Hadronic Reconstruction with the ATLAS Detector at the LHC

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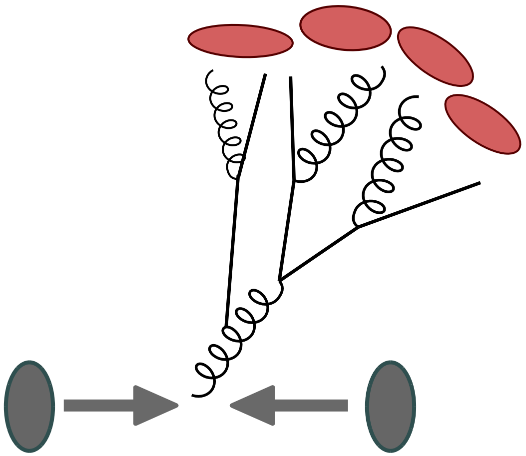
ICHEP 2022

Hadronic jets at the LHC

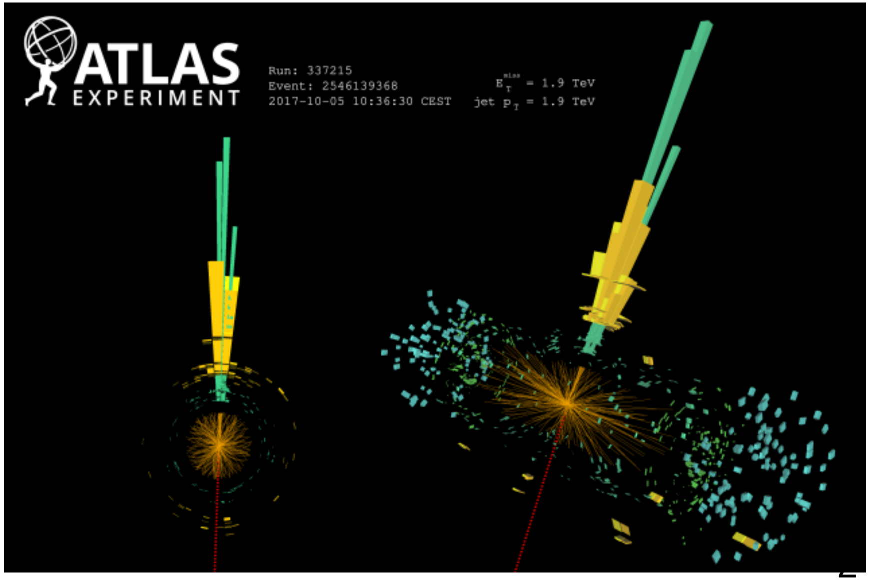


Hadronic jets

- 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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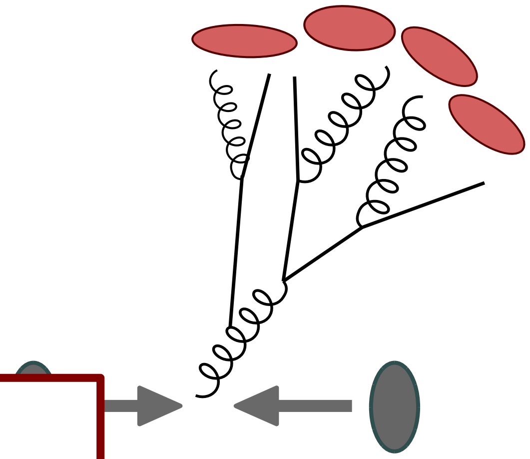
Hadronic jets at the LHC

