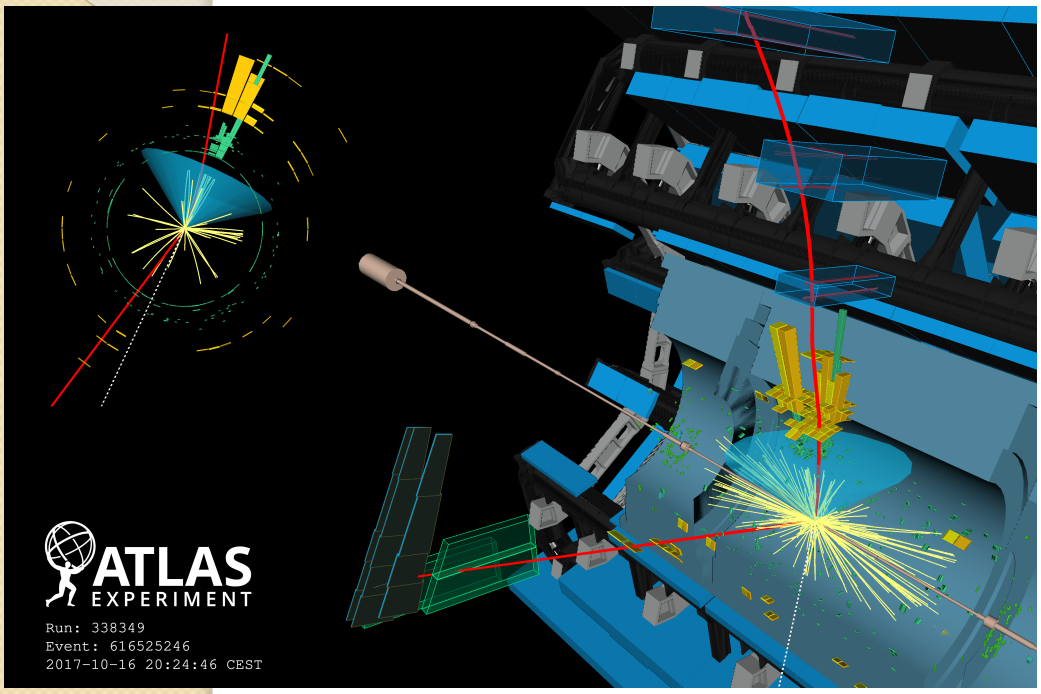
Flavour tagging and boosted objects



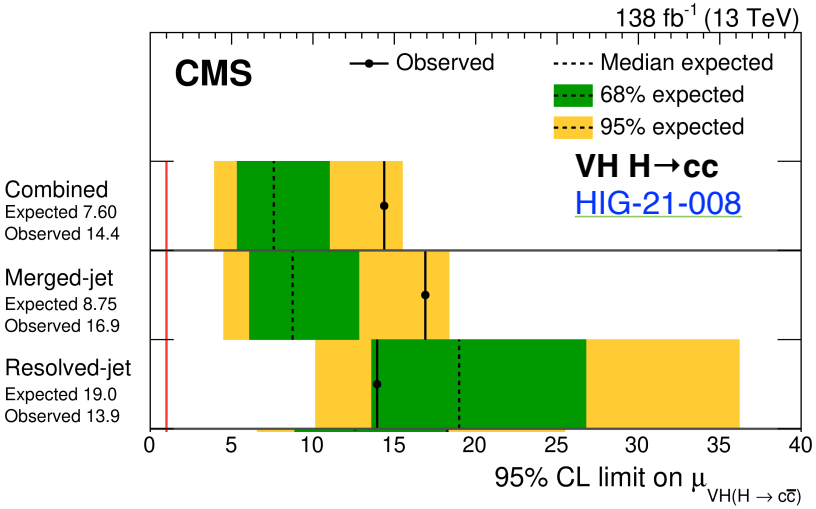
Thomas Strebler

Centre de Physique
des Particules de Marseille
Aix-Marseille Université / CNRS-IN2P3

on behalf of the ALICE, ATLAS & CMS collaborations

LHCP 2023 Belgrade
May 25th, 2023

Jet tagging at LHC

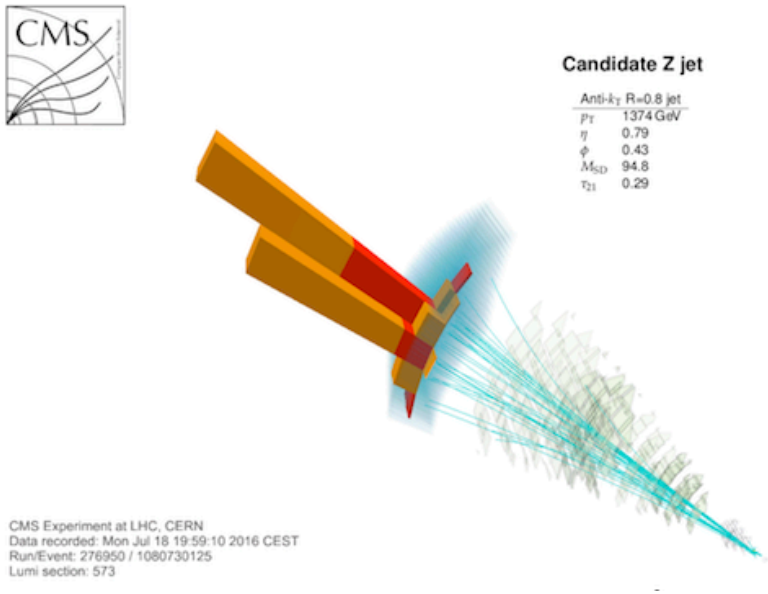


- Analyses of **hadronic final states** particularly challenging at LHC due to **overwhelming QCD background**

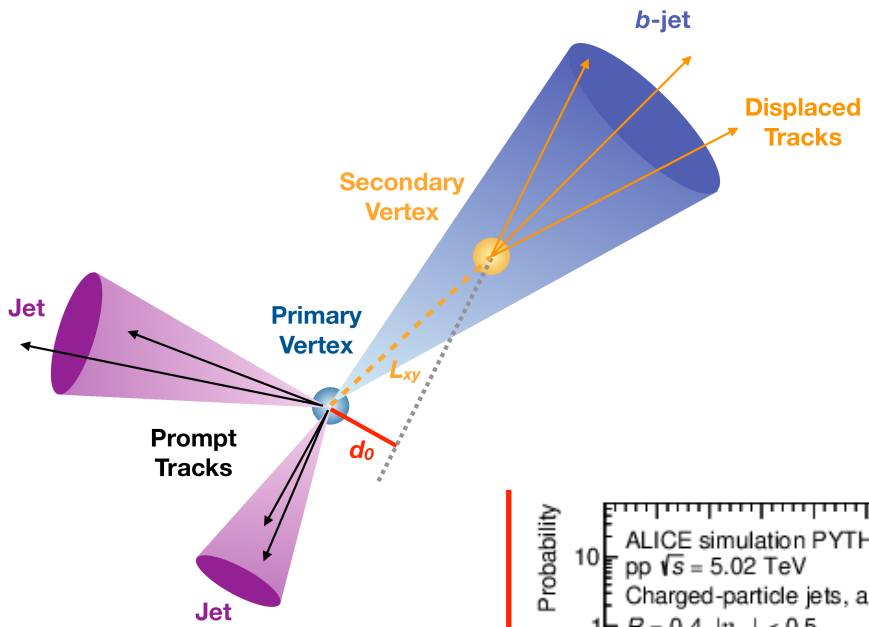
- Still hadronic final states very interesting to **measure SM properties and search for BSM physics:**
  - **top quarks** often strongly coupled to new physics
  - **Higgs** couplings to b/c quarks
  - larger hadronic BR for **vector bosons** in boosted phase space

- **Optimised jet tagging algorithms** powerful handles to reduce main **light quark + gluon jet background**

- **Jet reconstruction exploits information from tracker and/or calorimeters:**
  - clustering based on anti-kT / Cambridge-Aachen R=0.4 (resolved) or R=0.8 / 1.0 / 1.5 (boosted)

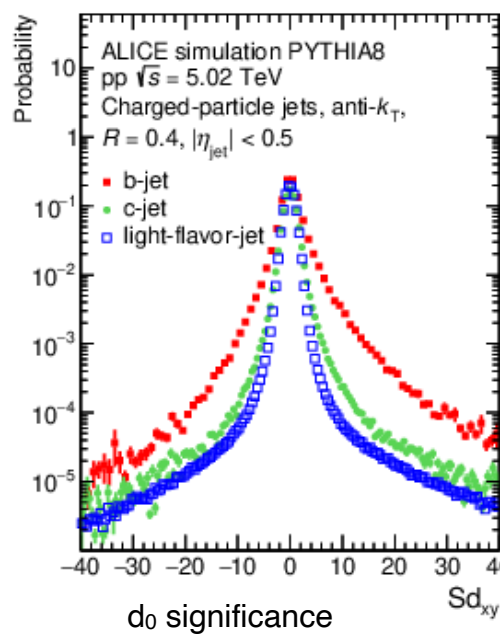


Flavour-tagging algorithms

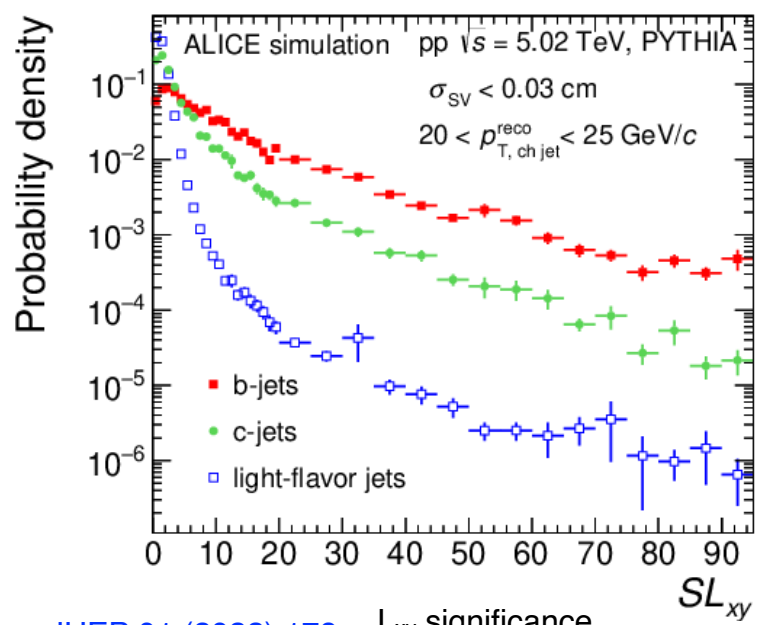


- **Flavour-tagging aims at separating b / c / light-jets** typically for AntiKt4 jets
- **Exploiting B-hadron properties:**
  - sizeable lifetime $\beta\gamma c\tau \sim 5$mm for p_T=50 GeV
    => displaced secondary vertices
  - large mass ~ 5 GeV
    => non-pointing tracks with sizeable impact parameters

- **Large sets of available inputs** can be ideally exploited through **machine-learning algorithms**



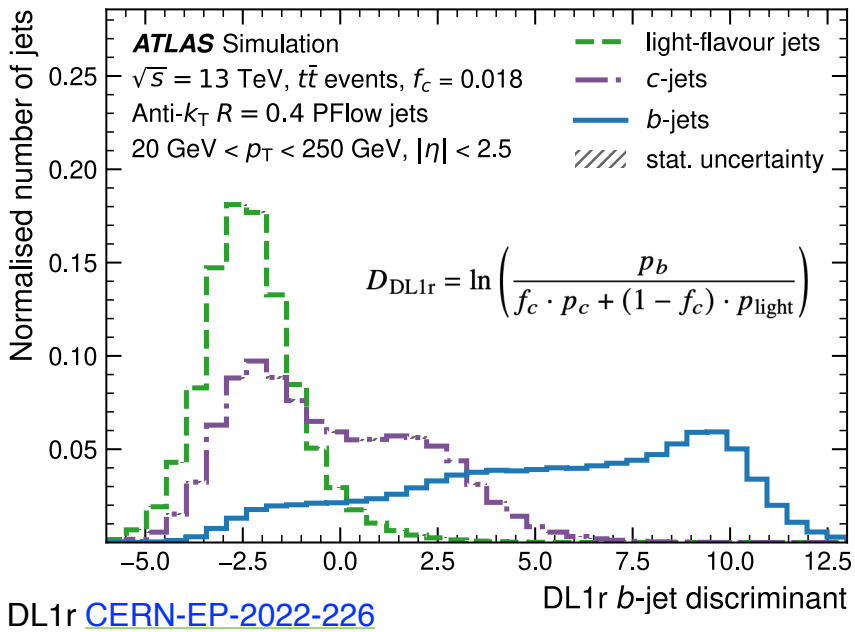
d_0 significance



JHEP 01 (2022) 178

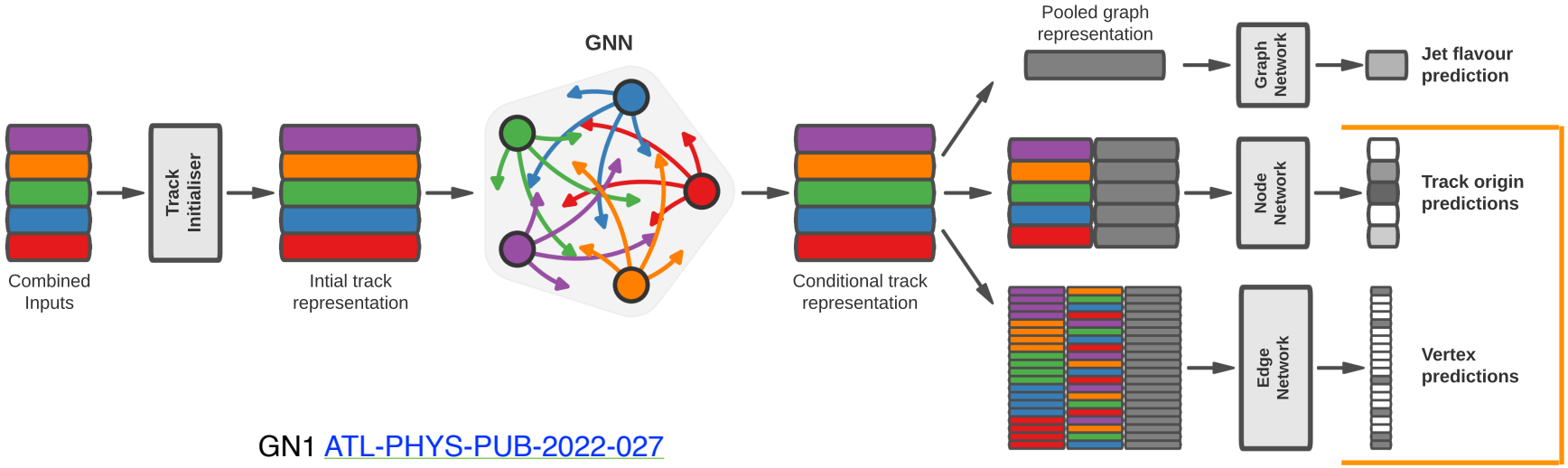
L_{xy} significance

Flavour-tagging algorithms



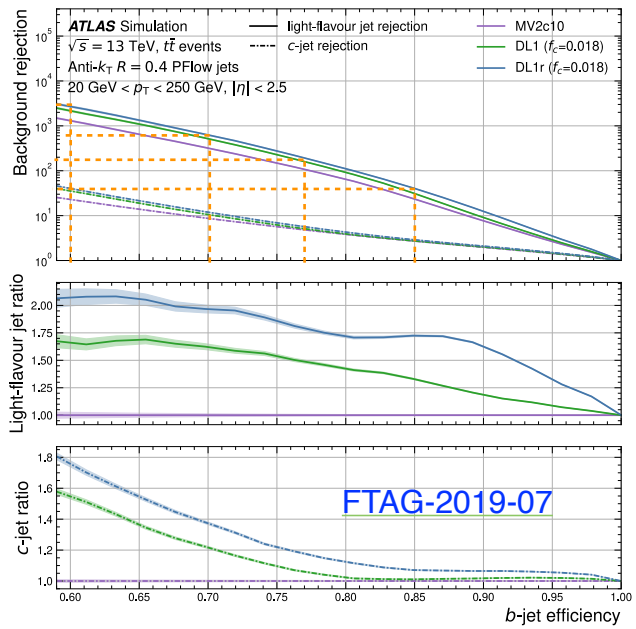
DL1r CERN-EP-2022-226

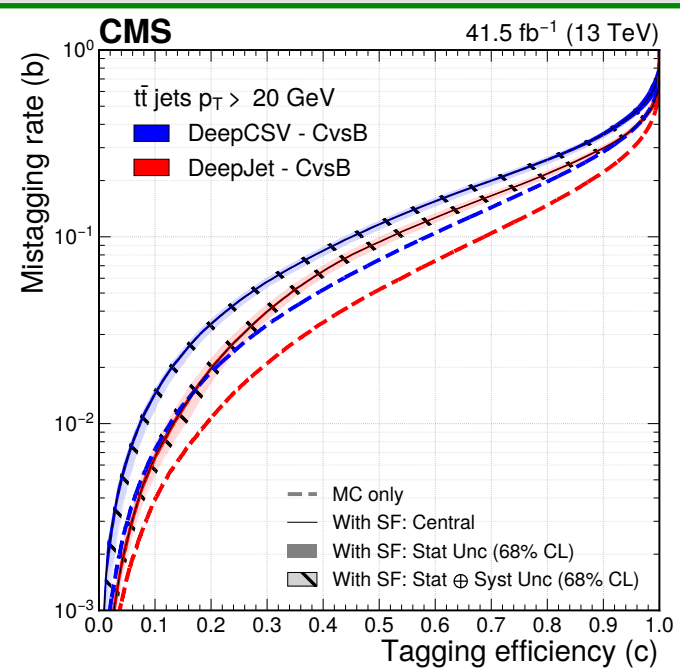
- Most recent algorithms used in ATLAS and CMS based on **Neural Network architectures, used as multi-classifier:**
  - ATLAS DL1r CERN-EP-2022-226 + GN1 ATL-PHYS-PUB-2022-027
  - CMS DeepCSV JINST 13 (2018) P05011 + DeepJet JINST 15 (2020) P12012
- Can be used both for **b-tagging and c-tagging**
- Last generations of taggers trained directly **from particle-level inputs with auxiliary training objectives**



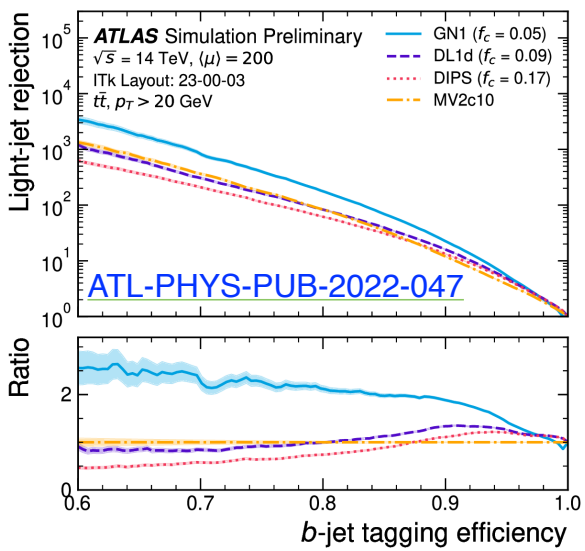
GN1 ATL-PHYS-PUB-2022-027

Flavour-tagging performance





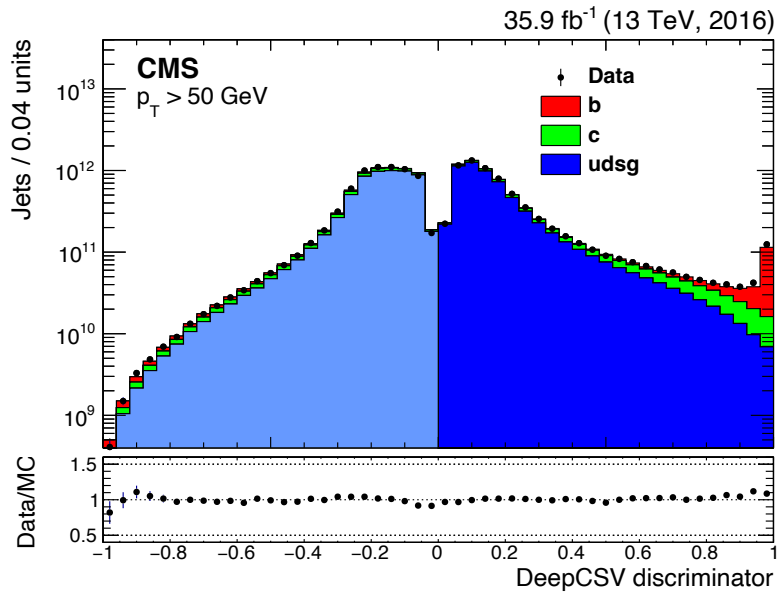
JINST 17 (2022) P03014



- **Very active area of developments at LHC** with continuous pace of improvements made available to analyses using **b-** and **c-tagging**:
  - **working points** with very similar performance available in ATLAS and CMS
  - **adaptation to harsh pile-up 200** conditions expected at HL-LHC already under study
  - **increasing background rejection** makes calibration in data very challenging

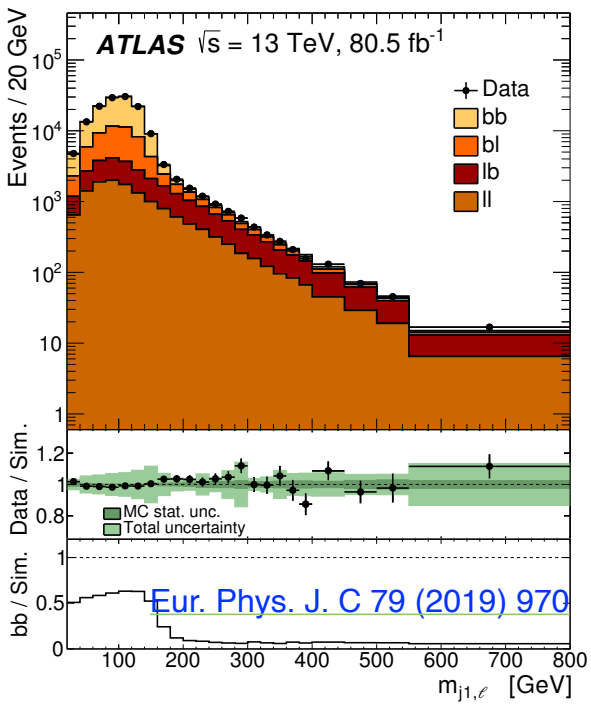
Performance in data

- **Baseline methods to measure performance in data include:**
  - **b-jet efficiency**
    in ttbar di-leptonic events or multi-jets with μ in jet
  - **c-jet mistag rate (efficiency)**
    in W+c or ttbar semi-leptonic events (W→ c+light q)
  - **light-jet mistag rate**
    negative tag method in multi-jets or Z+jets events

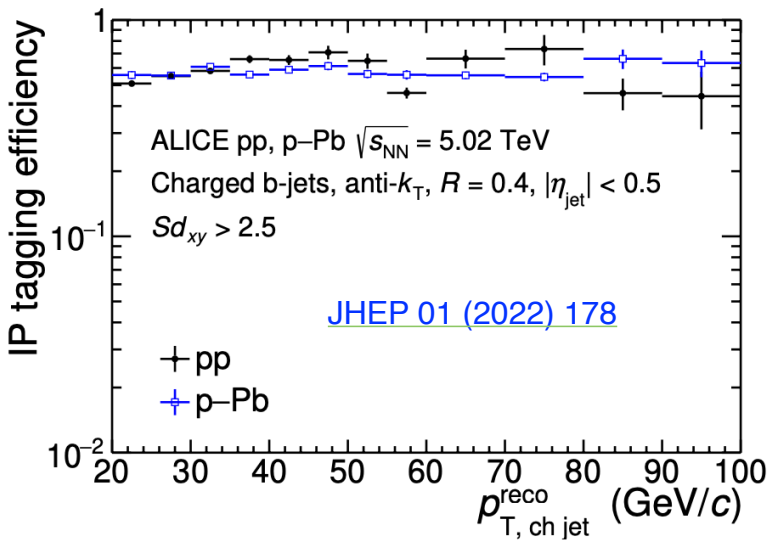


JINST 13 (2018) P05011 (CMS)

CERN-EP-2022-211 (ATLAS)



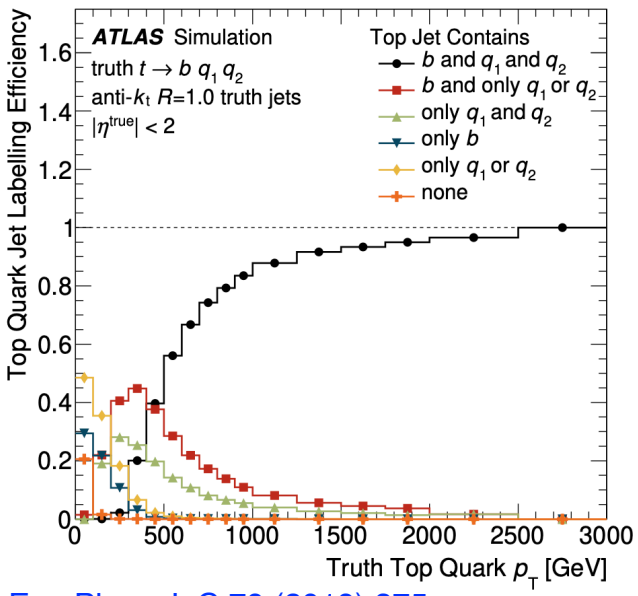
Eur. Phys. J. C 79 (2019) 970



JHEP 01 (2022) 178

- **Calibration of finite number of operating points** (ATLAS, ALICE) **or full flavour-tagging discriminator shape** (CMS)

Boosted object tagging



Eur. Phys. J. C 79 (2019) 375

- Boosted object tagging for pT regime where **decay products too collimated** to be reconstructed as resolved anti-kT R=0.4 jets
  => large R-jets anti-kT R=0.8 / 1.0 / CA R=1.5, **pT ≳ 500 GeV**

- Historically exploit **jet substructure** via **high-level variables:**
  - N-subjettiness $\tau_{NN-1} = \tau_N / \tau_{N-1}$ JHEP 03 (2011) 015

$$\tau_N = \frac{1}{d_0} \sum_k p_{T,k} \min\{\Delta R_{1,k}, \Delta R_{2,k}, \cdots, \Delta R_{N,k}\}$$

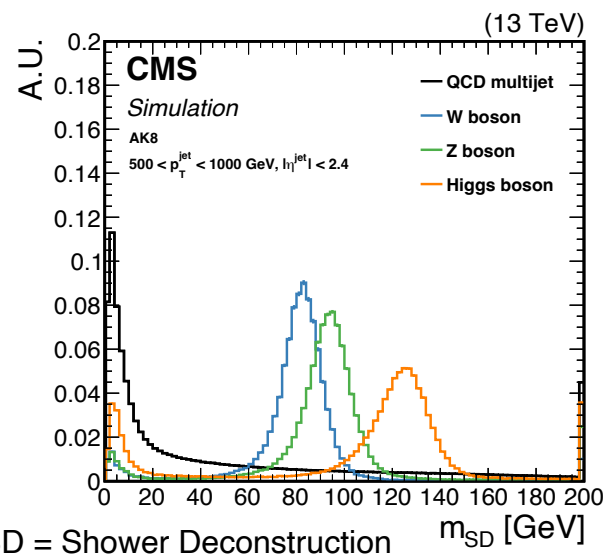
  - energy correlation functions JHEP 06 (2013) 108

$$z_i \equiv \frac{p_{Ti}}{\sum_{j \in \text{jet}} p_{Tj}}$$

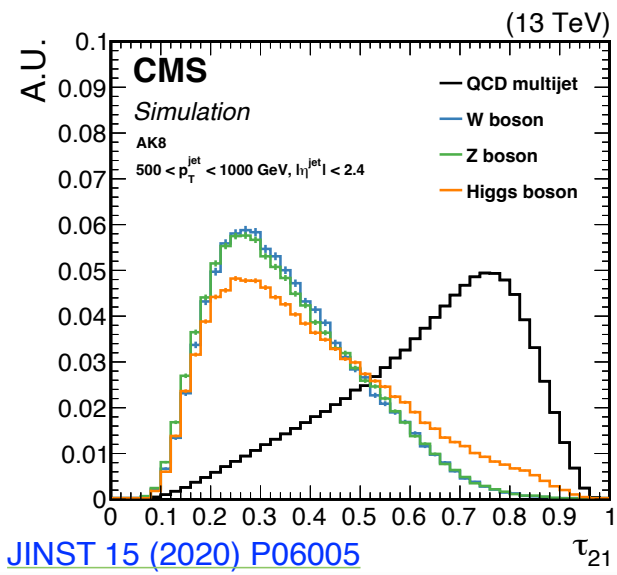
$$e_3^{(\beta)} = \sum_{1 \le i < j < k \le n_J} z_i z_j z_k \, \theta_{ij}^{\beta} \theta_{ik}^{\beta} \theta_{jk}^{\beta} \qquad \theta_{ij}^2 \equiv R_{ij}^2 = (\phi_i - \phi_j)^2 + (y_i - y_j)^2$$

- **Tagging algorithms typically combine in ML discriminants:**
  - substructure variables
  - kinematics information, invariant masses
  - b-tagging variables

or direct particle-level inputs for new-gen NN taggers



SD = Shower Deconstruction



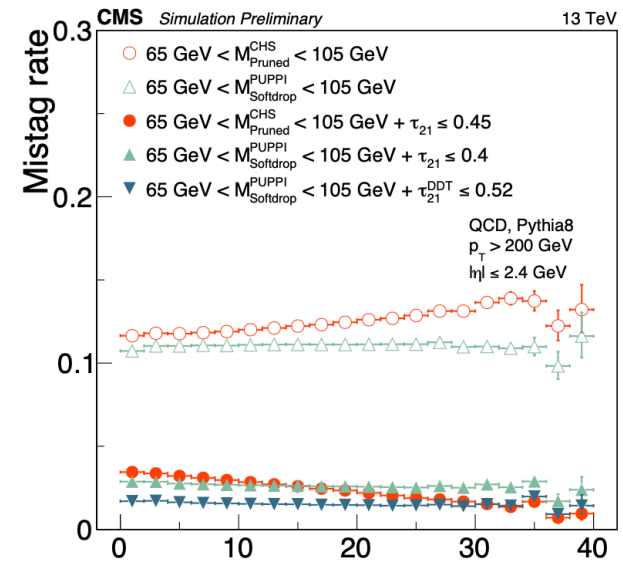
JINST 15 (2020) P06005

Jet substructure inputs

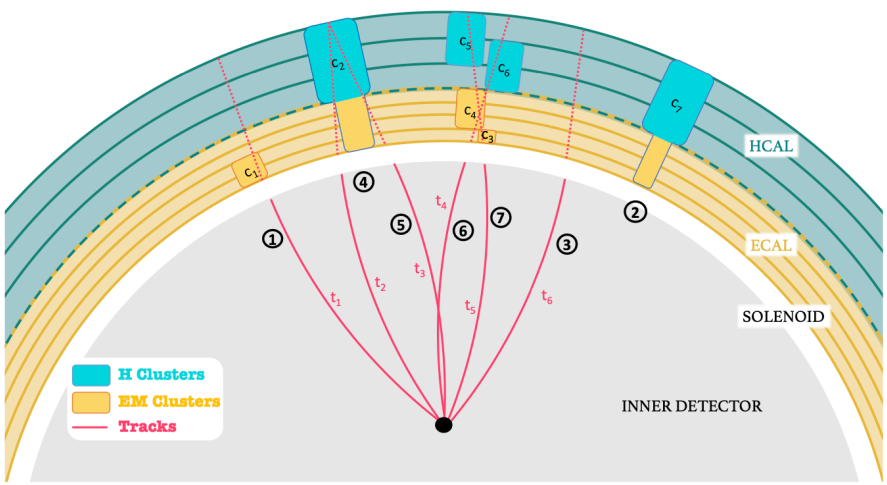
- Overlap of energy deposits in **calorimeters** in boosted jets significant, improved particle separation with **tracks**
  => PFlow (CMS baseline), TCC, **UFOs** (ATLAS baseline)
  JINST 12 (2017) P10003 Eur. Phys. J. C 81 (2021) 334

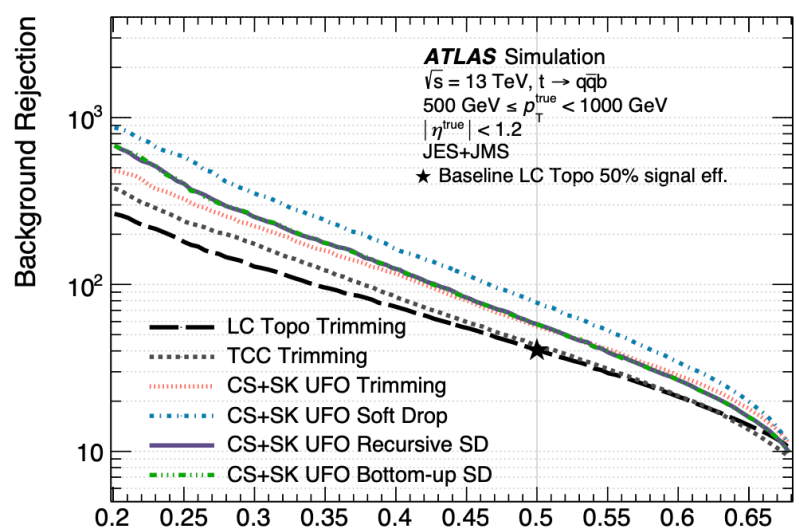
- **Tracks** also useful to **reduce pile-up dependence:** Charged Hadron Subtraction, PUPPI, Constituent Subtraction + Soft Killer…

