruct jets (SCA) which is IRC safe ($R=0.4$)



Datasets and analysis selections in pp 13.6 TeV

- Datasets **LHC22o apass7 minbias**  [665412](#) **LHC25a2b (anchored to 22o apass7)**  [641215](#)
- Event Selection
 - sel8
- Track Selections
 - QualityTrackswDCA
 - $0.15 < p_T < 250 \text{ GeV/c}$, $|\eta^{\max}| < 0.9$
 - $p_T^{\min} = 0.15 \text{ GeV/c}$
 - leadingConstituentPtMax = 100 GeV/c
 - Track to collision associator
 - Track tuner with p_T smearing
 - Remove migrating tracks from other jet-jet events
- Jets
 - Anti k_T ($R = 0.4$), charged jets
 - $5 < p_T < 250 \text{ GeV/c}$, $|\eta| < 0.5$
 - searchUpToQuark : True
 - Particle level $p_T^{\text{jet}} < 4 \times p_T^{\text{hat}}$
 - Detector level $p_T^{\text{jet}} < 8 \times p_T^{\text{hat}}$
- BDT Preselections
 - $N_{\text{track}} \geq 1$, $|d_z| < 1$
 - Transverse Impact Parameter (d_{xy}) ordering
 - p_T intervals (GeV/c)
 - [5-10] [10-15] [15-20] [20-30] [30-40]
[40-50] [50-70] [70-100] [100-140]
 - 500,000 jets per flavor per p_T interval
 - jetEventWeights as Sample Weights in training
 - Training features
 - jet p_T – $\sigma_{d_{xy}}(1,2,3)$
 - jet η – $d_z(1,2,3)$
 - jet ϕ – $\sigma_{d_z}(1,2,3)$
 - Number of tracks in the jet – $d_{xy}(1,2,3)$
 - $d_{xy}(1,2,3)$ – track $p_T(1,2,3)$

Jet Tagging - **BDTs with scanning methods (score)**

4 choices of cuts on scores: matching the BDT efficiency to the Track Counting efficiency or maximizing the 3 following quantities by scanning the BDT scores

$$\text{BDT efficiency} = \text{Track Counting efficiency}$$

maximizing

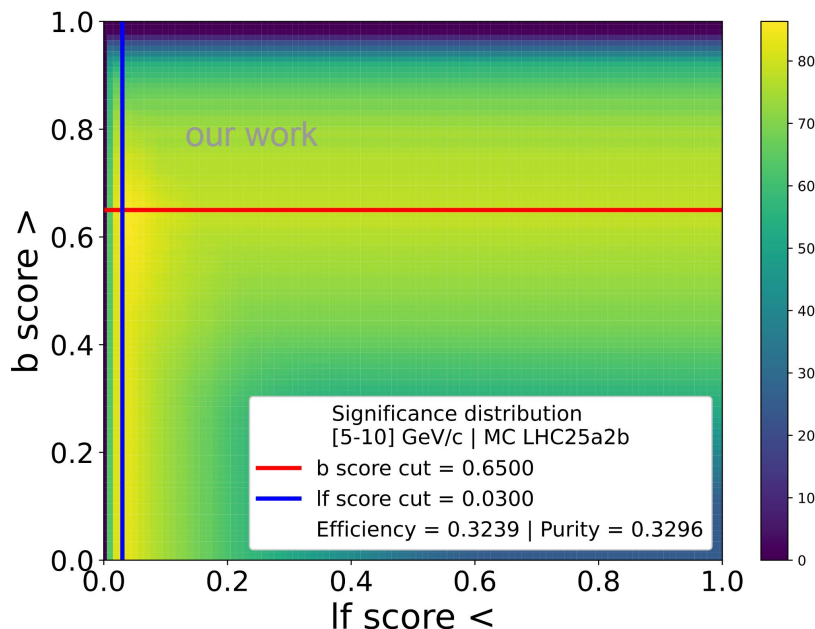
$$\text{Significance} = \frac{\text{Number of selected b-jets}}{\sqrt{\text{Total number of selected jets (b,c,lf)}}$$

$$\text{Significance alternative} = \frac{\text{Number of selected b-jets}}{\sqrt{\text{Number of selected b- and c-jets}}}$$

$$\text{Signal over Background} = \frac{\text{Number of selected b-jets}}{\text{Number of selected lf- and c-jets}}$$