Hadronic jets

- Phenomena resulting of a parton emission
- Ubiquitous in

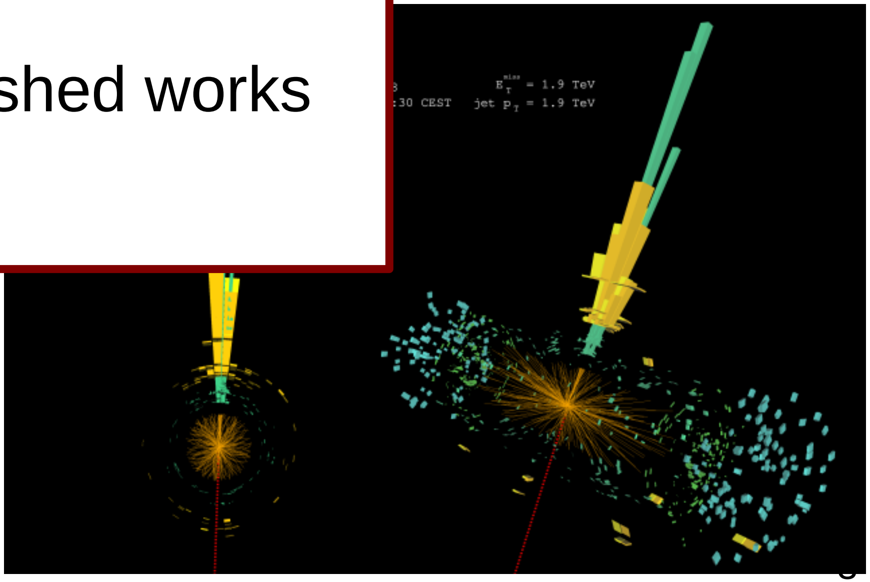


This talk

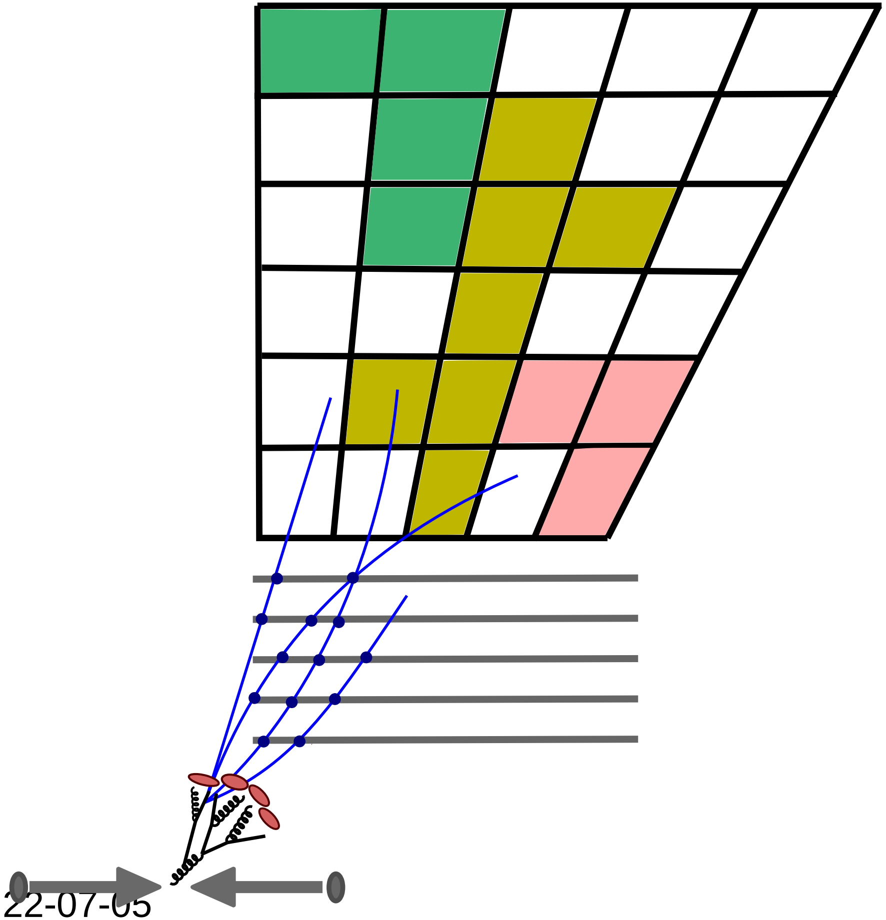
selection of 5 recent published works & results

Continuous work

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



Jet reconstruction with ATLAS



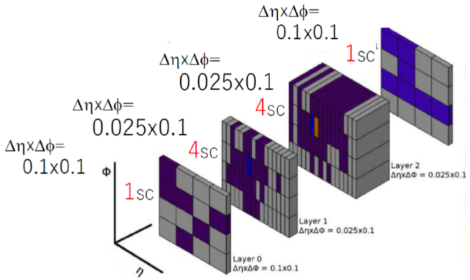
- Jet constituents: set of 4-vectors representing the hadronic flow. Build from
  - Calorimeter clusters
  - Tracks

- Reconstruct jets
  - Group constituents with a proper Jet Algorithm
  - Apply "grooming" (PU mitigation)
  - Calibrate E and M

Calorimeter cluster classification and calibration with Machine Learning (ML)

ATL-PHYS-PUB-2020-018 and JETM-2022-002

Cluster calibration with ML



- Calo 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

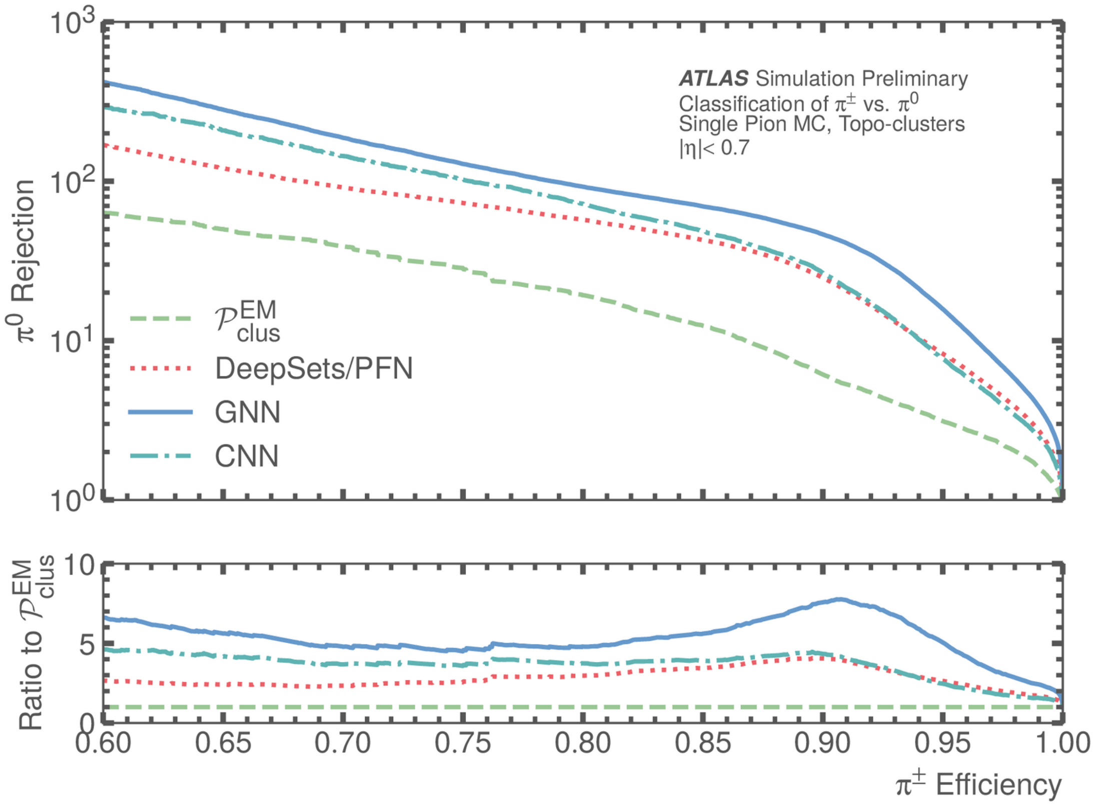
- Exploit advanced ML techniques to learn to classify and calibrate on **single pion simulated samples** (π^0,π^+,π^-)
  - charged π → hadronic showers
  - neutral π → EM showers