- **Jet grooming** also used to **reduce impact of pile-up + ISR:** trimming, pruning, Soft Drop…
  => can have visible impact on tagger performance



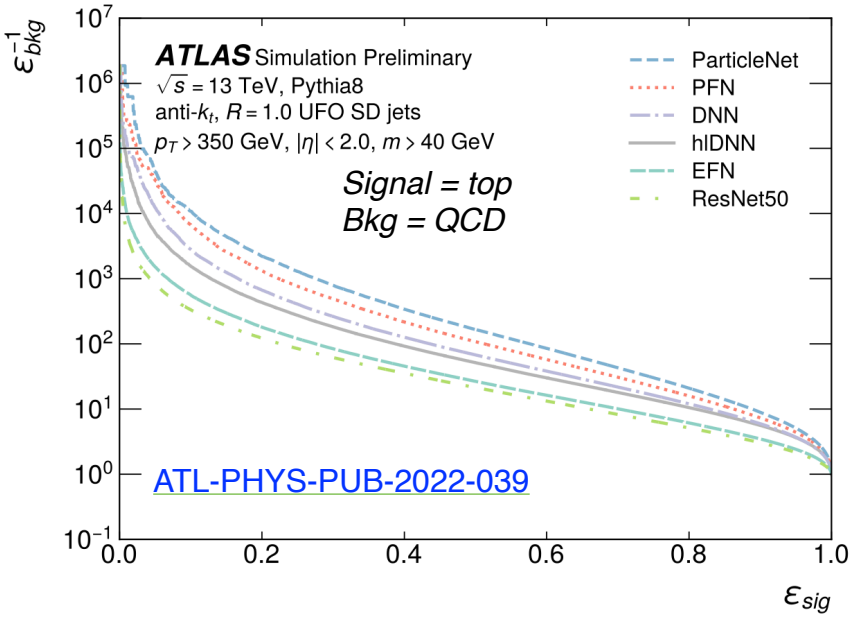
CMS-PAS-JME-16-003





Eur. Phys. J. C 81 (2021) 334

Boosted object tagging performance



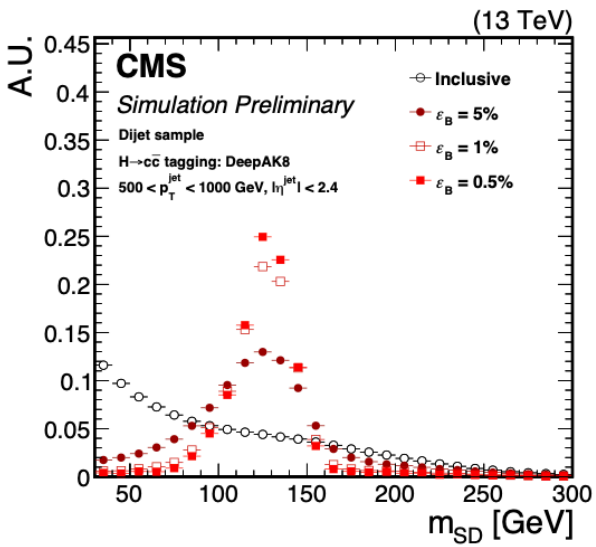
ATL-PHYS-PUB-2022-039

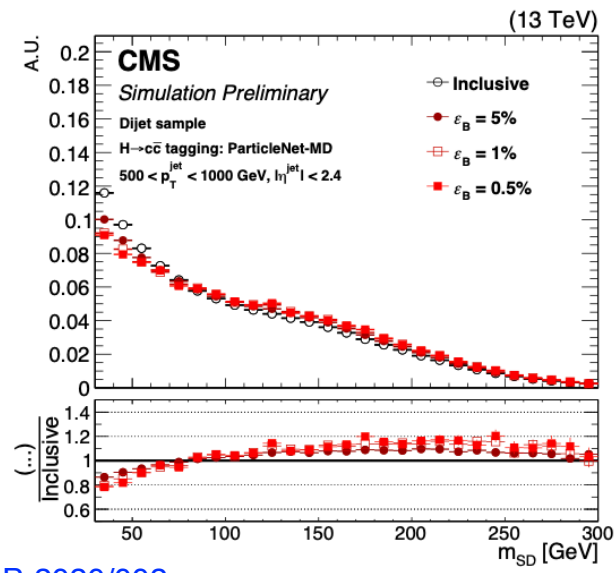
- **ParticleNet architecture state-of-the-art tagger** based on Dynamic Graph CNN Phys. Rev. D 101, 056019 (2020) using particle level inputs **investigated both in ATLAS and CMS**

- **Mass dependence of tagger also to be monitored:** impact on efficiency measurement, background estimation…

- Various techniques available to reduce **mass bias:** adversarial training, dedicated training samples…
  => compromise between mass decorrelation and absolute performance

- **Mass regression** also available for **model-independent resonance searches** CMS-DP-2021/017

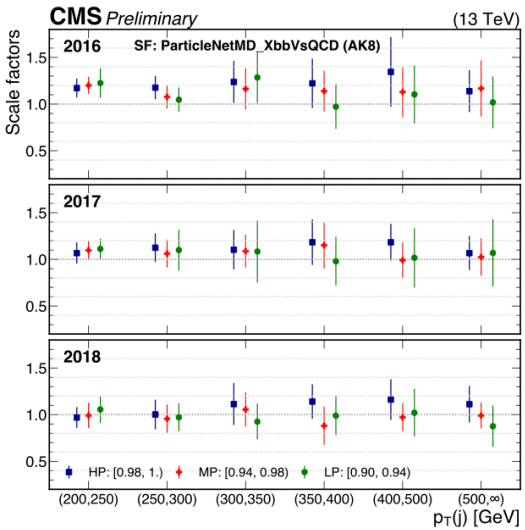




CMS-DP-2020/002

Performance in data

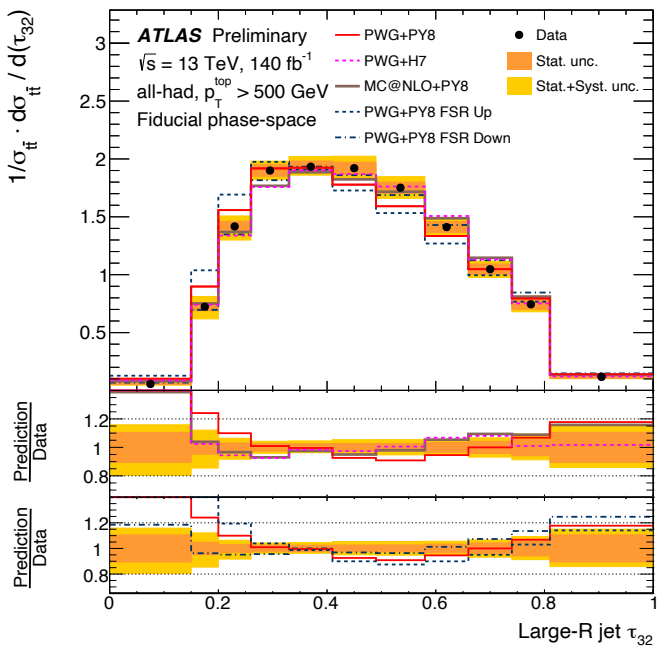
- Can be measured using:
  - **hadronic top/W decays in ttbar events**
  - **Z→bb/cc + γ/jets**
  - **gluon splitting g→bb/cc**: needs care to take into account different properties of gluons vs Higgs decays
  - **background QCD jets from di-jet + γ/jets events**



CMS-DP-2022/005

NEW for LHCP 2023!

ATLAS-CONF-2023-027

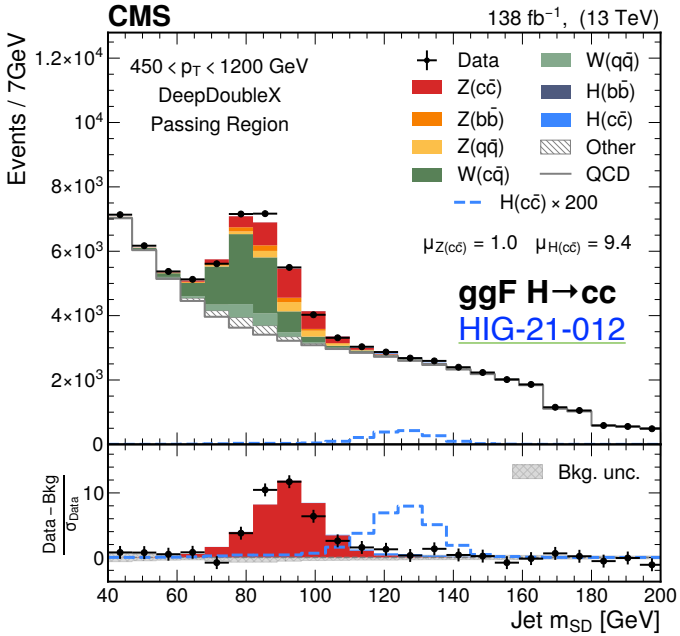


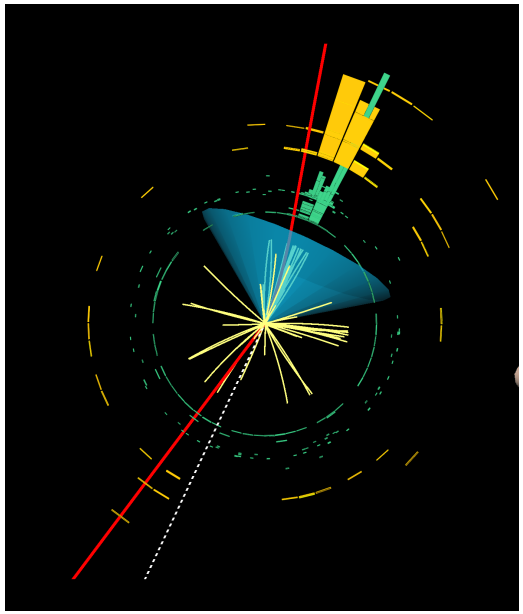
- **First unfolded measurement of top-jet substructure variables defined based on charged components** in ℓ+jets and all-hadronic ttbar events
  More plots in back up
- **Wide-range of substructure variables measured**
- **Better prediction with Herwig7 or increased α_S^{FSR}:** can help improving modelling in training samples for boosted top taggers

Summary

- **Physics with jets** essential to ensure wide coverage of LHC physics programme: **significant effort to improve / develop tools used for jet tagging** with great successes
  => Who could have imagined a ggF H→cc search 10 years ago?

- **Advanced machine-learning tools** key player in these developments:
  - move from high-level to **particle-level inputs**
  - **improved flexibility** to address known shortcomings of previous methods and tools





- But **machine-learning alone not enough** to guarantee successful **deployment of better taggers:**
  - **detector knowledge** increasingly useful as we move closer to detector-level inputs
  - **software integration and maintenance** to be carried with good coordination
  - **measurement of performance in data** require physics analyses of their own to provide high-precision data-MC scale factors

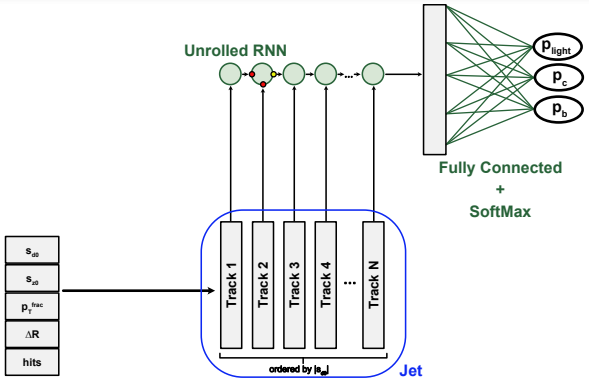
=> Only possible thanks to large collaborative efforts within LHC collaborations, thanks to all involved!

Back-up

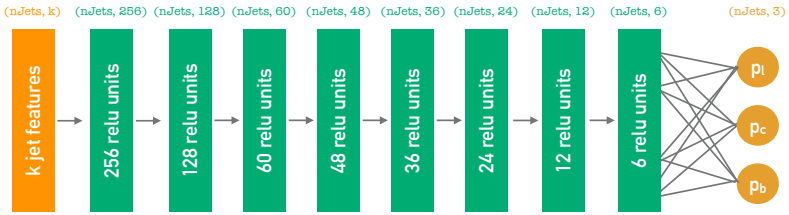
Flavour-tagging algorithms: ATLAS DL1r

FTAG-2019-07

Input	Variable	Description	SVKine	JFKine	DL1	DL1r
Kinematics	p_T	Jet p_T	✓	✓	✓	✓
	η	Jet $\lvert\eta\rvert$	✓	✓	✓	✓
IP2D, IP3D	$\log(P_b/P_{light})$	Likelihood ratio of the b-jet to light-flavour jet hypotheses			✓	✓
	$\log(P_b/P_c)$	Likelihood ratio of the b-jet to c-jet hypotheses			✓	✓
	$\log(P_c/P_{light})$	Likelihood ratio of the c-jet to light-flavour jet hypotheses			✓	✓
RNNIP	P_b	b-jet probability				✓
	P_c	c-jet probability				✓
	P_{light}	light-flavour jet probability				✓
SV1	$m(\mathrm{SV})$	Invariant mass of tracks at the secondary vertex assuming pion mass	✓		✓	✓
	$f_E(\mathrm{SV})$	Jet energy fraction of the tracks associated with the secondary vertex	✓		✓	✓
	$N_{\mathrm{TrkAtVtx}}(\mathrm{SV})$	Number of tracks used in the secondary vertex	✓		✓	✓
	$N_{\mathrm{2TrkVtx}}(\mathrm{SV})$	Number of two-track vertex candidates	✓		✓	✓
	$L_{xy}(\mathrm{SV})$	Transverse distance between the primary and secondary vertices	✓		✓	✓
	$L_{xyz}(\mathrm{SV})$	Distance between the primary and secondary vertices	✓		✓	✓
	$S_{xyz}(\mathrm{SV})$	Distance between the primary and secondary vertices divided by its uncertainty	✓		✓	✓
	$\Delta R(\vec{p}_{\mathrm{jet}}, \vec{p}_{\mathrm{vtx}})(\mathrm{SV})$	ΔR between the jet axis and the direction of the secondary vertex relative to the primary vertex.	✓		✓	✓
JetFitter	$m(\mathrm{JF})$	Invariant mass of tracks from displaced vertices		✓	✓	✓
	$f_E(\mathrm{JF})$	Jet energy fraction of the tracks associated with the displaced vertices		✓	✓	✓
	$\Delta R(\vec{p}_{\mathrm{jet}}, \vec{p}_{\mathrm{vtx}})(\mathrm{JF})$	ΔR between the jet axis and the vectorial sum of momenta of all tracks attached to displaced vertices		✓	✓	✓
	$S_{xyz}(\mathrm{JF})$	Significance of the average distance between PV and displaced vertices		✓	✓	✓
	$N_{\mathrm{TrkAtVtx}}(\mathrm{JF})$	Number of tracks from multi-prong displaced vertices		✓	✓	✓
	$N_{\mathrm{2TrkVtx}}(\mathrm{JF})$	Number of two-track vertex candidates (prior to decay chain fit)		✓	✓	✓
	$N_{\text{1-trk vertices}}(\mathrm{JF})$	Number of single-prong displaced vertices		✓	✓	✓
	$N_{\geq\text{2-trk vertices}}(\mathrm{JF})$	Number of multi-prong displaced vertices		✓	✓	✓
	$L_{xyz}(2^{\mathrm{nd}})(\mathrm{JF})$	Distance of 2nd vertex from PV		✓	✓	✓
	$L_{xy}(2^{\mathrm{nd}})(\mathrm{JF})$	Transverse displacement of the 2nd vertex		✓	✓	✓
	$m_{\mathrm{Trk}}(2^{\mathrm{nd}})(\mathrm{JF})$	Invariant mass of tracks associated with the 2nd vertex		✓	✓	✓
	$E(2^{\mathrm{nd}})(\mathrm{JF})$	Energy of the tracks associated with the 2nd vertex		✓	✓	✓
	$f_E(2^{\mathrm{nd}})(\mathrm{JF})$	Jet energy fraction of the tracks associated with the 2nd vertex		✓	✓	✓
	$N_{\mathrm{TrkAtVtx}}(2^{\mathrm{nd}})(\mathrm{JF})$	Number of tracks associated with the 2nd vertex		✓	✓	✓
	$\eta_{\mathrm{trk}}^{\mathrm{min,max,avg}}(2^{\mathrm{nd}})(\mathrm{JF})$	Min., max. and avg. pseudorapidity of tracks at the 2nd vertex		✓	✓	✓

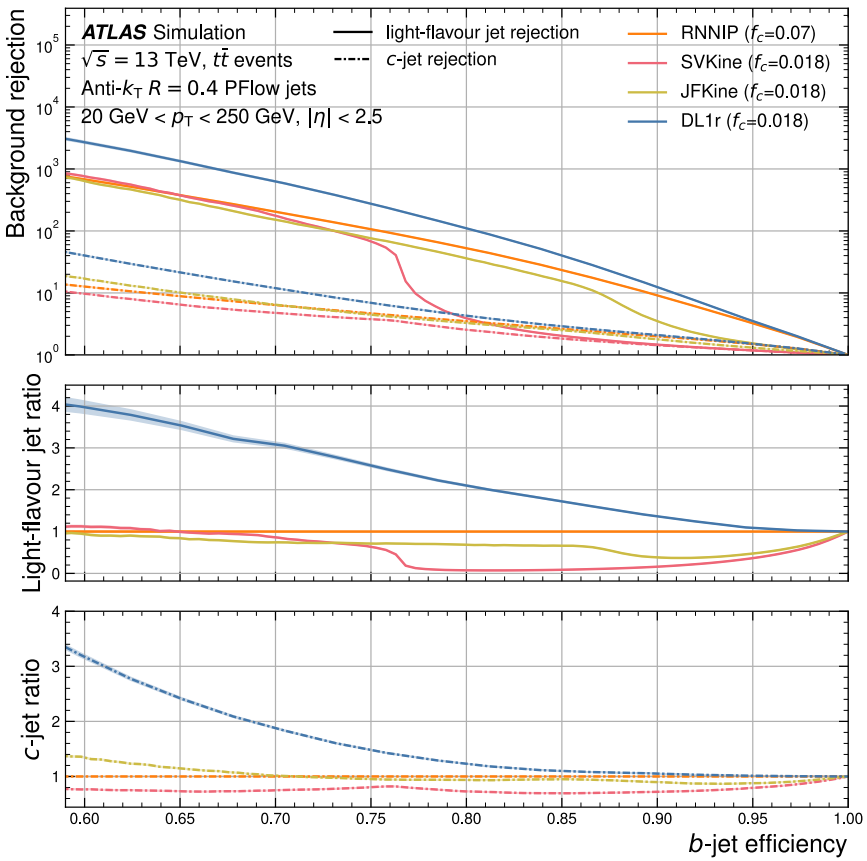


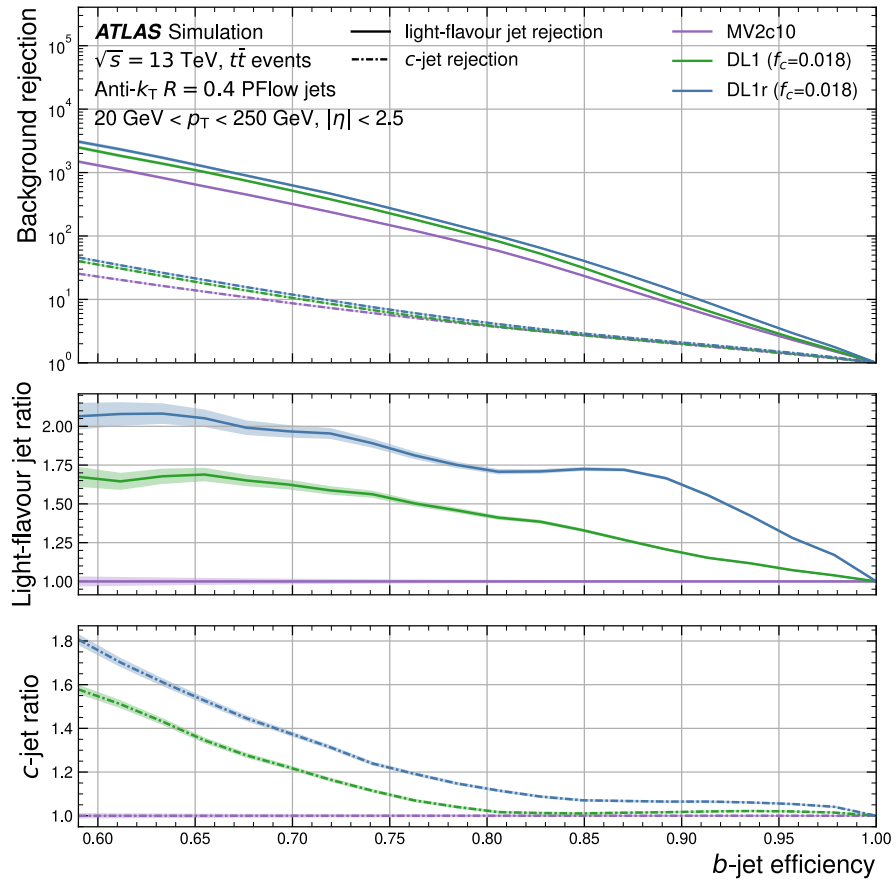
Hyperparameter	Value
Number of input variables	31
Number of hidden layers	8
Number of nodes [per layer]	[256, 128, 60, 48, 36, 24, 12, 6]
Learning rate	0.01
Training batch size	15 000
Activation function	ReLu
Number of training epochs	200
Free (trainable) parameters	59 275
Fixed parameters	1 140
Training sample size	22 M jets