The maximization of the significance was found to yield the best compromise between efficiency and purity compared to the other two

BDTs with scanning methods (score)



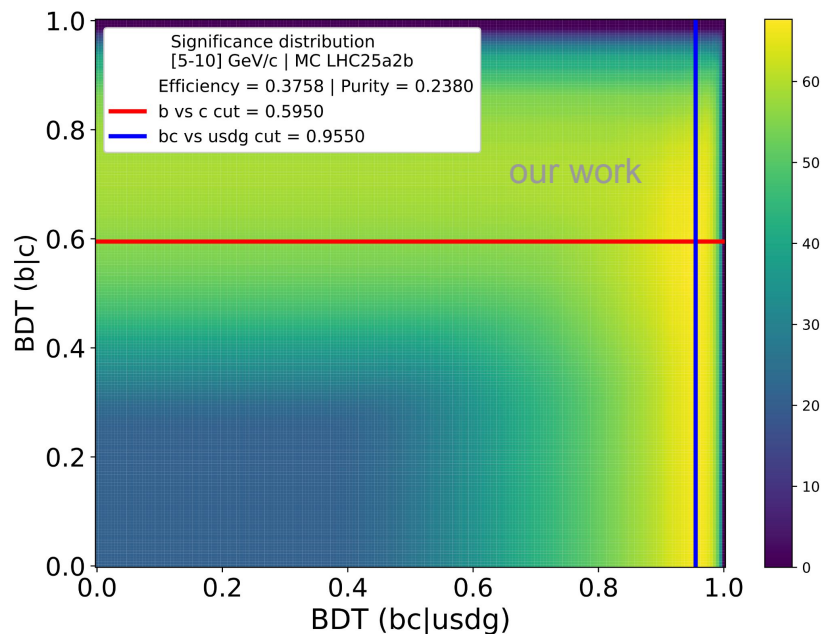
example of score scanning to
maximize the significance

$$\text{Significance} = \frac{\text{Number of selected b-jets}}{\sqrt{\text{Total number of selected jets (b,c,lf)}}$$

Two scanning methods to maximize the significance have been compared:

1. **scanning the scores: b vs. lf**
2. scanning the discriminants: BDT(bc|lf) vs. BDT(b|c)

BDTs with scanning methods (2D discriminant)



example of discriminant scanning to maximize the significance

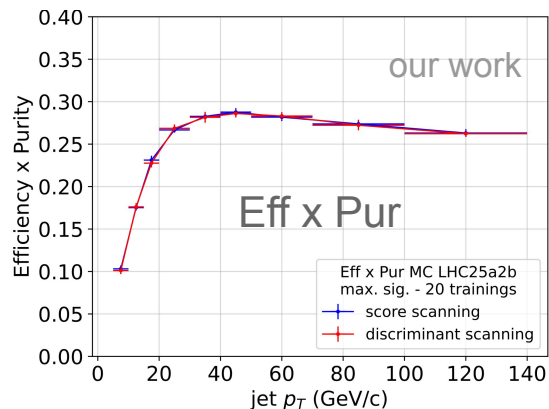
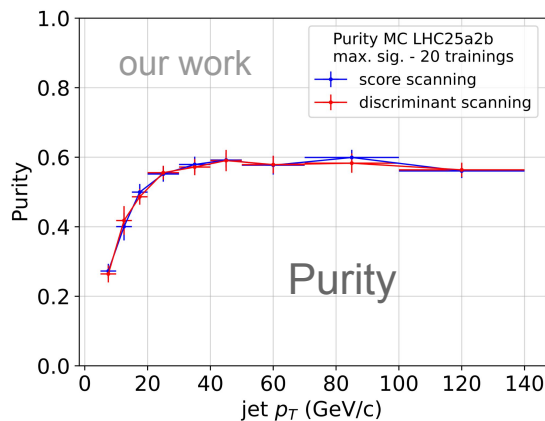
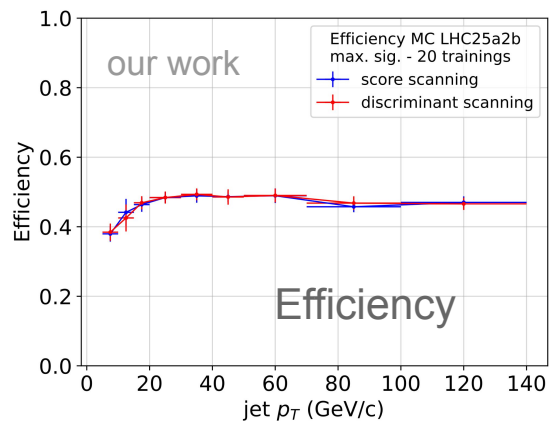
Two scanning methods to maximize the significance have been compared:

1. scanning the scores: b vs. lf
2. **scanning the discriminants: $\text{BDT}(\text{bc}|\text{lf})$ vs. $\text{BDT}(\text{b}|\text{c})$**

$$\text{BDT}(\text{bc}|\text{lf}) = \frac{\text{BDT}(\text{b}) + \text{BDT}(\text{c})}{\text{BDT}(\text{b}) + \text{BDT}(\text{c}) + \text{BDT}(\text{lf})}$$

$$\text{BDT}(\text{b}|\text{c}) = \frac{\text{BDT}(\text{b})}{\text{BDT}(\text{b}) + \text{BDT}(\text{c})}$$

BDTs with scanning methods - scores vs. discriminants



Maximized
significance

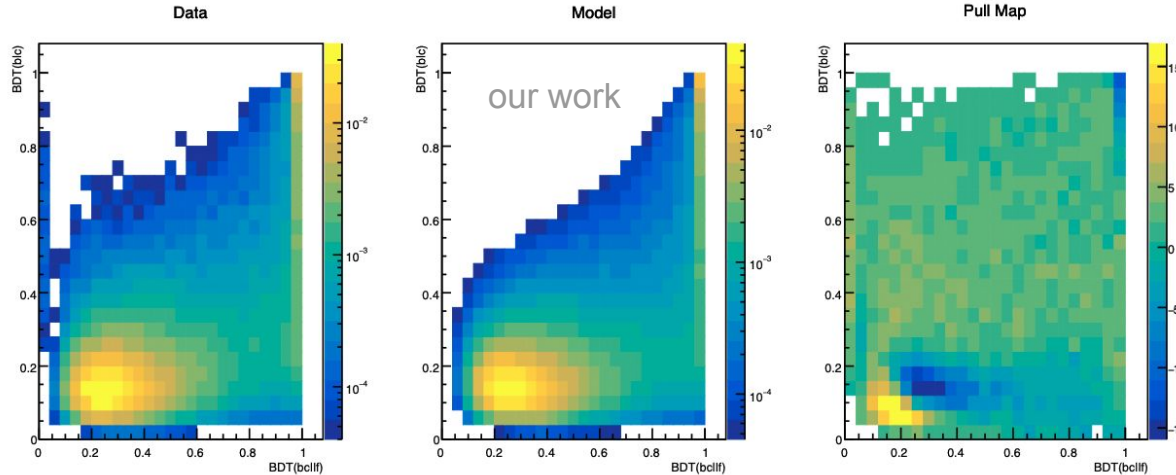
Mean and std dev obtained over 20 trainings by shuffling the training-testing sets during each training

The two scanning methods (score and discriminant) yield almost identical results (especially in the Efficiency x Purity distribution)

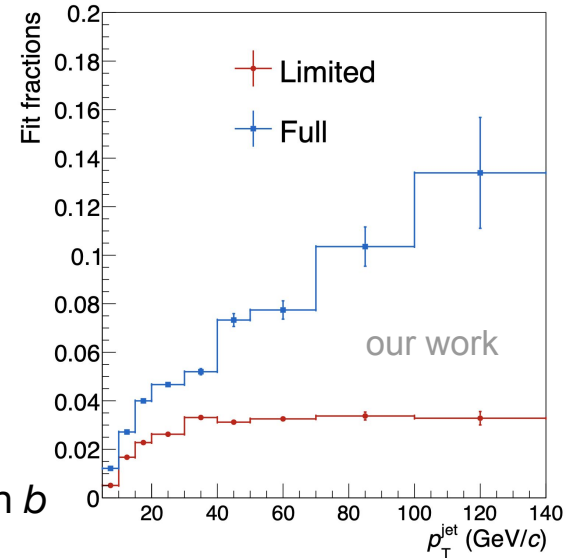
Full template fits

RooFit package, Templates controlled via RooAddPdf

$$T_{\text{model}} = f_b \times T_b + f_c \times T_c + (1 - f_c - f_b) \times T_{lf}$$



