# Tagging of hadronically decaying massive particles in ATLAS

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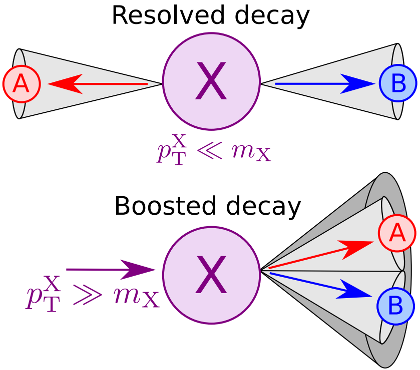
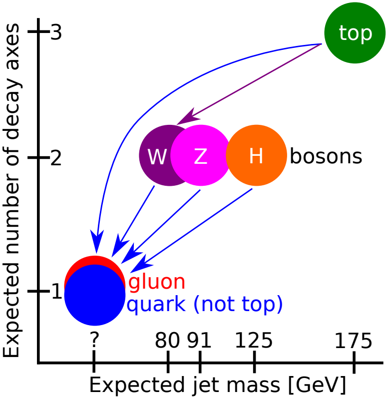
# Introduction

- There are many types of massive particles that can decay hadronically
  - This talk: the identification of boosted hadronic W, Z, and top decays
  - See Wednesday's talk by R. Jacobs for X→bb (including H→bb) and b/c-jet tagging

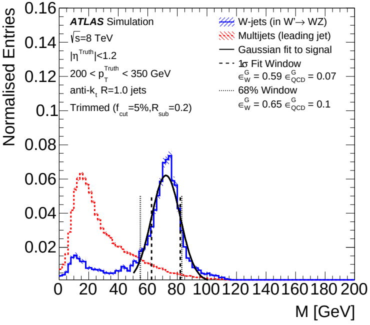


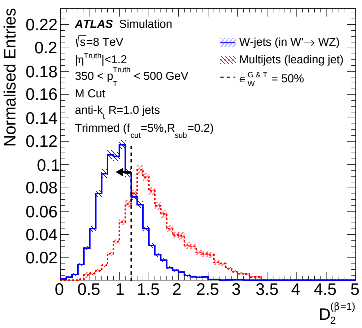



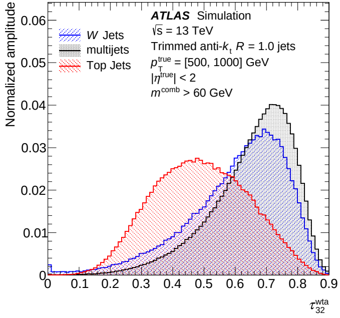
# Designing W/Z/top taggers

Left: PERF-2015-03
Middle: PERF-2015-03
Right: JETM-2018-03

- To first order, designing a tagger is as straightforward as the previous slide
  - Cut on the jet mass and other substructure variable(s) correlated to the number of decay axes
  - Common variables: $D_2^{(\beta=1)}$ for two-body decays (W/Z), $\tau_{32}^{\mathrm{WTA}}$ for three-body decays (top)
- Such a simple two-variable cut-based tagger provides a powerful starting reference



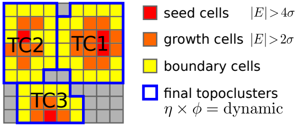



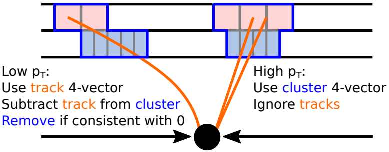
# Large-R jet reconstruction and tagging

- Primarily use trimmed ($R_{\mathrm{sub}} = 0.2$, $f_{\mathrm{cut}} = 5\%$) anti-$k_t$ $R = 1.0$ jets with LC cluster inputs
  - As seen in C. Wanotayaroj's talk from this morning, this is evolving
- This talk will focus on this dominantly used jet type, with some exceptions
  - First PFO results available (this talk), while TCCs are already used in high $p_{\mathrm{T}}$ searches
- The way in which you build the large-R jet **does matter** for the tagger performance