different calorimeter responses

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



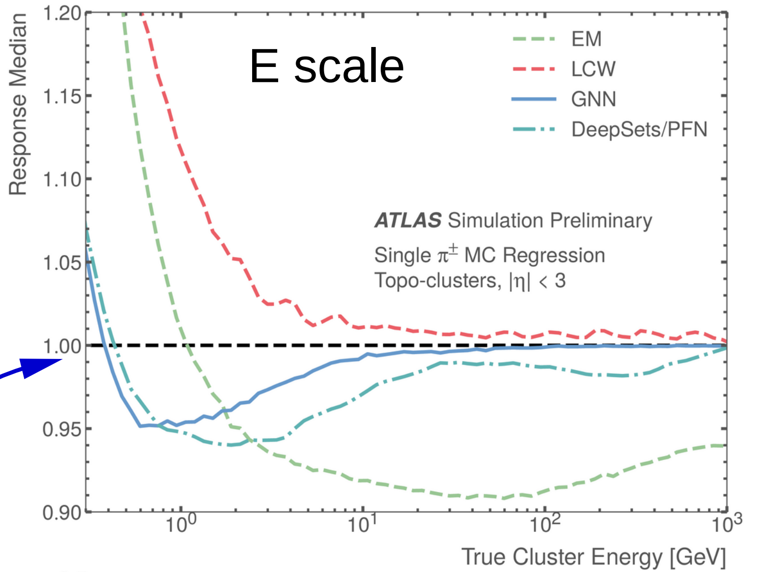
Cluster calibration with ML

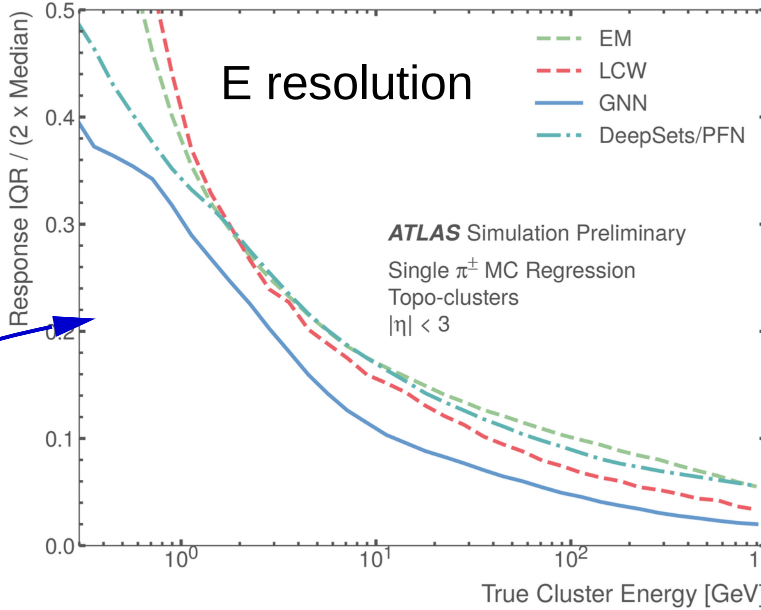
- Use ML to calibrate the hadronic response
  - Response : distribution of $r = E_{reco}/E_{true}$
- Compare to standard ATLAS uncalibrated (EM) and calibrated (LCW) clusters

ML improves significantly

scale

resolution





Measuring hadronic response in data

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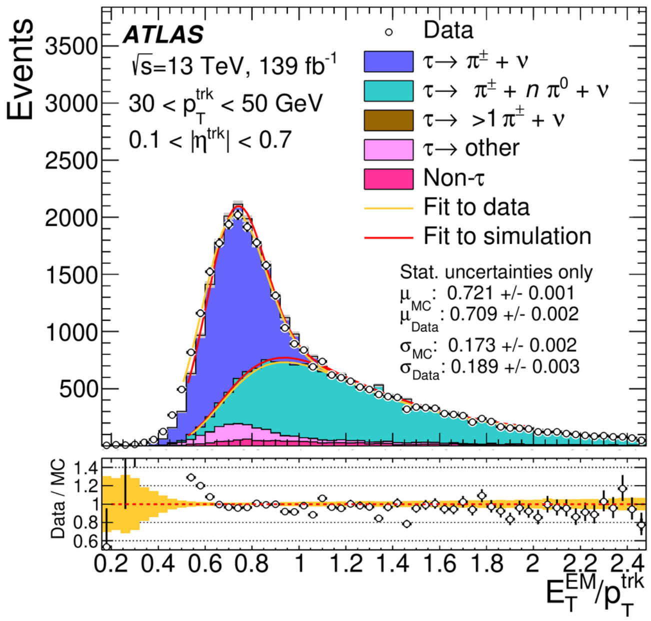
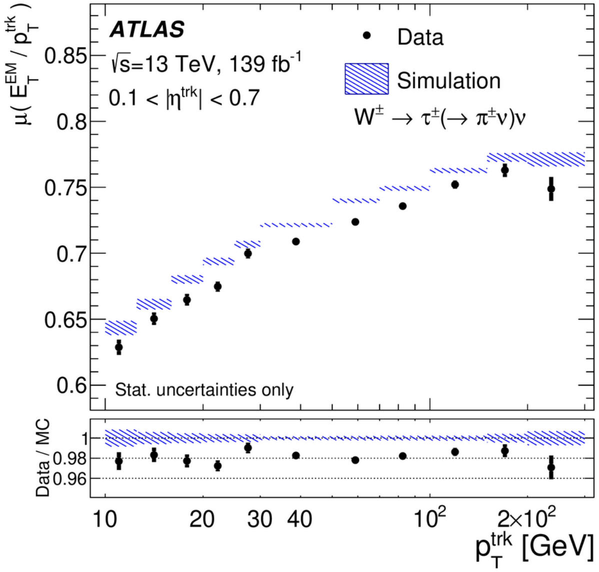
Measuring hadronic response

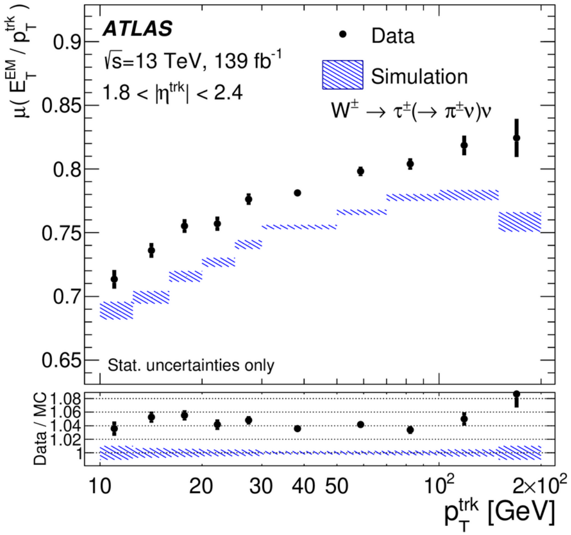
- Select $W \rightarrow \tau\, \nu_\tau \rightarrow \pi \nu_\tau \nu_\tau$ events
  - by requiring isolated tracks matched to hadronic clusters
  - Calculate E as sum E of clusters within $\delta R<0.15$
- Fit $E_{T(clus)}/p_{T(trk)}$ to measure hadronic response
- Study response scale, resolution, longitudinal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