Flavour-tagging algorithms: ATLAS DL1r

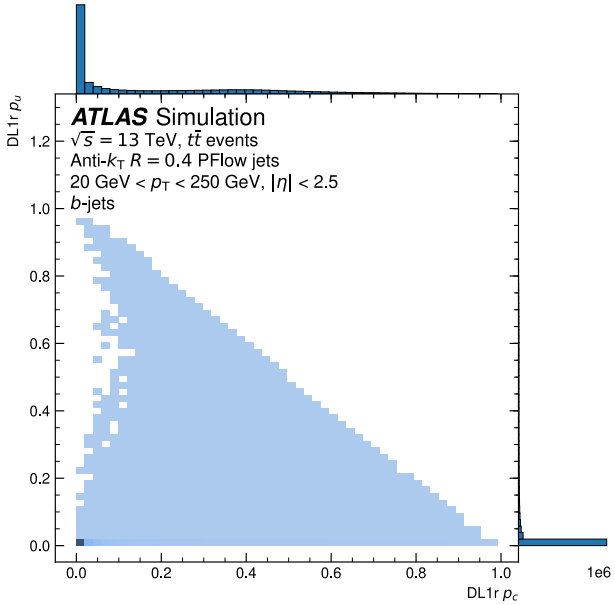
FTAG-2019-07

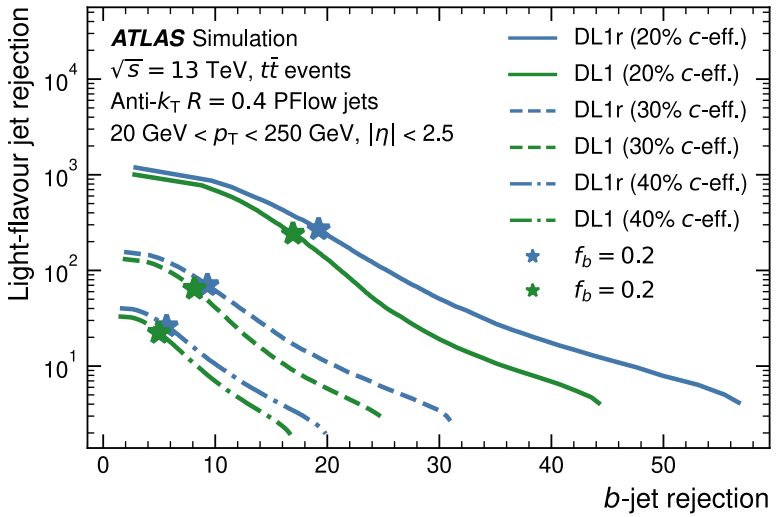


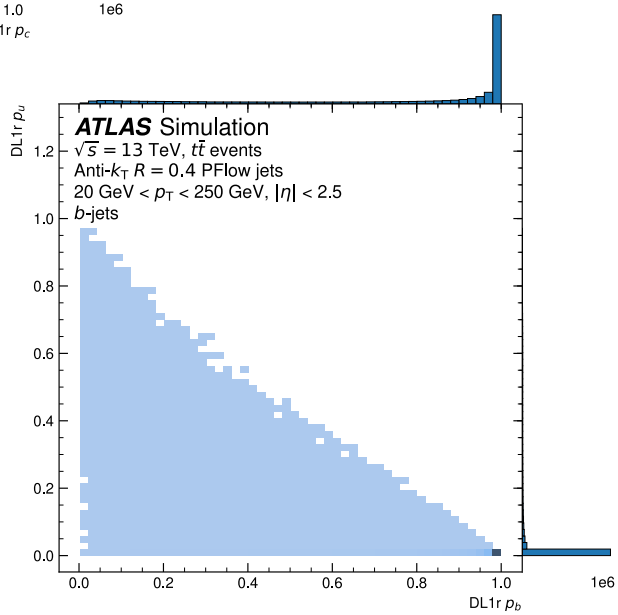


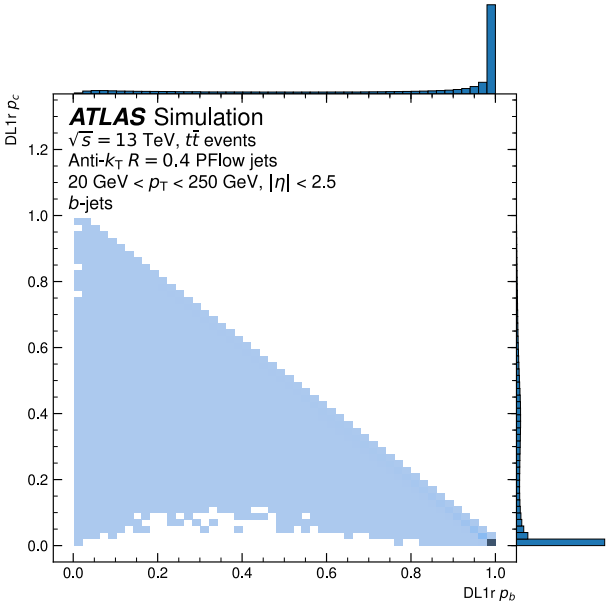
Flavour-tagging algorithms: ATLAS DL1r

FTAG-2019-07



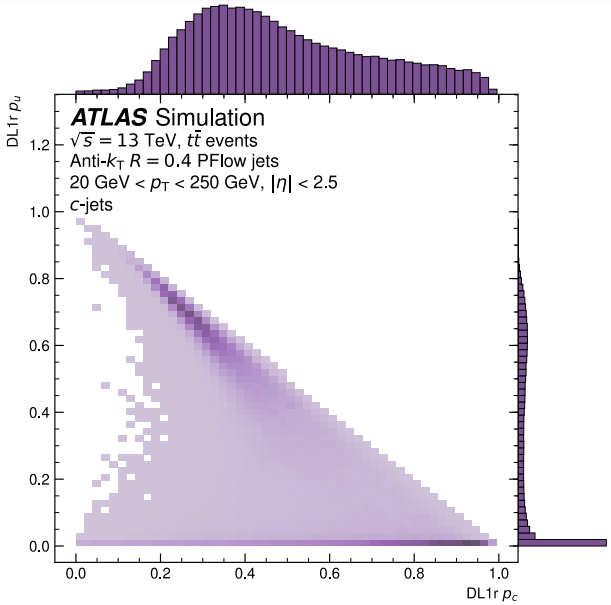


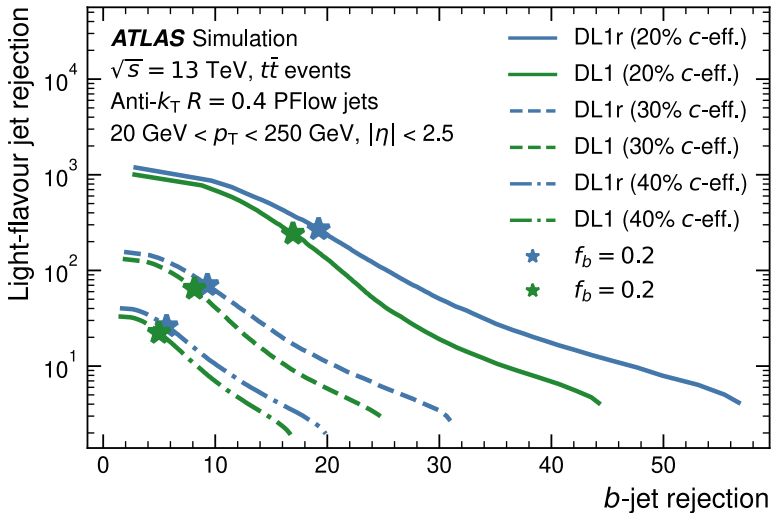


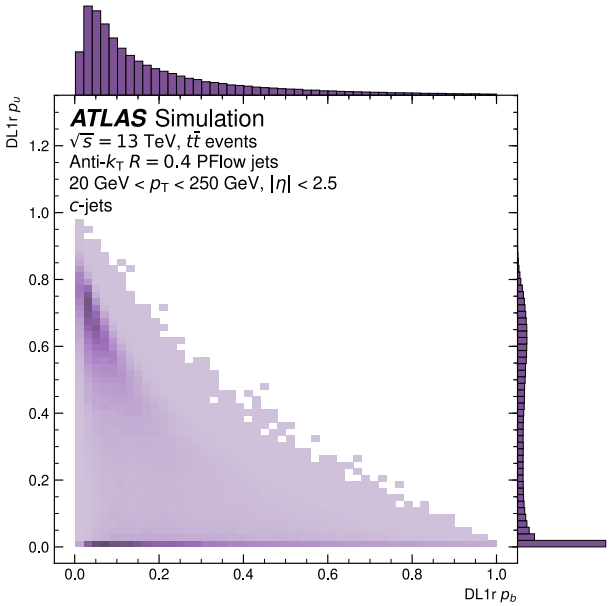


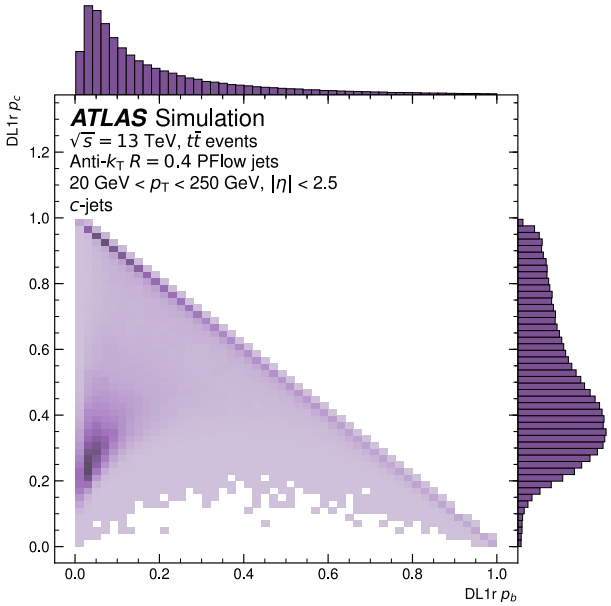
Flavour-tagging algorithms: ATLAS DL1r

FTAG-2019-07



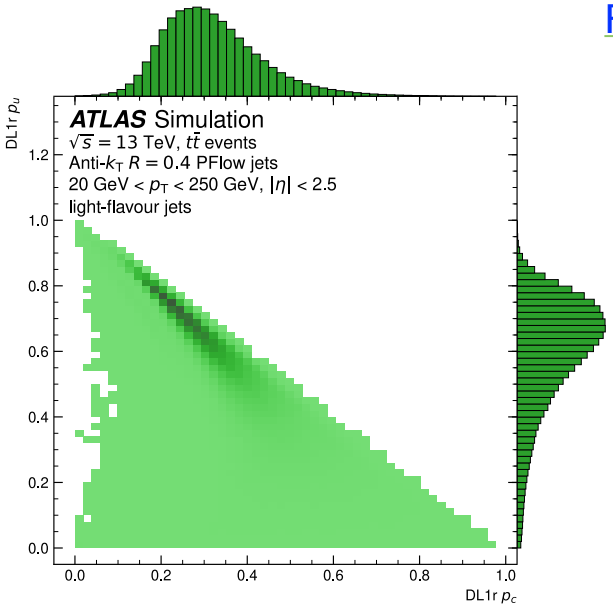


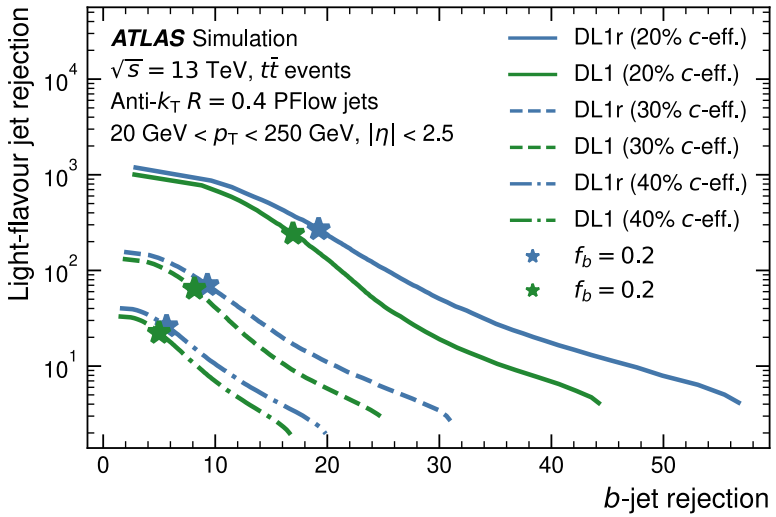


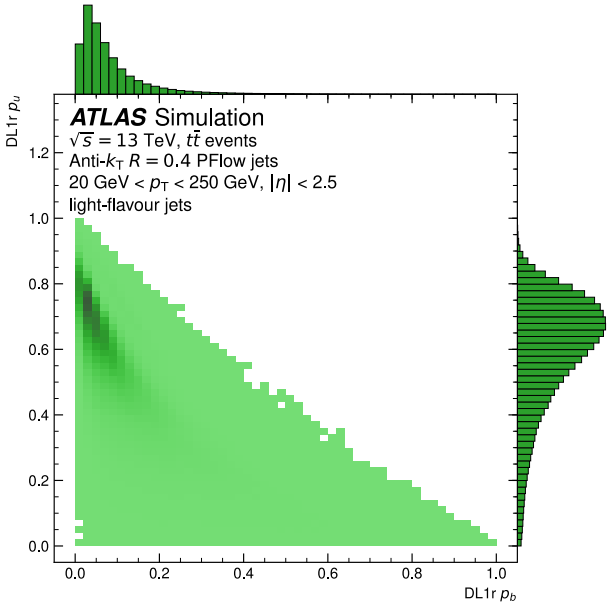


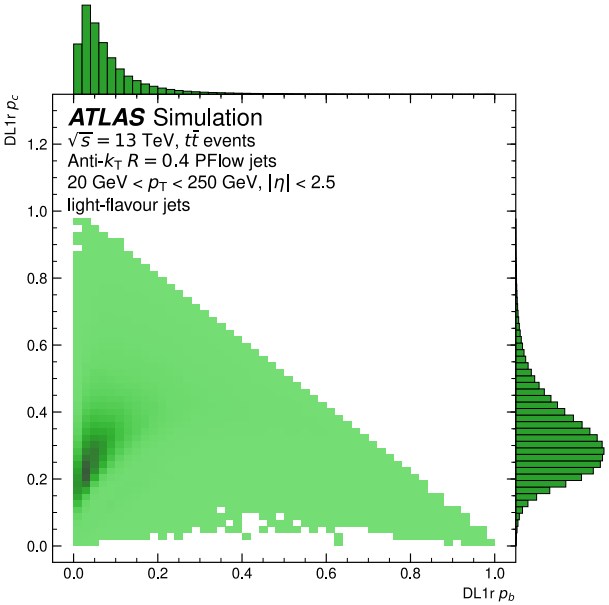
Flavour-tagging algorithms: ATLAS DL1r

FTAG-2019-07



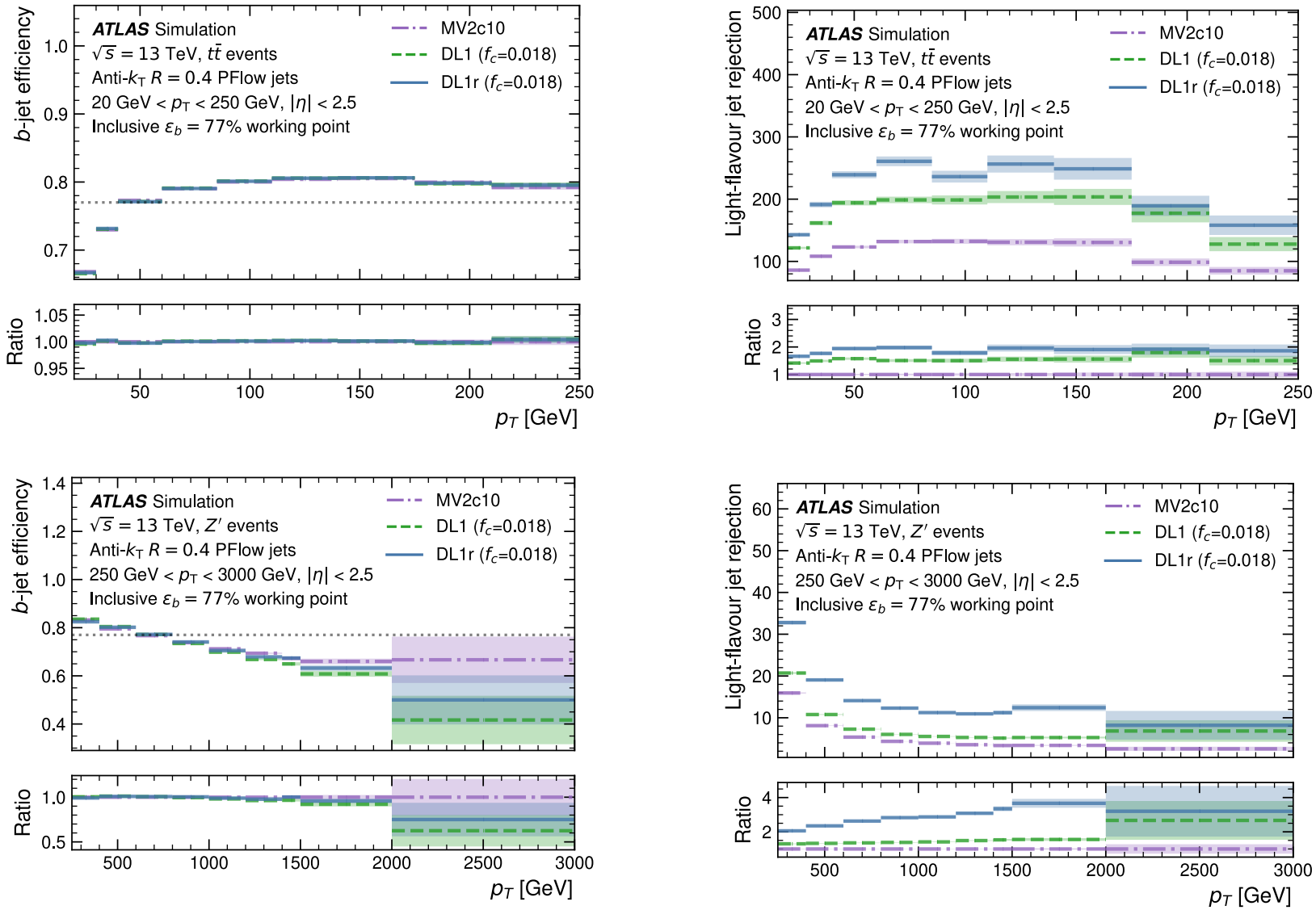






Flavour-tagging algorithms: ATLAS DL1r

FTAG-2019-07



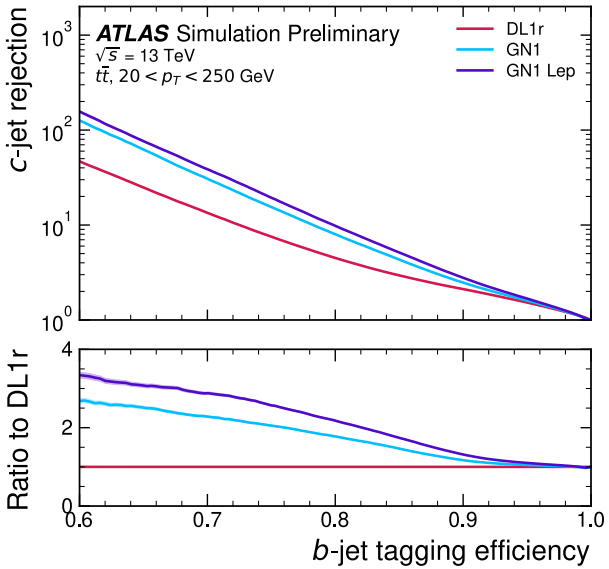
Flavour-tagging algorithms: ATLAS GN1

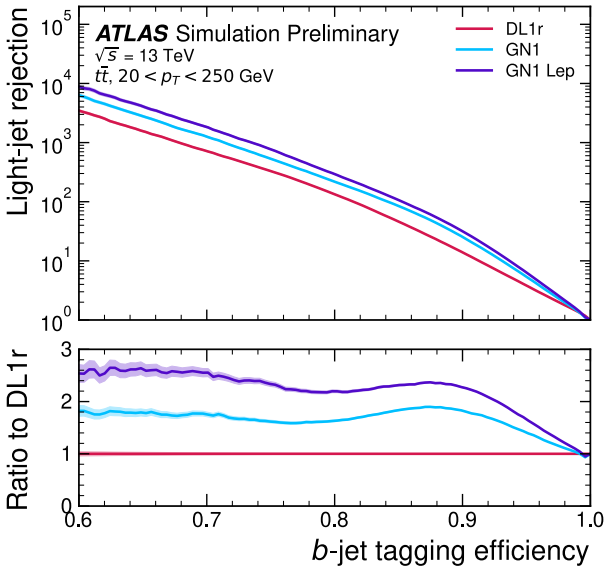
ATL-PHYS-PUB-2022-027

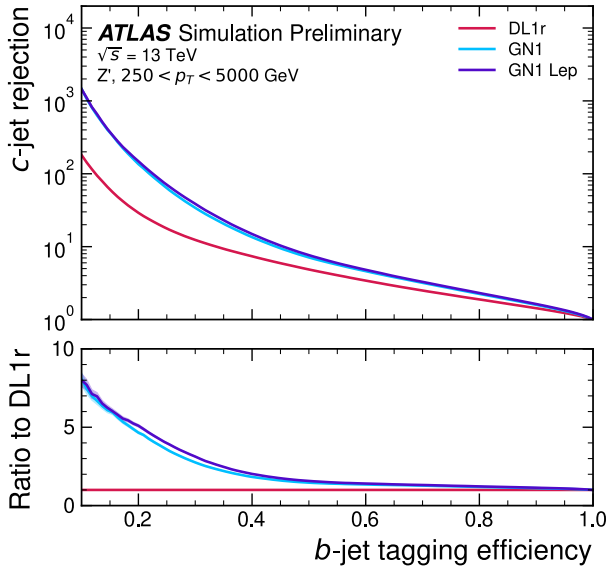
Jet Input	**Description**
p_{T}	Jet transverse momentum
η	Signed jet pseudorapidity
Track Input	**Description**
q/p	Track charge divided by momentum (measure of curvature)
$\mathrm{d}\eta$	Pseudorapidity of the track, relative to the jet η
$\mathrm{d}\phi$	Azimuthal angle of the track, relative to the jet ϕ
d_0	Closest distance from the track to the PV in the longitudinal plane
$z_0 \sin\theta$	Closest distance from the track to the PV in the transverse plane
$\sigma(q/p)$	Uncertainty on q/p
$\sigma(\theta)$	Uncertainty on track polar angle θ
$\sigma(\phi)$	Uncertainty on track azimuthal angle ϕ
$s(d_0)$	Lifetime signed transverse IP significance
$s(z_0)$	Lifetime signed longitudinal IP significance
nPixHits	Number of pixel hits
nSCTHits	Number of SCT hits
nIBLHits	Number of IBL hits
nBLHits	Number of B-layer hits
nIBLShared	Number of shared IBL hits
nIBLSplit	Number of split IBL hits
nPixShared	Number of shared pixel hits
nPixSplit	Number of split pixel hits
nSCTShared	Number of shared SCT hits
nPixHoles	Number of pixel holes
nSCTHoles	Number of SCT holes
leptonID	Indicates if track was used in the reconstruction of an electron or muon (only for GN1 Lep)

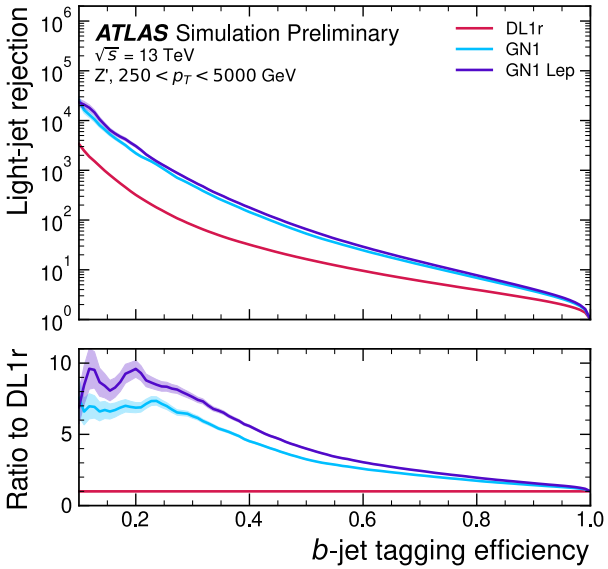
Flavour-tagging algorithms: ATLAS GN1

ATL-PHYS-PUB-2022-027

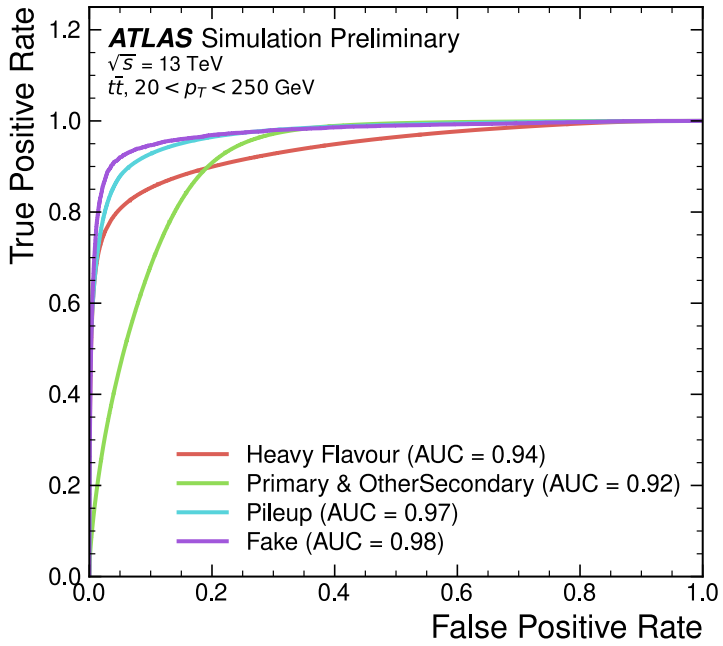


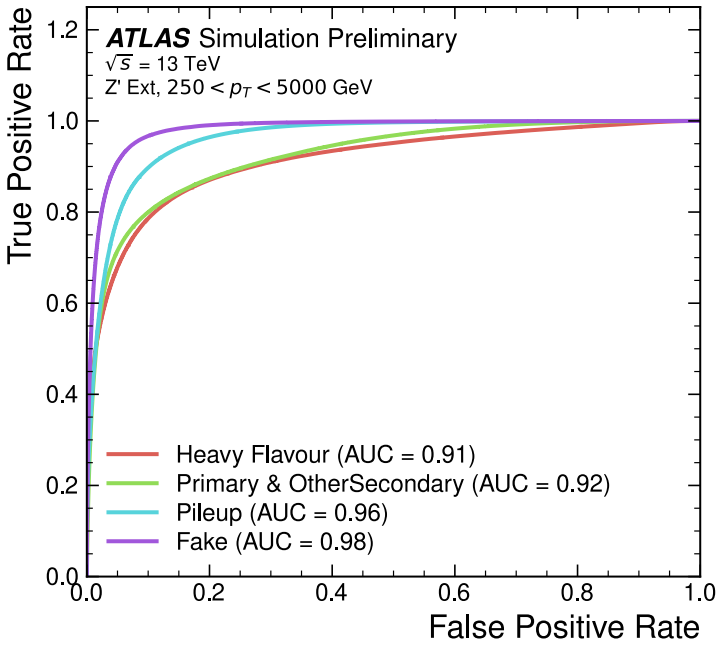


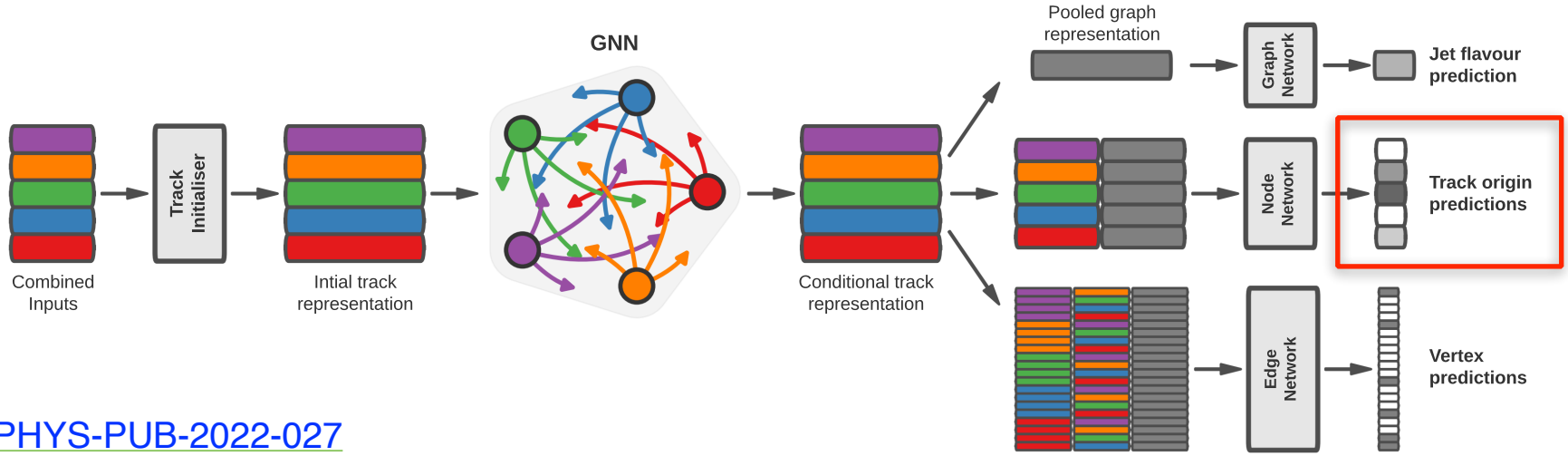




Flavour-tagging algorithms: ATLAS GN1

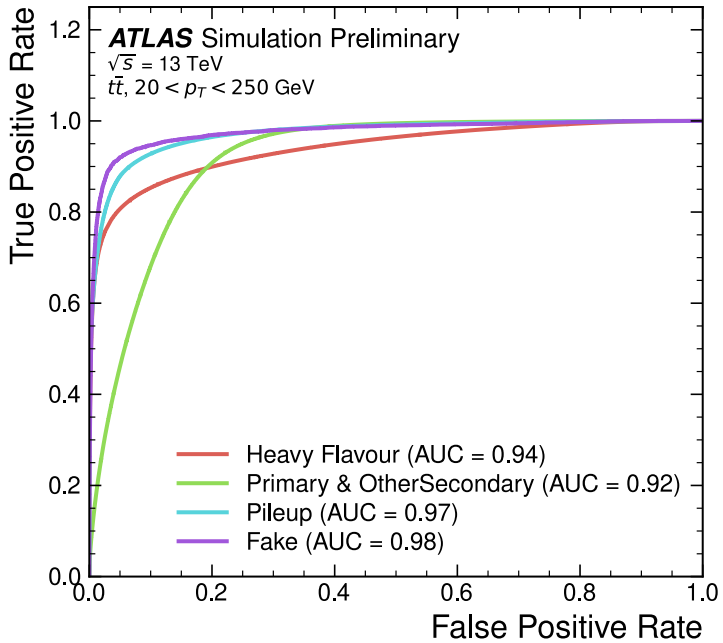


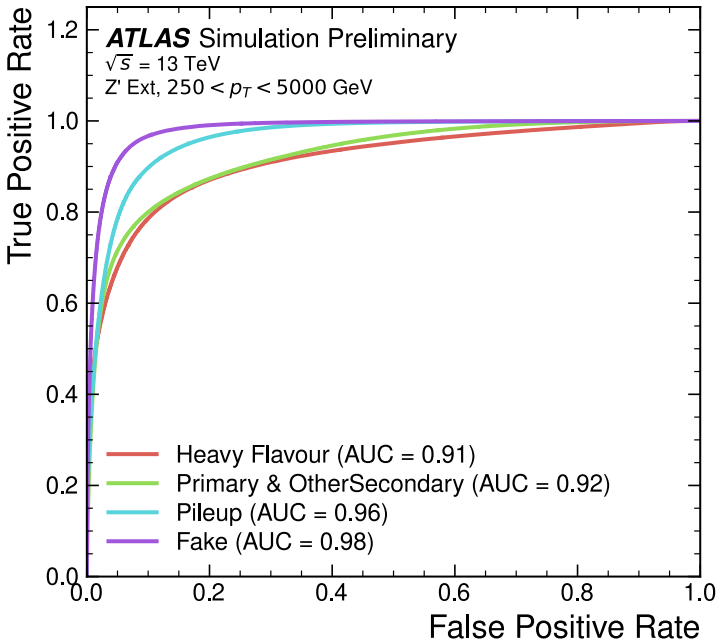




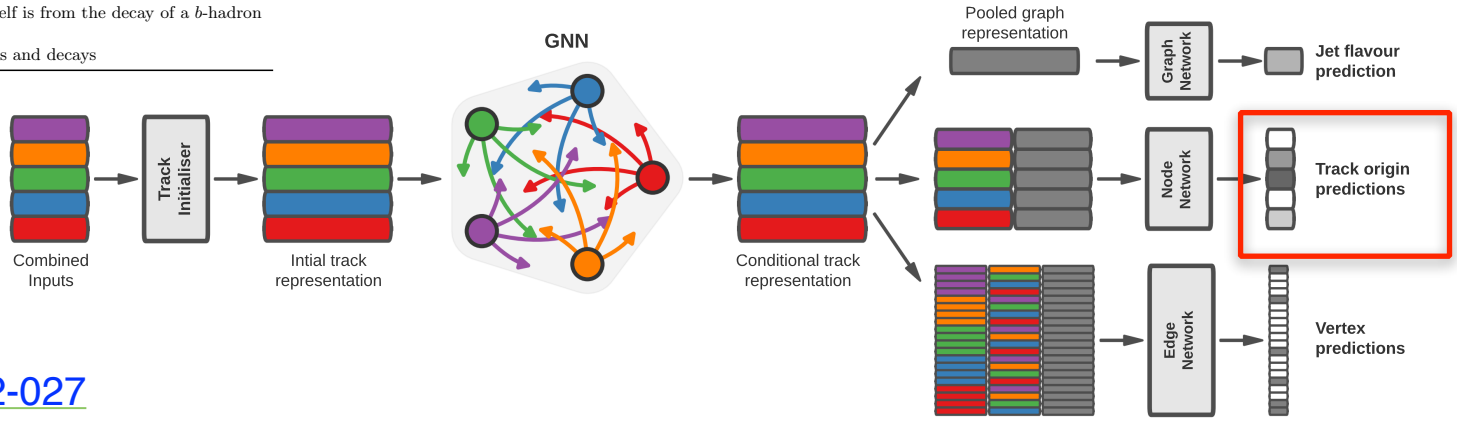
ATL-PHYS-PUB-2022-027

Flavour-tagging algorithms: ATLAS GN1





Truth Origin	Description
Pileup	From a *pp* collision other than the primary interaction
Fake	Created from the hits of multiple particles
Primary	Does not originate from any secondary decay
fromB	From the decay of a *b*-hadron
fromBC	From a *c*-hadron decay, which itself is from the decay of a *b*-hadron
fromC	From the decay of a *c*-hadron
OtherSecondary	From other secondary interactions and decays



ATL-PHYS-PUB-2022-027

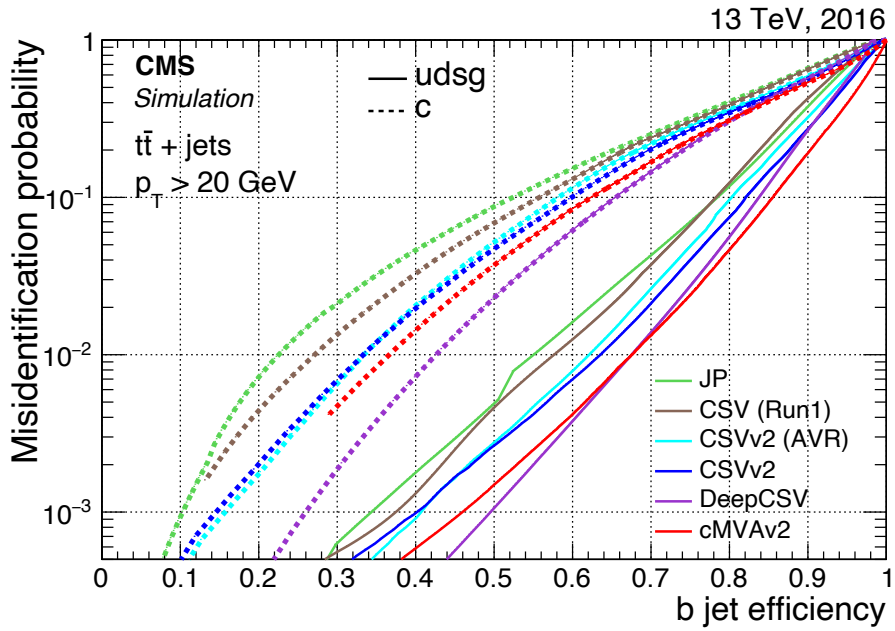
Flavour-tagging algorithms: CMS DeepCSV

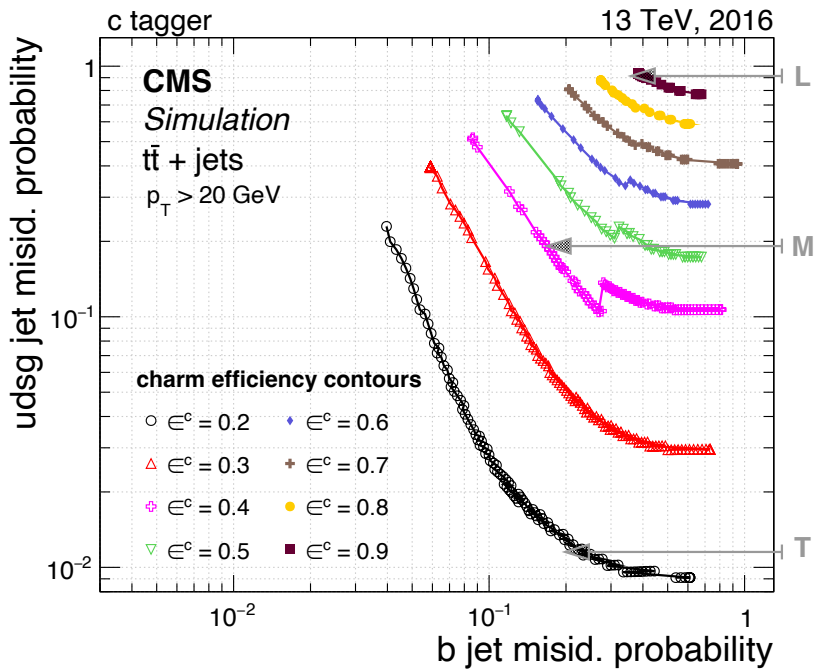
JINST 13 (2018) P05011

Input variable	Run 1 CSV	CSVv2
SV 2D flight distance significance	x	x
Number of SV	—	x
Track η_{rel}	x	x
Corrected SV mass	x	x
Number of tracks from SV	x	x
SV energy ratio	x	x
$\Delta R(\mathrm{SV, jet})$	—	x
3D IP significance of the first four tracks	x	x
Track $p_{\mathrm{T,rel}}$	—	x
$\Delta R(\mathrm{track, jet})$	—	x
Track $p_{\mathrm{T,rel}}$ ratio	—	x
Track distance	—	x
Track decay length	—	x
Summed tracks E_{T} ratio	—	x
$\Delta R(\mathrm{summed\ tracks, jet})$	—	x
First track 2D IP significance above c threshold	—	x
Number of selected tracks	—	x
Jet p_{T}	—	x
Jet η	—	x

Flavour-tagging algorithms: CMS DeepCSV

JINST 13 (2018) P05011

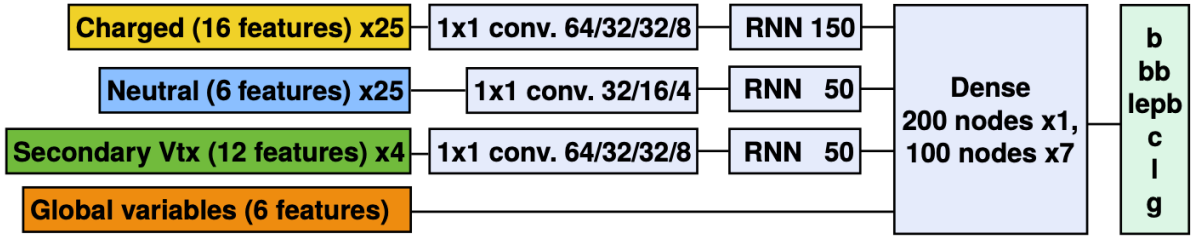


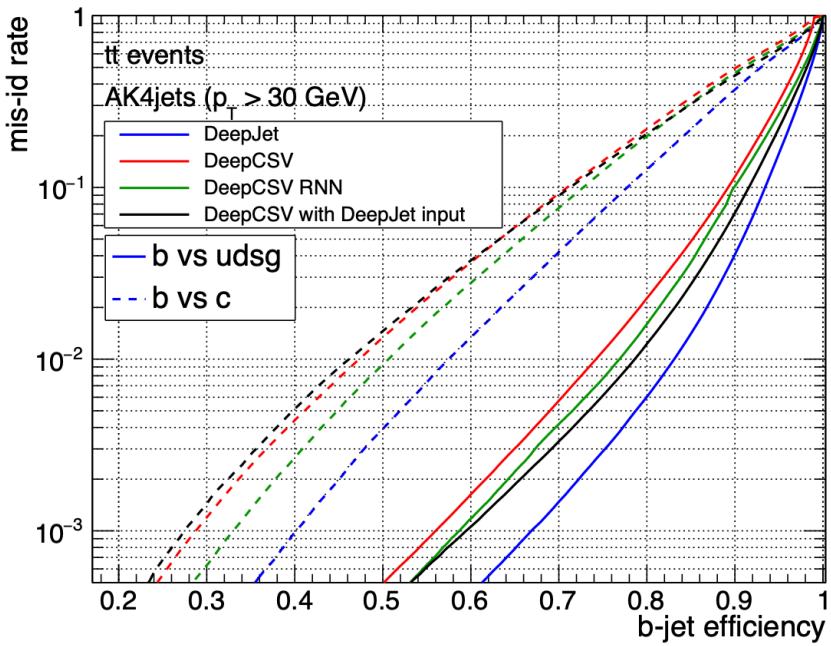


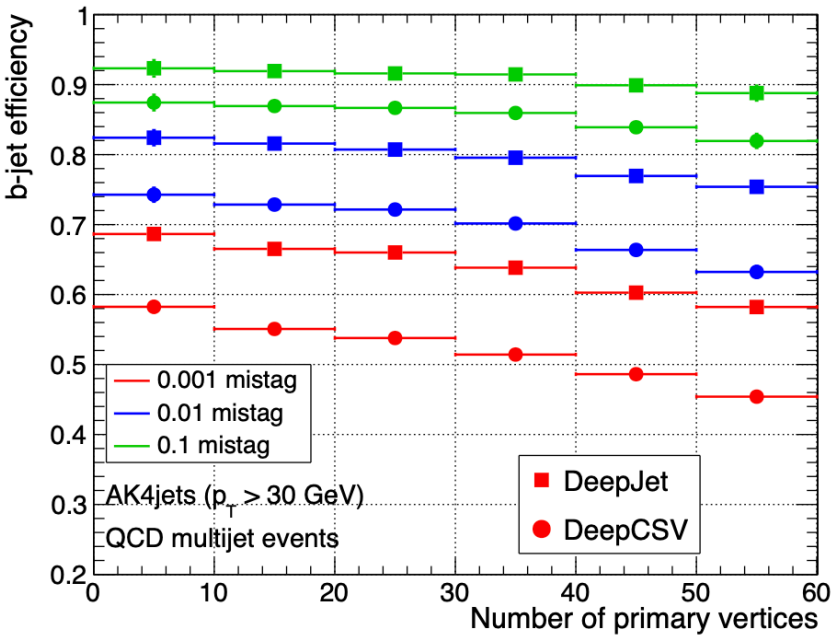
Tagger	Working point	ε_b (%)	ε_c (%)	ε_{udsg} (%)
Jet probability (JP)	JP L	78	37	9.6
	JP M	56	12	1.1
	JP T	36	3.3	0.1
Combined secondary vertex (CSVv2)	CSVv2 L	81	37	8.9
	CSVv2 M	63	12	0.9
	CSVv2 T	41	2.2	0.1
Combined MVA (cMVAv2)	cMVAv2 L	84	39	8.3
	cMVAv2 M	66	13	0.8
	cMVAv2 T	46	2.6	0.1
Deep combined secondary vertex (DeepCSV) $P(b) + P(bb)$	DeepCSV L	84	41	11
	DeepCSV M	68	12	1.1
	DeepCSV T	50	2.4	0.1