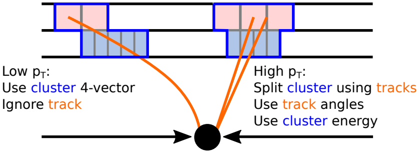
Topo-clusters (EM or LC)
[Most ATLAS results]




Particle Flow Objects (PFOs)
[First studies in this talk]

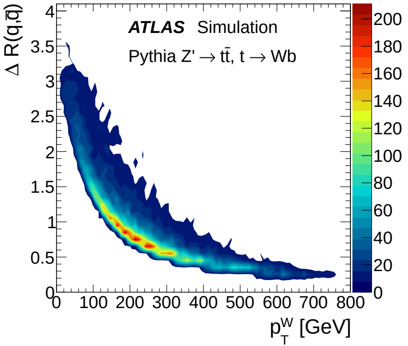


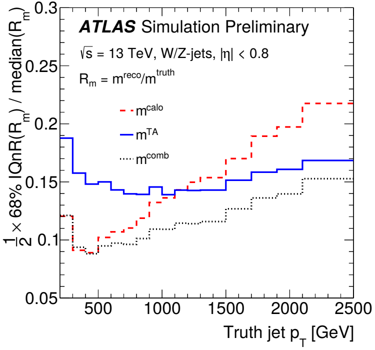

Track-CaloClusters (TCCs)
[Used for highest $p_{\mathrm{T}}$ results]



# Why jet inputs matter for tagging

- As the boost of the system increases, so does the collimation of the decay products
  - $\Delta R \approx 2m/p_{\mathrm{T}} \implies$ for a W boson with $p_{\mathrm{T}} = 1.6\,\mathrm{TeV}$, $\Delta R \approx 0.1$
  - ATLAS calorimeter barrel cell sizes in $\eta \times \phi$: $0.025 \times 0.025$ (EM), $0.1 \times 0.1$ (hadronic)
- The calorimeter loses its angular resolving power, but the tracker can help
  - $m^{\mathrm{TA}} = m^{\mathrm{track}} \cdot p_{\mathrm{T}}^{\mathrm{calo}} / p_{\mathrm{T}}^{\mathrm{track}}$, and $m^{\mathrm{comb}} = A \cdot m^{\mathrm{calo}} + B \cdot m^{\mathrm{TA}}$

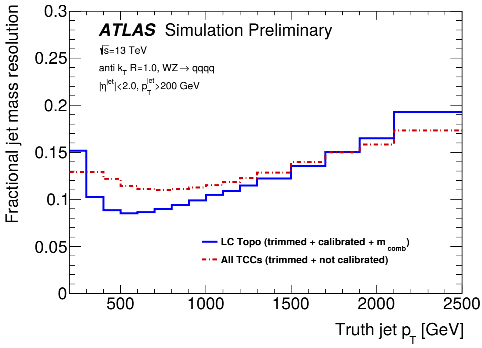


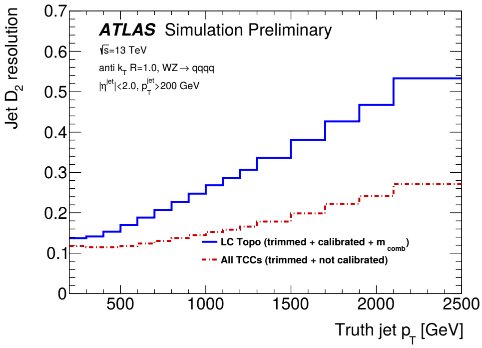



# Focusing on the high $p_T$ regime

Both: PUB-2017-015

- As mentioned earlier, TCCs split and assign cluster energy to matching track(s)
  - Degrades low $p_T$ mass performance vs $m_{comb}$, but significantly improves $D_2$ at high $p_T$
  - Recall that our simple reference W/Z tagger cuts on mass and $D_2$
- Jets built from TCCs support powerful taggers at high $p_T$; LC jets are better at low $p_T$

