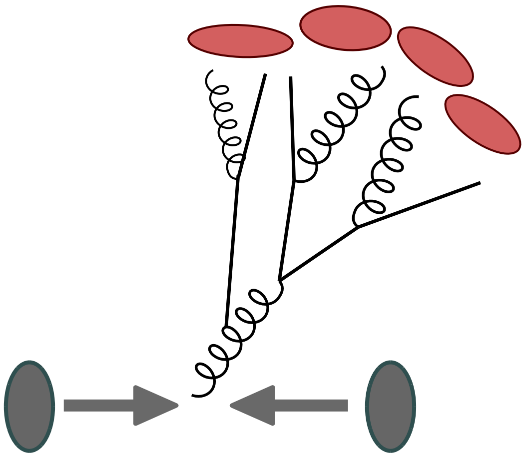
Reconstructing, classifying and calibrating hadronic objects in ATLAS

Pierre-Antoine Delsart
DIS 2024

Hadronic jets at the LHC

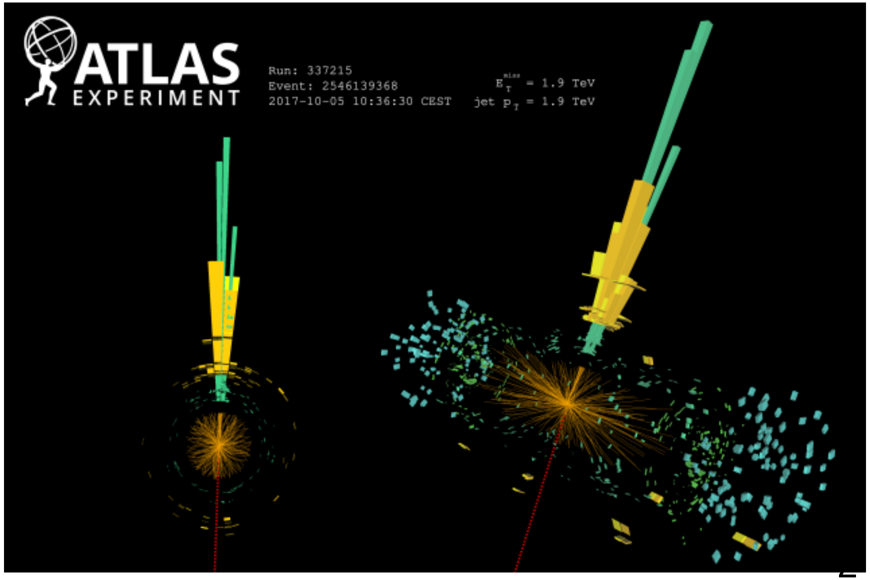


Hadronic jets

- QCD phenomena resulting of a parton emission
- Ubiquitous in LHC analyses

Continuous work in ATLAS to optimize

- Energy and Mass scale and resolution
- Uncertainties on E and Mass
- Discrimination between different types of jets



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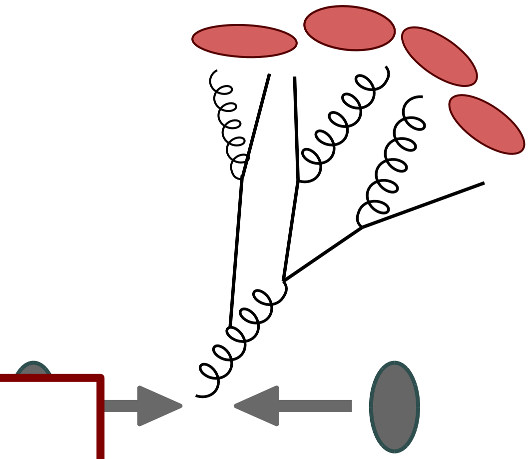
Hadronic jets at the LHC



Hadronic jets

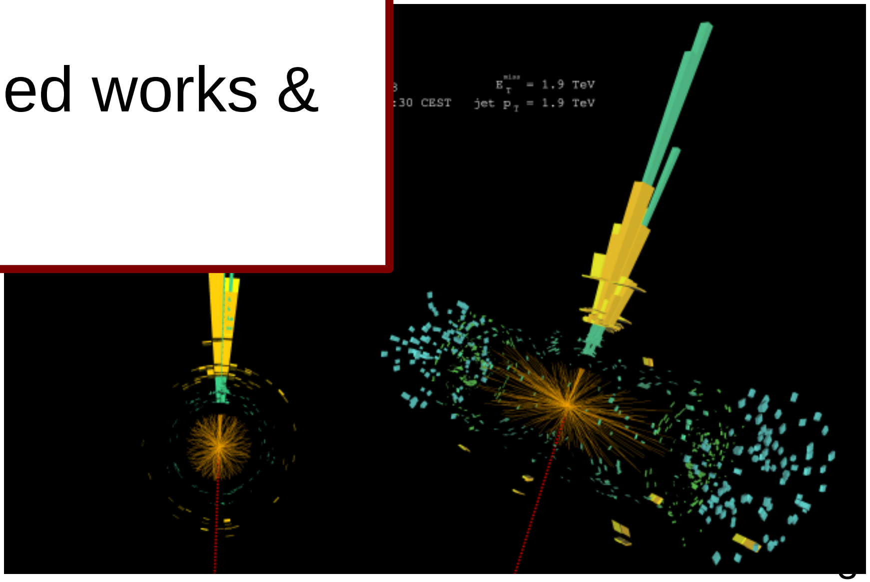
- QCD phenomena resulting of a parton emission
- Ubiquitous in

This talk:

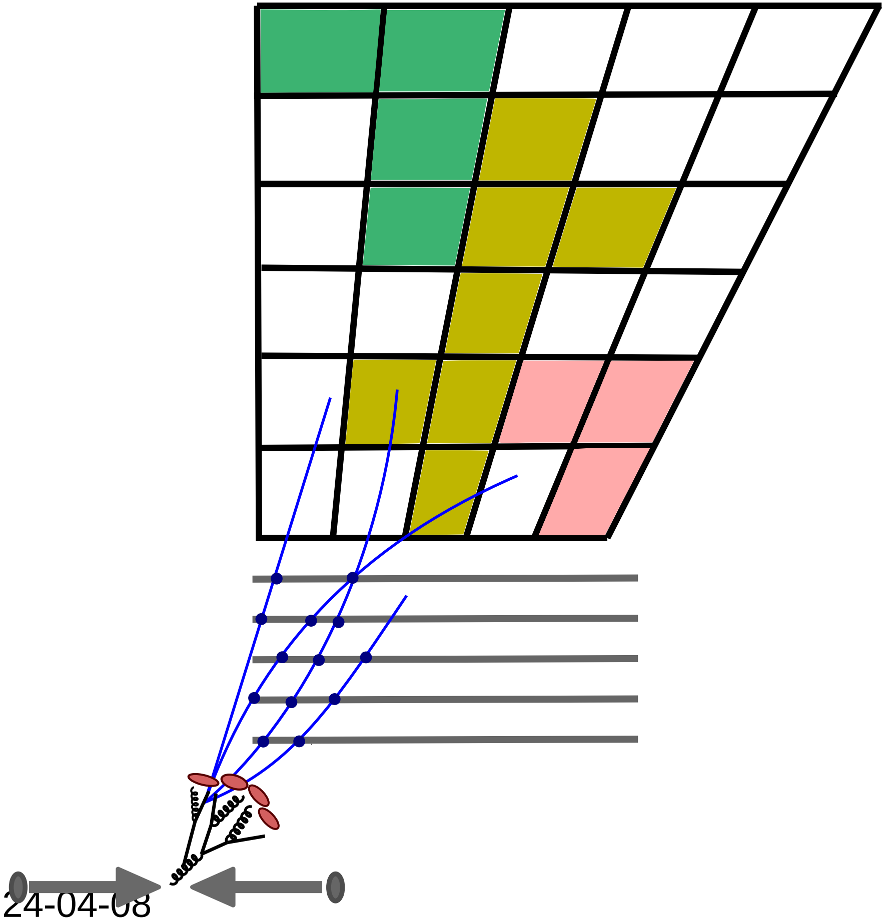
selection of recent published works & results

Continuous worl

- Energy and M
- Uncertainties on E and Mass
- Discrimination between different types of jets



Hadronic flow reconstruction in ATLAS

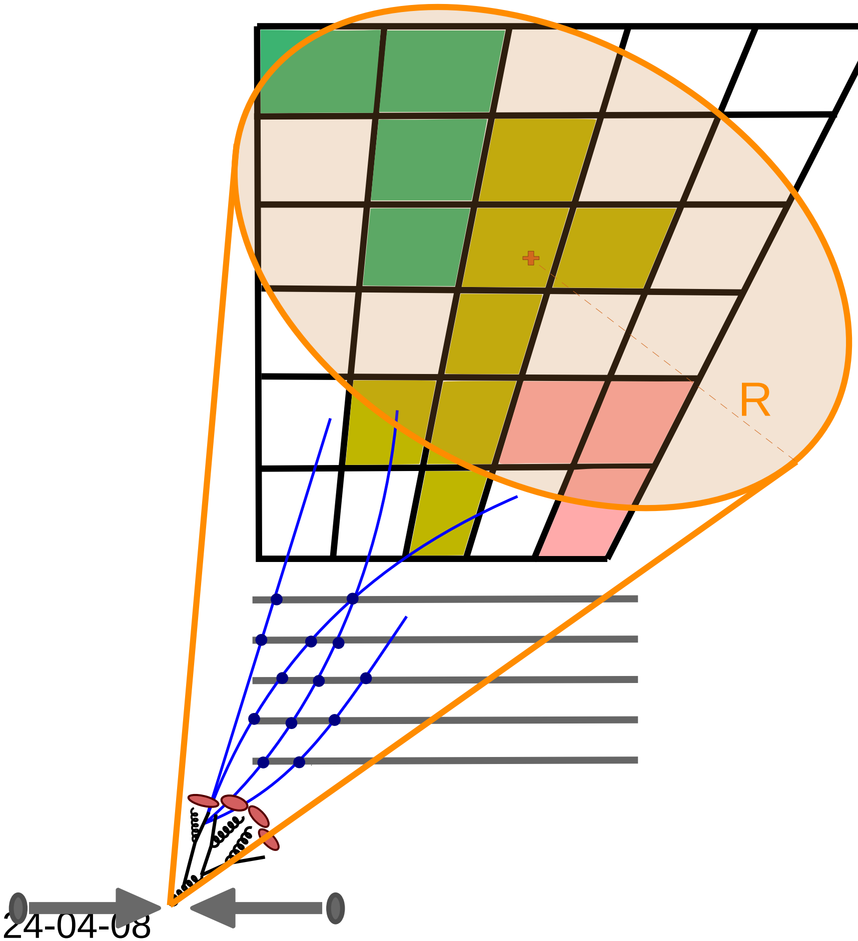


- Flow of hadronic particles == constituents of jets
  - set of 4-vectors

2 possible type of primary signals :