$50 < p_T < 70 \text{ GeV}/c$



Full range fits yield “inflated” b -jet fractions

- lf template mismodelling $\rightarrow$ Minor effect in $lf \rightarrow$ large effect in b
- Limited range fits to remove lf effects

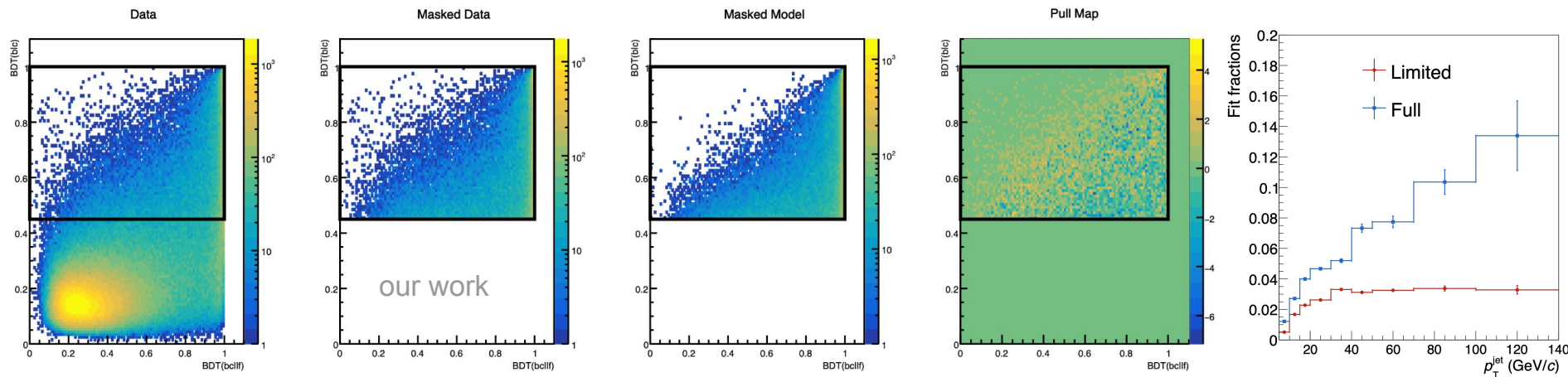
2D template fits

$$T_{\text{model}} = f_b \times T_b + f_c \times T_c + (1 - f_c - f_b) \times T_{\text{lf}}$$

$$\frac{dN_{\text{bjets}}}{dp_{\text{T, jet}}} = \frac{dN_{\text{incl}} \times f_b}{dp_{\text{T, jet}}}$$

Fit the model to the data → deduce the b-fraction f_b

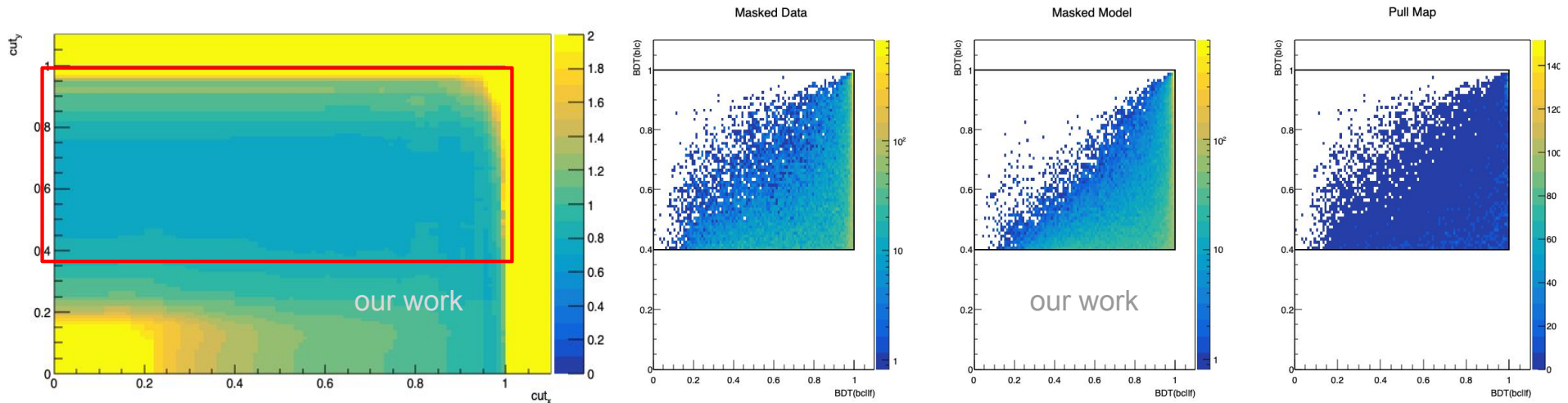
Limited range fits to mitigate inflation of b-fraction extraction from template mismodelling. Region chosen where $\chi^2/\text{bins} \sim 1$