Hadronic scale in data

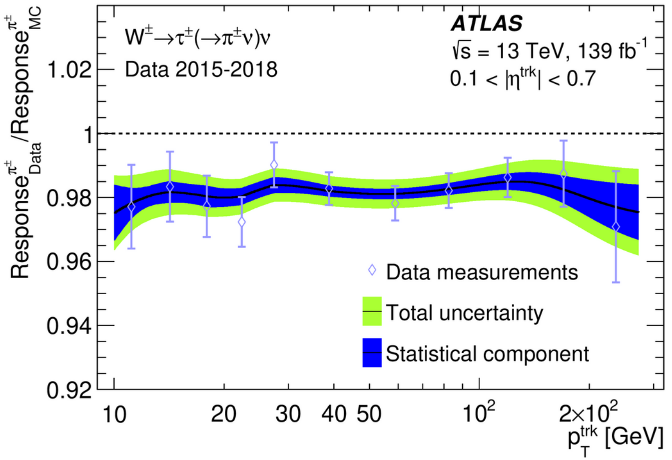
- Hadronic scale measured with good precision
  - <1% up to p_T=185GeV in barrel
    - <0.6% up to 120GeV
- Scale ~2% under-estimated in central, ~4% over-estimated in forward
  - consistent with other measurements

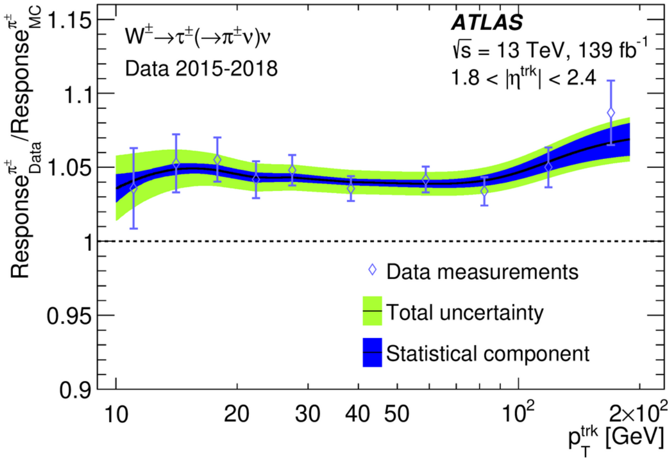




Hadronic scale in data

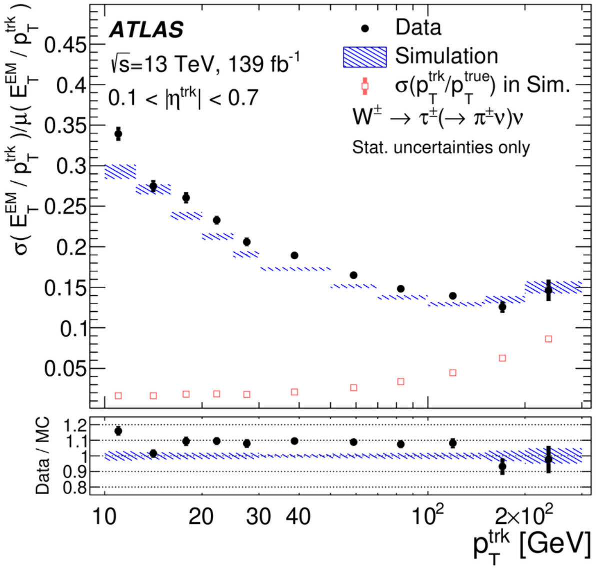
- Hadronic scale measured with good precision
  - <1% up to p_T=185GeV in barrel
    - <0.6% up to 120GeV
- Scale ~2% under-estimated in central, ~4% over-estimated in end-cap
  - consistent with other measurements

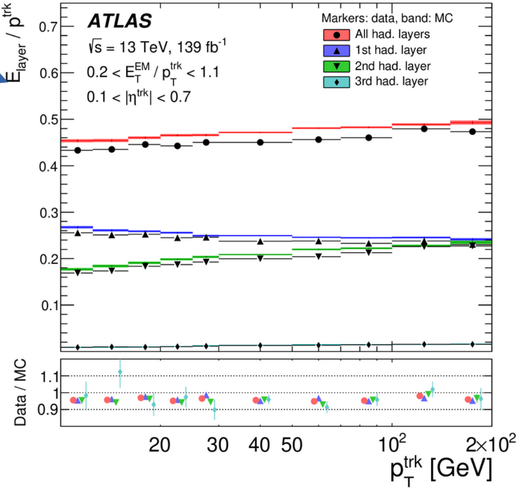




Other hadronic measurements

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





Improving large-R jet building

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Jet constituents building

- How to combine Tracks & cluster to build constituents ?

Tracks

LCTopo
calibrated calo **clusters**

Combined objects

Particle Flow (**PFlow**)

tracks (low-p_T)
complemented with E from clusters

TrackCaloCluster (**TCC**)

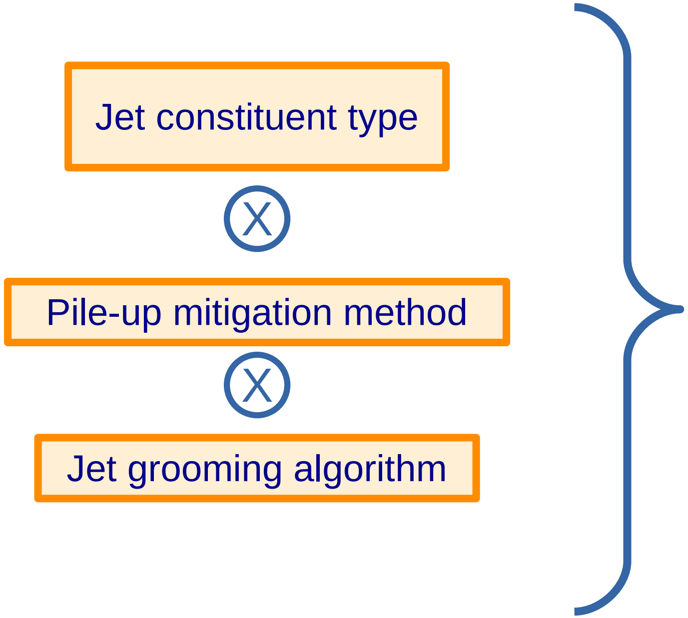
CaloClusters Energies
re-positioned on angular positions of matched tracks

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

Combine advantages :

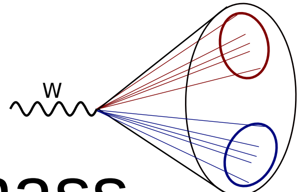
- Best p_T resolution at all regime
  - low p_T, charged $\rightarrow$ from tracker
  - high p_T $\rightarrow$ from calo
- Best angular resolution for ALL charged