- Calorimeter clusters
  - 3D cell clustering using ATLAS's 7 layers depth
  - Good reconstructed energy (E) at high p_T
  - limited granularity
- Inner Detector tracks
  - Excellent spatial resolution
  - Good reconstructed p_T at lower p_T
  - Limited to charged particles

Hadronic jet reconstruction in ATLAS



- Jet = group of constituents
- groups formed by a Jet algorithm with a distance parameter R
  - ex: "anti-k_T"
- ATLAS uses
  - R=0.4 : "standard" jets
  - R=1.0 : "large-R" jets to collect boosted hadronic decays of heavy particles (W/Z, top, Higgs,...)

Calorimeter cluster classification and **calibration** with Machine Learning (ML)

2 types of studies :

- "Low level" using calorimeter cells information
  - single π simulations,
  - proof of concepts using advanced ML (CNN, Graph NN, "point clouds")
  - promising results : ATL-PHYS-PUB-2020-018 and JETM-2022-002
- "Higher level" using only cluster variables → next slides

Higher-level cluster calibration with DNN

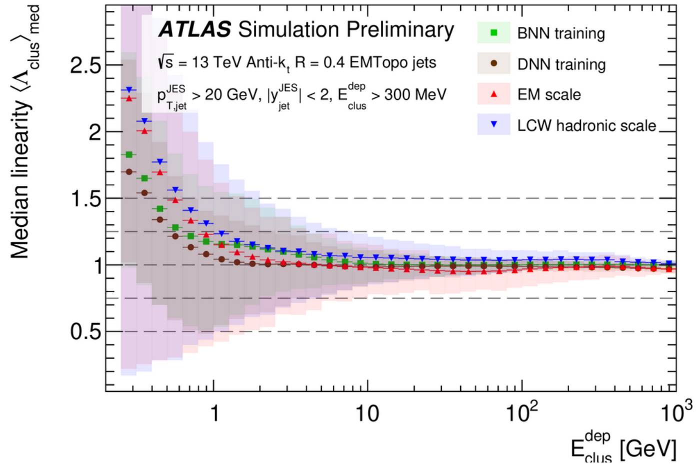
ATL-PHYS-PUB-2023-019

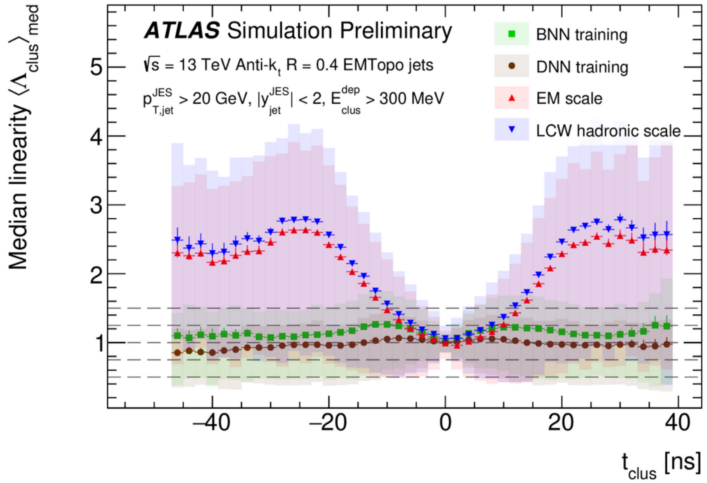
- Can ML using "engineered" **cluster-level** variables perform as well as ML using full cell info ?
  - In practice cluster-level approach much easier & faster to train and use in analysis
- Train DNN to predict response w.r.t deposited E
  - Using simulated clusters inside Jet in realistic multijet events
  - Based on 15 chosen variables
  - Also testing Bayesian NN

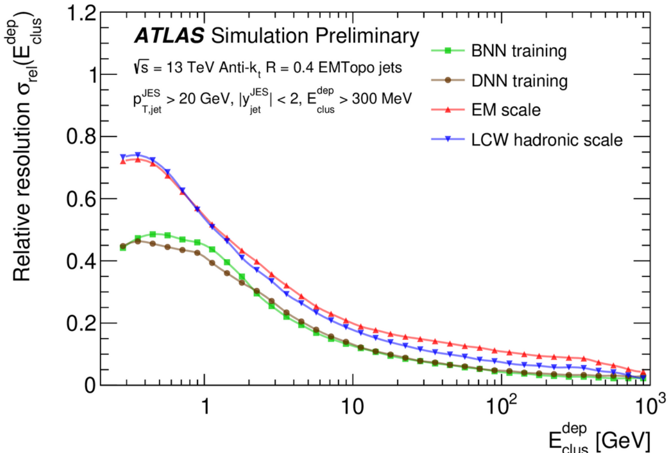
Category	Symbol	LCW	Comment
kinematics	$E_{\mathrm{clus}}^{\mathrm{EM}}$	yes	Signal at the electromagnetic energy scale (A)
	$y_{\mathrm{clus}}^{\mathrm{EM}}$	yes	Rapidity at the electromagnetic energy scale (B)
signal strength timing	$\zeta_{\mathrm{clus}}^{\mathrm{EM}}$	no	Signal significance (E)
	t_{clus}	no	Signal timing (C,D,F)
	$\mathrm{Var}_{\mathrm{clus}}(t_{\mathrm{cell}})$	no	Variance of t_{cell} distribution (D,F)
shower depth shower shape compactness	λ_{clus}	yes	Distance of centre-of-gravity from calorimeter front face (C,D)
	$\lvert\vec{c}_{\mathrm{clus}}\rvert$	no	Distance of centre-of-gravity from nominal vertex (C,D)
	f_{emc}	no	Fraction of energy in electromagnetic calorimeter (C)
	$\langle\rho_{\mathrm{cell}}\rangle$	yes	Cluster signal density measure (C,D)
	$\langle\mathfrak{m}_{\mathrm{long}}^2\rangle$	no	Energy dispersion along main cluster axis (C)
	$\langle\mathfrak{m}_{\mathrm{lat}}^2\rangle$	no	Energy dispersion perpendicular to main cluster axis (C)
	$p_{\mathrm{T}}D$	no	Signal compactness measure (C,D)
topology	f_{iso}	no	Cluster isolation measure (F)
pile-up	N_{PV}	no	Number of reconstructed primary vertices (F)
	μ	no	Number of interactions per bunch crossing (F)

Higher-level cluster calibration with DNN

- Compared to no (**EM**) and "standard hadron calibration" (**LCW** see Eur. Phys. J. C 77 (2017) 490)
- Very encouraging results with improved E response and resolution



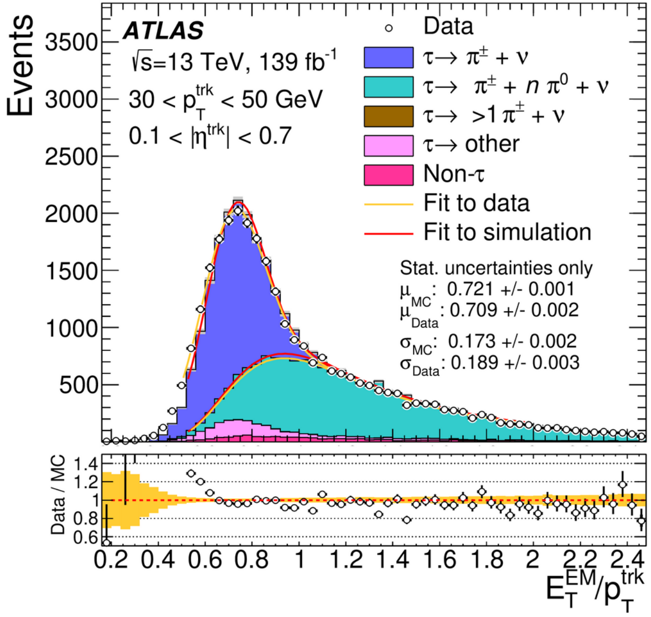




Measuring hadronic response in data

Measuring hadronic response

- Select $W \to \tau\, \nu_\tau \to \pi \nu_\tau \nu_\tau$ events
  - by requiring isolated tracks matched to hadronic clusters
  - Calculate E as sum E of clusters within $\delta R<0.15$
- Fit $E_{T(clus)}/p_{T(trk)}$ to measure **hadronic response**
- Study response scale, resolution, longitudinal profile