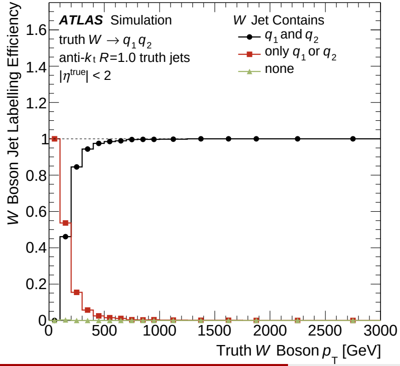


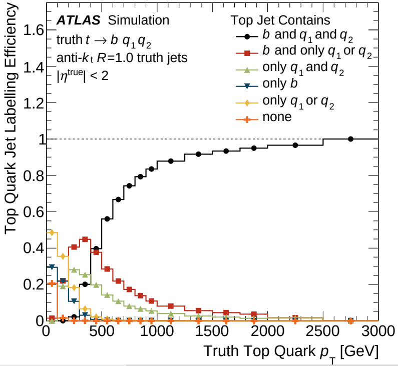



# Defining the tagger target

Both: JETM-2018-03

- Taggers are typically defined with respect to a truth definition of the object of interest
  - W/Z jet: jet is matched to a truth W/Z boson and both quark decay products ($q_1$&$q_2$)
  - Top jet: jet is matched to a truth top quark and all three quark decay products ($b$&$q_1$&$q_2$)
- We typically optimize with respect to these "contained" truth labels, vs QCD background

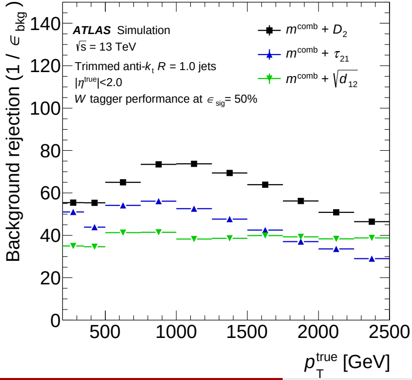


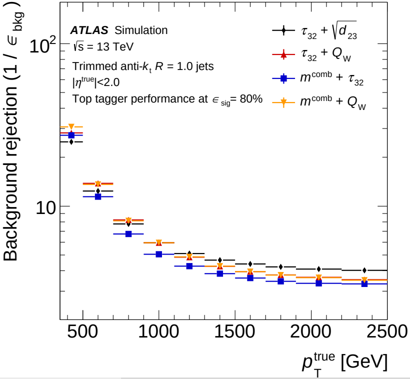



# Revisiting simple two-variable taggers

Both: JETM-2018-03

- As mentioned earlier, two-variable taggers are already quite powerful
  - W-tagging: mass+$D_2$ has $\sim 60\times$ background rejection for 50% signal efficiency
  - Top-tagging: mass+$\tau_{32}$ (among others) has $\sim 5\times$ background rejection for 80% signal eff.
- However, we can definitely improve upon these simple taggers

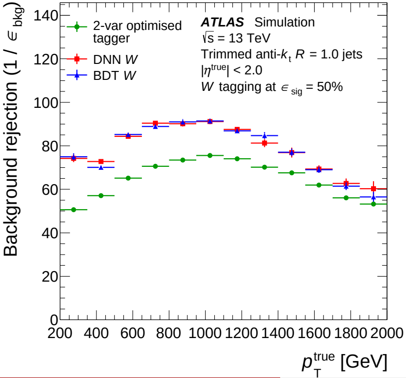


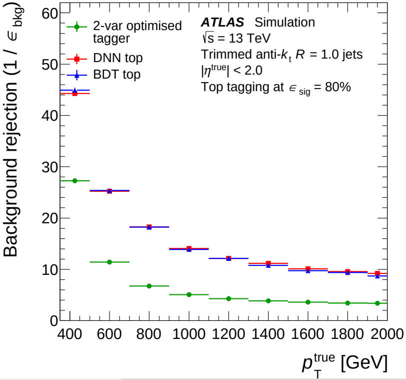



# Moving towards machine learning

Both: JETM-2018-03

- Trained BDTs and DNNs for W/top-tagging with $\mathcal{O}(10)$ jet substructure variables
  - Small gain for W-tagging: $60\times \rightarrow 80\times$ QCD rejection for 50% signal eff ($\sim$ 30% gain)
  - Large gain for top-tagging: $5\times \rightarrow 12\times$ QCD rejection for 80% signal eff ($\sim$ 240% gain)
- Performance limited by amount of unique info: substructure variables are highly correlated