Large-R jet building



- 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, $|\eta^{true}| < 1.2$

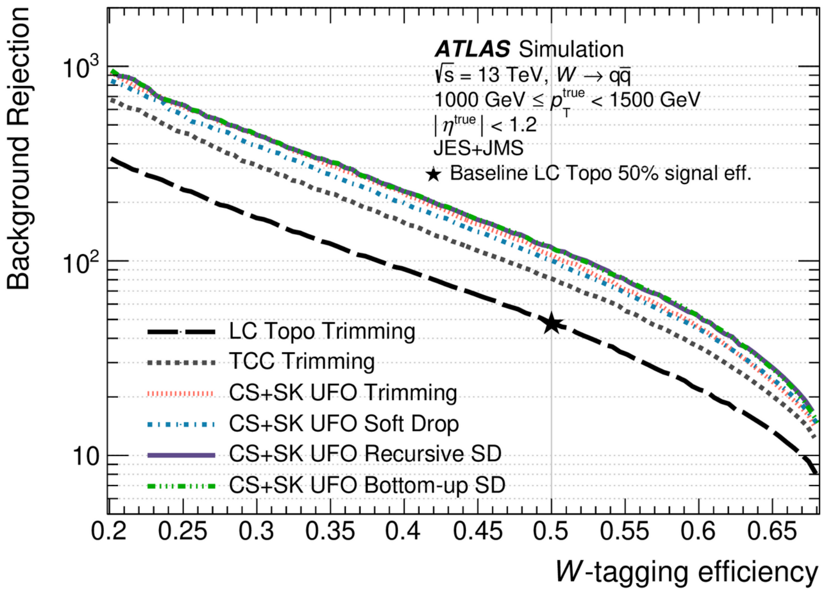
ATLAS choice

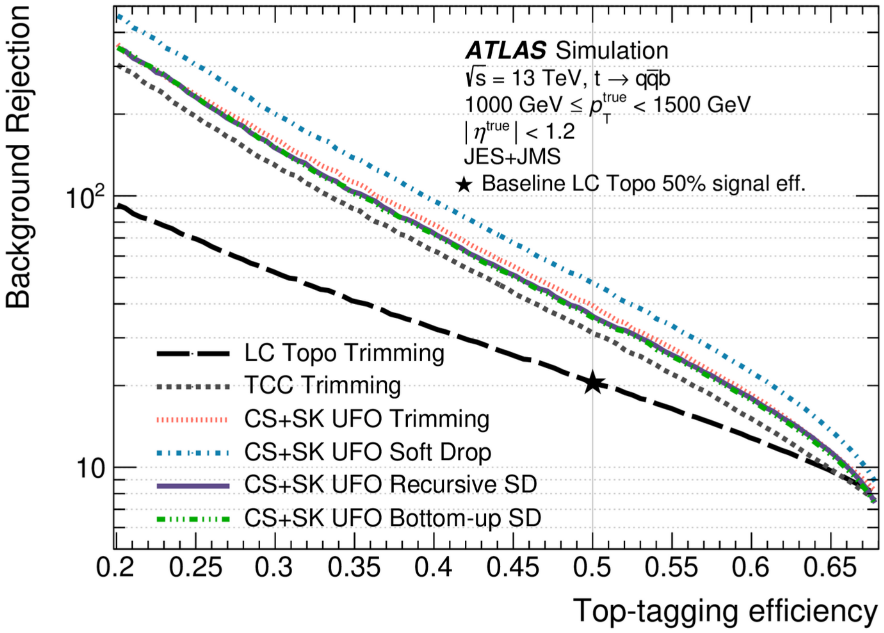
$\delta \langle m^{reco} \rangle / \delta N_{PV}$ [GeV]

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	$z_{cut} = 0.1, \beta = 0.0$	0.74	0.02	0.24	0.06	0.12	-0.03	-0.27	0.23	0.06
	$z_{cut} = 0.1, \beta = 1.0$	1.99	0.03	0.29	0.06	0.12	0.18	-0.27	0.28	0.06
Recursive SD	$z_{cut} = 0.05, \beta = 0.0, N = \infty$	2.86	0.06	0.35	0.05	0.09	0.62	-0.22	0.33	0.04
	$z_{cut} = 0.1, \beta = 0.0, N = \infty$	0.37	0.01	0.08	0.02	0.05	-0.09	-0.20	0.08	0.02
	$z_{cut} = 0.05, \beta = 1.0, N = \infty$	3.35	0.16	0.95	0.11	0.14	0.86	-0.24	0.92	0.11
	$z_{cut} = 0.1, \beta = 1.0, N = \infty$	1.65	0.05	0.25	0.06	0.10	0.13	-0.25	0.24	0.05
	$z_{cut} = 0.05, \beta = 0.0, N = 3$	3.18	0.06	0.42	0.06	0.10	0.78	-0.23	0.39	0.05
	$z_{cut} = 0.1, \beta = 0.0, N = 3$	0.47	0.01	0.10	0.03	0.07	-0.09	-0.22	0.09	0.02
	$z_{cut} = 0.05, \beta = 1.0, N = 3$	3.41	0.16	0.99	0.11	0.14	0.91	-0.24	0.97	0.11
	$z_{cut} = 0.1, \beta = 1.0, N = 3$	1.64	0.04	0.26	0.06	0.10	0.15	-0.25	0.26	0.05
Bottom-up SD	$z_{cut} = 0.05, \beta = 0.0$	2.97	0.07	0.47	0.06	0.09	0.71	-0.22	0.43	0.05
	$z_{cut} = 0.1, \beta = 0.0$	0.46	0.02	0.10	0.03	0.05	-0.07	-0.20	0.09	0.02
	$z_{cut} = 0.05, \beta = 1.0$	3.37	0.17	0.96	0.11	0.14	0.89	-0.24	0.95	0.11
	$z_{cut} = 0.1, \beta = 1.0$	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