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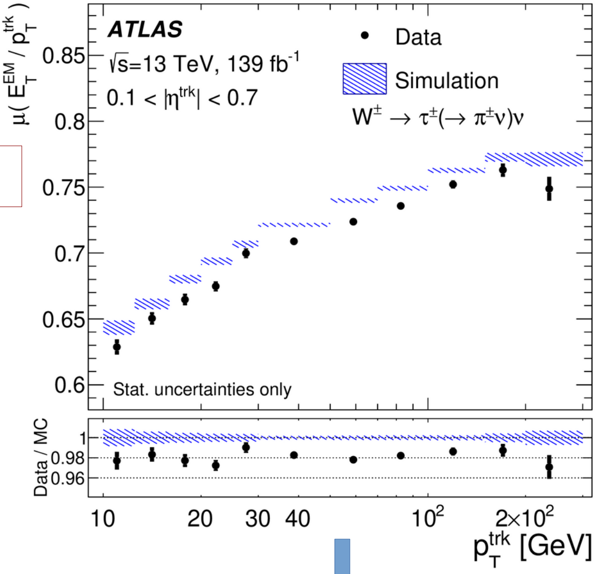
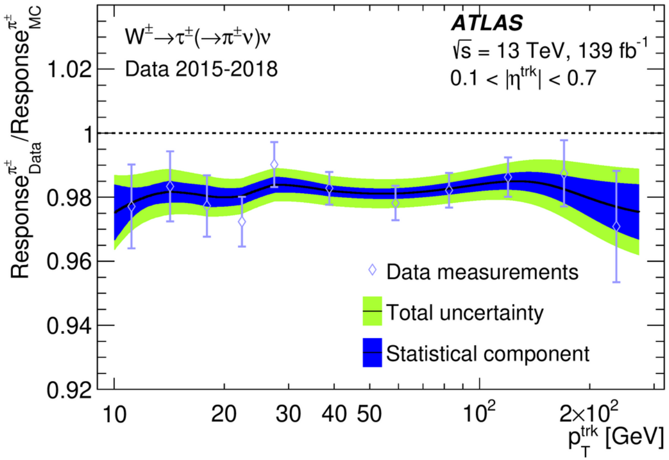
Hadronic scale in data

Eur. Phys. J. C 82 (2022) 223

- Hadronic scale measured with good precision
  - <1% up to p_T=185GeV in barrel
    - <0.6% up to 120GeV
- Ex: scale ~2% under-estimated in central
  - consistent with other measurements

Help to constrain jet E uncertainty at high p_T





Advanced constituents building to improve jet reconstruction

Jet constituents building

- How to combine Tracks & cluster to build constituents ?

Tracks

Calorimeter Cluster

Combined objects

Particle Flow (**PFlow**)

tracks (low-p_T)
complemented with E from clusters

TrackCaloCluster (**TCC**)

CaloClusters Energies
re-positioned on angular positions of matched tracks

Unified Flow Object (**UFO**)
combining PFlow & TCC methods

Combine advantages :

- p_T resolution driven by
  - tracker at low p_T, charged
  - calorimeter at high p_T
- Use angular position for charged at **all** p_T
  - better mass resolution

Jet constituents building

- Ho[...]nts ?

New ATLAS default choice for large-R jets

- **UFO** constituents
- **CSSK** : "Charged Subtraction"+"Soft Killer" P-U mitigation
- **Soft Drop** (Z=0.1,β=1) grooming

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UFO also proven to be suitable for **small-R jets**

- similar performance than regular Pflow
- ATL-PHYS-PUB-2022-038

Combined objects

tra

co

s

es :

d

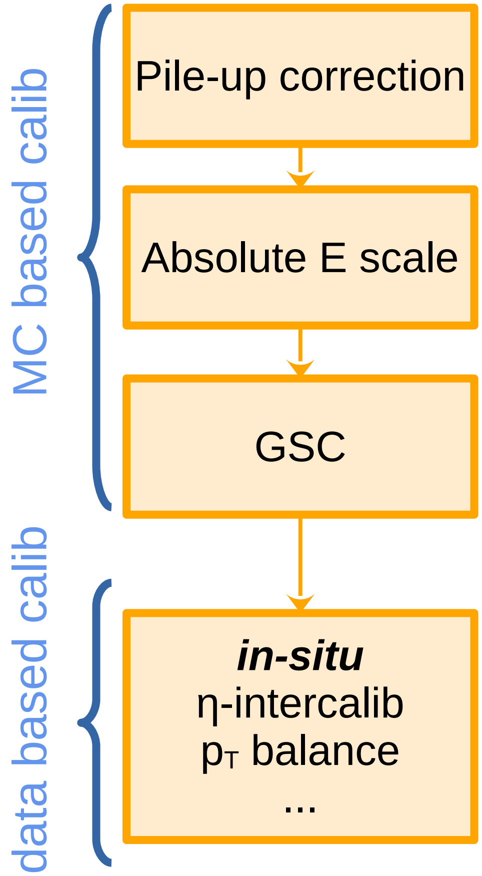
calorimeter at high p_T

- Use angular position for charged at **all** p_T
  - better mass resolution

Improving Jet Calibration

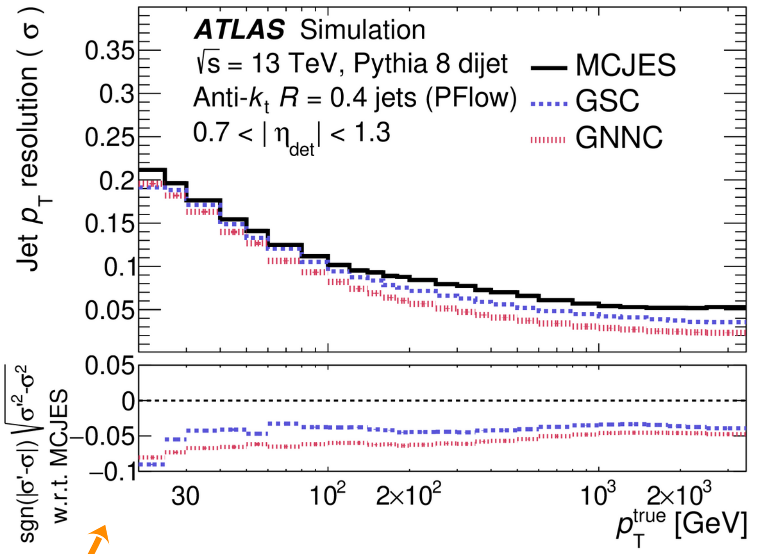
Small R jet E calibration

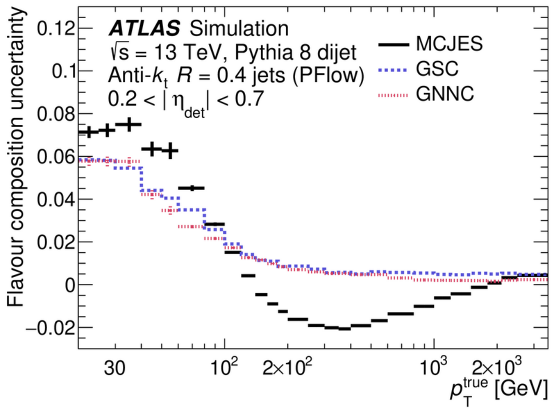
- E scale, resolution & uncertainties of small-R jets are crucial for analysis
- Complex multi-step calib procedure developed since Run1
- Works & refinements at each steps. Example:
  - GSC
  - in-situ



Small R jet E calibration : GSC

- GSC=Global Sequential Calibration
  - Adjustment calibrations, each correcting dependency on 1 variable
  - aim at improving resolution without changing the scale
- Replaced by a single DNN
  - accounting for correlations between variables
  - Improves resolution
  - lower sensitivity on q/g flavour → lower uncertainties





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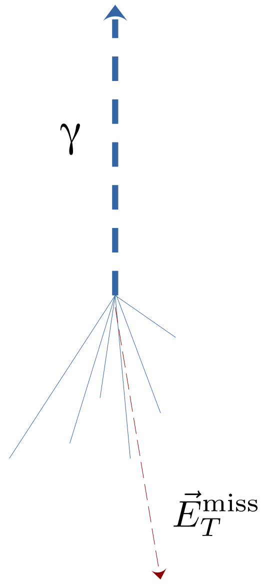
Small R jet E calibration : in-situ



- Use real data to correct for data/MC difference in E scale
- Based on pT balance between
  - reference object (γ, Z, …)
  - 1 (or+) jets or hadronic recoil
  - extract correction factors from balance equation
- Example : MPF
  - missing projection fraction

$$\vec{p_T}^{ref} + r_{\mathrm{MPF}}\, \vec{p_T}^{\mathrm{recoil}} = -\vec{E}_T^{\mathrm{miss}}$$