Flavour-tagging algorithms: CMS DeepJet

JINST 15 (2020) P12012

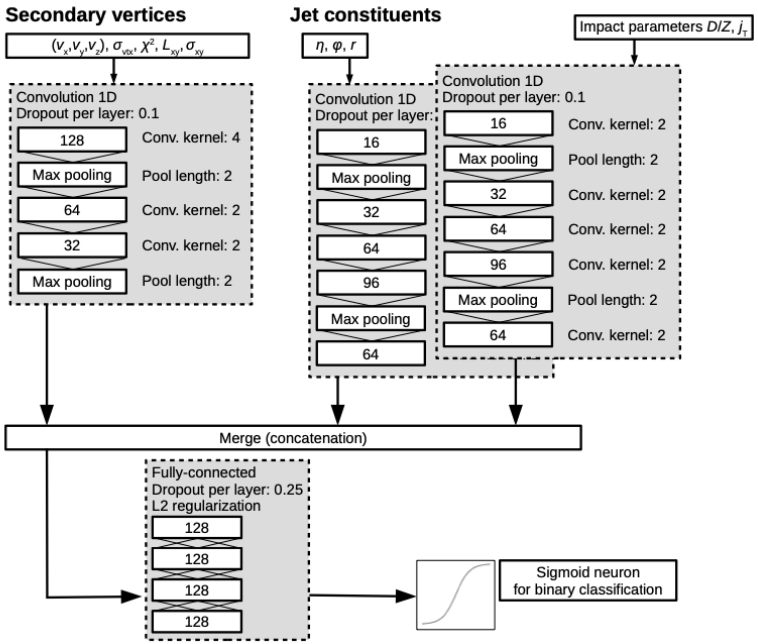


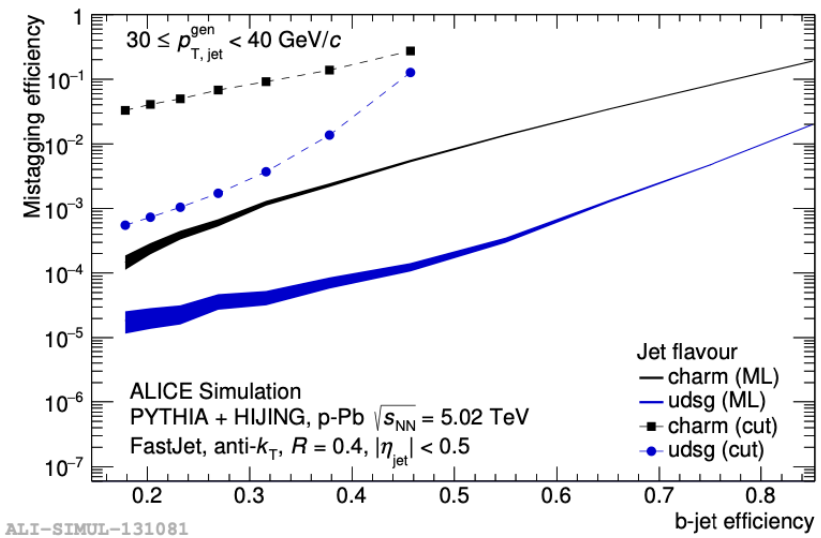




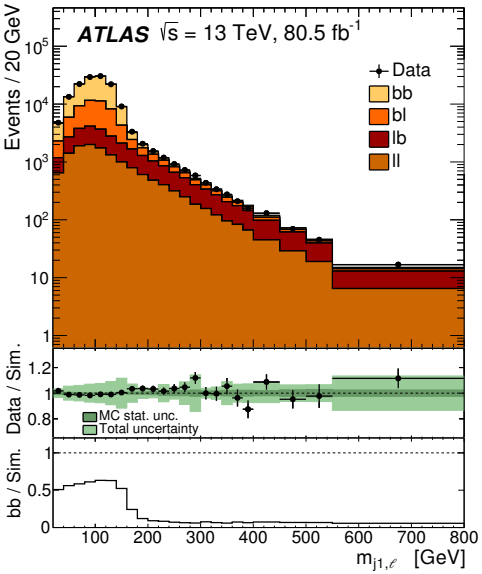
Flavour-tagging algorithms: ALICE ML-tagger

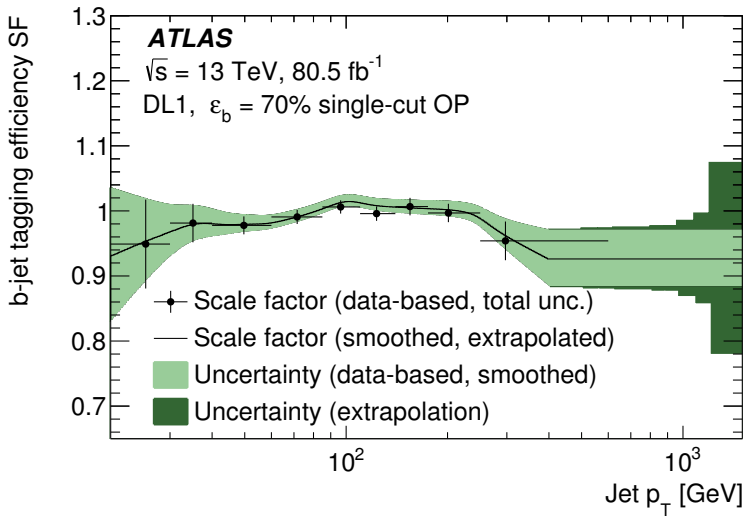
https://arxiv.org/abs/1709.08497



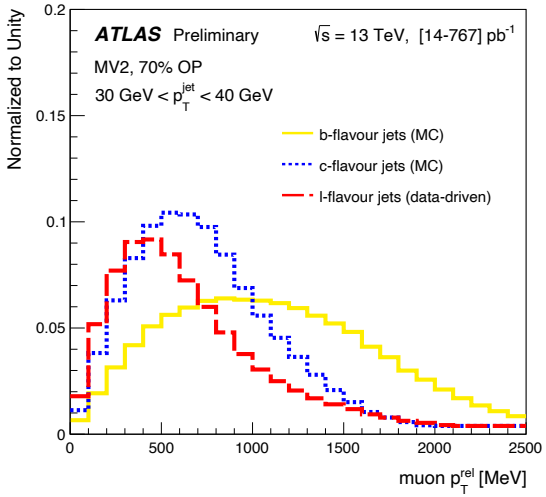


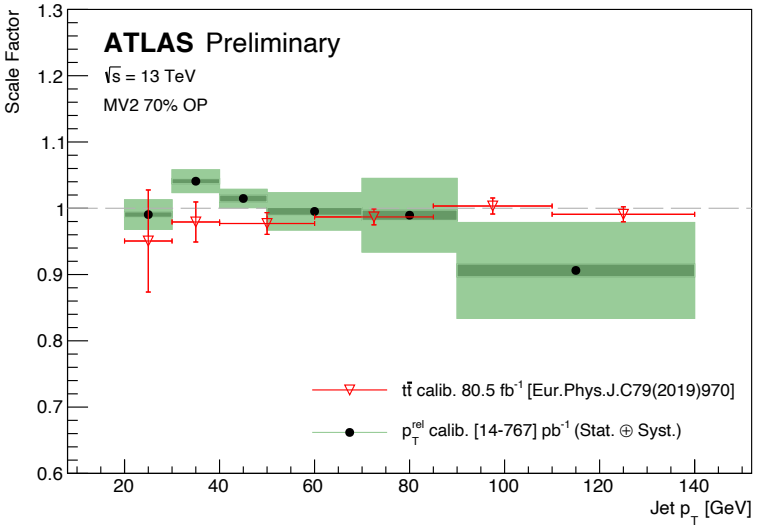
Performance in data: ATLAS b-jet efficiency





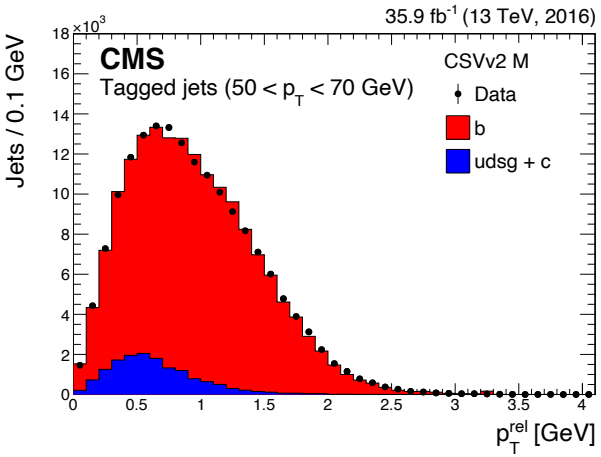
Eur. Phys. J. C 79 (2019) 970
ttbar l+jets

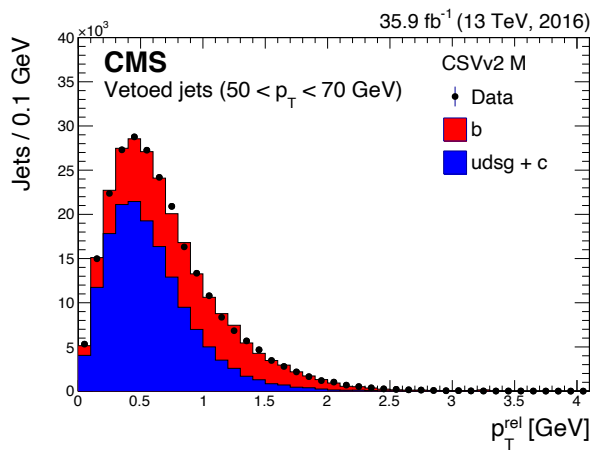




ATL-PHYS-PUB-2022-025
multi-jets with μ in jet

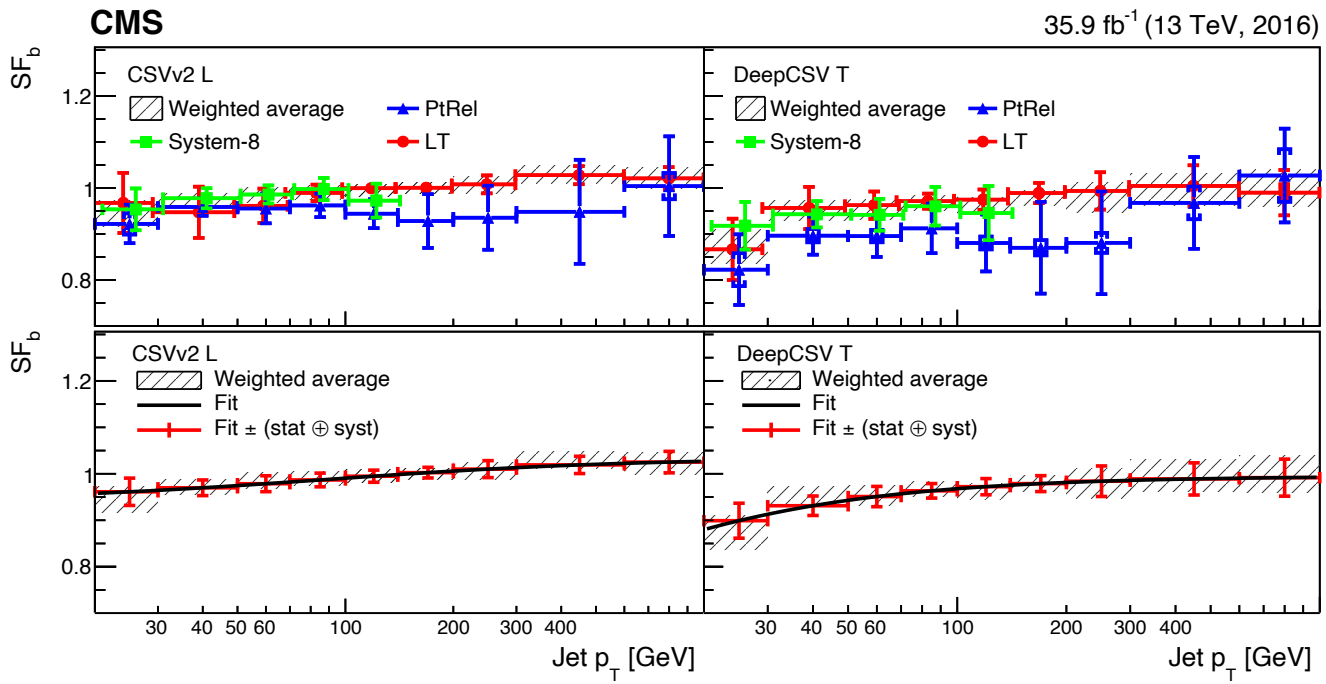
Performance in data: CMS b-jet efficiency





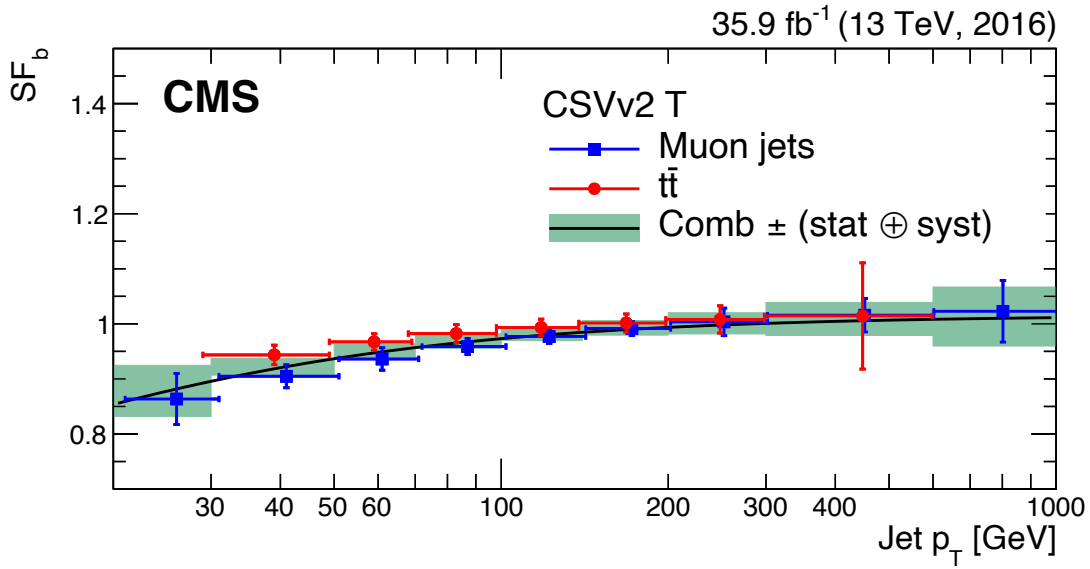
JINST 13 (2018) P05011

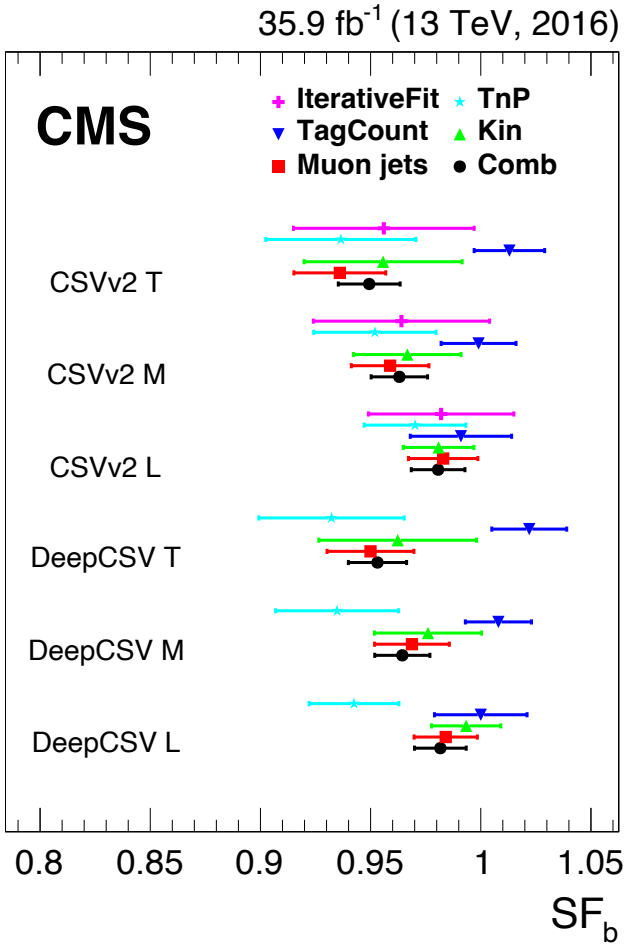
multi-jets with μ in jet



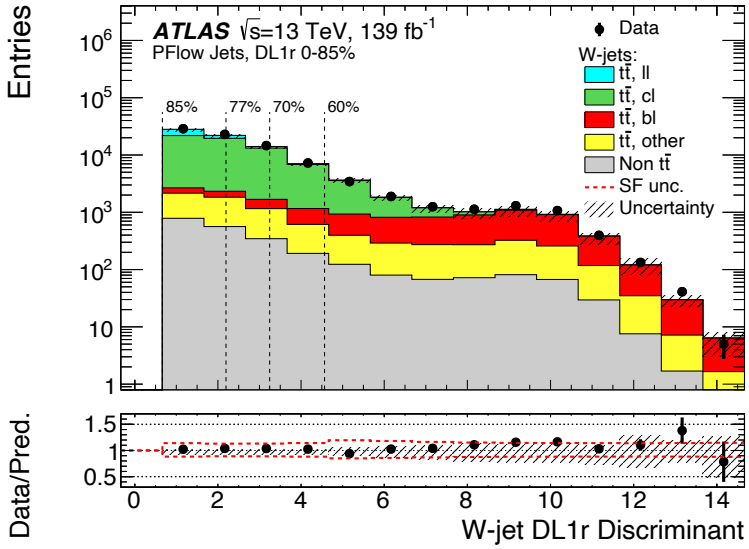
Performance in data: CMS b-jet efficiency

JINST 13 (2018) P05011



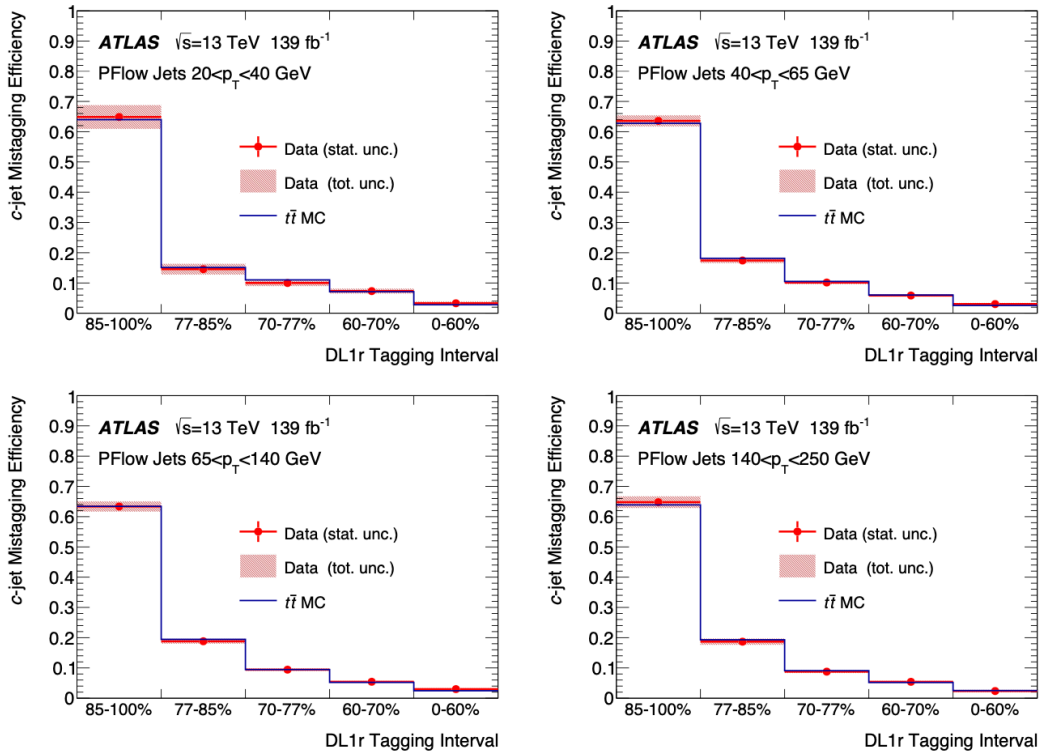


Performance in data: ATLAS c-jet efficiency



Eur. Phys. J. C 82 (2022) 95

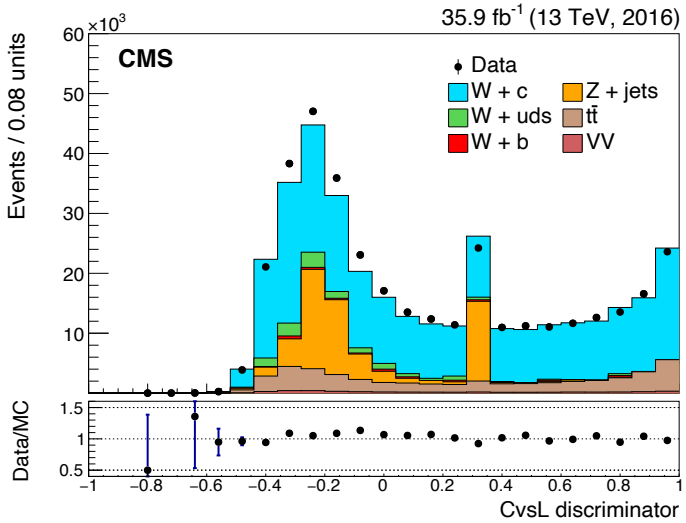
ttbar l+jets

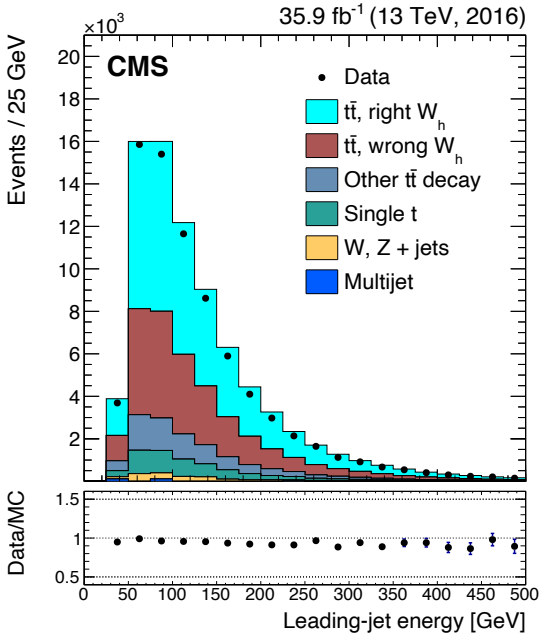


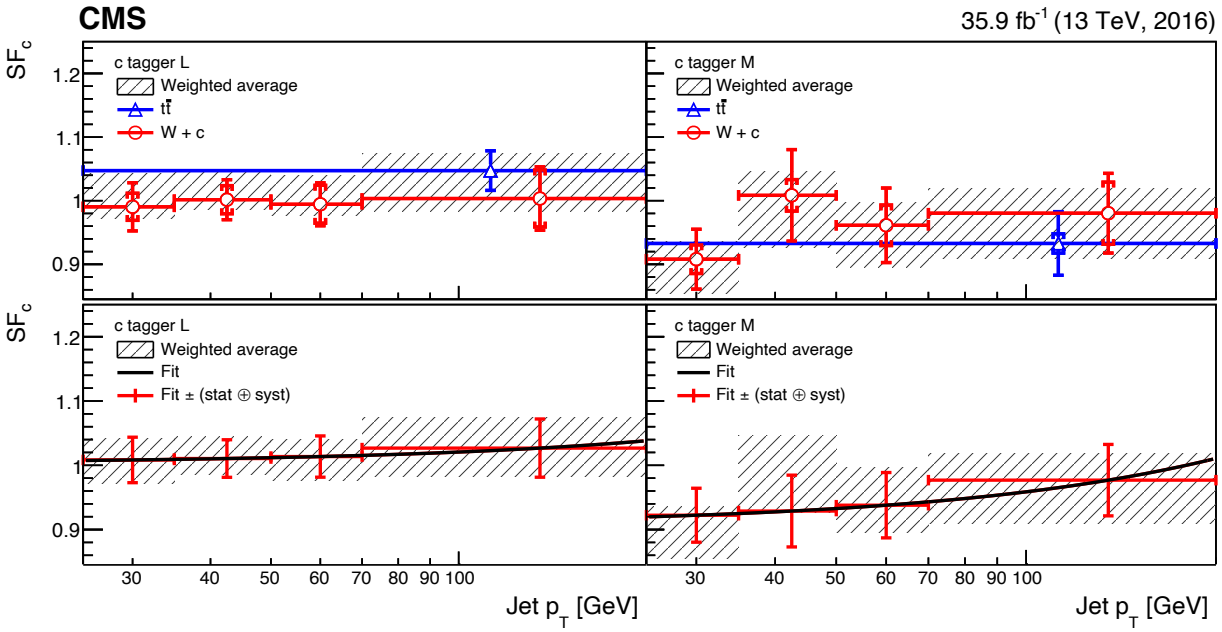
Performance in data: CMS c-jet efficiency

JINST 13 (2018) P05011

W+c and ttbar l+jets

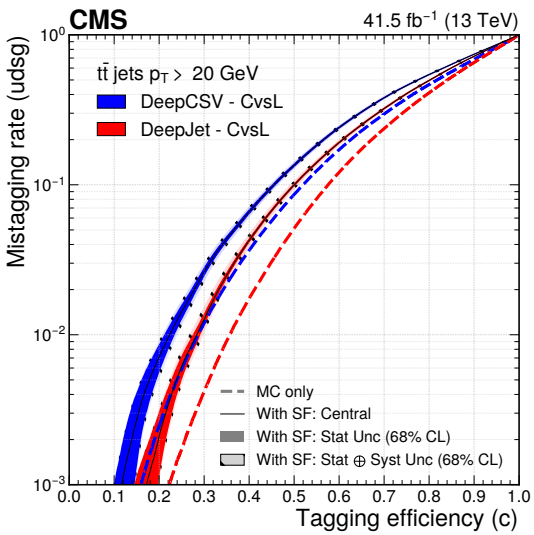


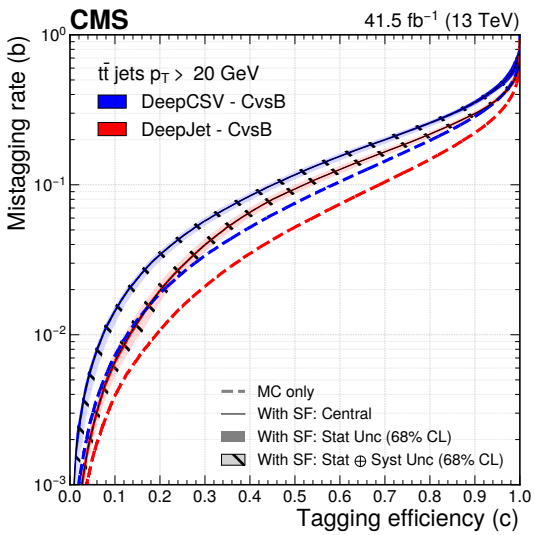


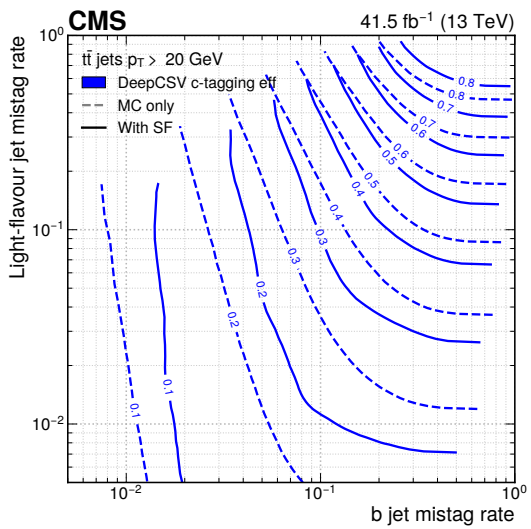


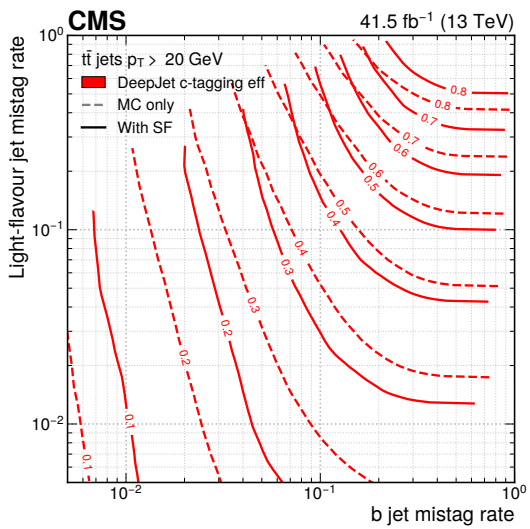
Performance in data: CMS c-jet efficiency

JINST 17 (2022) P03014

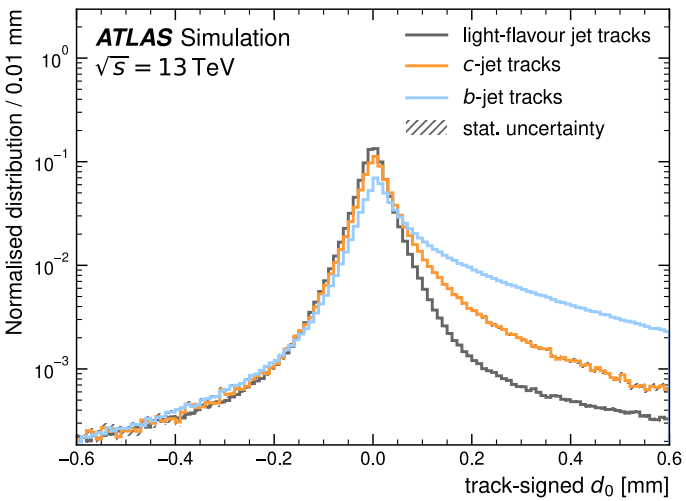






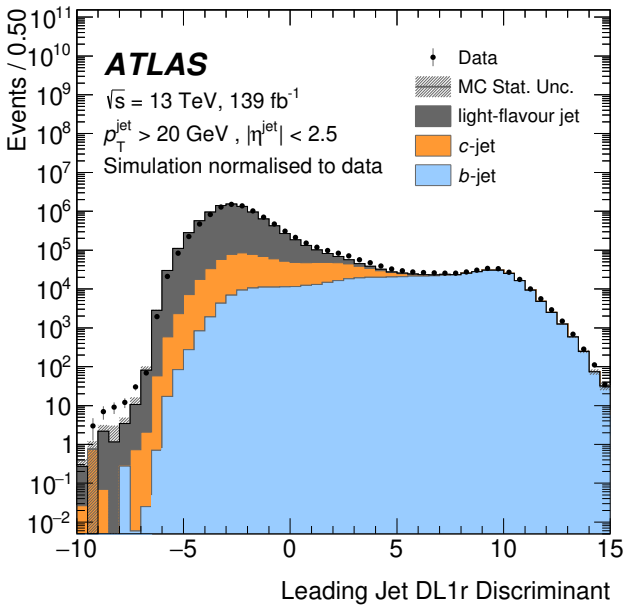


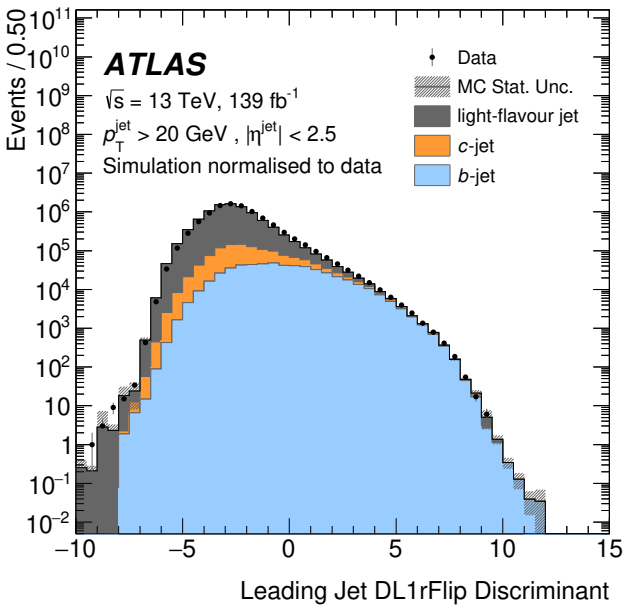
Performance in data: ATLAS light-jet mistag