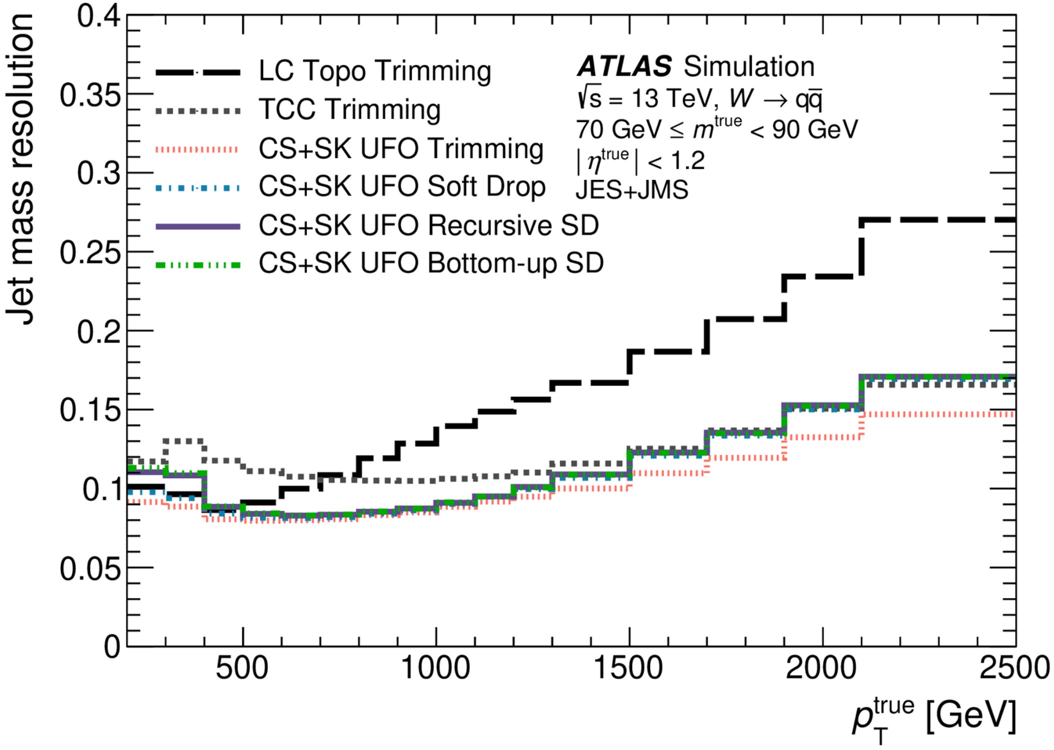
Large-R W&top tagging performances





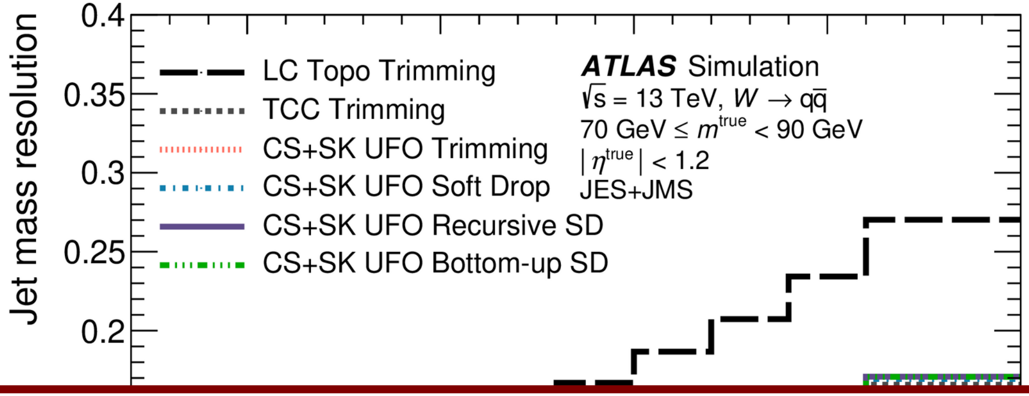
Choice of UFO constituent **improves background rejection** by **factor 2**

Large-R jet mass resolution



mass resolution optimal on full range for UFO-based jets

Large-R jet mass resolution



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

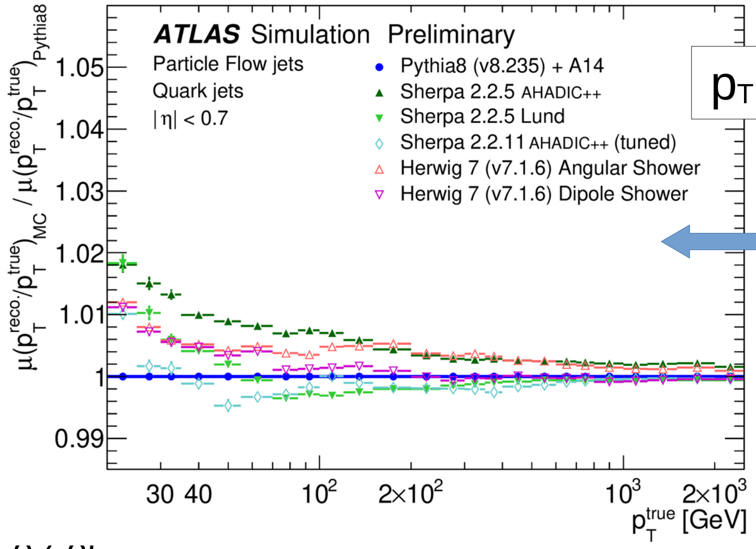
mas… jets

Hadronic flavour content impact on Jet Energy

ATL-PHYS-PUB-2022-021

Flavour impact on p_T response

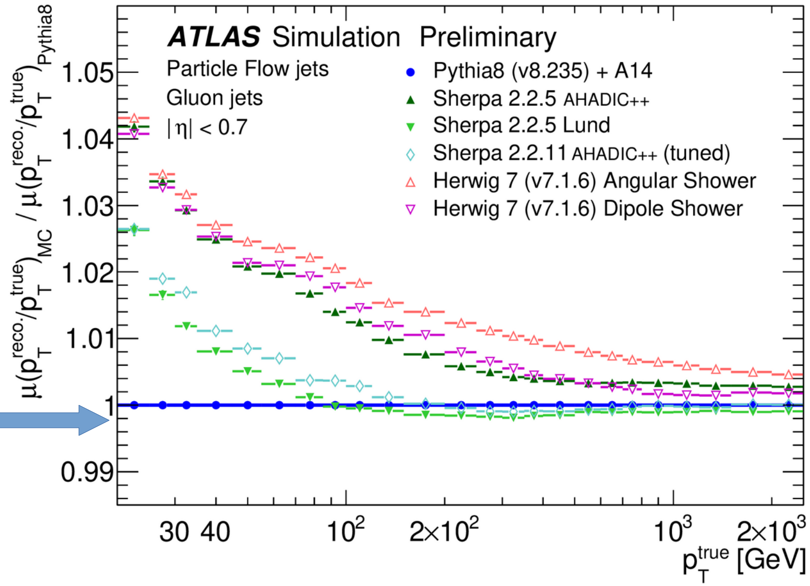
- p_T response differences in q-initiated vs g-initiated jets
- depends on MC generator
- Important contribution to Jet p_T uncertainty (mid to low-p_T)