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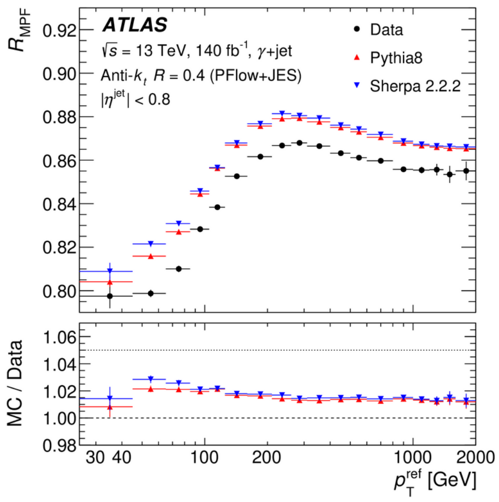
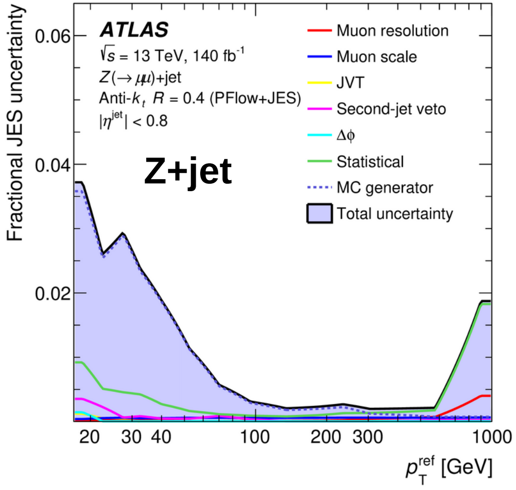
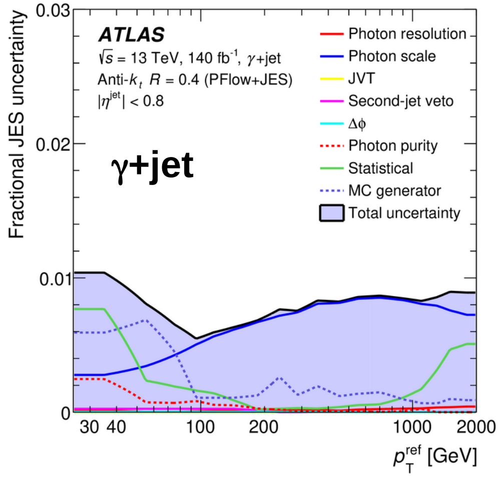
Small R jet E calibration : in-situ

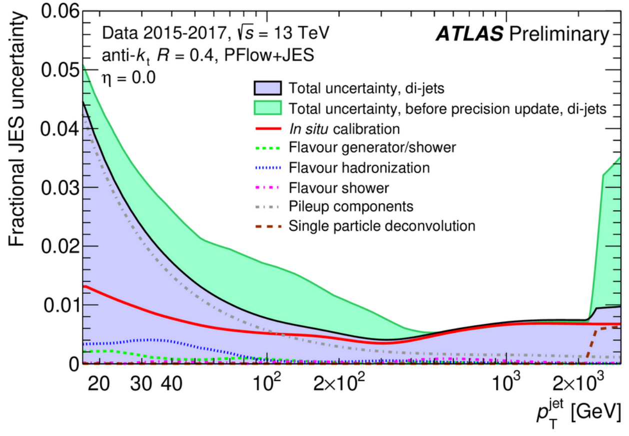
- In-situ techniques provide E scale factors between MC & data
- together with uncertainties on E scale







Combine



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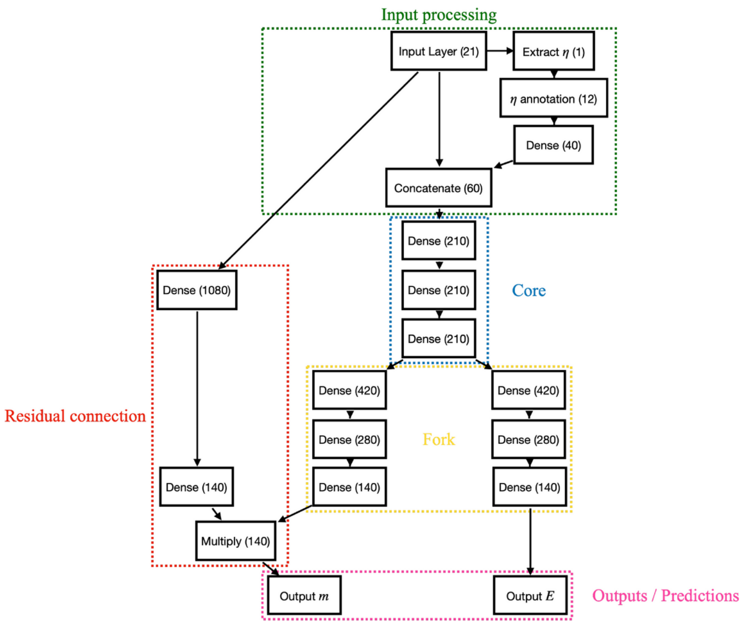
Large-R jet : E&mass calib with DNN

- Large-R jet E and mass calib important for heavy particle searches
- Exploit correlations between E, mass and many jet-variables with a single NN predicting both E&mass response
- More than a simple DNN regression !
  - encoding of jet position w.r.t detector
  - special loss to learn response distribution mode
  - special architecture & training

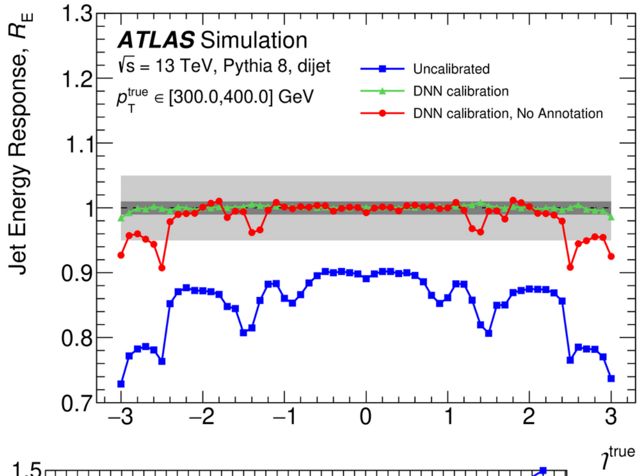


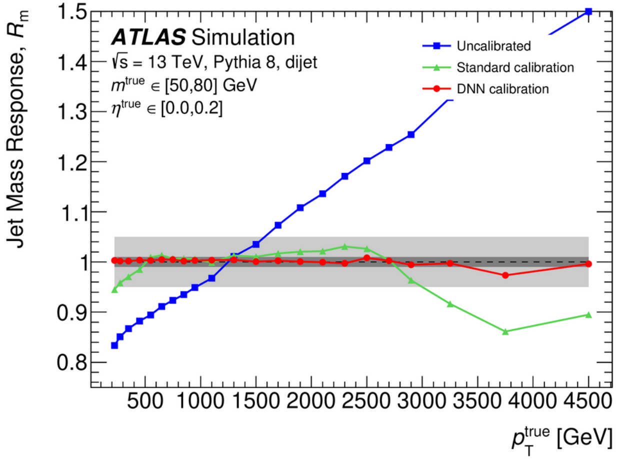
JETM-2023-02 (submitted to MLST)

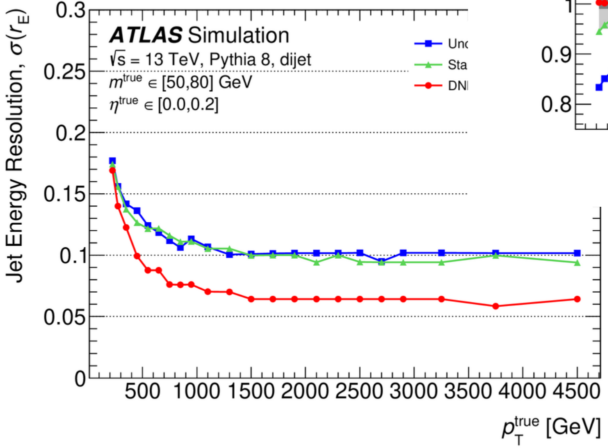
Large-R jet : E&mass calib with DNN

- η annotation necessary to predict sharp variations vs η
- Superior performance of DNN calib
  - E and mass scale and resolution
  - lower PU and generator dependency
- Will be the **legacy Run2 & Run3 calibration** for large-R jets

JETM-2023-02 (submitted to MLST)



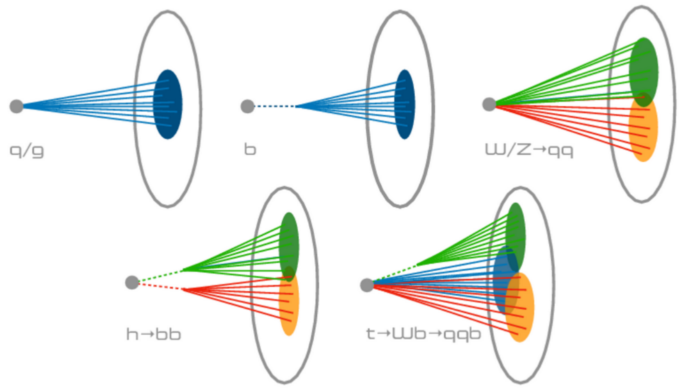




Improving large-R jet Identification

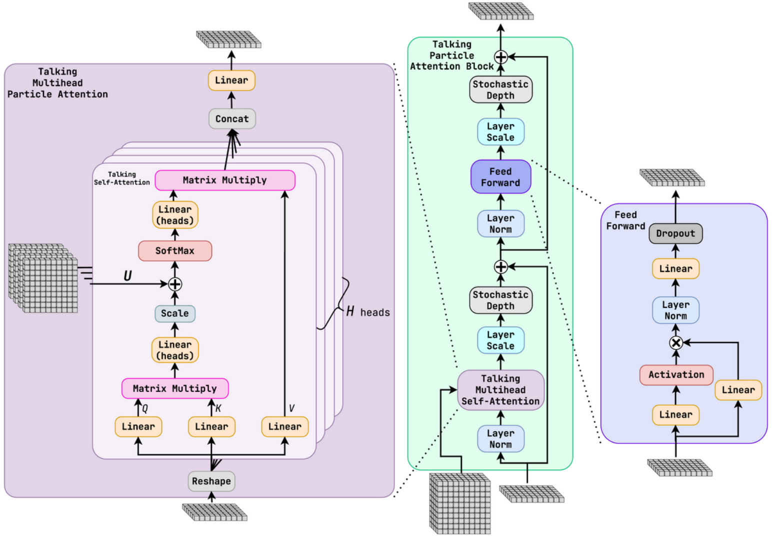
Jet W/Z, top or q/g tagging

- Identifying & distinguishing source of hadronic decay is crucial for many physics analysis
- Long history of evolving approaches including
  - technical aspects (cuts based, various ML)
  - physics insight (structure variable, shower history)
- Latest round of ATLAS studies involve advanced techniques
  - using jet constituents
  - advanced ML
  - Applied to top, W or quark vs gluon tagging