Partial template fits

RooFit package, Templates controlled via RooAddPdf

$$T_{\text{model}} = f_b \times T_b + f_c \times T_c + (1 - f_c - f_b) \times T_{\text{lf}}$$



Fit region decision $\rightarrow$ Find $[\mathbf{x}_{\min}, \mathbf{y}_{\min}]$ where $\chi^2/\text{bins} \sim 1$

b-jet cross section - computation

$$\frac{d^2 \sigma_{\text{bjet}}}{dp_{T, \text{jet}} d\eta_{\text{jet}}} = \frac{1}{\mathcal{L}_{\text{int}}} \frac{d^2 N_{\text{bjet}}}{dp_{T, \text{jet}} d\eta_{\text{jet}}} \quad \text{with} \quad \frac{dN_{\text{bjets}}}{dp_{T, \text{jet}}} = \frac{dN_{\text{incl}} \times f_b}{dp_{T, \text{jet}}}$$

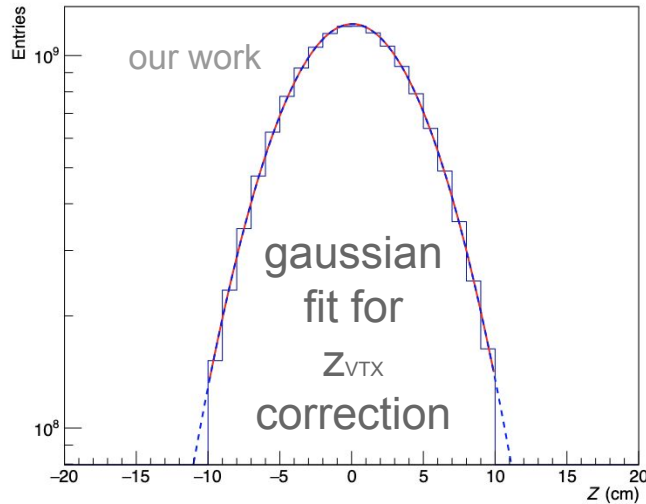
- $|\eta_{\text{jet}}| < 0.5 = 0.9 - R_{\text{jet}}$
- $dp_T^{\text{jet}} = 5, 5, 5, 10, 10, 10, 20, 30, 40 \text{ GeV/c}$ (width of the p_T^{jet} bins)
- $L_{\text{int}} = L_{\text{TVX}} * (59.4 / 52.8)$ (correction based on 2023 luminosity and TVX luminosity reference in O2Physics)
- N_{bjets} was corrected three times: for unfolding, for $|z_{\text{VTX}}| < 10 \text{ cm}$ and for time-frame border of the TVX detector

$$\frac{dN_{\text{bjets}}}{dp_{T, \text{jet}}} = \frac{1}{\epsilon_{\text{rec}} \epsilon_{\text{kin}}} \text{Unfold} \left(P_{\text{reco}} \frac{dN_{\text{bjets}}}{dp_{T, \text{jet}}} \right)$$

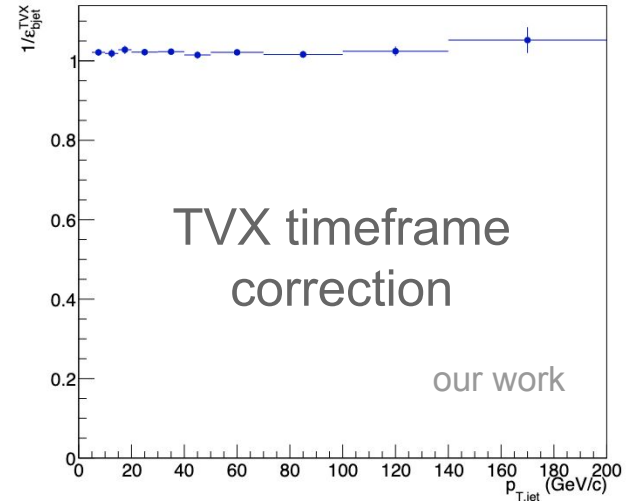
$$N_{\text{bjets}} = N_{\text{bjets}} / (\epsilon_{z_{\text{VTX}}} \epsilon_{\text{bjet}}^{\text{TVX}})$$