p_T response w.r.t Pythia

quark jets

gluon jets



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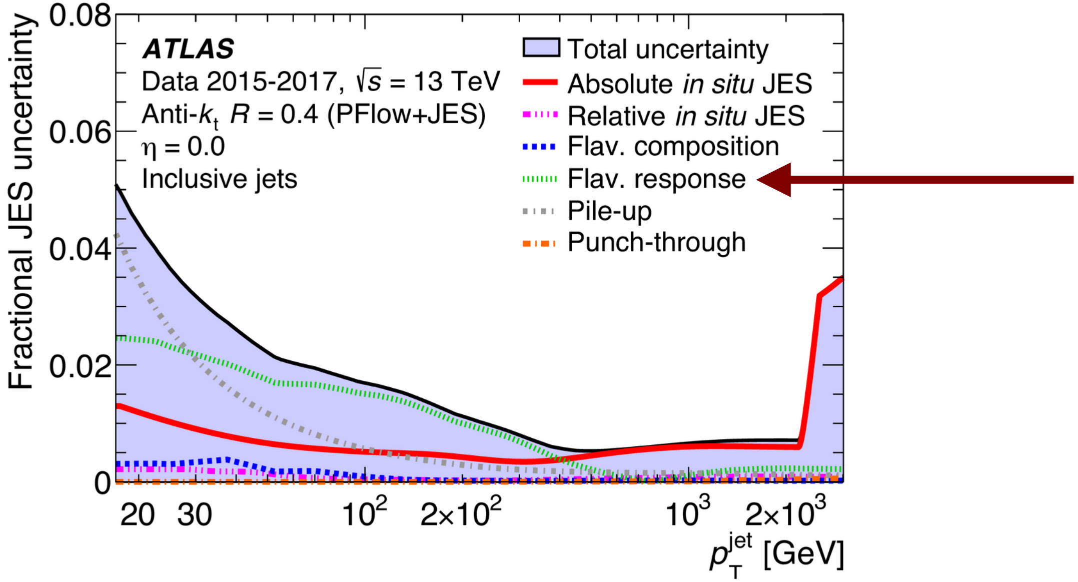
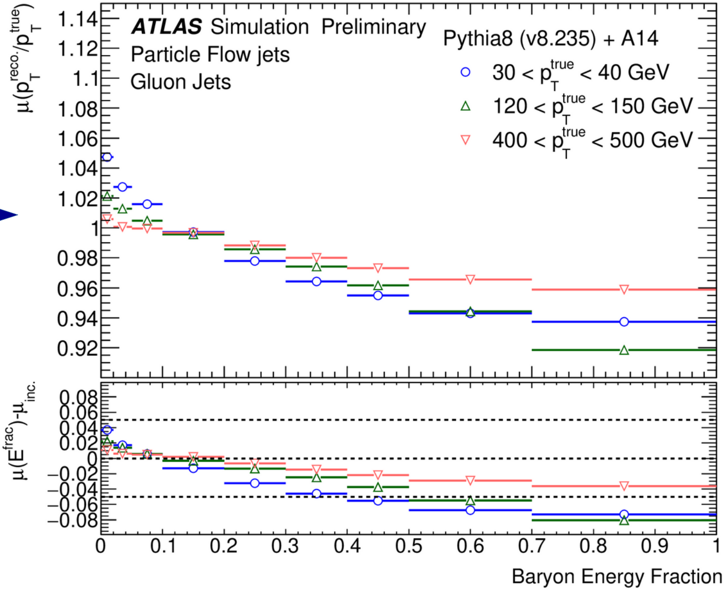
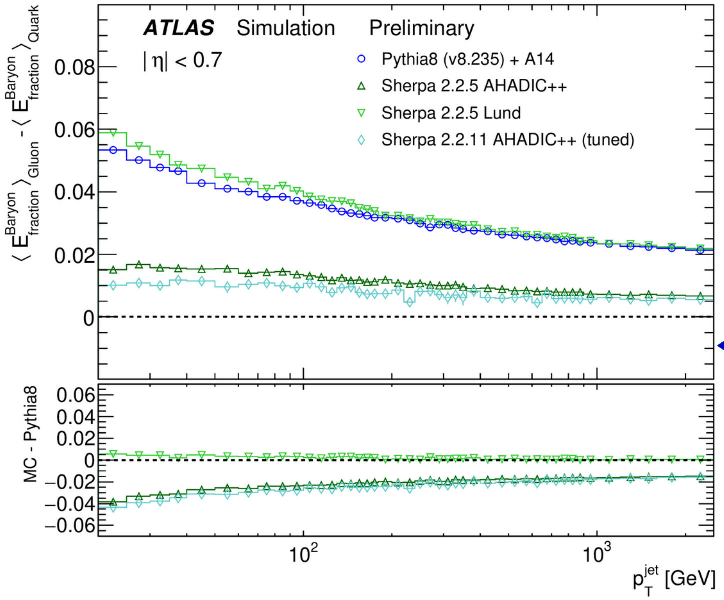


Understanding the different responses

- 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 1^{st} time
- Re-weighting baryon/kaon distributions reduces majority of differences across generators
- Motivates further generator tuning and measurements to better constraint uncertainties