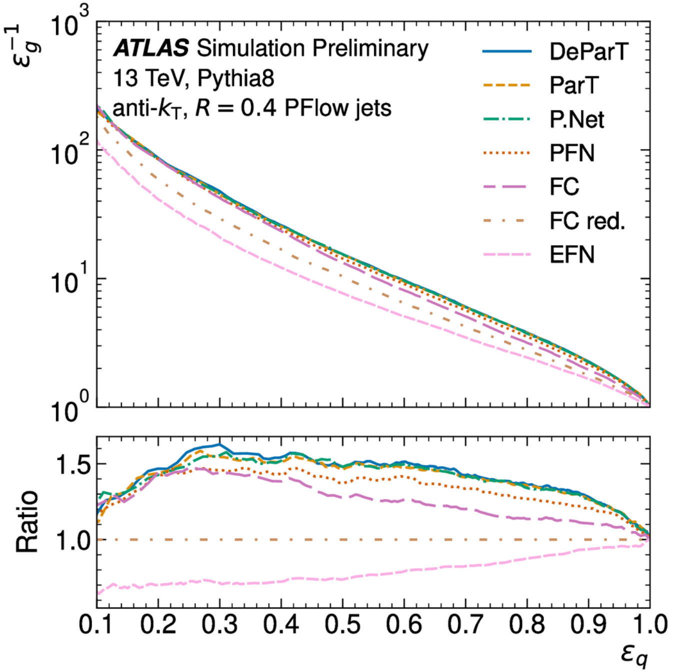
Advanced tagging techniques

- Using constituents
  - access complete information on jet structure
  - angular relations → build graphs → Graph NN usage
- Common ML models tested :
  - Energy Flow Network (IRC-safe NN → **EFN**)
  - **ParticleNet** (4-vector GNN models)
  - Particle Transformer ("transformer" models for particles → **ParT** , **DeParT**)

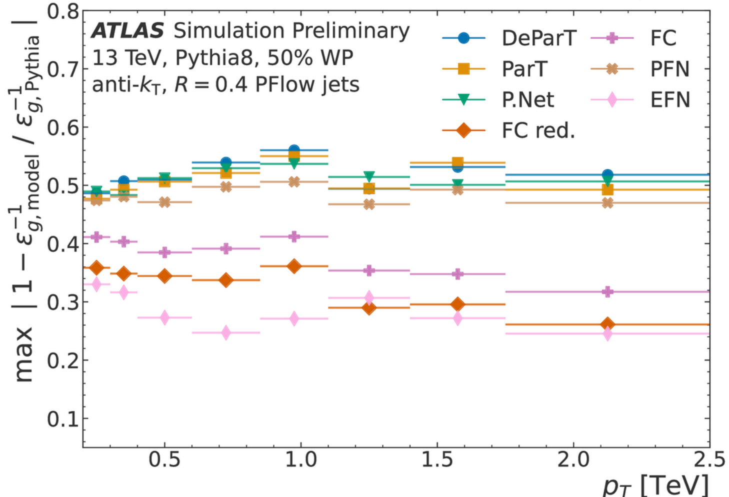


Quark vs gluon tagging

- Advanced constitutents-based taggers **outperform** jet-level taggers
  - except EFN



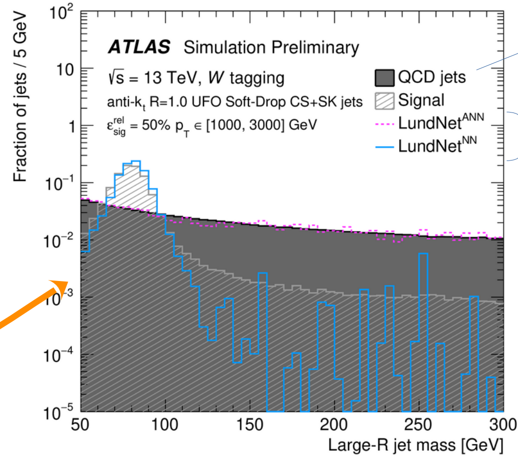
- Tested modelling sensitivity by comparing tagging efficiencies on different generators
- Advanced tagger are more sensitive



ATL-PHYS-PUB-2023-032

W tagging

- ML taggers shape the jet mass bkg distribution
  - very problematic when estimating bkg
  - Development of Adverserial NN to enforce mass/tagger decorrelation
- Use of physics motivated jet structure
  - **Lund jet plan** ↔ history of jet shower
  - allow to build meaningful graph of the jet → GNN
- Lund-plan tagging comparable to advanced constits-based taggers
  - and better than jet-level taggers
- Mass decorrelation decreases performance

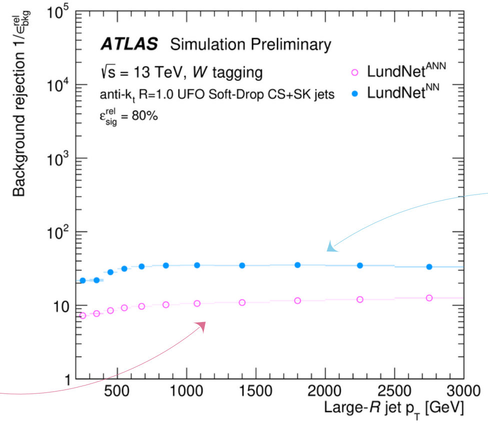


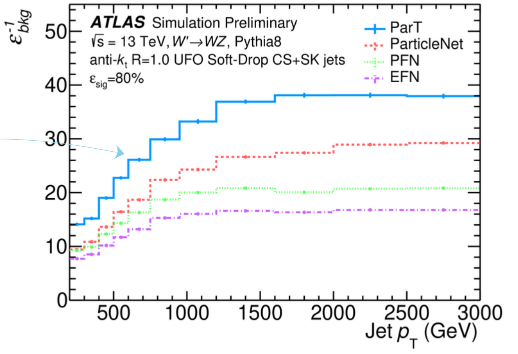
before tagging

after tagging

ATL-PHYS-PUB-2023-017

ATL-PHYS-PUB-2023-020





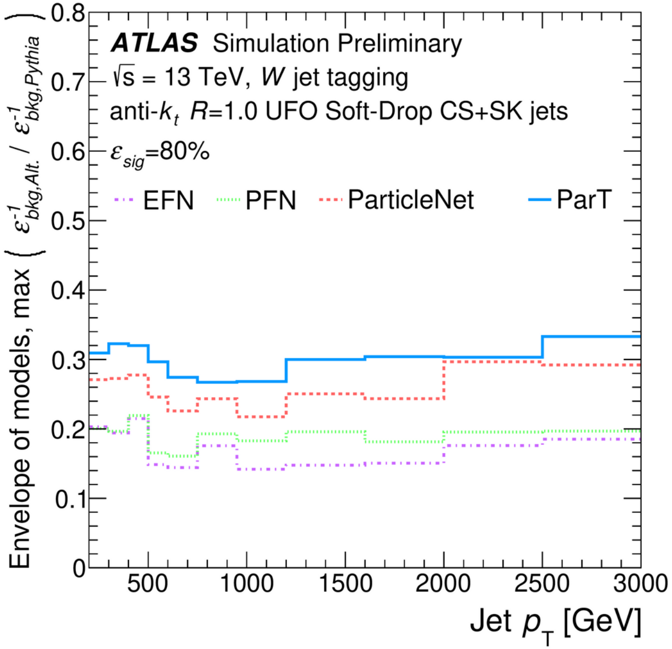
W tagging

- Sensitivity to modelling also tested :

better tagging performance

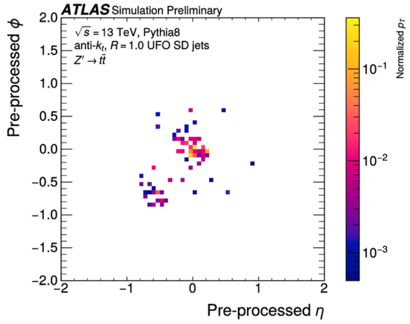
<==>

higher sensitivity to modelling

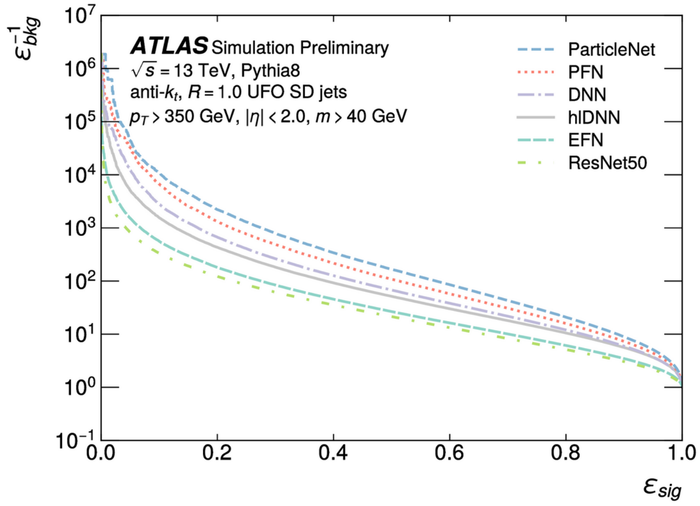


Top tagging

ATL-PHYS-PUB-2022-039



- Also testing Convolutional NN on "jet images" (**ResNet**)
  - obtained by mapping constits on a pixel grid
- Same tendencies : advanced constituents-based taggers perform better