TVX and Z_{VTX} corrections

$$N_{\text{bjets}} = N_{\text{bjets}} / (\epsilon_{z_{\text{VTX}}} \epsilon_{\text{bjet}}^{\text{TVX}})$$



$$\epsilon_{z_{\text{VTX}}} = \frac{\int_{-10}^{+10} \text{Gaus}(z_{\text{VTX}}) dz_{\text{VTX}}}{\int_{-\infty}^{+\infty} \text{Gaus}(z_{\text{VTX}}) dz_{\text{VTX}}}$$



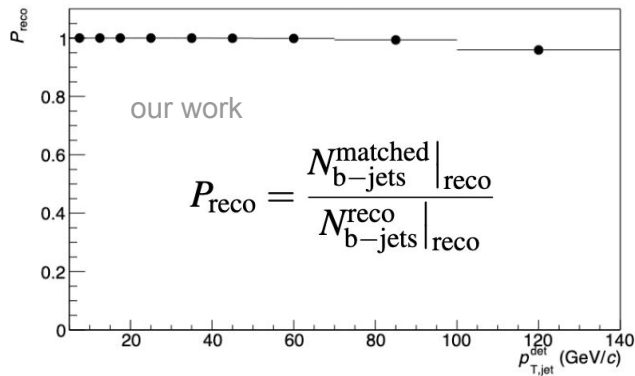
$$\epsilon_{\text{bjet}}^{\text{TVX}} = \frac{N_{\text{bjet}}^{\text{TVX}}}{N_{\text{bjet}}^{\text{INEL}}} \Big|_{\text{MC}}$$

Unfolding for detector effects 1/2

$$\frac{dN_{b\text{jets}}}{dp_{T,\text{jet}}} = \frac{1}{\epsilon_{\text{rec}} \epsilon_{\text{kin}}} \text{Unfold} \left(P_{\text{reco}} \frac{dN_{b\text{jets}}}{dp_{T,\text{jet}}} \right)$$

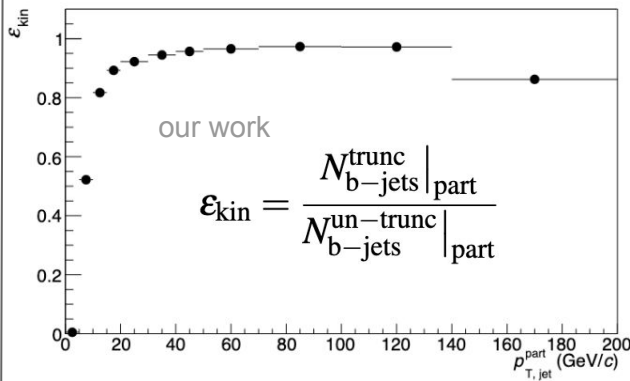
reconstruction purity

ratio of matched jets to the total reconstructed b -jets in the measured p_T intervals



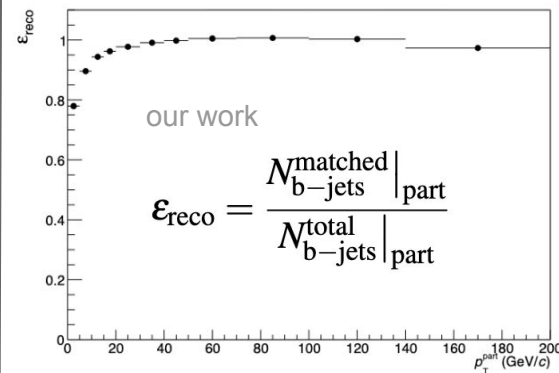
kinematic efficiency

associated correction with measured (truncated) and unfolding (un-truncated) kinematic regions