Improving Missing p_T with ML

ATL-PHYS-PUB-2021-025

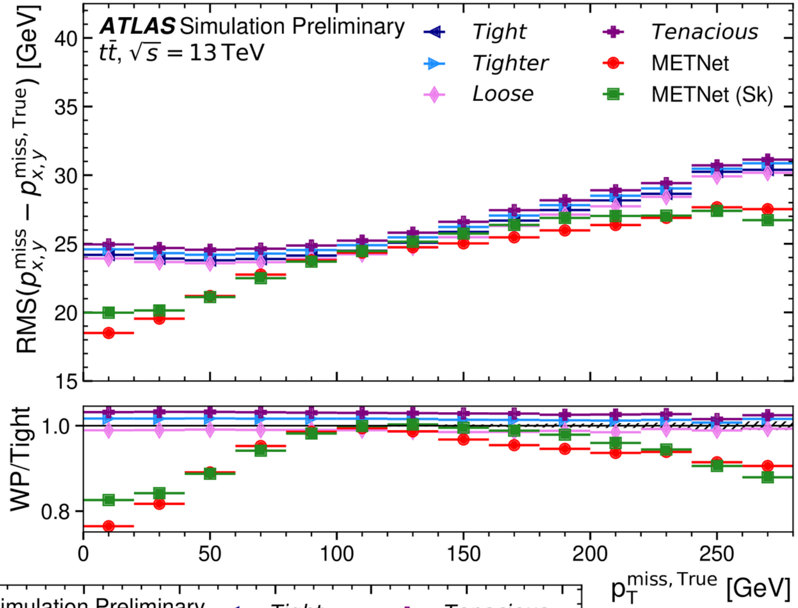
Missing p_T reconstruction with ML

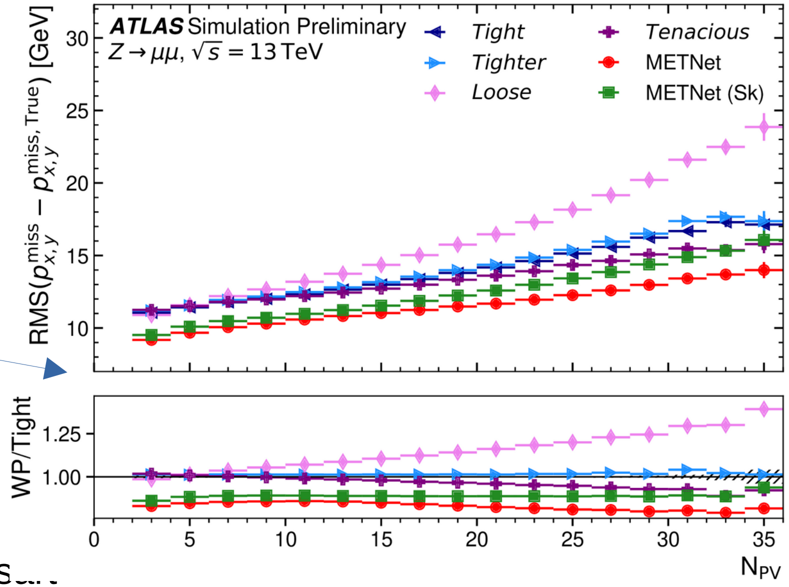
- ATLAS provides different Working Points for p_{Tmiss}
  - ex: reject p_{Tmiss} vs use in calculations such as m_T
  - different use cases ↔ different jet selection entering p_{Tmiss} definition ↔ different sensitivity to PU
- Use all WP inputs+other event-level variables to perform NN regression of p_{xmiss} & p_{ymiss}
- Train on mix of samples with various p_{Tmiss} topologies
  - $t\bar{t}$, $ZZ \rightarrow \nu\nu ll$, $WW \rightarrow \nu l \nu l$

→ **METNet** network

METNet performances

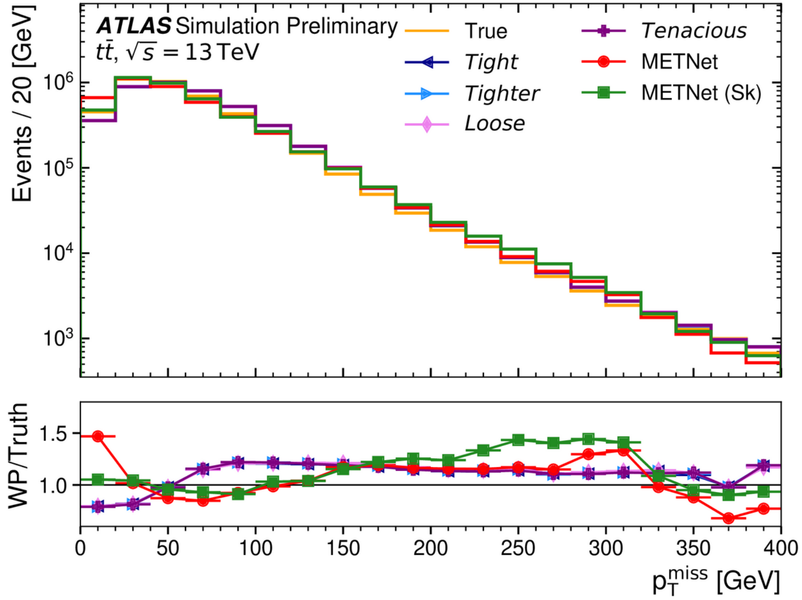
- Compare NN prediction to standard WP
  - vs p_{Tmiss}
  - vs NPV (PU sensitivity)
- Better resolution in all cases
- Including on Z→ μμ not used during training

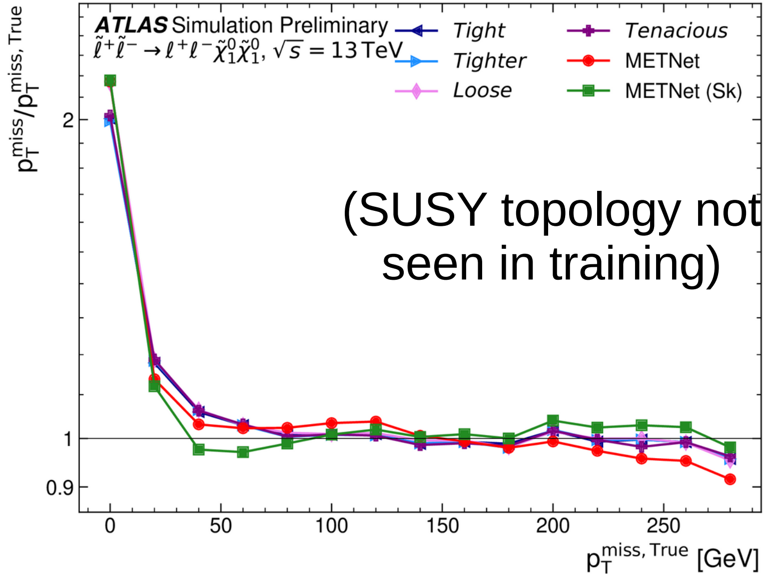




METNet performances

- Good $p_{T miss}$ response and distribution bias
  - Use of additional "Sinkhorn" loss can help with tails
- Promising technique
  - W.i.P , can be refined (ex, including track information)
  - Seem adaptable to any topology





Conclusions

- After decades ATLAS continues to refine its hadronic and p_{Tmiss} reconstruction
- Many recent and on-going works at every levels
  - from low-level cluster calibration…
  - … to jet uncertainties
- Using more and more powerful ML tools
  - but also exploring leftover details

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