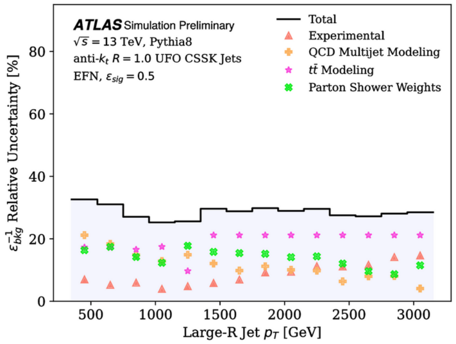


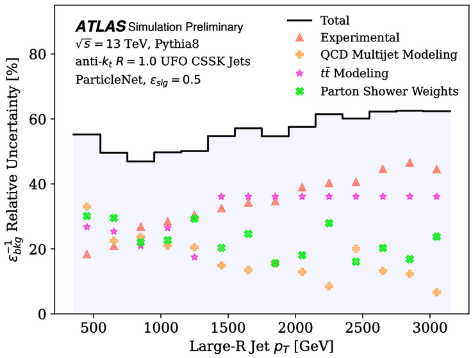
Top tagging

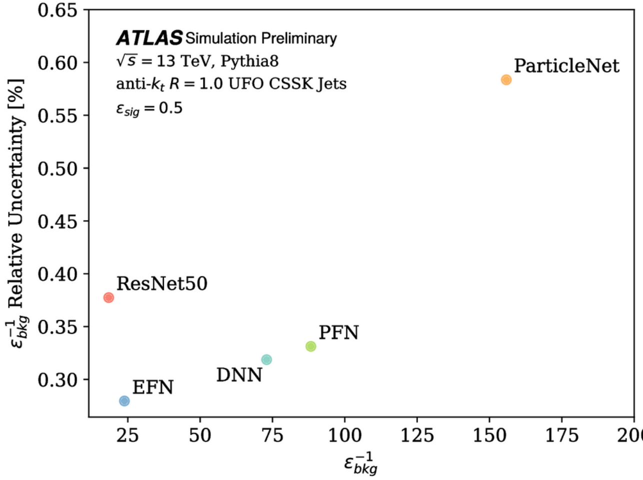
JETM-2023-004 (updated results to come soon!)

- First estimations of full uncertainties on rejection rate
  - propagating constit-level uncertainties+modelling

higher uncertainties for stronger tagger







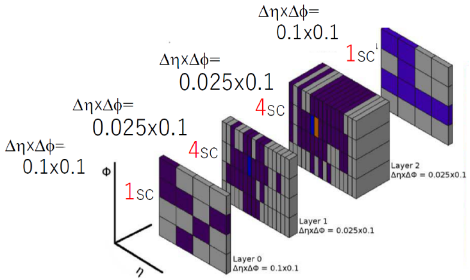
Conclusions

- After decades ATLAS continues to improve its hadronic jet reco chain
- Many recent and on-going works at every levels
  - from low-level cluster calibration…
  - … to reduced jet uncertainties
- ML tools are unavoidable
  - Promising performances in almost every domains
  - but also bring complexity and difficulties
    - in particular: uncertainties in jet tagging

Necessary for optimal physics analysis from precision measurements to BSM exploration … and to face HL-LHC challenges

Back-up

Low-level cluster calibration with ML



- Calorimeter clusters are build of many cells spatially connected
- can be represented as
  - images (1 cell= 1pixel)
  - point clouds (1 cell = 1 point)
  - graphs (1 cell = 1 node)

Convolutional NN

DeepSets / ParticleFlow Network

Graph NN

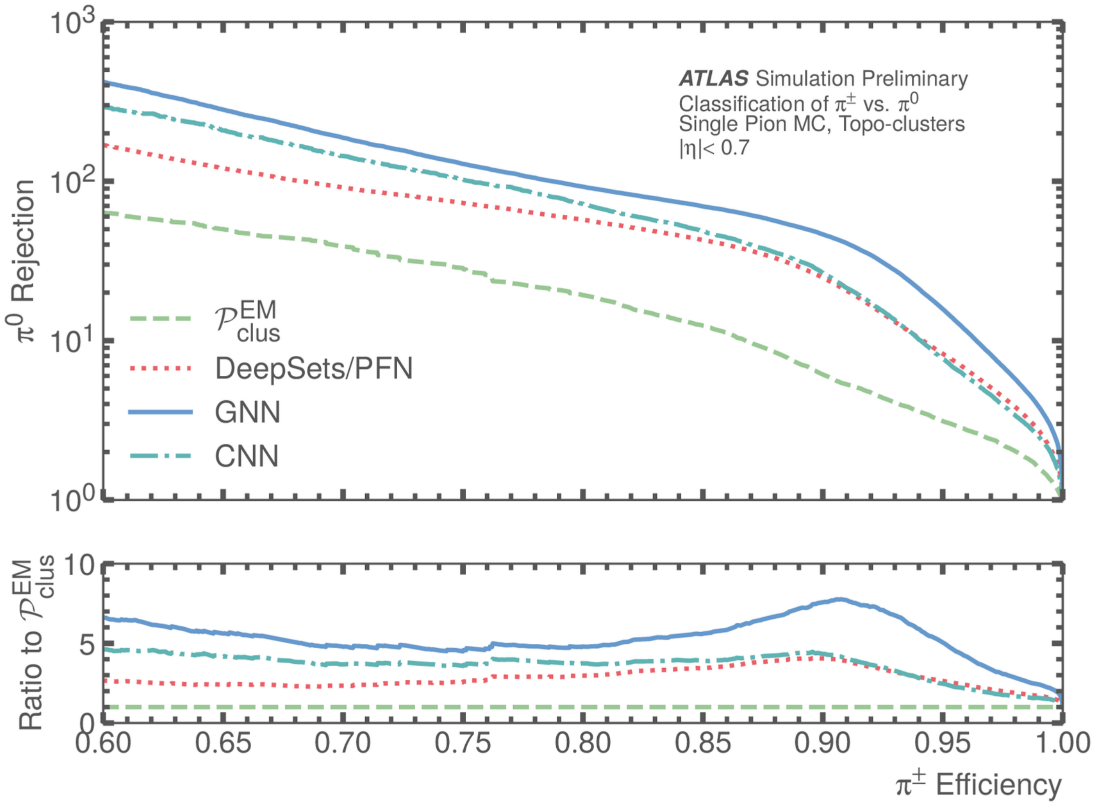
- Exploit advanced ML techniques to learn to classify and calibrate on **single pion simulated samples** (π^0,π^+,π^-)
  - charged π → hadronic showers
  - neutral π → EM showers

different calorimeter responses

Low-level cluster classification with ML

- Use ML to classify charged vs neutral pions
- Compare to standard ATLAS technique
  - cut based on cluster variables
  - "P^{EM}"

ML improves rejection by factor >5



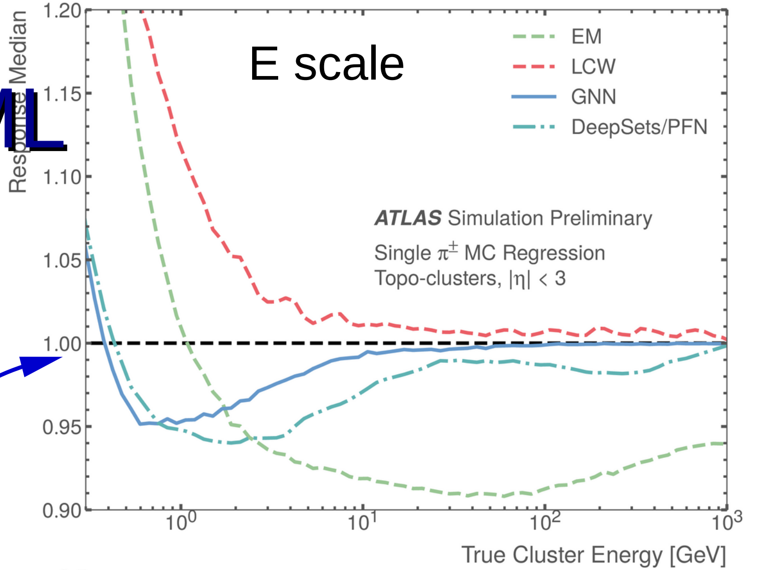
Low-level cluster calibration with ML

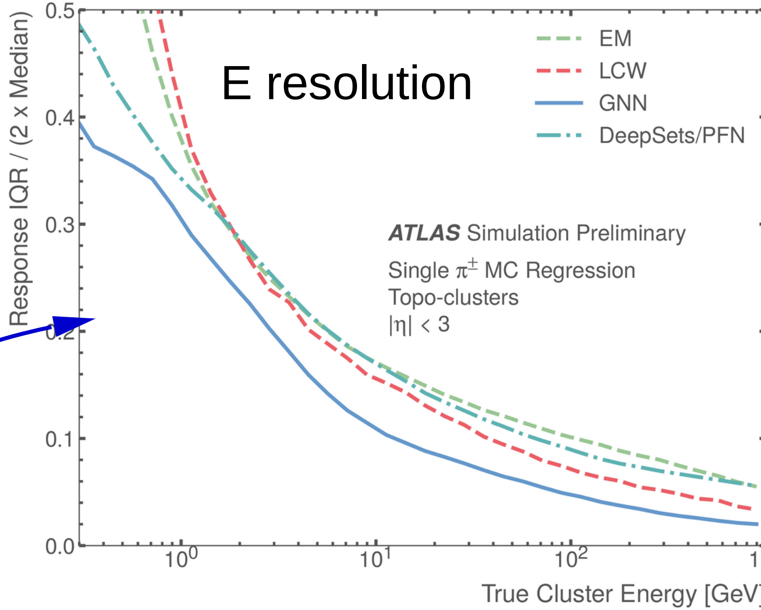
- Use ML to calibrate the hadronic response
  - Response : $< E_{reco}/E_{true} >$
- Compare to standard ATLAS uncalibrated (EM) and calibrated (LCW) clusters