FTAG-2019-02

Negative tag

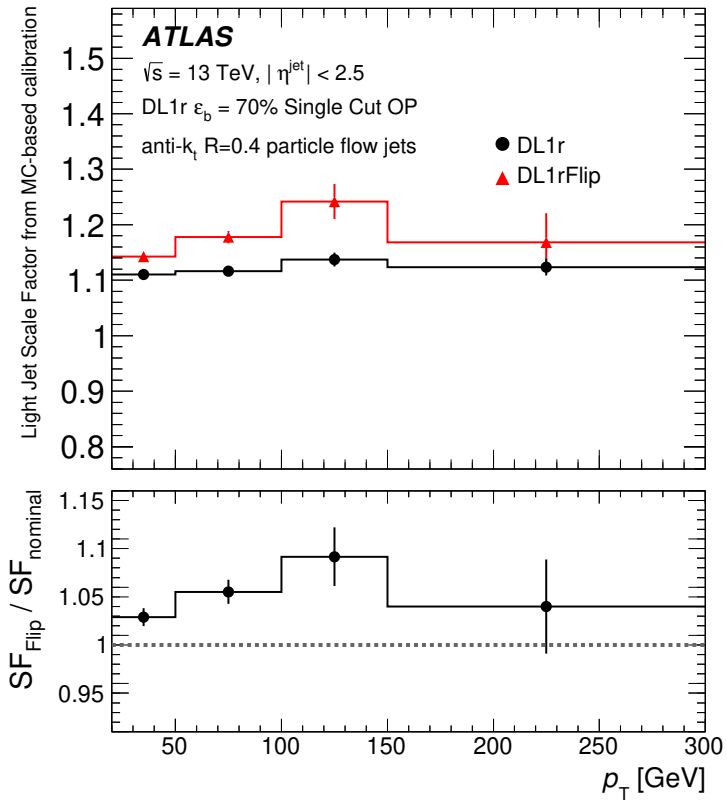


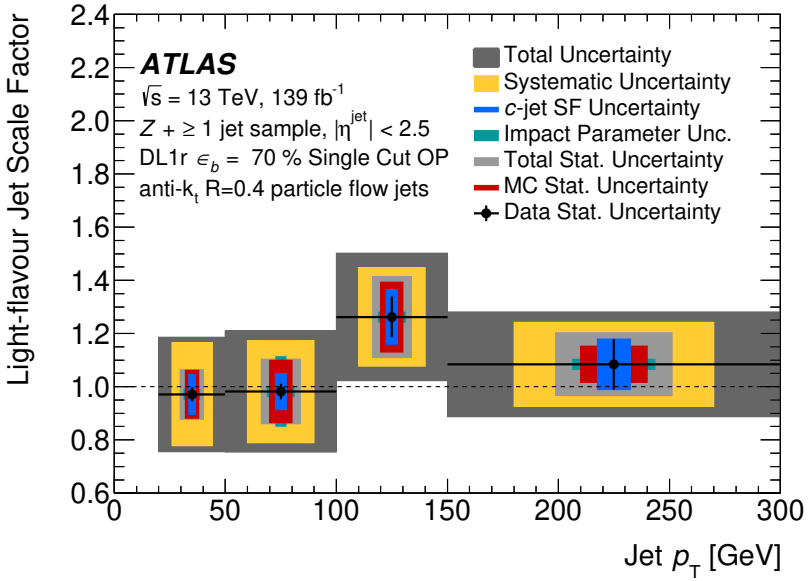


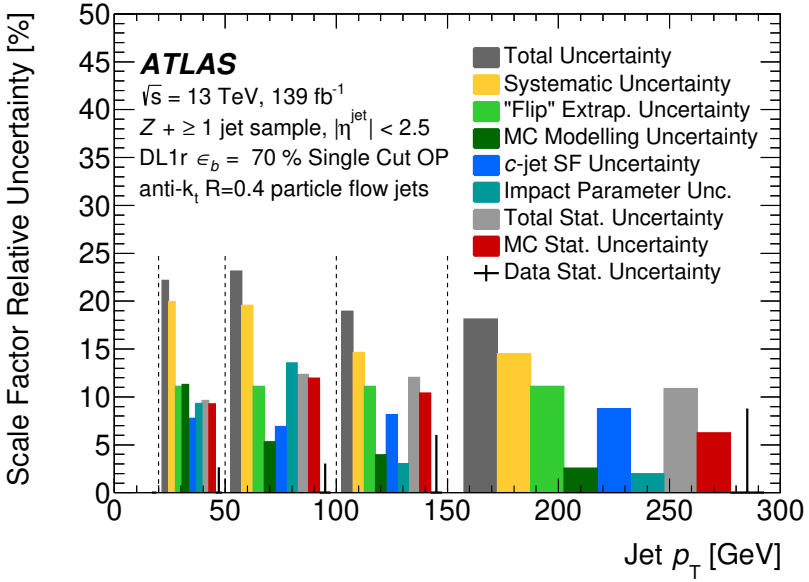
Performance in data: ATLAS light-jet mistag

FTAG-2019-02

Negative tag



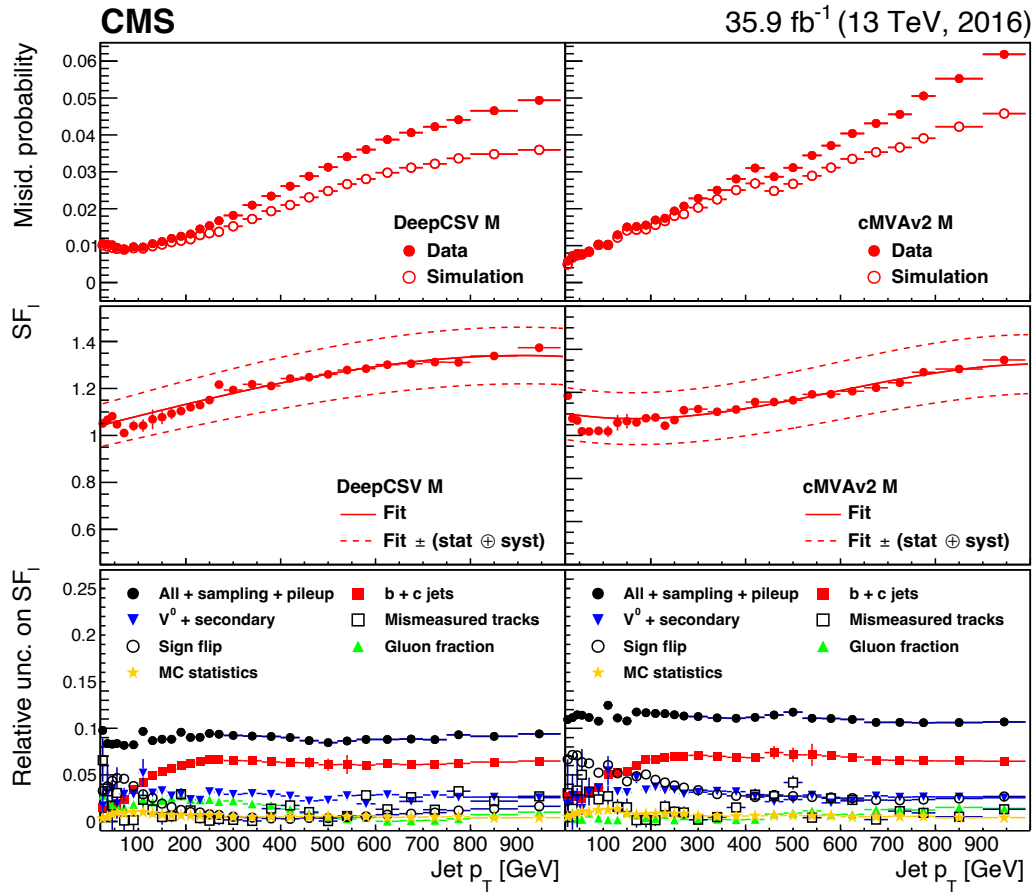


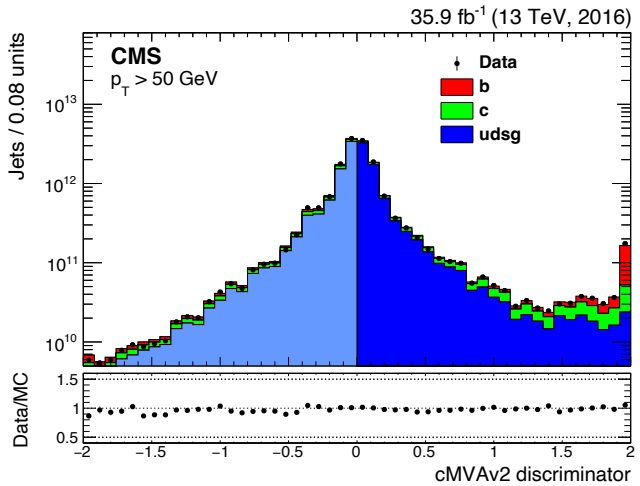


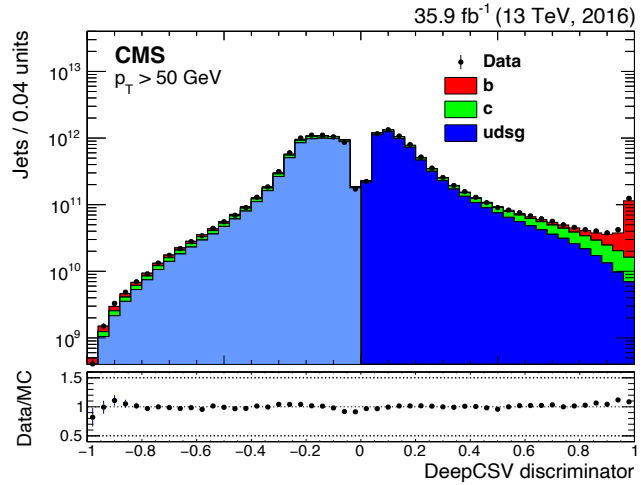
Performance in data: CMS light-jet mistag

JINST 13 (2018) P05011

Negative tag

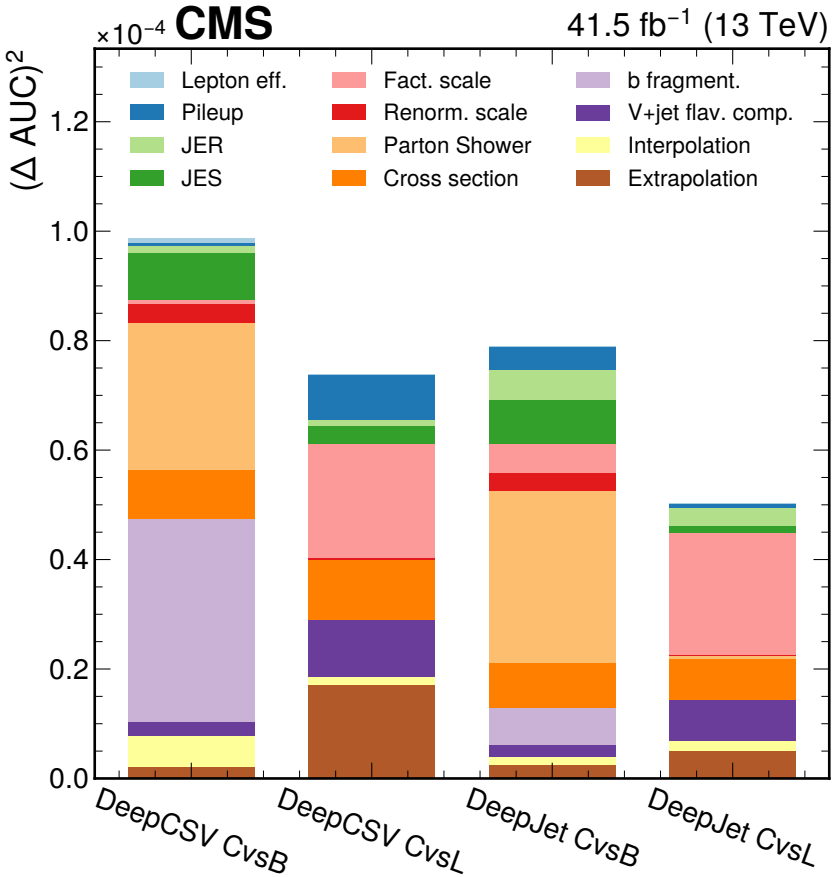


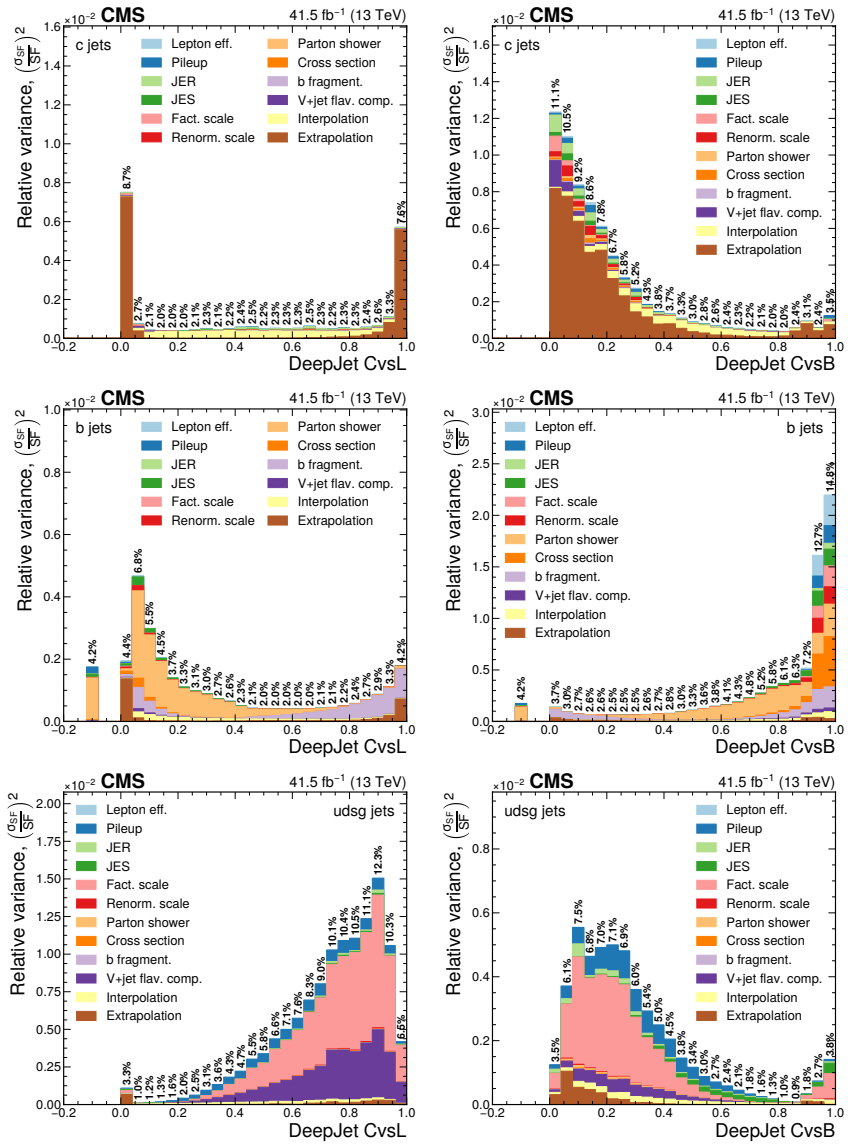




Performance in data: CMS

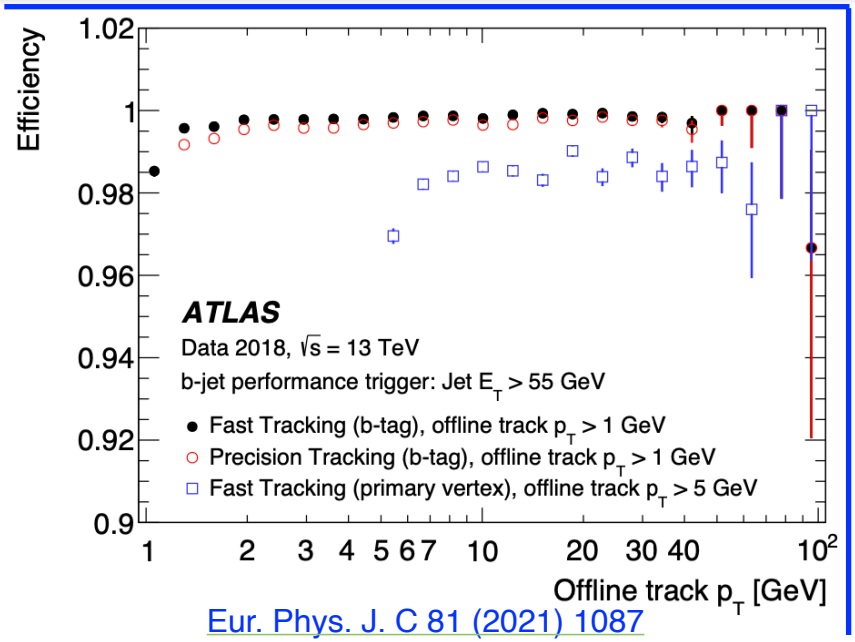
JINST 17 (2022) P03014



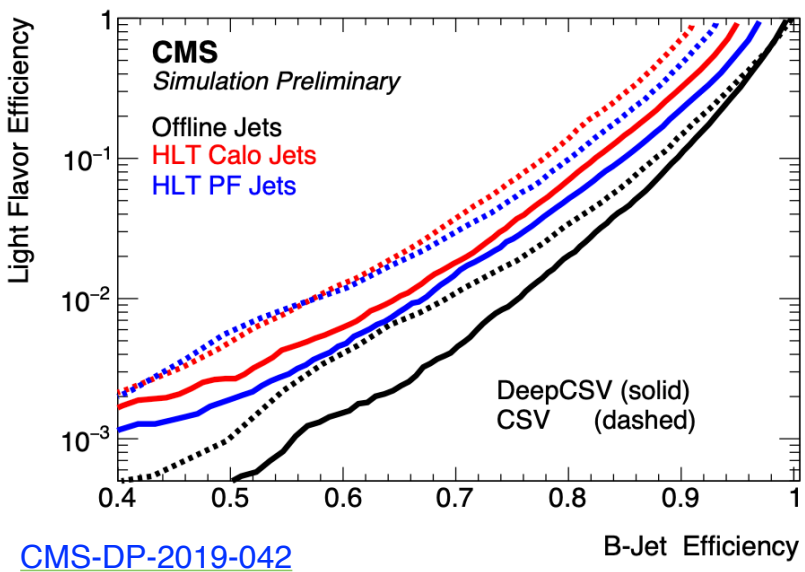


Flavour-tagging in trigger

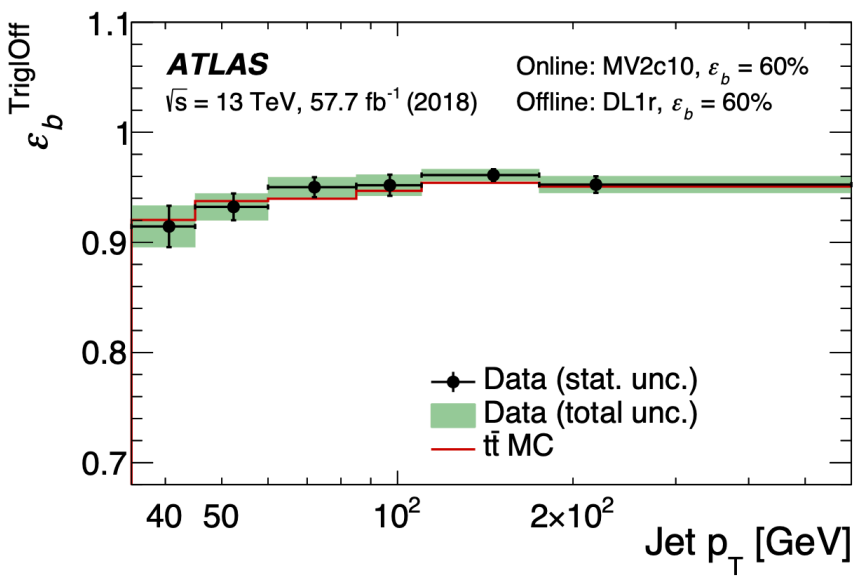
- b-tagging not only used for offline physics analysis but also to reduce rate in **fully hadronic final states at trigger level**
- b-jet triggers seeded by L1 Calo jets, **tracking information only available from HLT** in RoI around calo jets with configurations optimised for timing
- **Trigger b-tagging algorithms** closely following **ML developments for offline b-tagging:** typically more than 90% efficient wrt offline