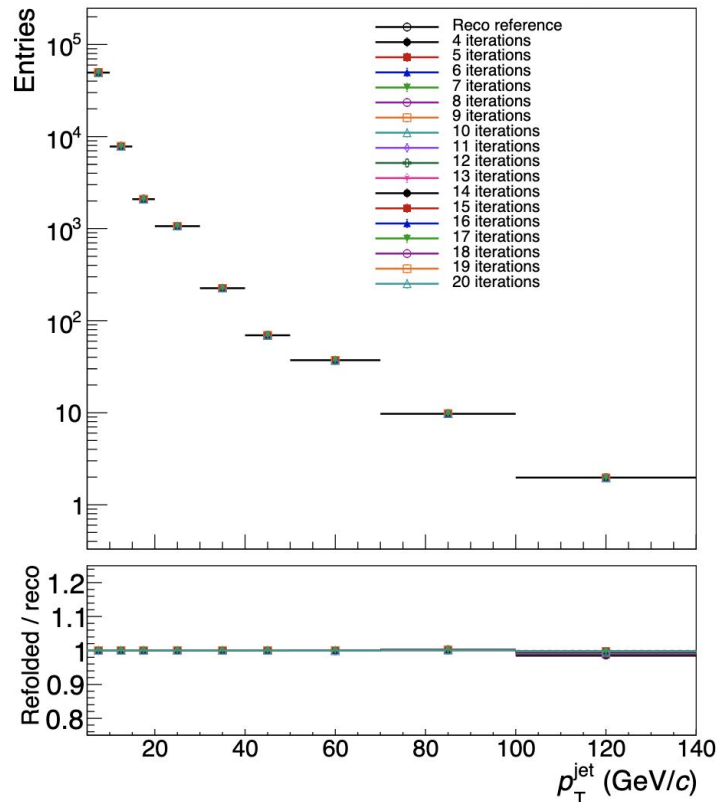
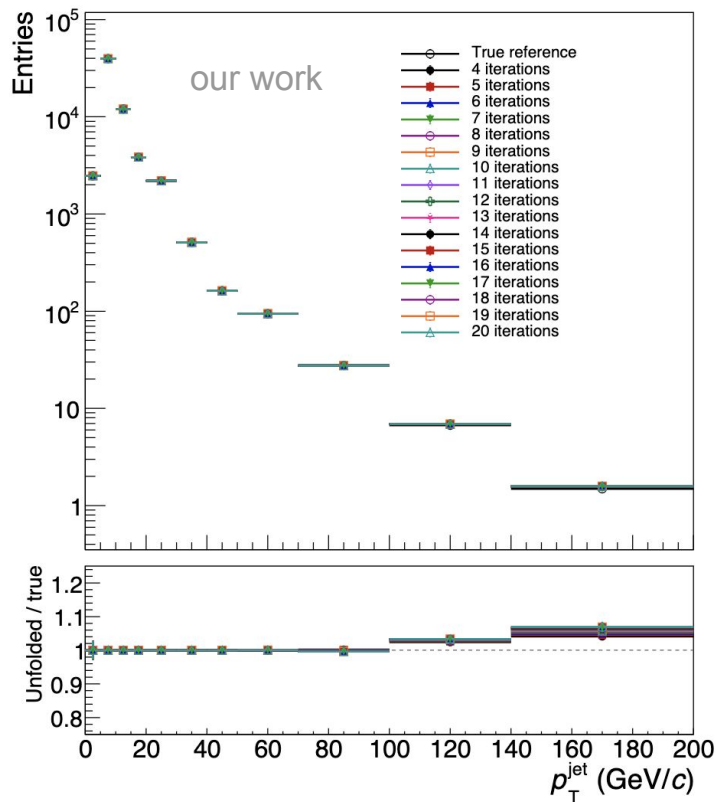
reconstruction efficiency

number of reconstructed (matched) particle level jets to total number of particle level jets



Unfolding for detector effects 2/2

Bayesian
unfolding
and
refolding
4 to 20
iterations
for systematics



Systematic uncertainties 1/3 - BDT selections

Random seed: changing the random seed while creating the training and testing sets twice. Systematic = RMSE to nominal value

Hyperparameter variation: trying a different set of hyperparameters to train the model. Systematic = RMSE from nominal value