ML improves significantly

scale

resolution



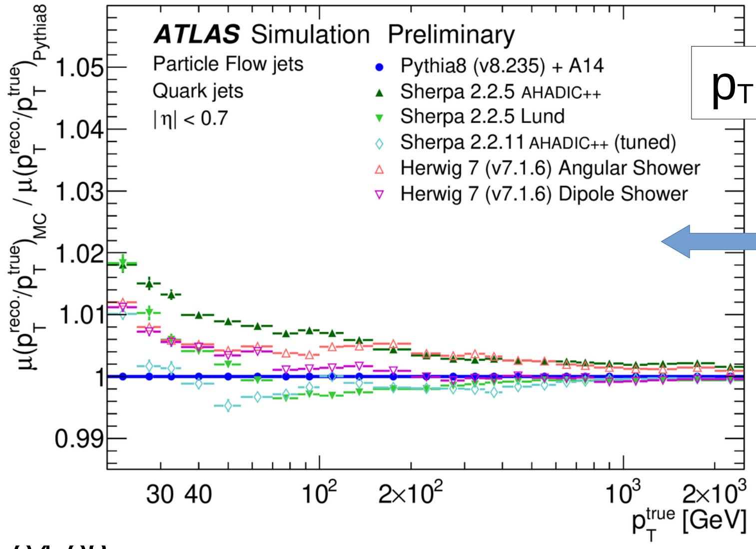


Hadronic flavour content impact on Jet Energy

ATL-PHYS-PUB-2022-021

Flavour impact on p_T response

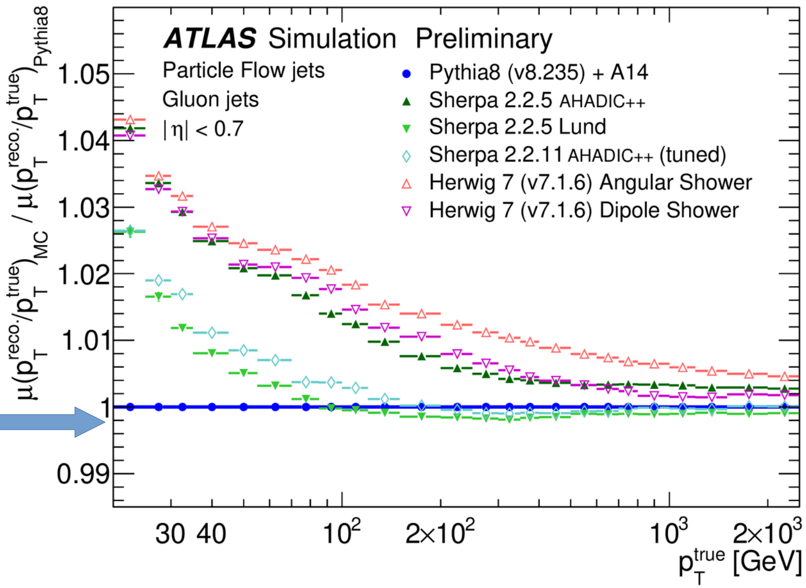
- p_T response differences in q-initiated vs g-initiated jets
- depends on MC generator
- Important contribution to Jet p_T uncertainty (mid to low-p_T)



p_T response w.r.t Pythia

quark jets

gluon jets



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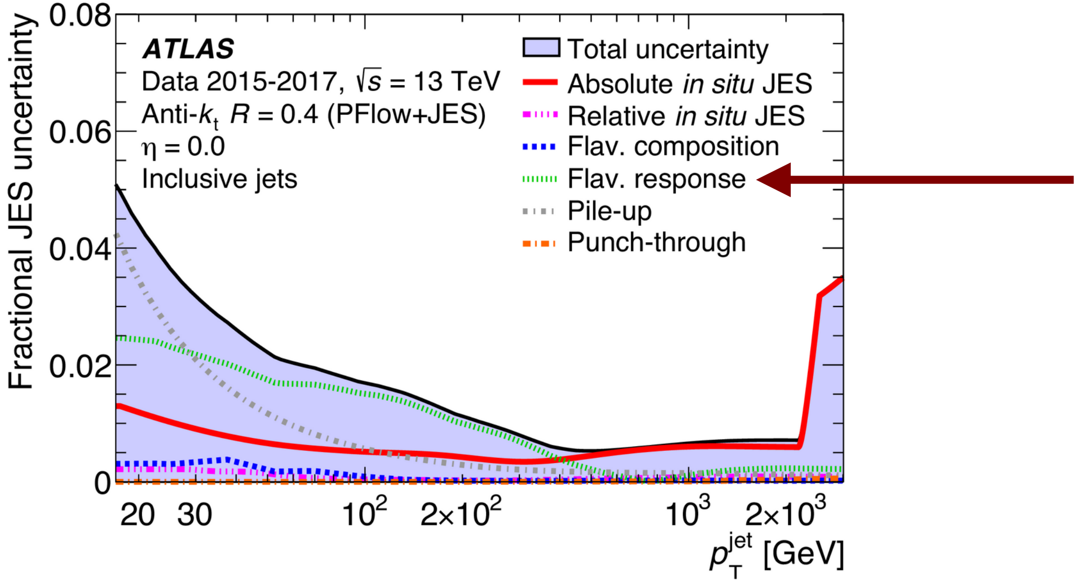
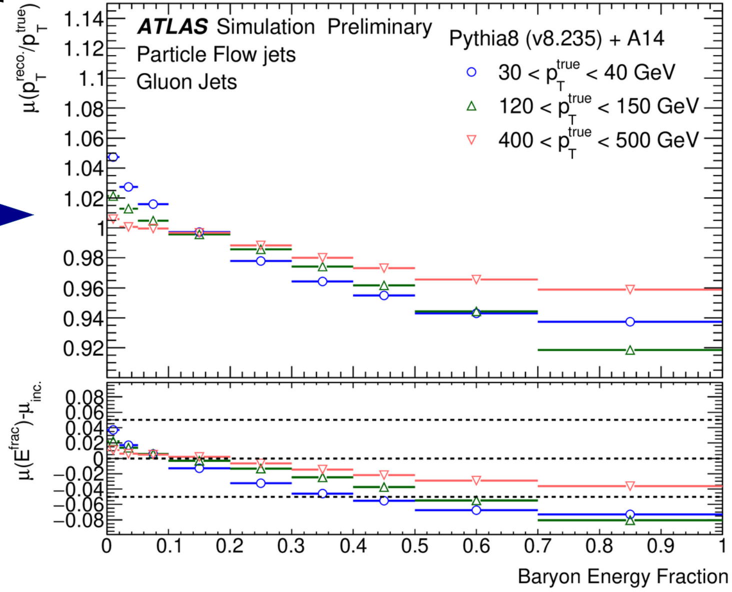
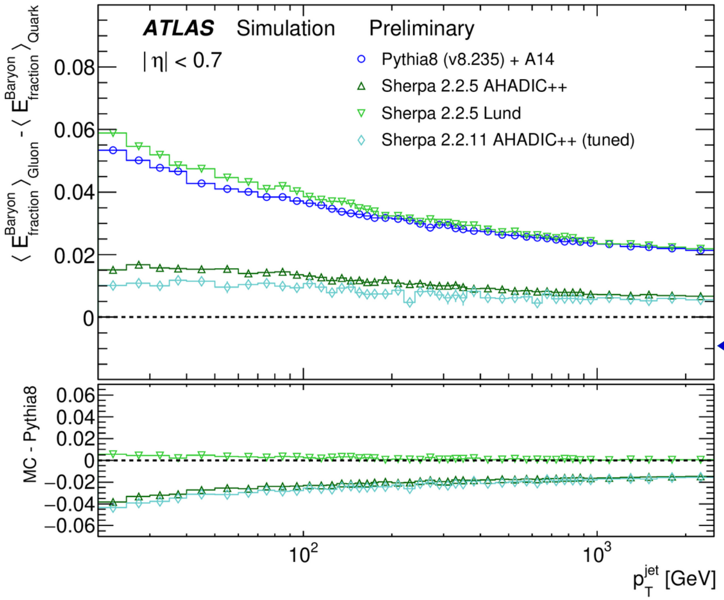


Understanding the different responses

- Jet response depends on the Baryon & Kaon E fraction





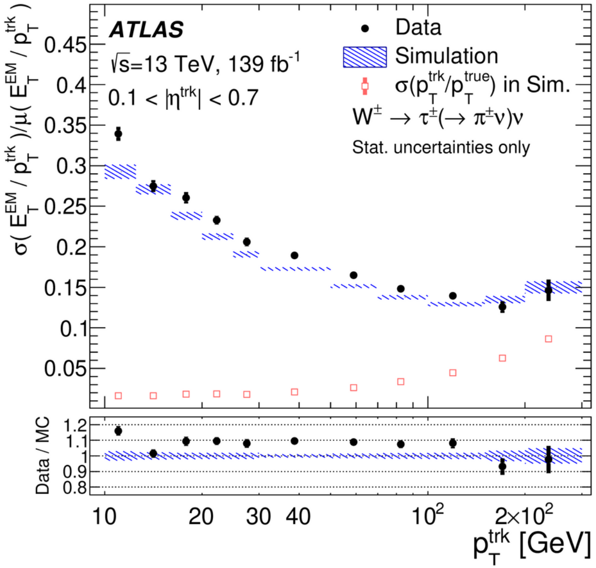
- These fractions vary with the generator
- and in quark vs gluon jets