Eur. Phys. J. C 81 (2021) 1087

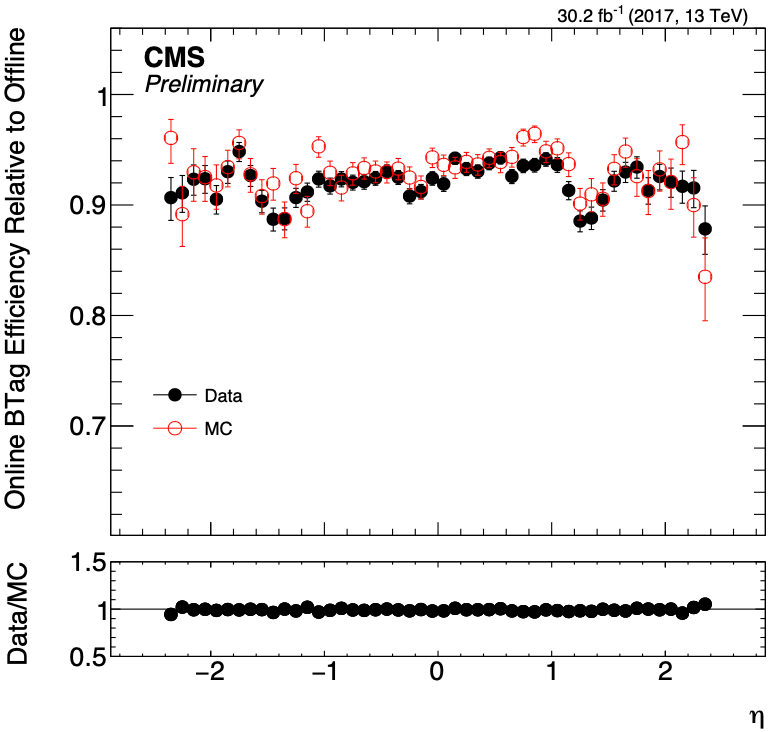


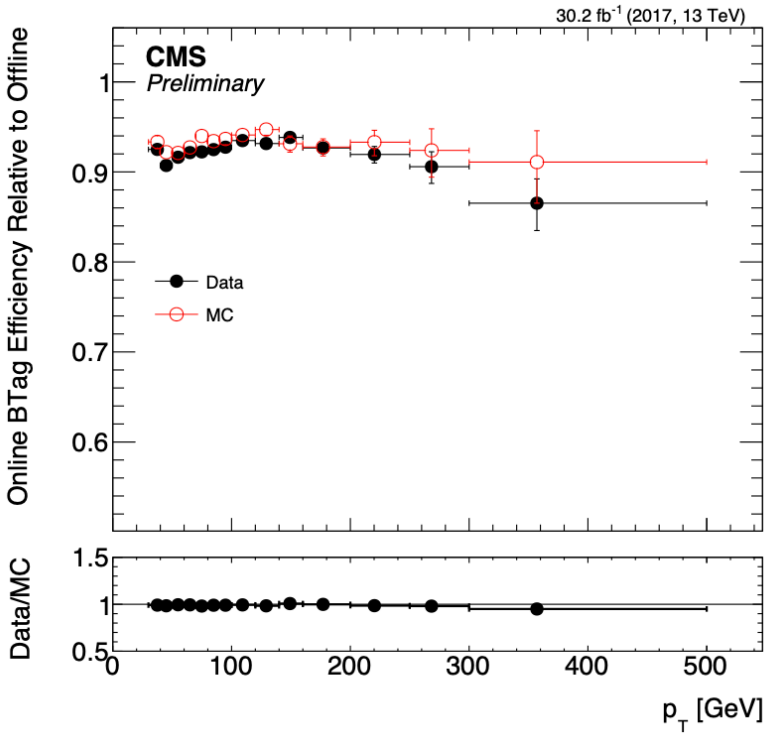
CMS-DP-2019-042



Flavour-tagging in trigger: CMS

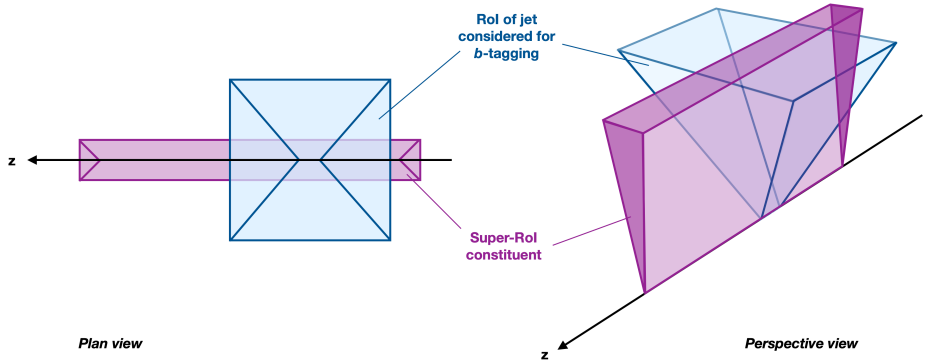
CMS-DP-2019-042

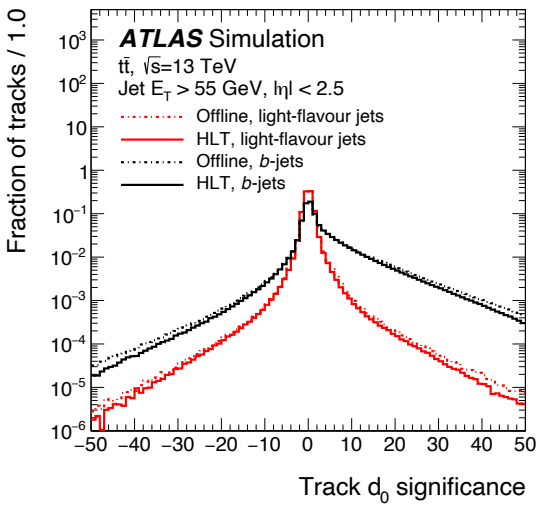


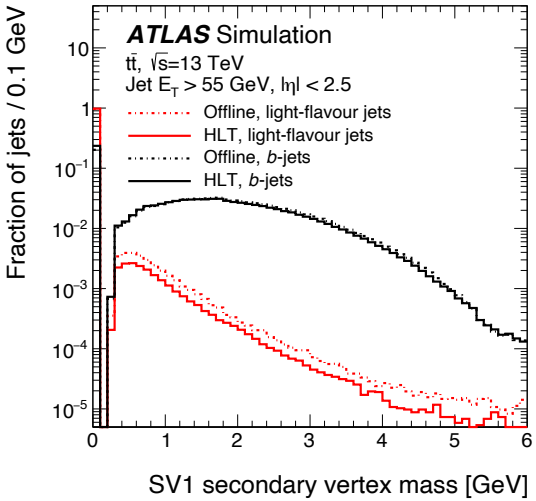


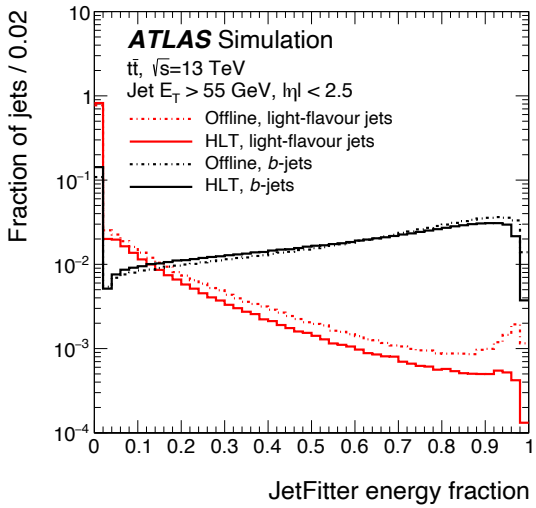
Flavour-tagging in trigger: ATLAS

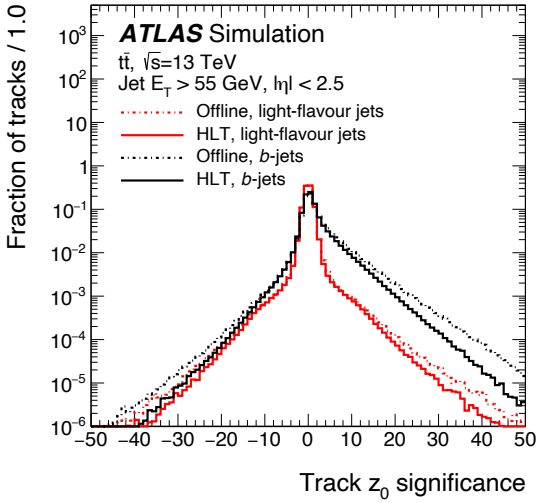
Eur. Phys. J. C 81 (2021) 1087





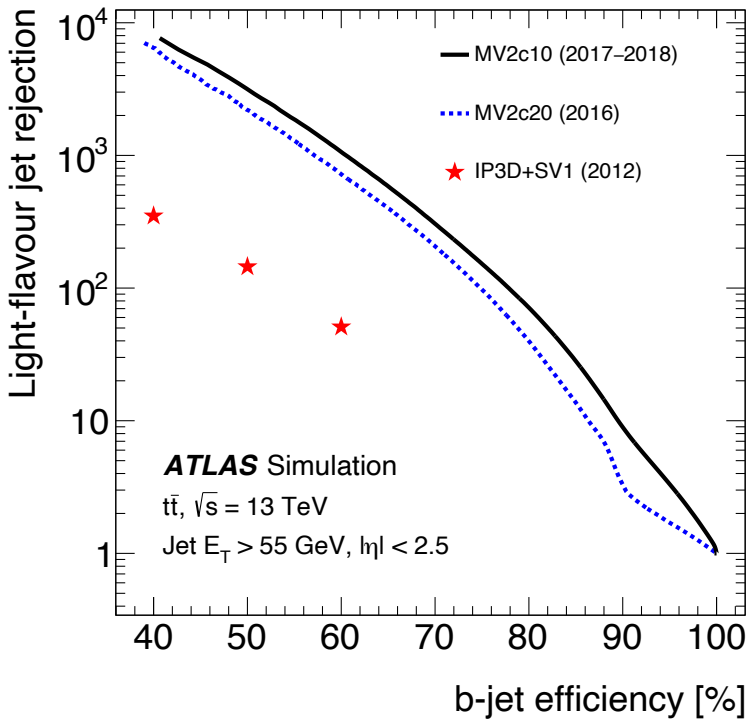


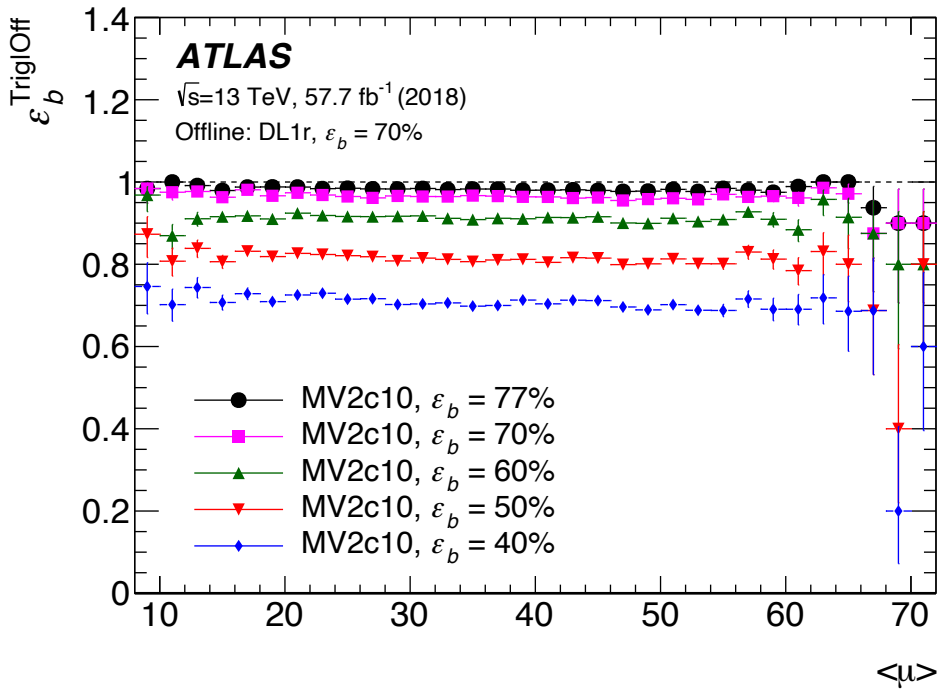




Flavour-tagging in trigger: ATLAS

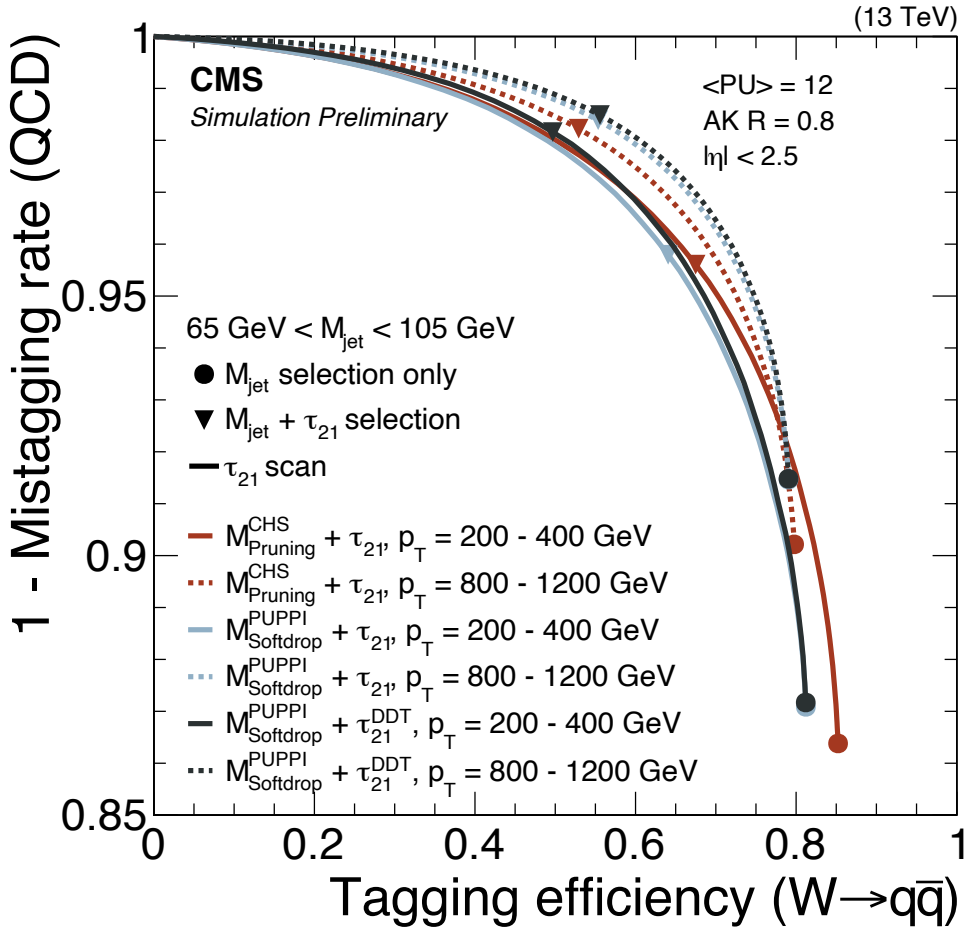
Eur. Phys. J. C 81 (2021) 1087



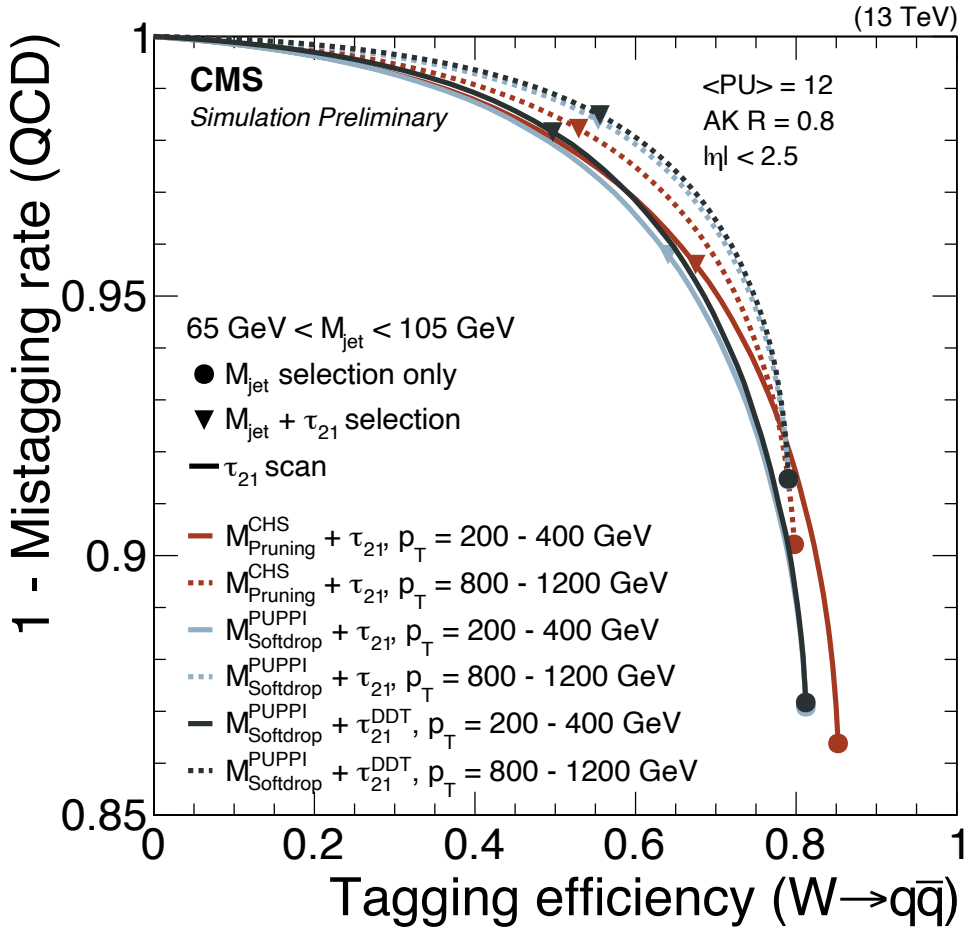


Jet substructure inputs: CMS

CMS-PAS-JME-16-003



Jet substructure inputs: CMS



Jet substructure inputs: ATLAS

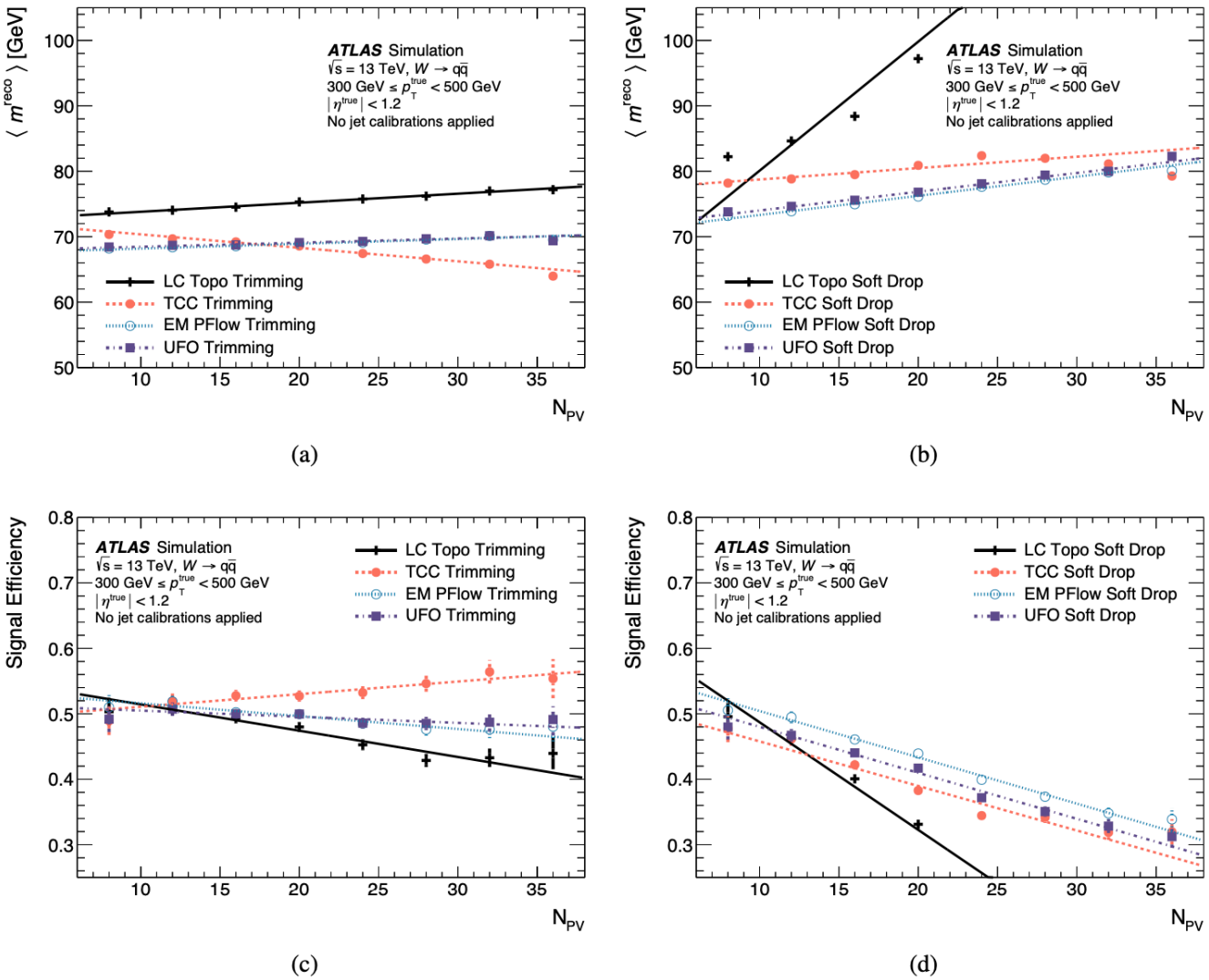
Eur. Phys. J. C 81 (2021) 334

	Algorithm	Abbreviation	Settings
Jet input objects	Topological Clusters	Topoclusters	N/A
	Particle-Flow	PFlow	N/A
	Track-CaloClusters	TCCs	N/A
	Unified Flow Objects	UFOs	N/A
Pile-up mitigation algorithms	Constituent Subtraction	CS	$A_g = 0.01$ $\Delta R_{\mathrm{max}} = 0.25$ $\alpha = 0$
	Voronoi Subtraction (*)	VS	N/A
	SoftKiller	SK	$\ell = 0.6$
	Pile-up Per Particle Identification	PUPPI	$R_{\mathrm{min}} = 0.001$ $R_0 = 0.3$ $a = 200$ MeV $b = 14$ MeV
Jet grooming algorithms	Soft-Drop	SD	$z_{\mathrm{cut}} = 0.1$ $\beta = 0, 1, 2(*)$
	Bottom-up Soft-Drop	BUSD	$z_{\mathrm{cut}} = 0.05, 0.1$ $\beta = 0, 1, 2(*)$
	Recursive Soft-Drop	RSD	$z_{\mathrm{cut}} = 0.05, 0.1$ $\beta = 0, 1, 2(*)$ $N = 3, 5(*), \infty$
	Pruning	N/A	$z_{\mathrm{cut}} = 0.015$ $R_{\mathrm{cut}} = 0.25$
	Trimming	N/A	$f_{\mathrm{cut}} = 5\%, 9\%$ $R_{\mathrm{sub}} = 0.1, 0.2$

Category	Input Objects	Grooming Algorithm	Configuration
Baseline definitions	LCW Topoclusters	Trimmed	$R_{\mathrm{sub}} = 0.2$, $f_{\mathrm{cut}} = 0.05$
	TCCs	Trimmed	$R_{\mathrm{sub}} = 0.2$, $f_{\mathrm{cut}} = 0.05$
Studied definitions	CS+SK UFOs	Trimmed	$R_{\mathrm{sub}} = 0.2$, $f_{\mathrm{cut}} = 0.05$
	CS+SK UFOs	SD	$z_{\mathrm{cut}} = 0.1$, $\beta = 1.0$
	CS+SK UFOs	RSD	$z_{\mathrm{cut}} = 0.05$, $\beta = 1.0$, $N = \infty$
	CS+SK UFOs	BUSD	$z_{\mathrm{cut}} = 0.05$, $\beta = 1.0$
Additional definitions	UFOs	Trimmed	$R_{\mathrm{sub}} = 0.2$, $f_{\mathrm{cut}} = 0.05$
	PFOs	Trimmed	$R_{\mathrm{sub}} = 0.2$, $f_{\mathrm{cut}} = 0.05$
	UFOs	SD	$z_{\mathrm{cut}} = 0.1$, $\beta = 1.0$

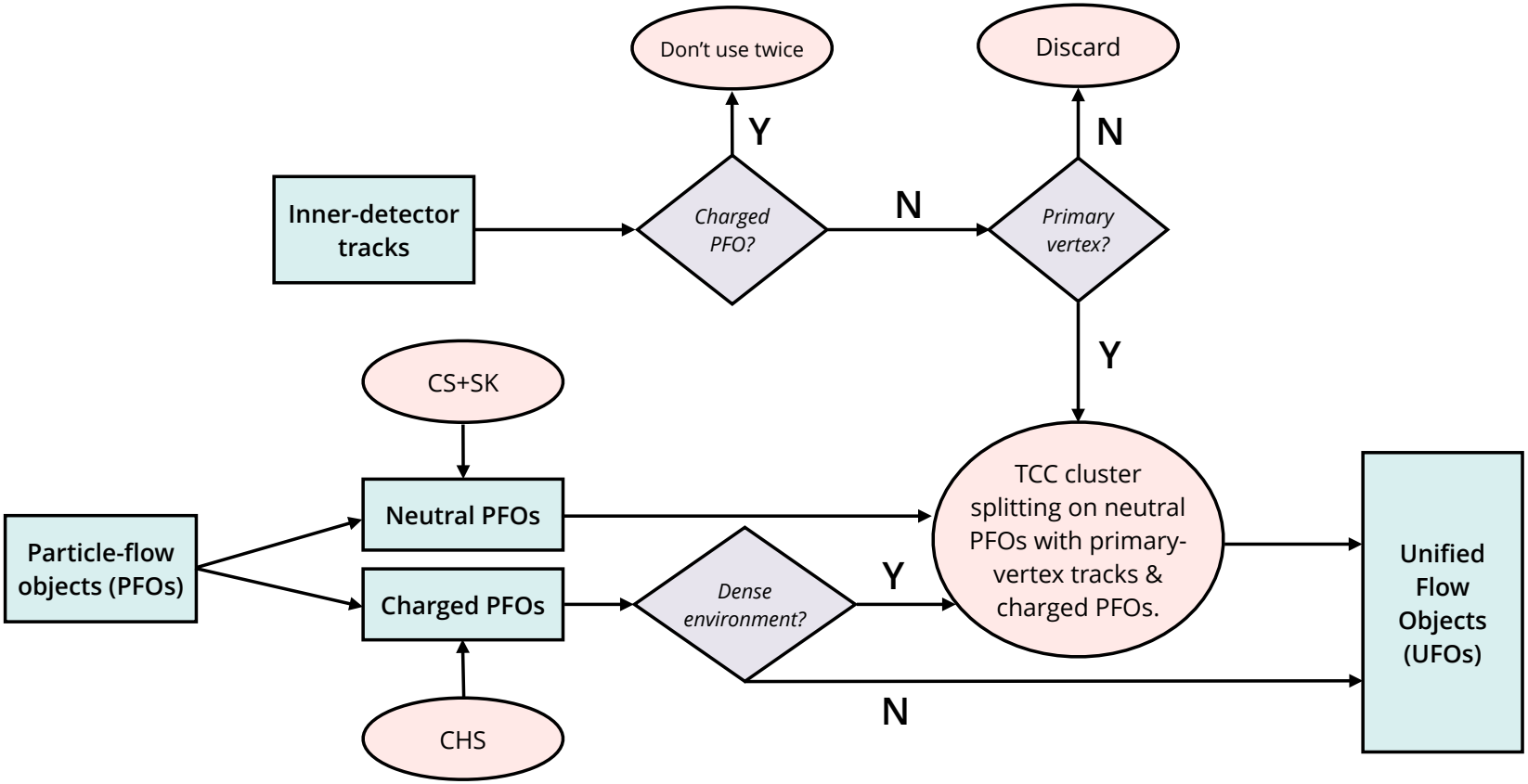
Jet substructure inputs: ATLAS

Eur. Phys. J. C 81 (2021) 334



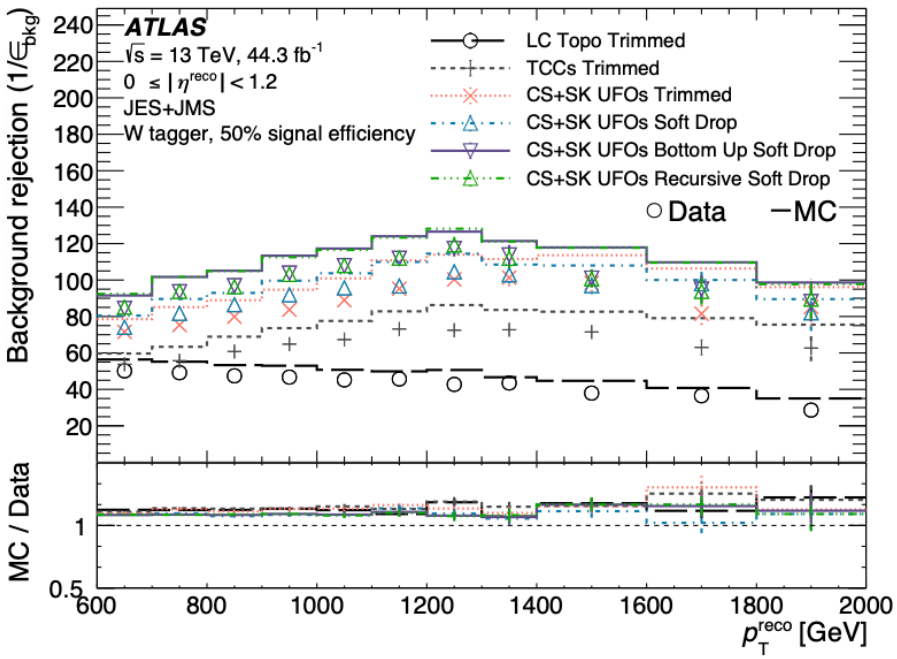
Jet substructure inputs: ATLAS

Eur. Phys. J. C 81 (2021) 334

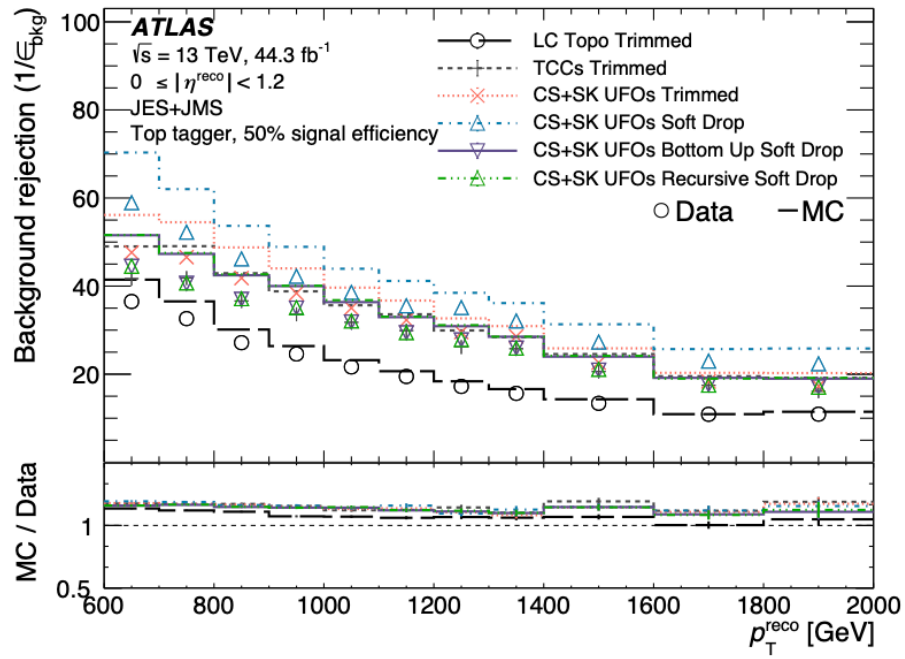


Jet substructure inputs: ATLAS

Eur. Phys. J. C 81 (2021) 334



(a)

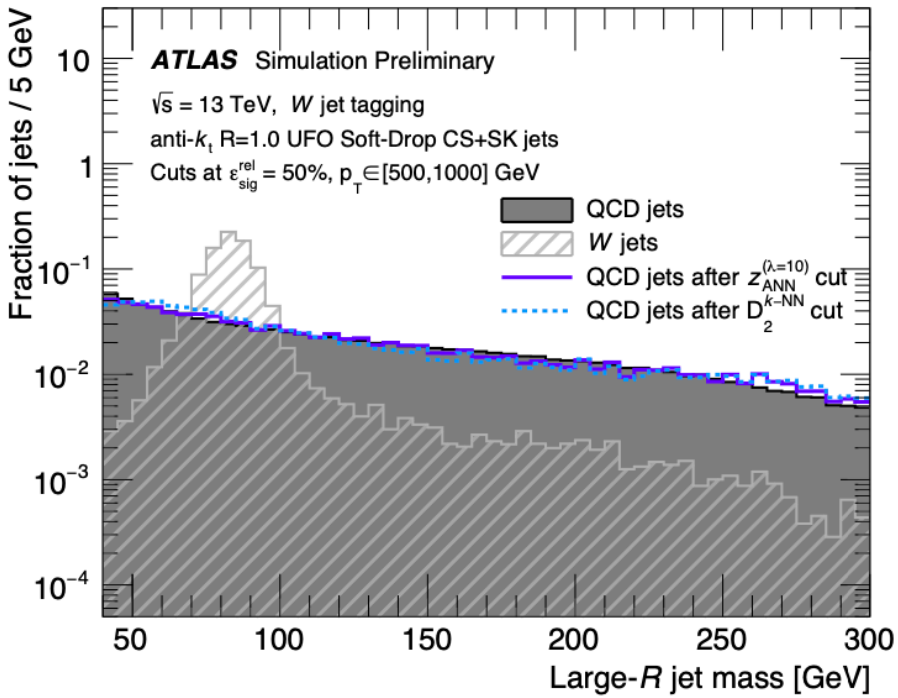


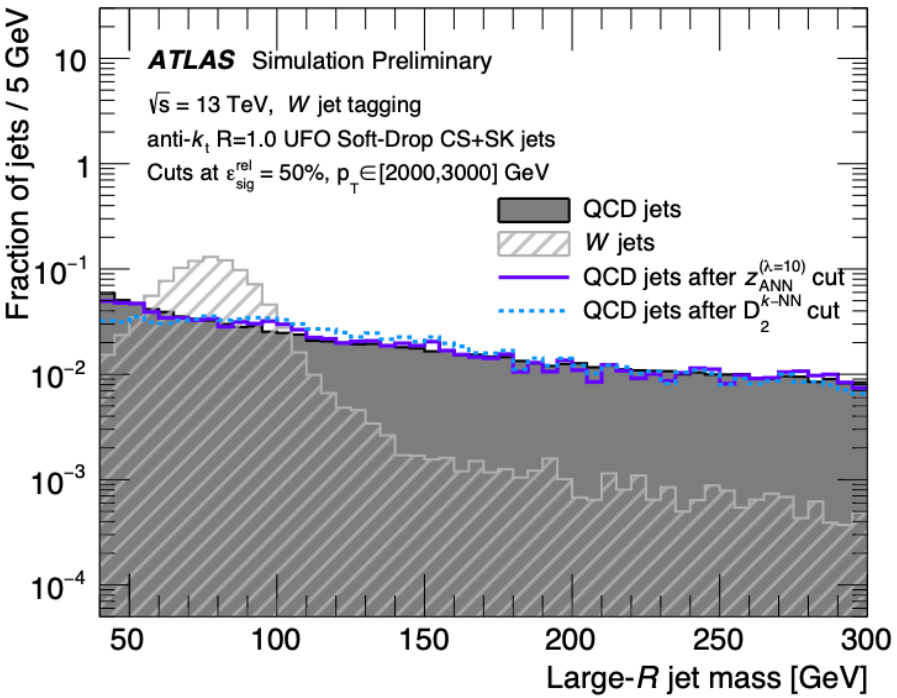
(b)

Boosted object tagging: W-tagging ATLAS

ATL-PHYS-PUB-2021-029

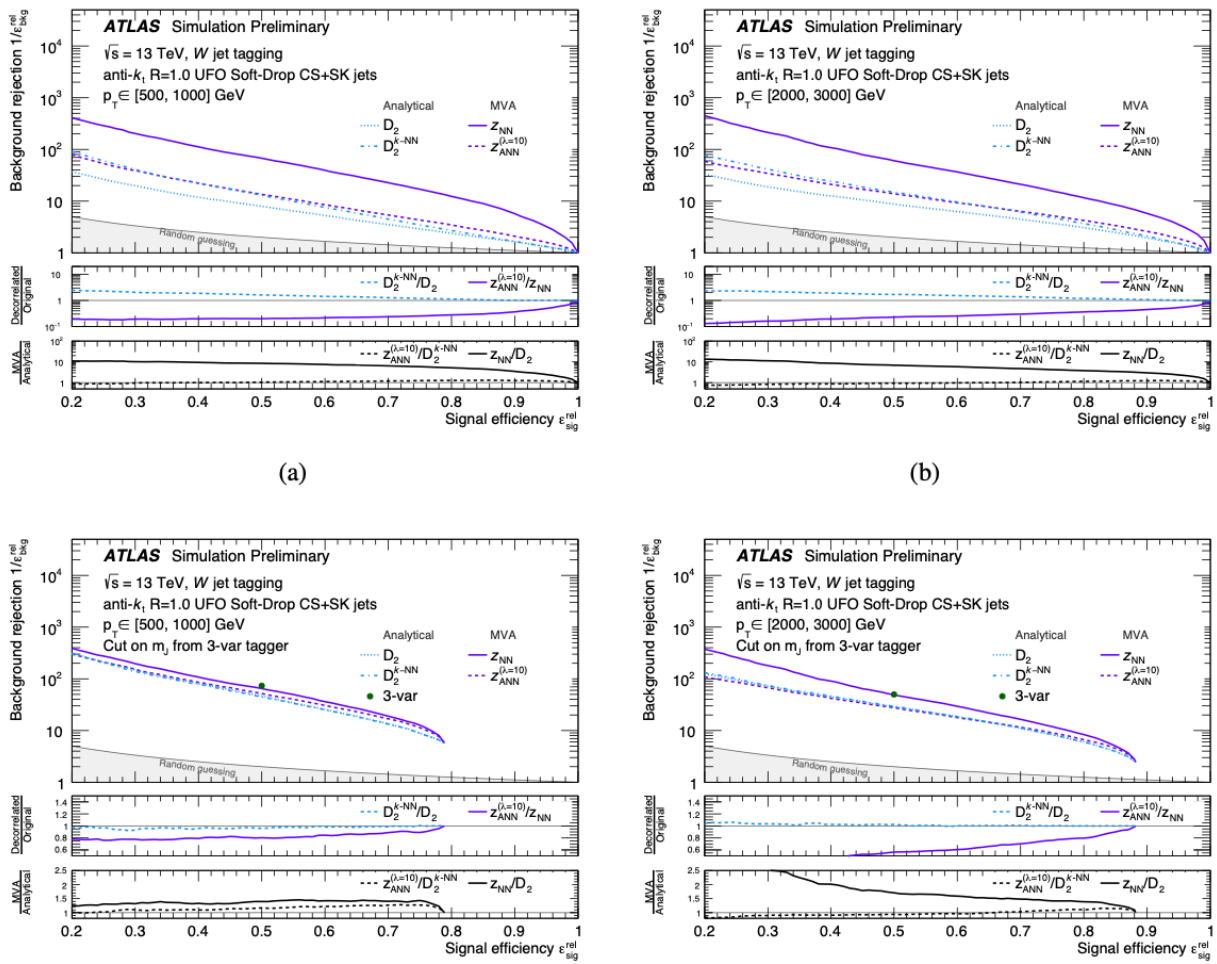
Variable	Description	Reference
D_2, C_2	Energy correlation ratios	[30]
τ_{21}	N-subjettiness	[41]
R_2^{FW}	Fox-Wolfram moment	[42]
$\mathcal{P}$	Planar flow	[43]
a_3	Angularity	[44]
A	Aplanarity	[45]
Z_{cut}, $\sqrt{d_{12}}$	Splitting scales	[33,46]
$Kt\Delta R$	k_t-subjet ΔR	[47]





Boosted object tagging: W-tagging ATLAS

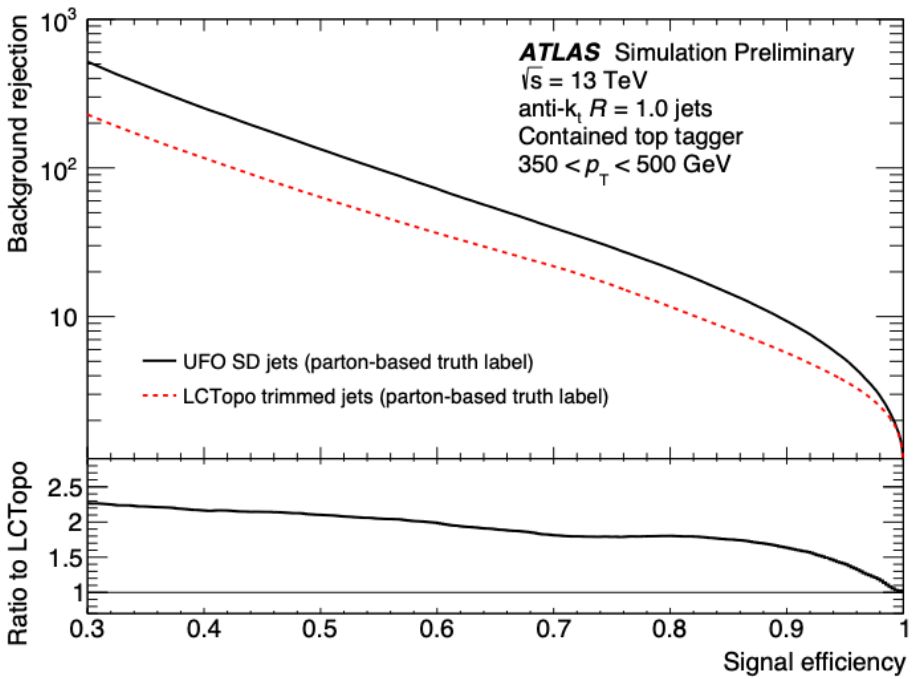
ATL-PHYS-PUB-2021-029

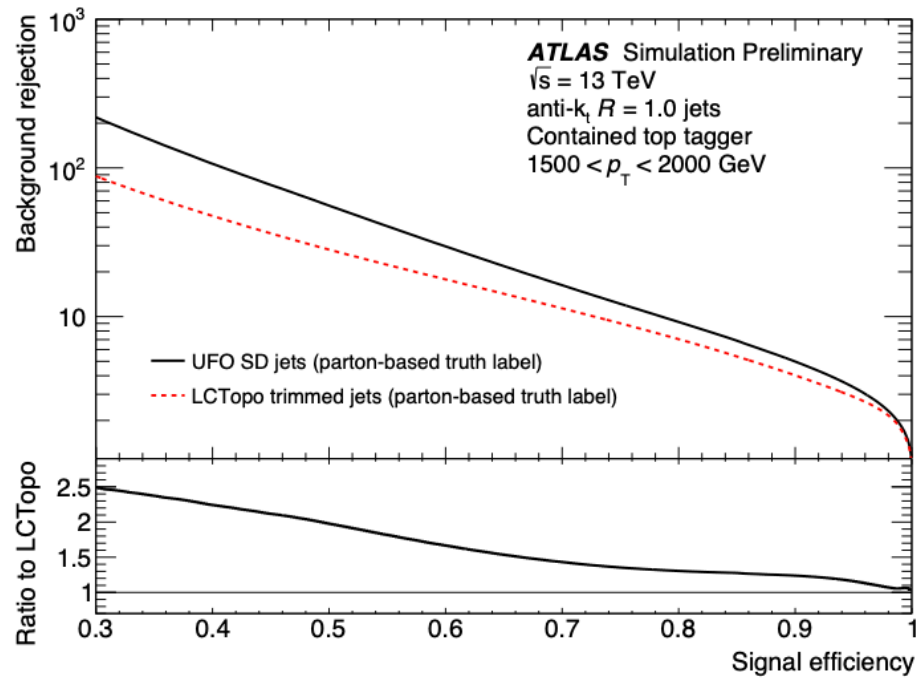


(a) (b) (c) (d)