Systematic uncertainties 2/3 - Template fits and luminosity

Template fit range: Vary the fit range and compute the b -fraction. Systematic = RMS to central value

Template shape: Build templates from independent MC. Systematic = deviation from nominal value

Luminosity: unfinished Van der Meer scan $\rightarrow$ 10% systematic uncertainty assigned

Systematic uncertainties 3/3 - Unfolding

MC closure test: Systematic = ratio between the test MC particle spectra and the unfolded spectra

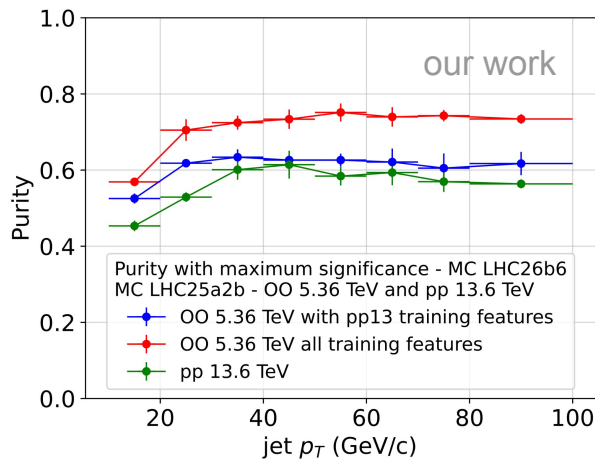
RooUnfoldBayes: the Bayesian method is repeated with different number of iterations. Systematic = deviation from central value (iteration #8)

Method dependence: use Singular Value Decomposition (SVD) method. Unfolded spectrum compared to the one from Bayesian unfolding. Systematic = deviation from unity in the ratios

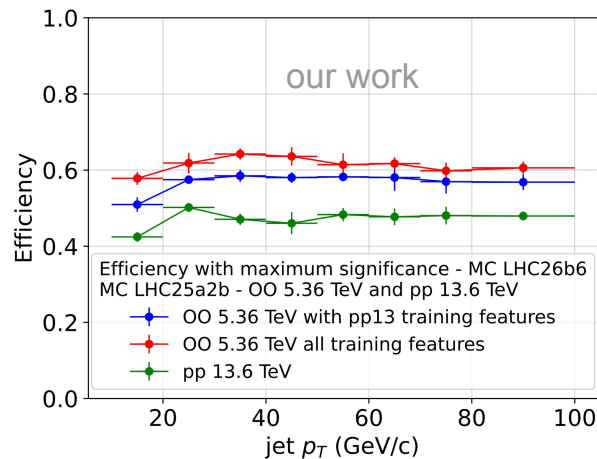
Track reconstruction efficiency: related to reconstruction efficiency of ITS-TPC matched tracks. Randomly selecting a % of reconstructed tracks in MC. The unfolded spectrum from the response matrix is compared to the nominal values. Systematic = deviation from unity

Track momentum resolution: related to the use of track tuner for the MC samples. Changing the Gaussian track pT smearing parameter from 1.5 to 1.2 and 1.8 then use them in response matrix. Unfolded distributions compared to central distribution. Systematic = largest deviation from unity

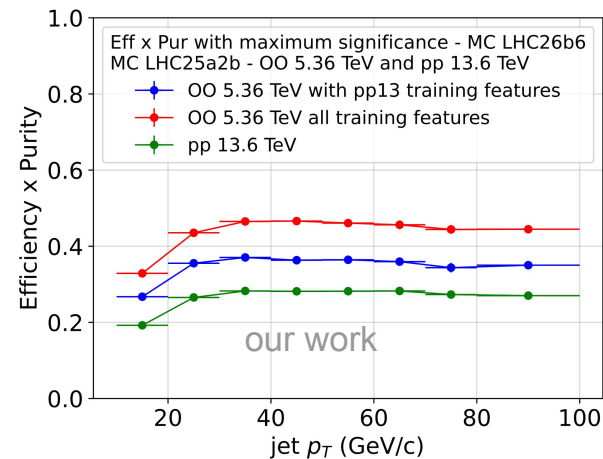
Performance: proton-proton 13.6 TeV and O-O 5.36 TeV



Purity



Efficiency



Efficiency x Purity

Better performance is also observed with the maximization of the significance:

OO 5.36 TeV best > OO 5.36 TeV trained like pp13 > pp 13.6 TeV

End of BACK UP