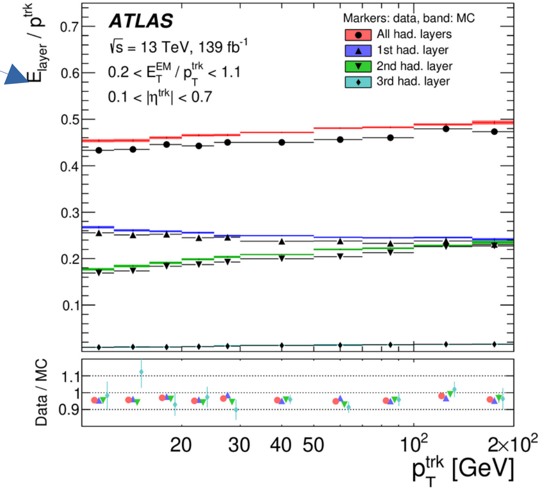
Understanding the different responses

- Impact of hadron content on jet response quantified for the 1st time
- Re-weighting baryon/kaon distributions reduces majority of differences across generators
- Motivates further generator tuning and measurements to better constraint uncertainties

Other hadronic measurements

- Response resolution
- longitudinal profile
- Important handles in
  - constraining jet E scales
  - τ lepton hadronic scale
  - jet substructure measurements
  - tune run3 response





Advanced constituents building to improve jet reconstruction

Impact on large-R jet building

Jet constituent type

X

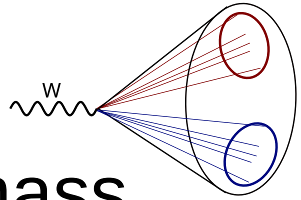
Pile-up mitigation method

X

Jet grooming algorithm

- Many different combinations studied
- Compared with different metrics
  - Jet E and M resolution
  - W/Z/top tagging performance
  - Pile-Up (PU) stability

Pile-Up dependence of Large-R jet Mass



- Number Primary Vertex (NPV) impact on W-jet mass

ATLAS Simulation
$\sqrt{s}$ = 13 TeV, $W \to q\bar{q}$

Anti-k_t R=1.0 jets, no jet calibrations applied
300 GeV $\leq p_T^{true} <$ 500 GeV, $|\eta^{true}| < 1.2$

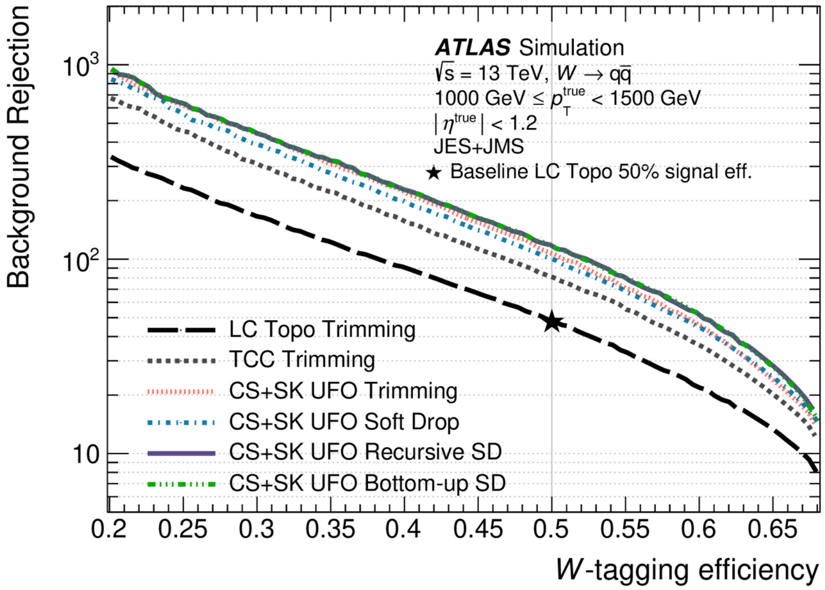
ATLAS choice

$\delta \langle m^{reco} \rangle / \delta N_{PV}$ [GeV]

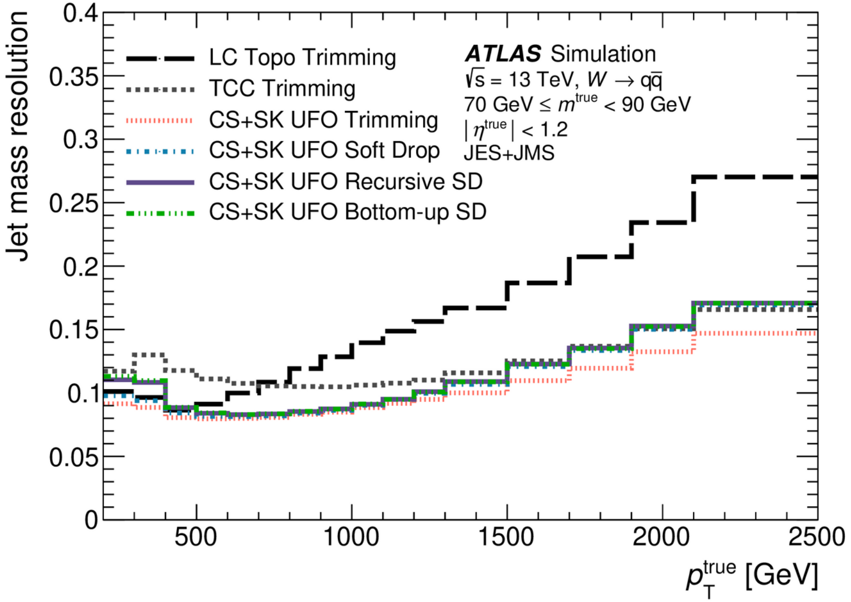
Jet Grooming Algorithm		LC Topo Unmodified	LC Topo CS+SK	PFlow Unmodified	PFlow CS+SK	PFlow PUPPI	TCC Unmodified	TCC CS+SK	UFO Unmodified	UFO CS+SK
Soft Drop	z_{cut} = 0.1, β = 0.0	0.74	0.02	0.24	0.06	0.12	-0.03	-0.27	0.23	0.06
	z_{cut} = 0.1, β = 1.0	1.99	0.03	0.29	0.06	0.12	0.18	-0.27	0.28	0.06
Recursive SD	z_{cut} = 0.05, β = 0.0, $N = \infty$	2.86	0.06	0.35	0.05	0.09	0.62	-0.22	0.33	0.04
	z_{cut} = 0.1, β = 0.0, $N = \infty$	0.37	0.01	0.08	0.02	0.05	-0.09	-0.20	0.08	0.02
	z_{cut} = 0.05, β = 1.0, $N = \infty$	3.35	0.16	0.95	0.11	0.14	0.86	-0.24	0.92	0.11
	z_{cut} = 0.1, β = 1.0, $N = \infty$	1.65	0.05	0.25	0.06	0.10	0.13	-0.25	0.24	0.05
	z_{cut} = 0.05, β = 0.0, N = 3	3.18	0.06	0.42	0.06	0.10	0.78	-0.23	0.39	0.05
	z_{cut} = 0.1, β = 0.0, N = 3	0.47	0.01	0.10	0.03	0.07	-0.09	-0.22	0.09	0.02
	z_{cut} = 0.05, β = 1.0, N = 3	3.41	0.16	0.99	0.11	0.14	0.91	-0.24	0.97	0.11
	z_{cut} = 0.1, β = 1.0, N = 3	1.64	0.04	0.26	0.06	0.10	0.15	-0.25	0.26	0.05
Bottom-up SD	z_{cut} = 0.05, β = 0.0	2.97	0.07	0.47	0.06	0.09	0.71	-0.22	0.43	0.05
	z_{cut} = 0.1, β = 0.0	0.46	0.02	0.10	0.03	0.05	-0.07	-0.20	0.09	0.02
	z_{cut} = 0.05, β = 1.0	3.37	0.17	0.96	0.11	0.14	0.89	-0.24	0.95	0.11
	z_{cut} = 0.1, β = 1.0	1.74	0.04	0.26	0.06	0.10	0.15	-0.25	0.24	0.05
Pruning	R_{cut} = 0.15, Z_{cut} = 0.25	0.27	0.00	0.11	0.02	0.04	-0.11	-0.19	0.10	0.01
Trimming	f_{cut} = 5%, R_{sub} = 0.1	-0.03	-0.04	-0.01	-0.02	0.00	-0.16	-0.18	0.01	0.00
	f_{cut} = 9%, R_{sub} = 0.1	-0.03	-0.05	-0.03	-0.04	-0.03	-0.13	-0.16	-0.01	-0.02
	f_{cut} = 5%, R_{sub} = 0.2	★ 0.14	-0.01	0.07	0.02	0.06	-0.21	-0.25	0.06	0.02
	f_{cut} = 9%, R_{sub} = 0.2	0.10	-0.03	0.05	0.01	0.05	-0.20	-0.25	0.05	0.00

Jet Constituent Type

Large-R W&top tagging & mass resolution



UFO constituent **improves background rejection** by **factor 2**



UFO constituent : **improved** mass resolution **for all p_T**