Boosted object tagging: top-tagging ATLAS

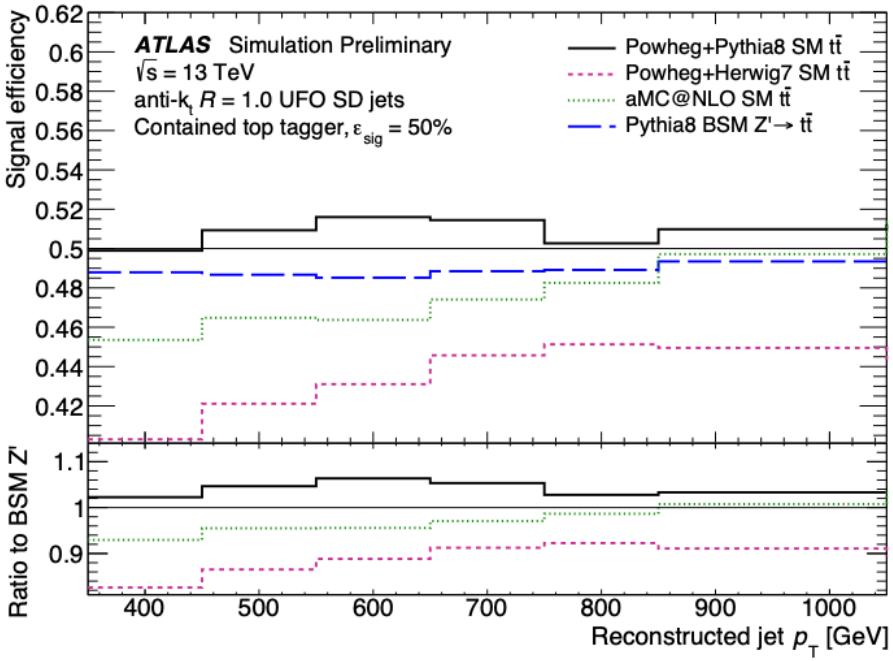
ATL-PHYS-PUB-2021-029

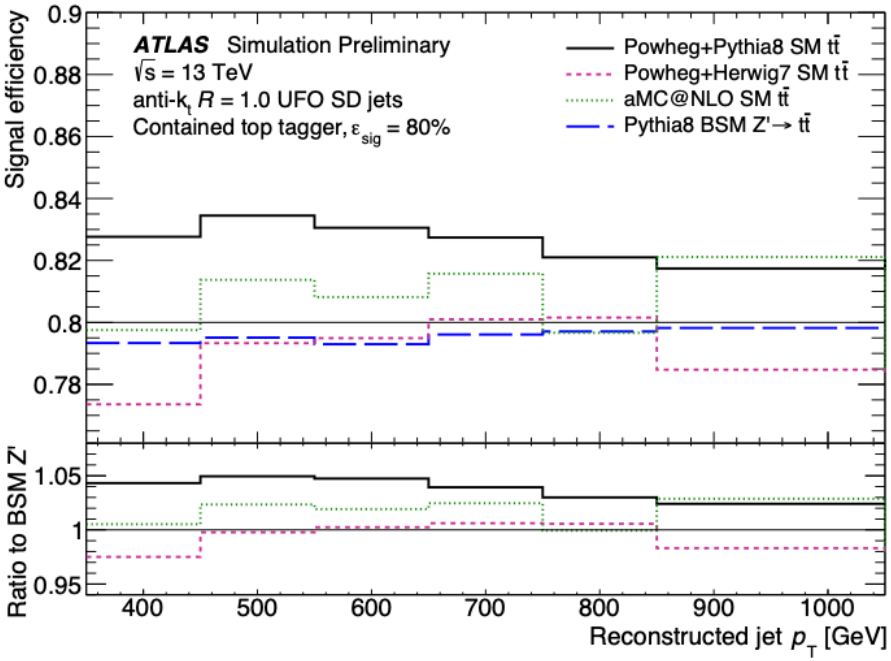




Boosted object tagging: top-tagging ATLAS

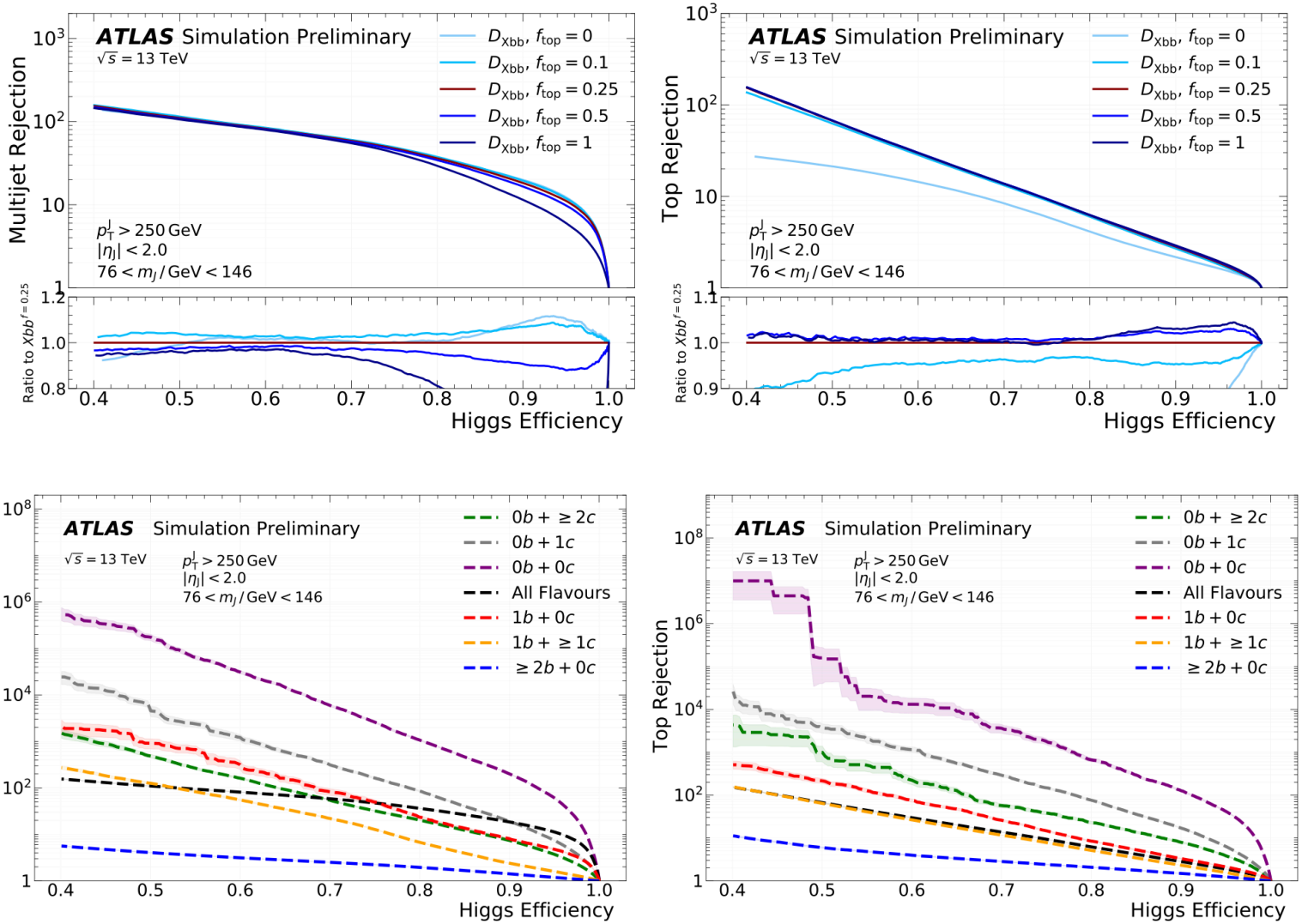
ATL-PHYS-PUB-2021-029





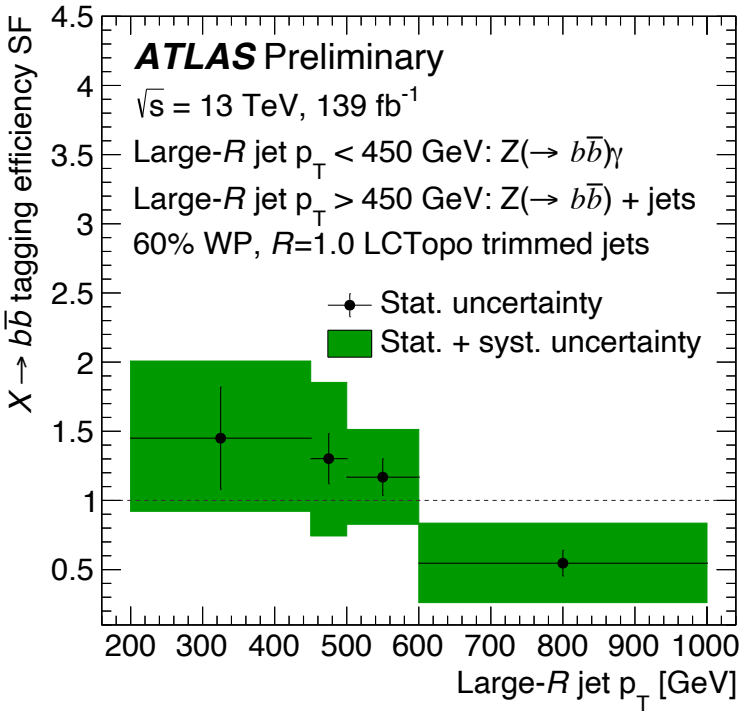
Boosted object tagging: X→bb ATLAS

ATL-PHYS-PUB-2021-035



Boosted object tagging: X→bb ATLAS

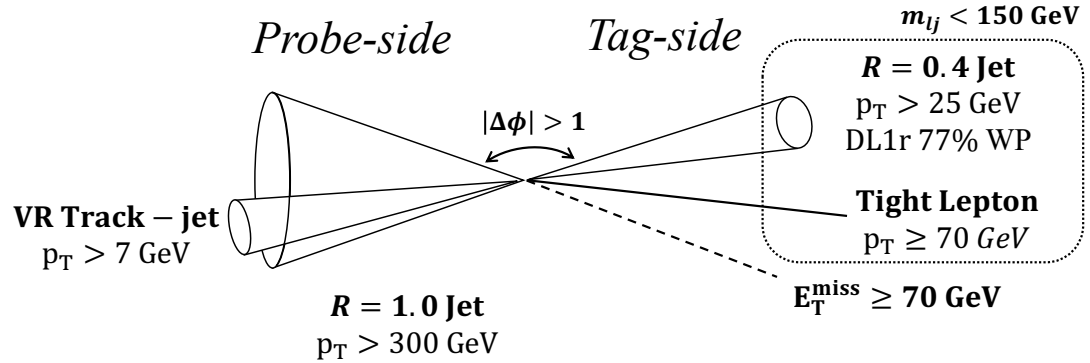
ATL-PHYS-PUB-2021-035

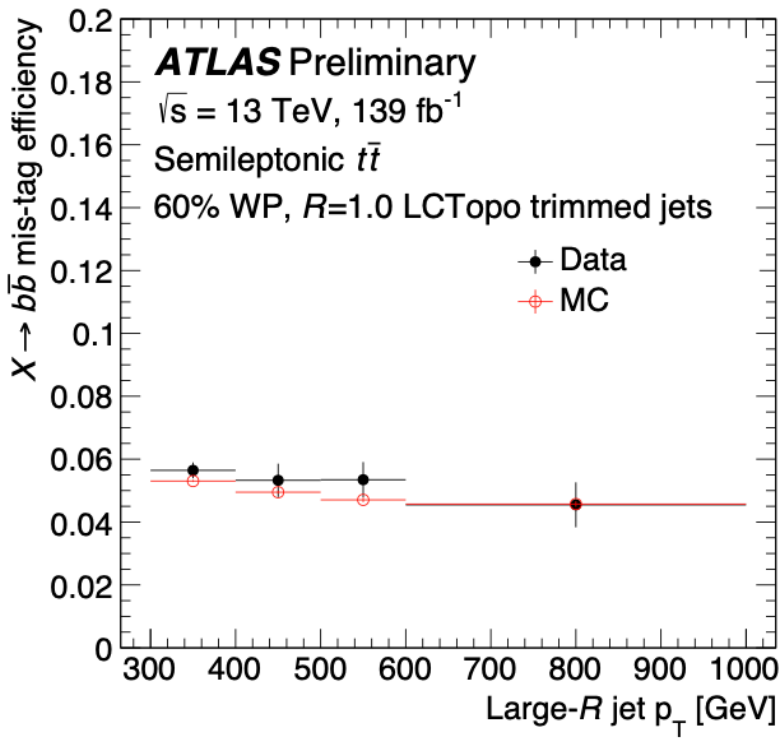


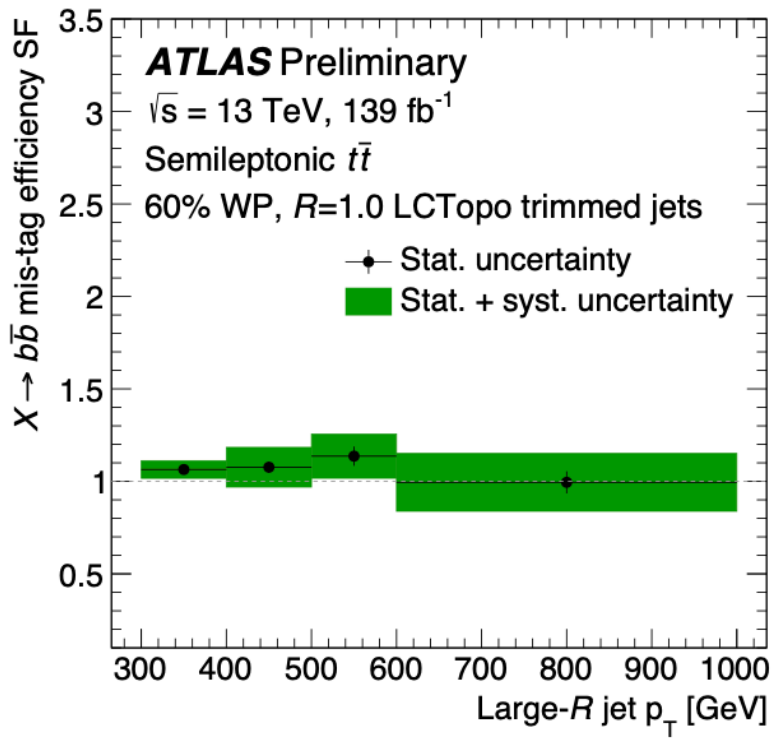
Calibration	$Z(\to b\bar{b})\gamma$	$Z(\to b\bar{b})$ + jets		
p_T [GeV]	200 − 450	450 − 500	500 − 600	600 − 1000
$\mu_{\text{post-tag}}$	1.33	1.32	1.10	0.51
$\mu_{\text{pre-tag}}$	0.92	1.01	0.94	0.93
SF	1.45	1.30	1.17	0.55
Uncertainties ($\pm\sigma$)				
Statistical	±0.37	±0.18	±0.13	±0.09
Z-boson modelling	$^{+0.24}_{-0.19}$	–	–	–
Z + jets modelling	–	$^{+0.21}_{-0.28}$	±0.15	±0.18
Fit model	0.14	0.39	0.22	0.16
Spurious signal	±0.26	±0.11	±0.07	±0.07
Other background modelling	±0.05	±0.03	±0.02	±0.01
Lepton & Photon related	±0.02	$^{+0.06}_{-0.07}$	$^{+0.06}_{-0.07}$	±0.03
Jet mass scale	±0.05	$^{+0.02}_{-0.01}$	±0.01	$^{+0.02}_{-0.01}$
Jet mass resolution	$^{+0.03}_{-0.02}$	$^{+0.22}_{-0.15}$	$^{+0.11}_{-0.09}$	$^{+0.09}_{-0.07}$
Jet energy scale	$^{+0.06}_{-0.07}$	±0.09	±0.09	±0.05
Others	$^{+0.14}_{-0.16}$	±0.01	$< \pm0.01$	$< \pm0.01$
Total uncertainty	$^{+0.53}_{-0.56}$	$^{+0.55}_{-0.56}$	$^{+0.35}_{-0.34}$	$^{+0.29}_{-0.28}$

Boosted object tagging: X→bb ATLAS

ATL-PHYS-PUB-2021-035

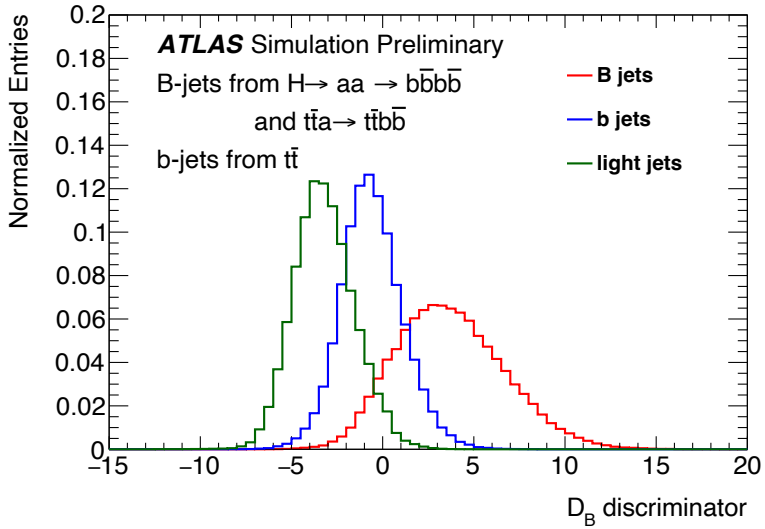


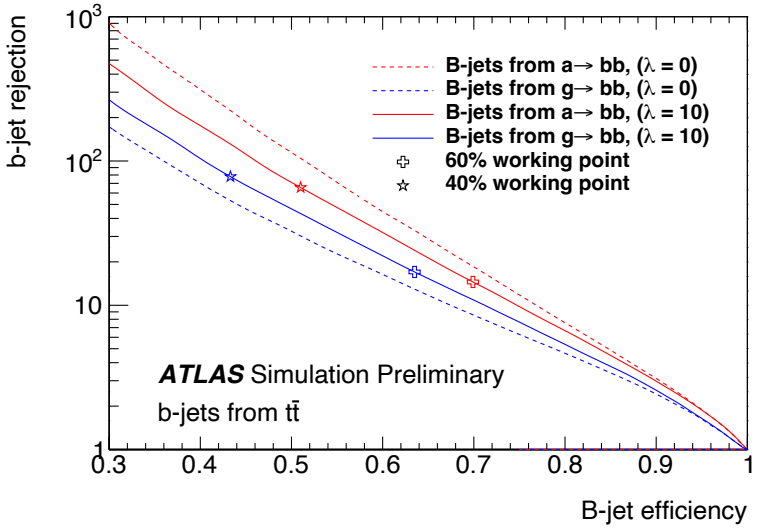




Low-pT object tagging: X→bb ATLAS

ATL-PHYS-PUB-2022-042

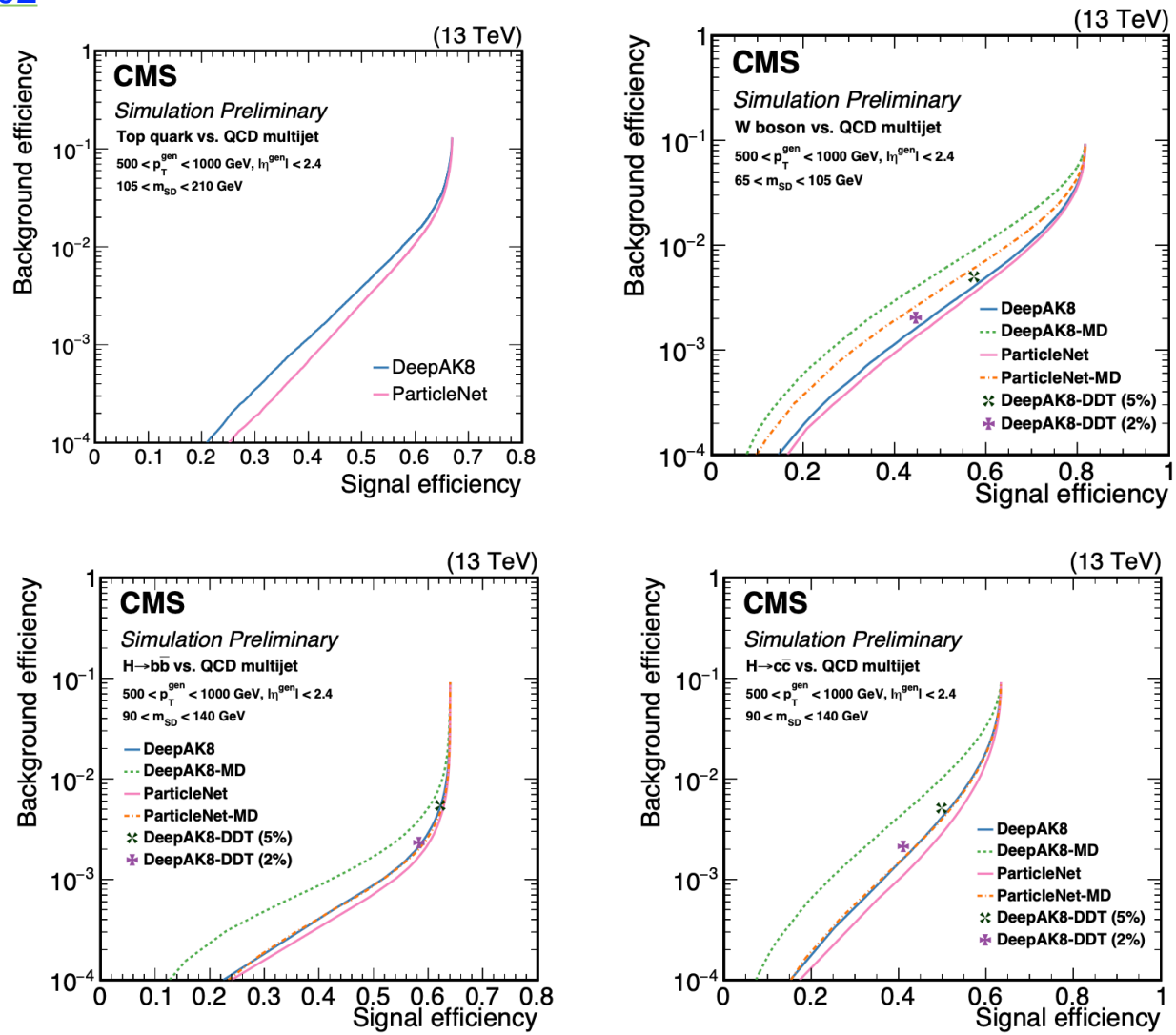




Feature	Description
Jet	
p_{T}	Jet transverse momentum
η	Jet pseudorapidity
Track	
$\log p_{\mathrm{T}}^{\mathrm{frac}}$(track, PFlow jet)	$\log p_{\mathrm{T}}^{\mathrm{track}}/p_{\mathrm{T}}^{\mathrm{PFlow\ jet}}$ the p_{T} fraction between track and PFlow jet p_{T}
$\Delta\eta$ (track, Ex$k_t^{(2)}$ track jet)	Pseudorapidity difference between track and Ex$k_t^{(2)}$ jet
$\Delta\phi$ (track, Ex$k_t^{(2)}$ track jet)	Angular difference between between track and Ex$k_t^{(2)}$ jet
d_0	Transverse impact parameter
$z_0 \sin\theta$	Longitudinal impact parameter
S_{d_0}	d_0/σ_0 : transverse IP significance
$S_{z_0 \sin\theta}$	$z_0 \sin\theta/\sigma_{z_0 \sin\theta}$: longitudinal IP significance
PIX1 hits	Number of hits in the first pixel layer
IBL hits	Number of hits in the IBL
Shared IBL Hits	Number of shared hits in the IBL
Split IBL Hits	Number of split hits in the IBL
Shared pixel hits	Number of shared hits in the pixel layers
Split pixel hits	Number of split hits in the pixel layers
Shared SCT hits	Number of shared hits in the SCT
nPixHits	Number of hits in the pixel layers
nSCTHits	Number of hits in the SCT layers
Secondary Vertex	
$\log(m)$	Track mass of the secondary vertex
$\log p_{\mathrm{T}}^{\mathrm{frac}}$(vertex, PFlow jet)	$\log p_{\mathrm{T}}^{\mathrm{SV}}/p_{\mathrm{T}}^{\mathrm{PFlow\ jet}}$ the p_{T} fraction between the secondary vertex and PFlow p_{T} jet
$\Delta\eta$ (vertex, Ex$k_t^{(2)}$ track jet)	Pseudorapidity difference between the secondary vertex and the Ex$k_t^{(2)}$ jet
$\Delta\phi$ (vertex, Ex$k_t^{(2)}$ track jet)	Angular difference between between the secondary vertex and the Ex$k_t^{(2)}$ jet
L_{xy}	Transverse decay length relative to primary vertex
L_z	Longitudinal decay length relative to primary vertex
$S_{L_{xy}}$	Transverse decay length significance
S_{L_z}	Longitudinal decay length significance

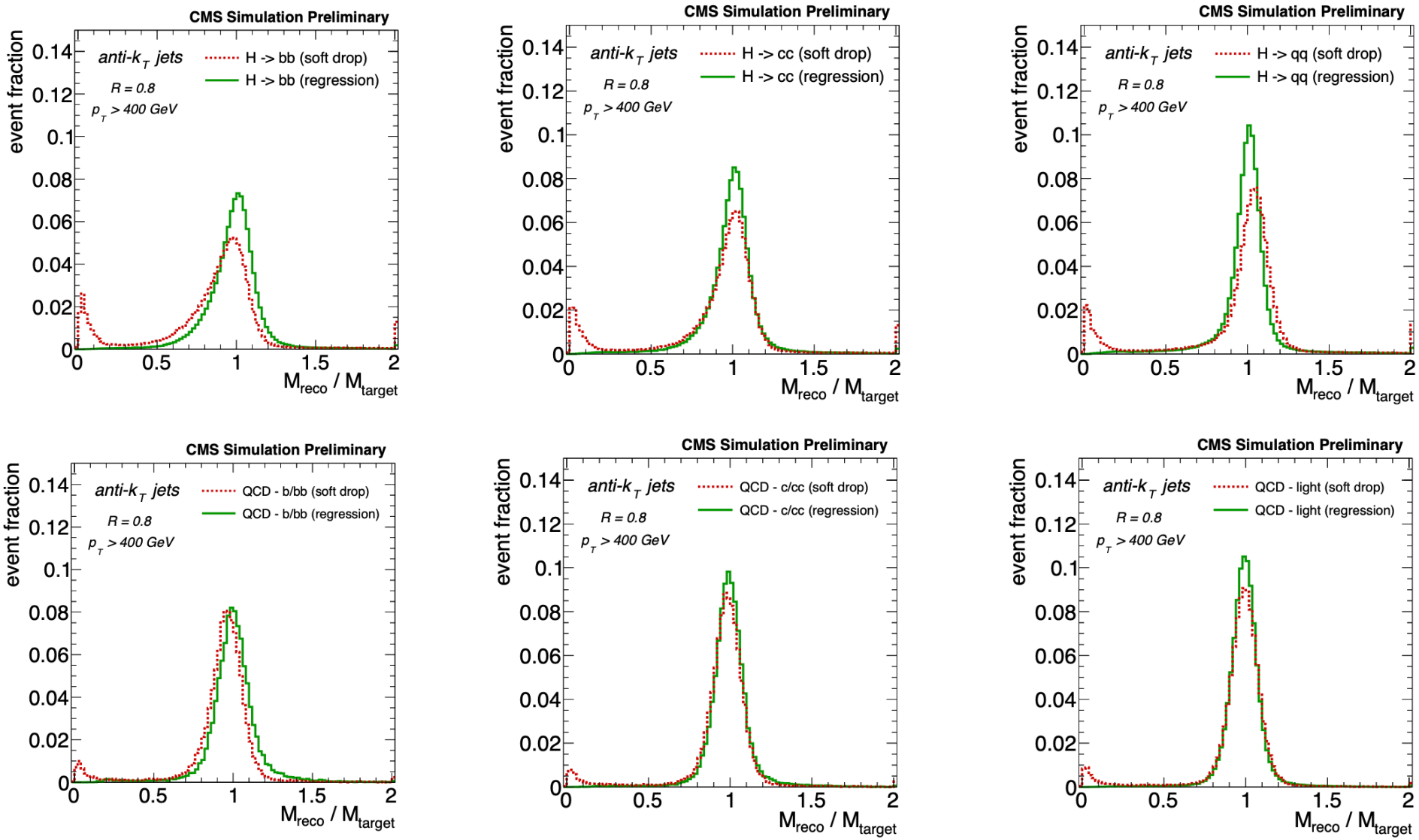
Boosted object tagging: CMS

CMS-DP-2020/002



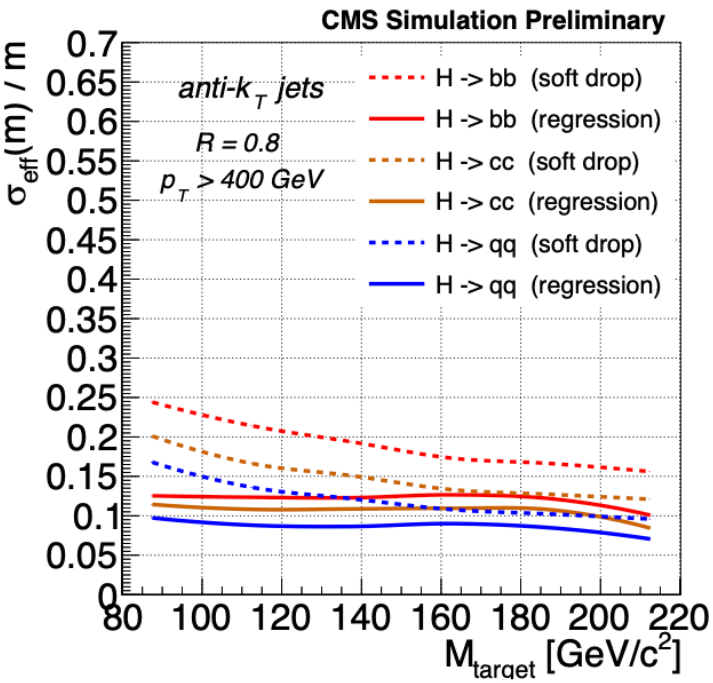
Boosted object tagging: CMS

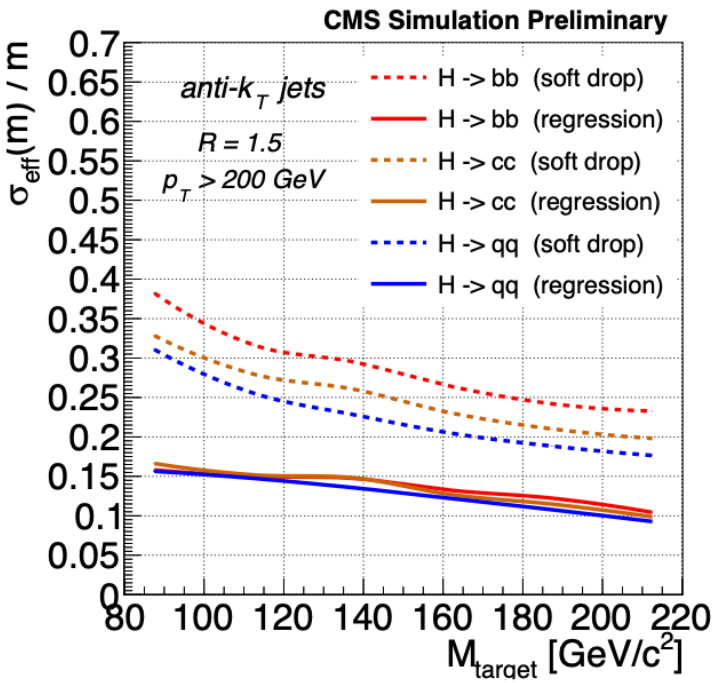
CMS-DP-2021/017



Boosted object tagging: CMS

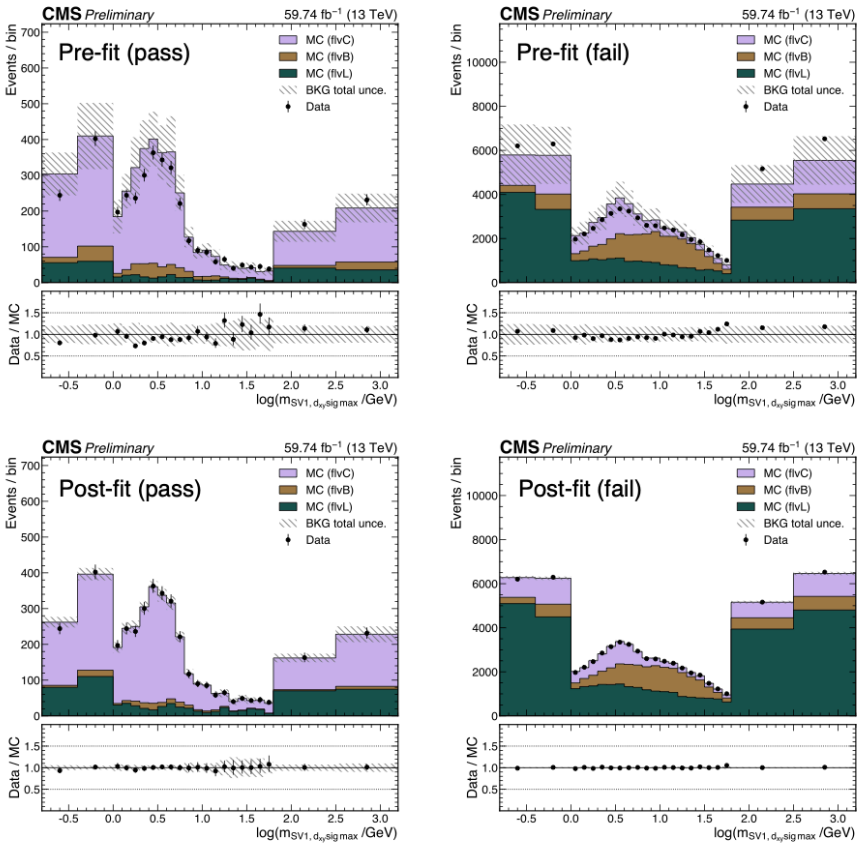
CMS-DP-2021/017

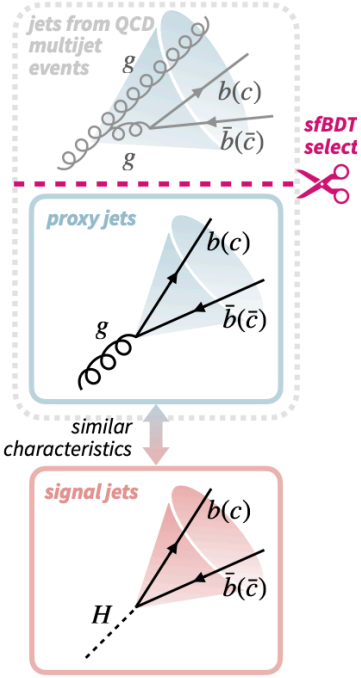


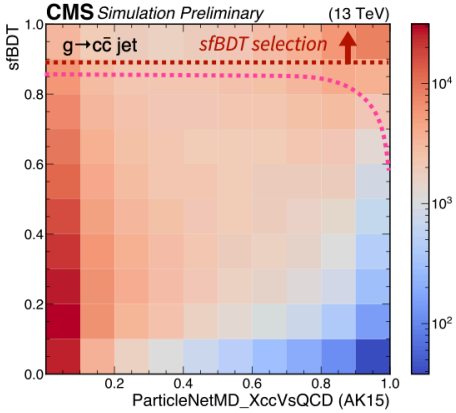


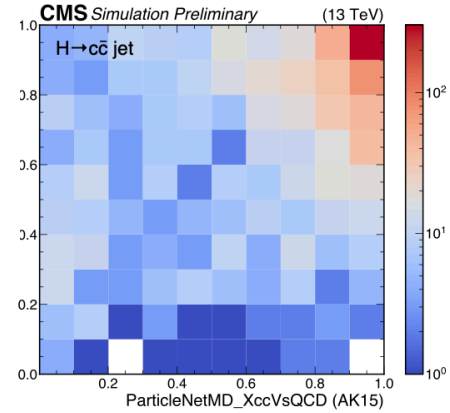
Boosted object tagging: CMS

CMS-DP-2022/005



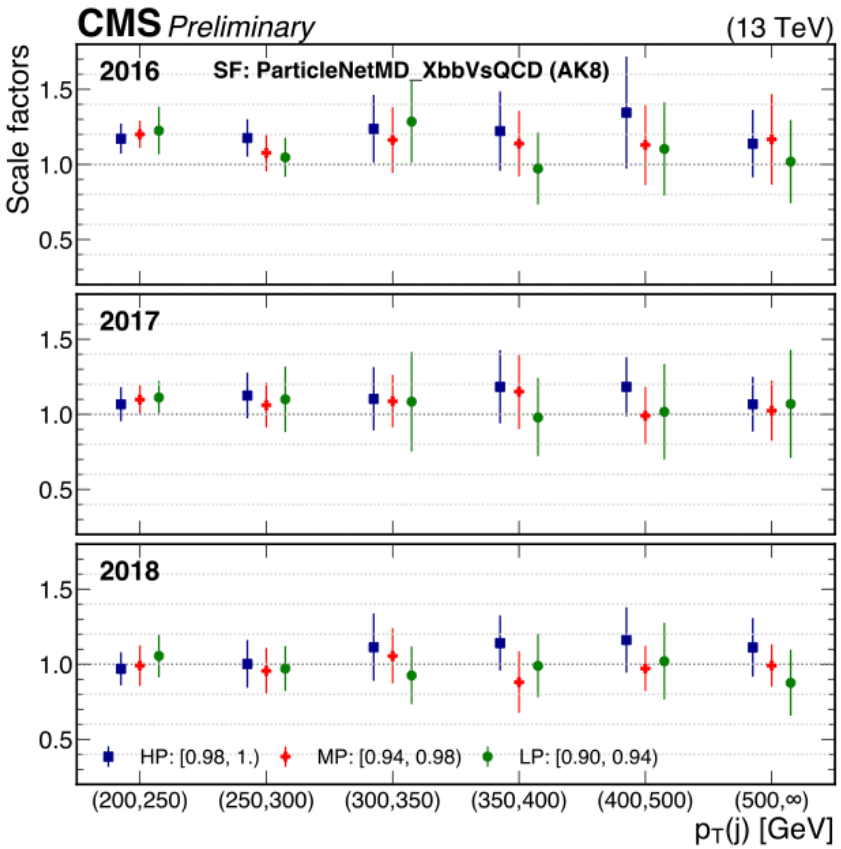


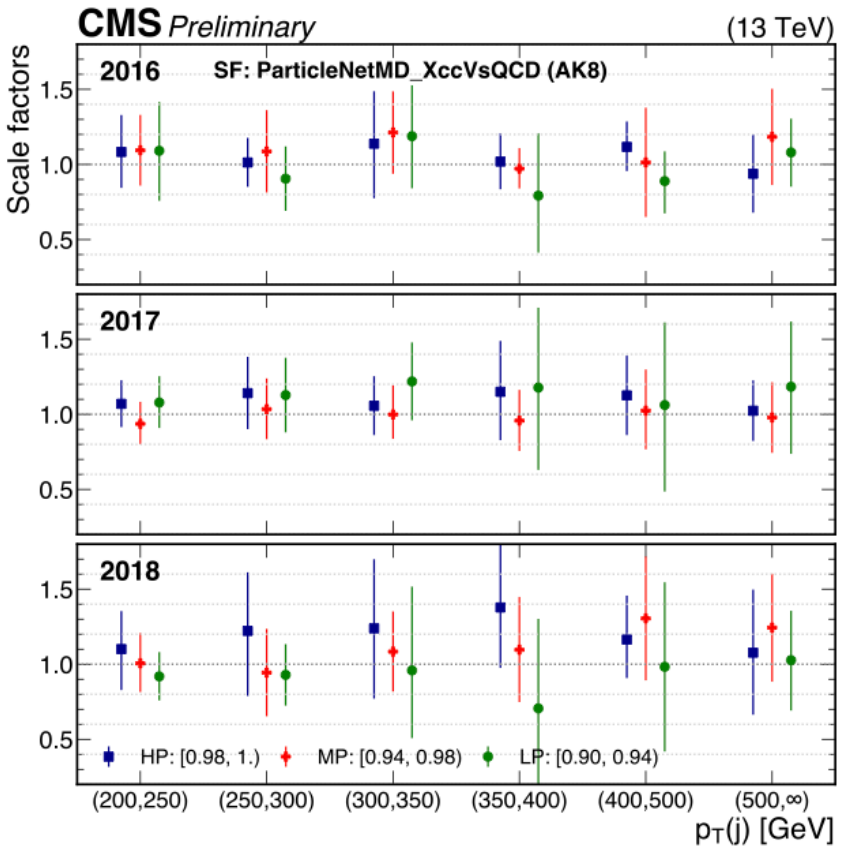




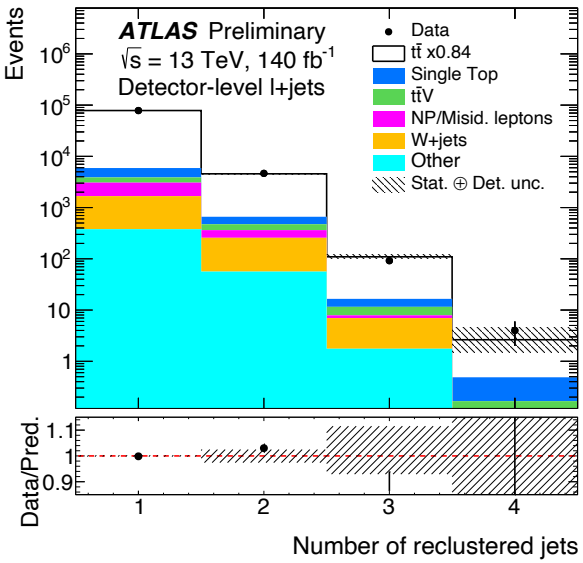
Boosted object tagging: CMS

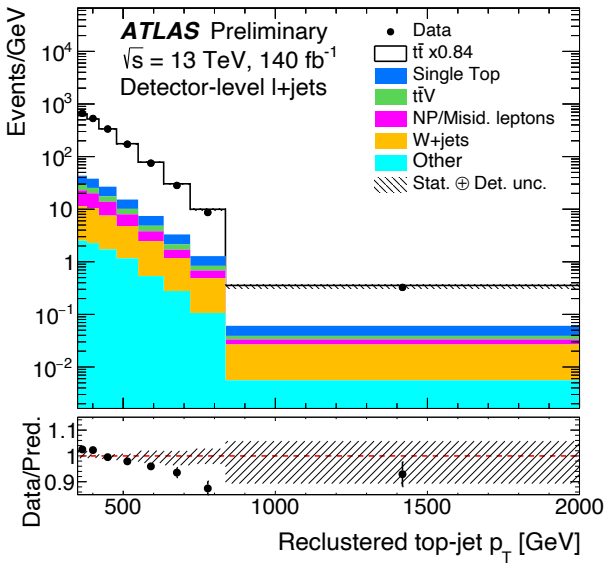
CMS-DP-2022/005

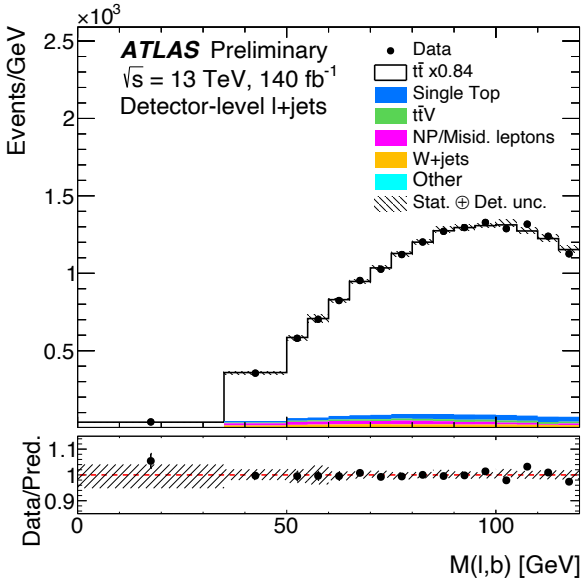


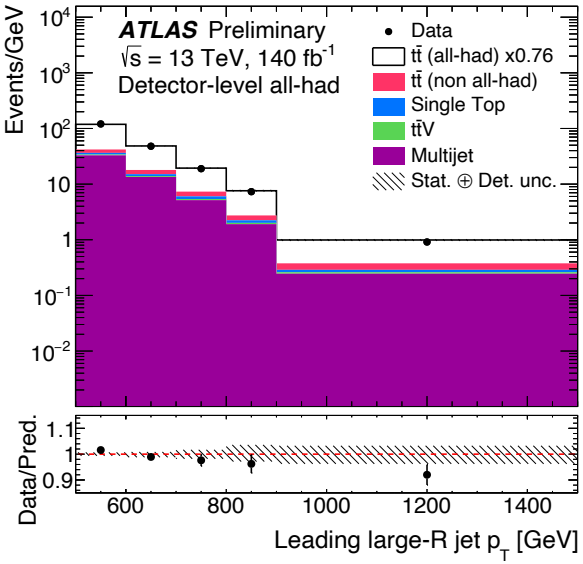


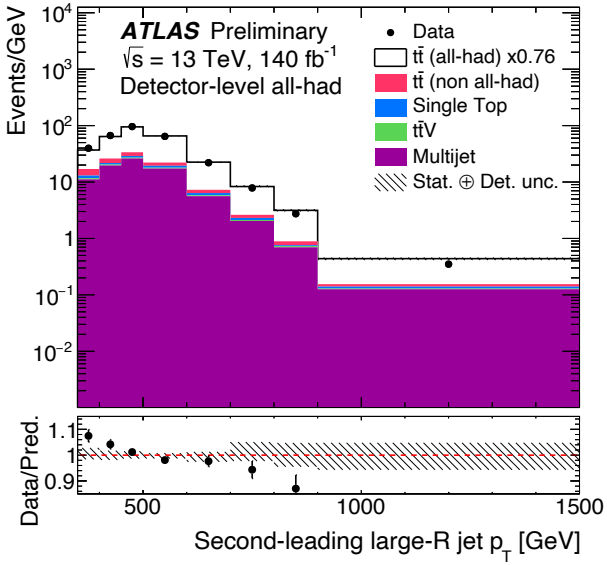
Jet substructure measurement in tt events: ATLAS

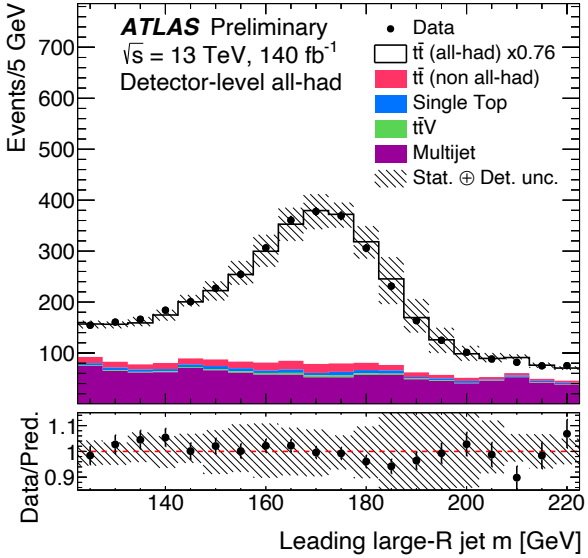




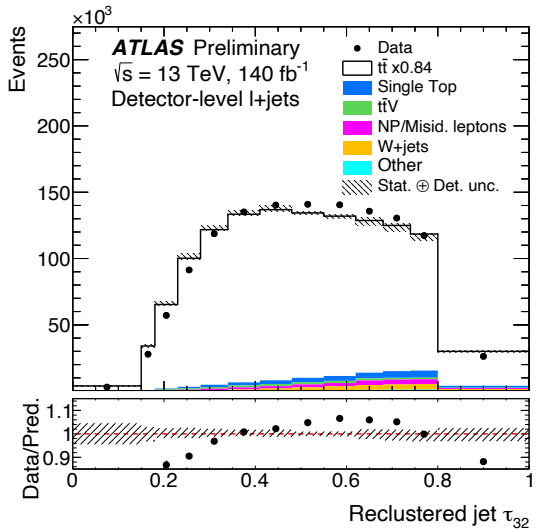


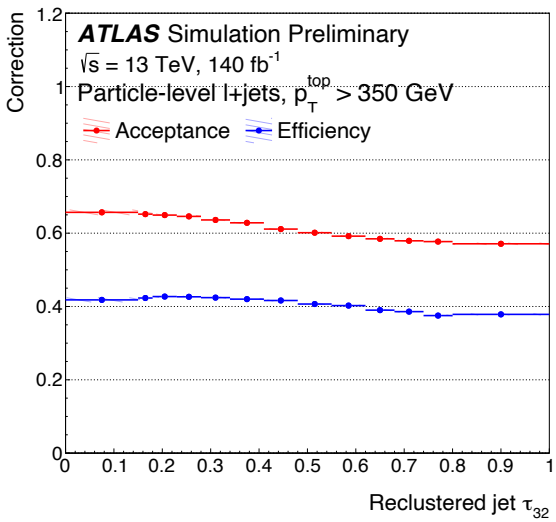


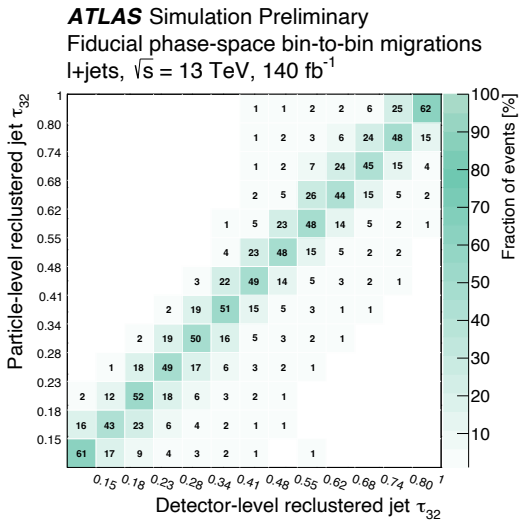


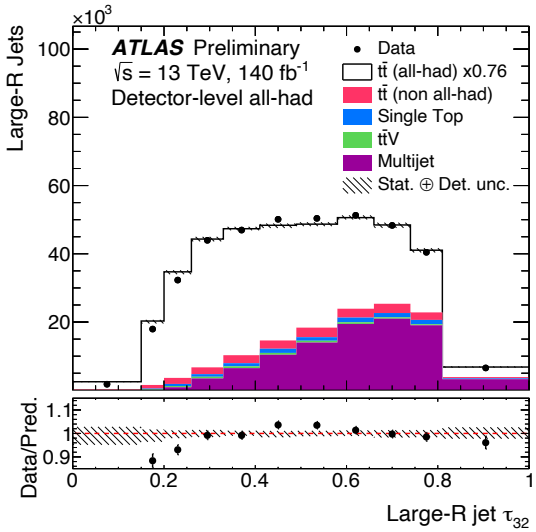


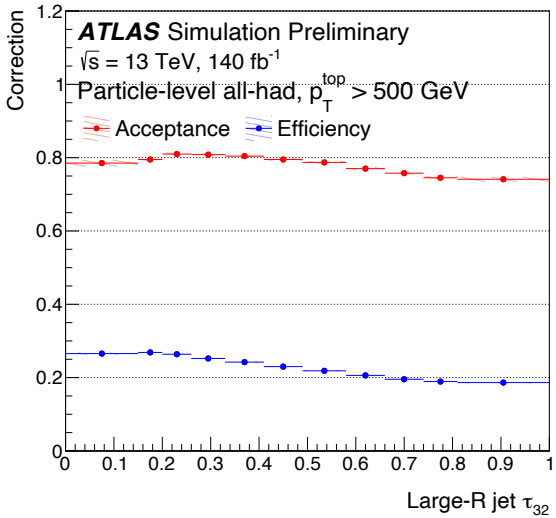
Jet substructure measurement in tt events: ATLAS

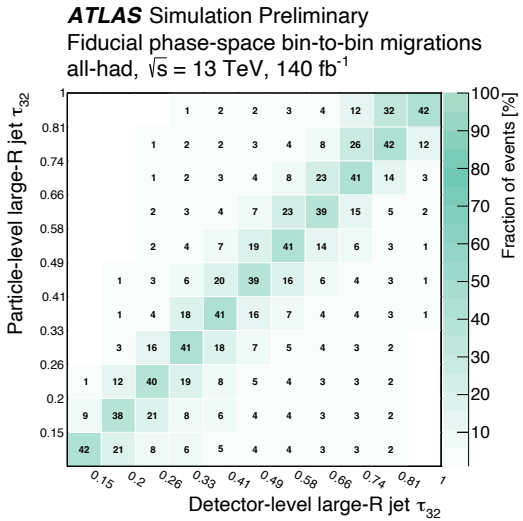




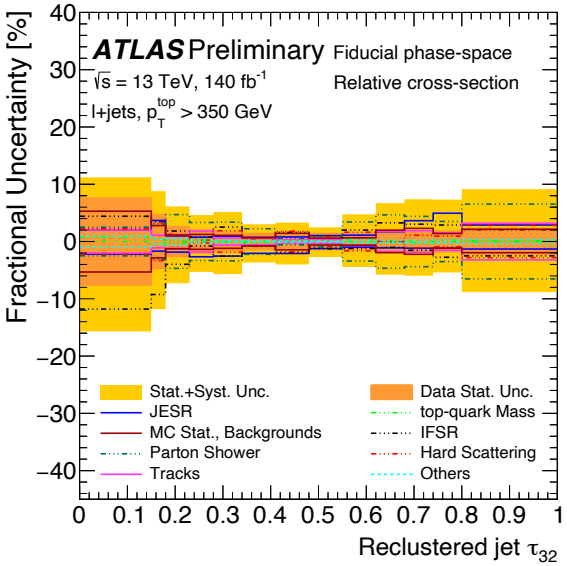


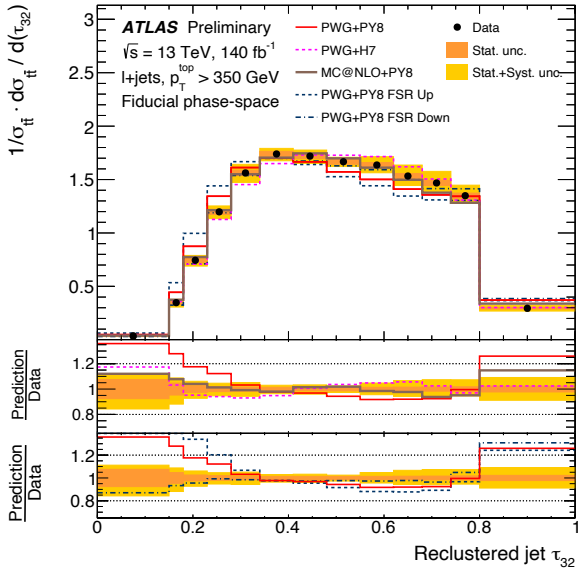


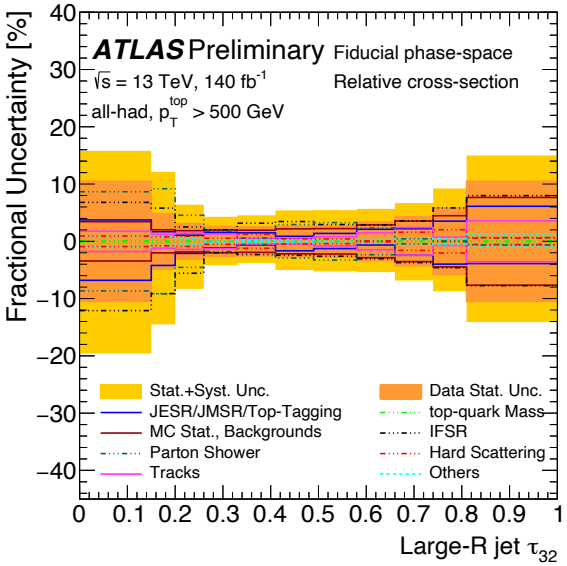


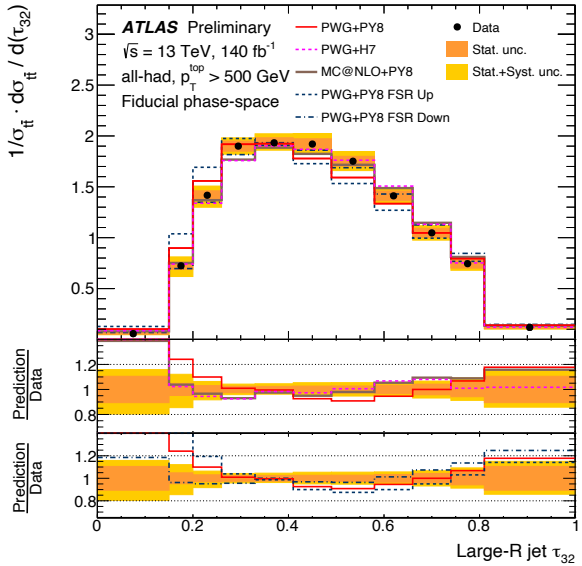


Jet substructure measurement in tt events: ATLAS

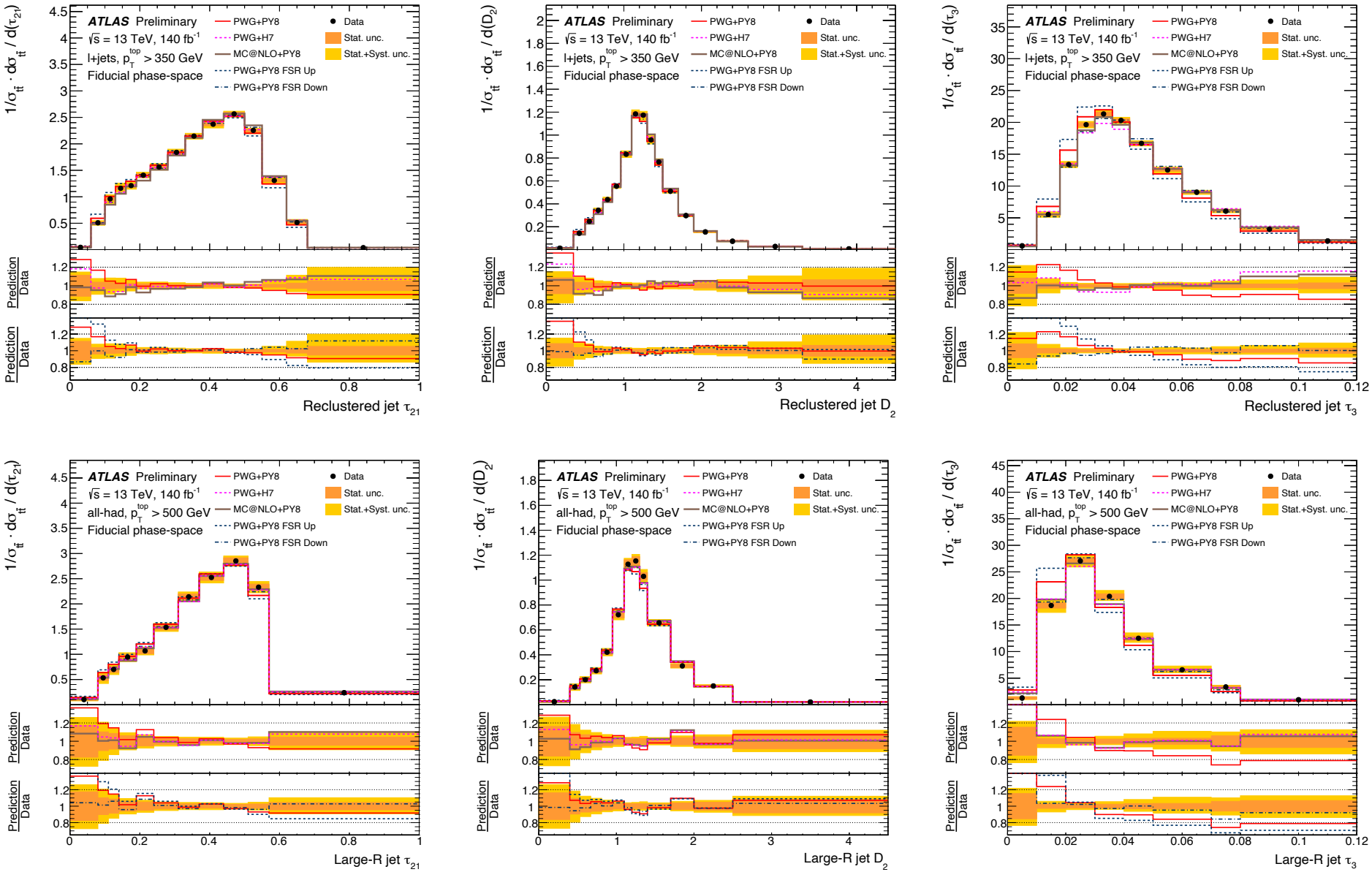




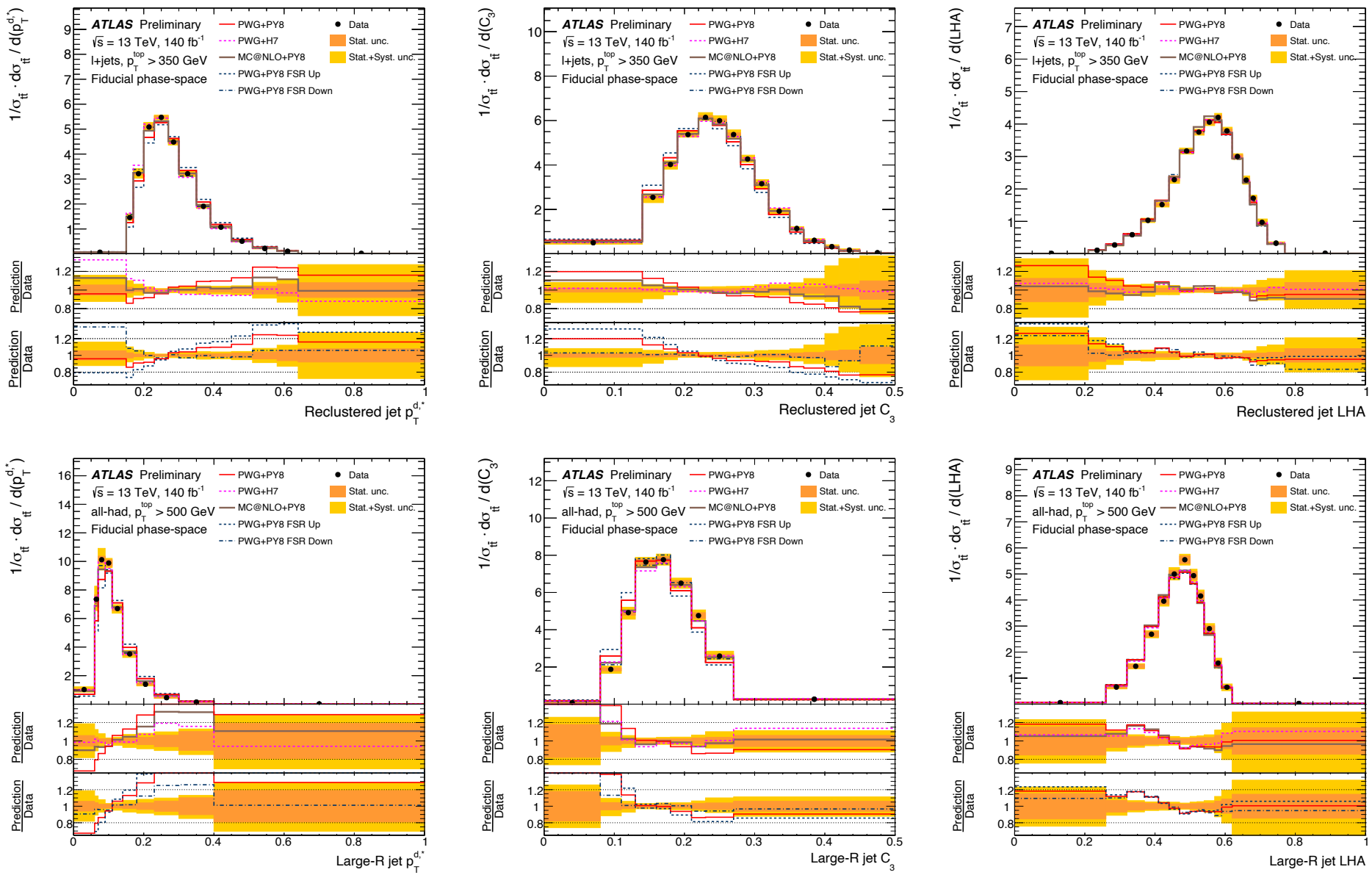




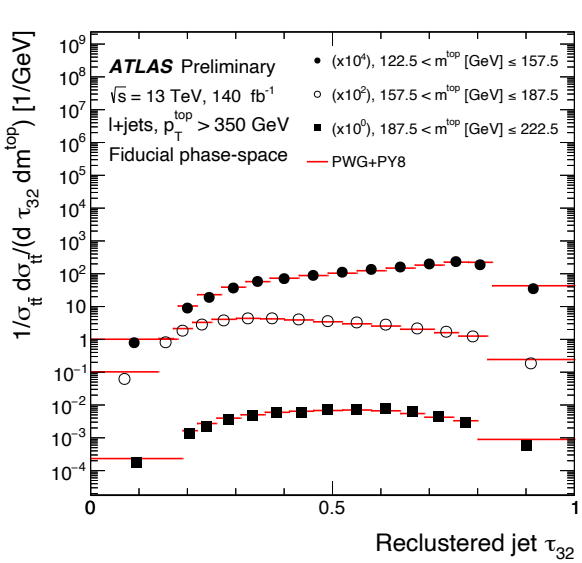
Jet substructure measurement in tt events: ATLAS

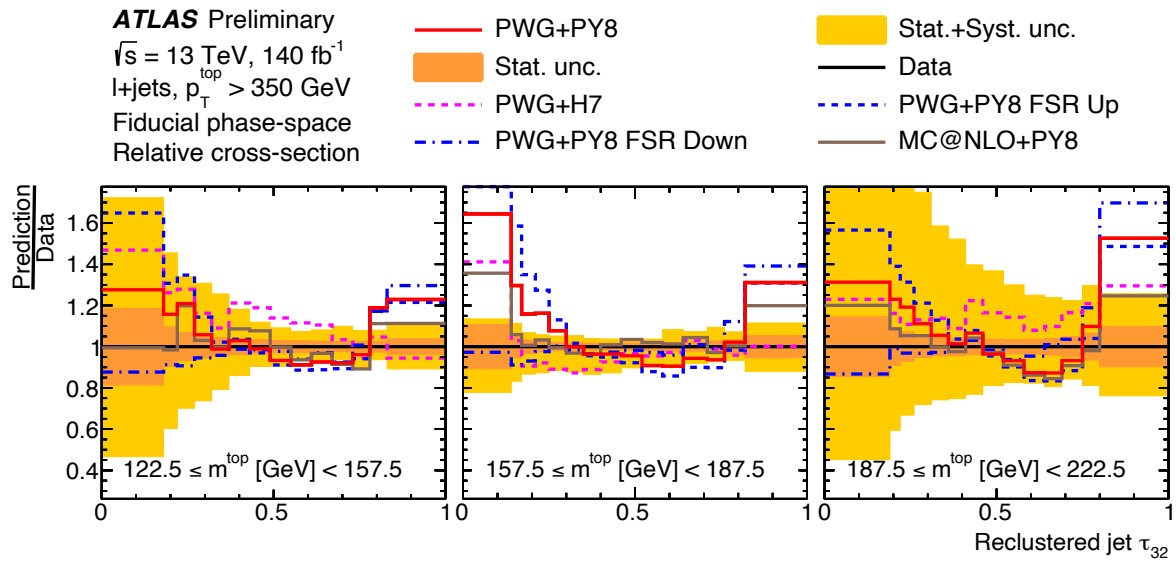


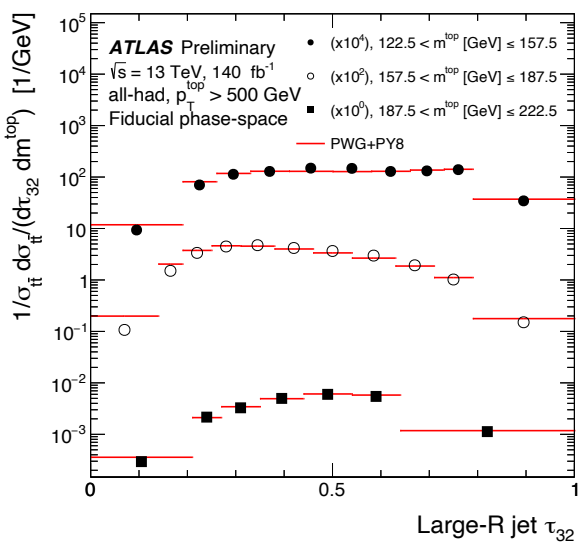
Jet substructure measurement in tt events: ATLAS

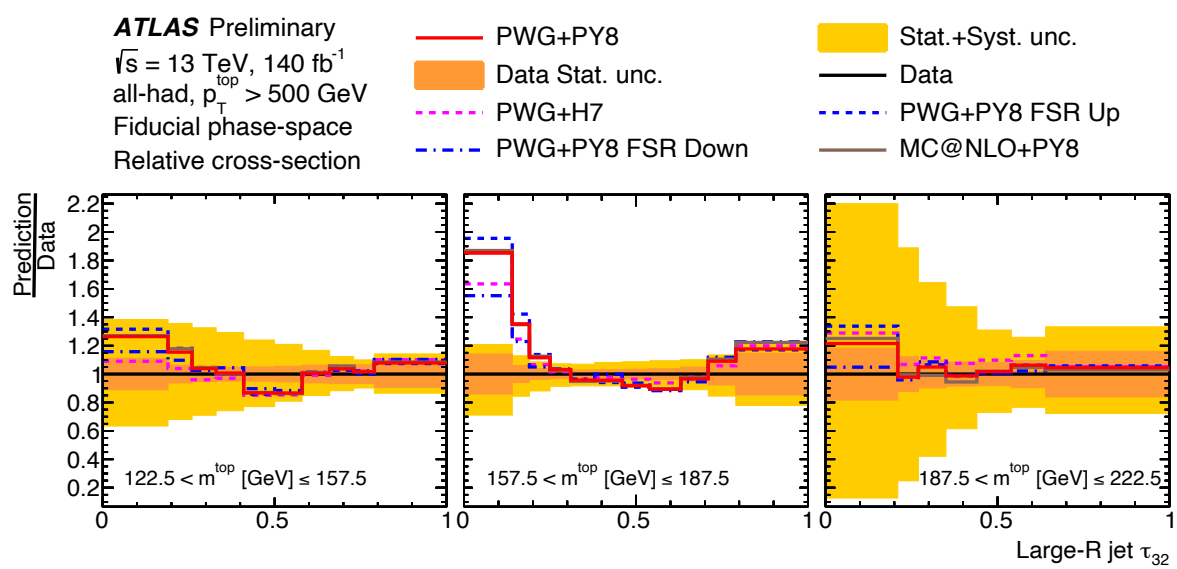


Jet substructure measurement in tt events: ATLAS









Jet substructure measurement in tt events: ATLAS