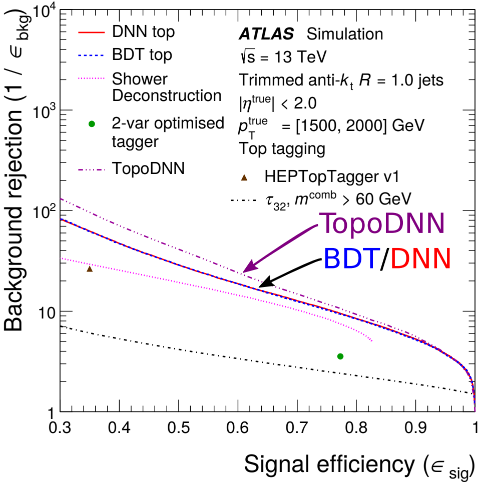


# Going deeper into machine learning

Plot: JETM-2018-03

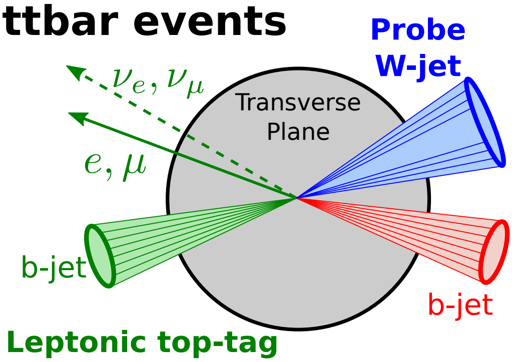
- Studied DNN with topocluster inputs, not substructure variables (TopoDNN)
  - Trained specifically for high $p_{\mathrm{T}}$
  - Better than BDT,DNN in this regime
- Still, could be improved
  - Tagging power depends on jet inputs
  - Use of more precise inputs to DNN should provide further gains
  - Note: no $b$-tagging used so far



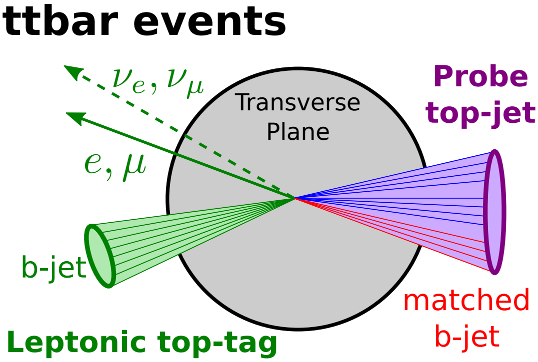
# Deriving tagging efficiency signal scale factors

- Semi-leptonic $t\bar{t}$ events are very pure in hadronic W and top jets
  - We can use these events to derive the tagging efficiency in data and compare to simulation

$200\,\mathrm{GeV} < p_{\mathrm{T}}^{\mathrm{W}} \lesssim 500\,\mathrm{GeV}$



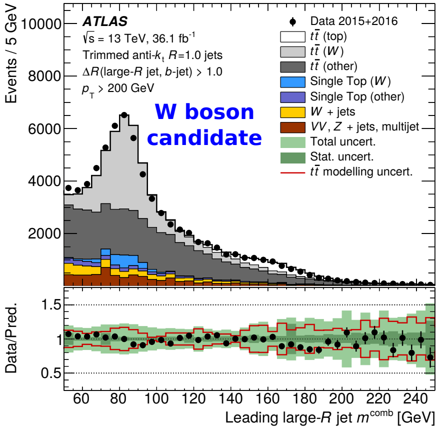

$350\,\mathrm{GeV} < p_{\mathrm{T}}^{\mathrm{top}} \lesssim 1000\,\mathrm{GeV}$

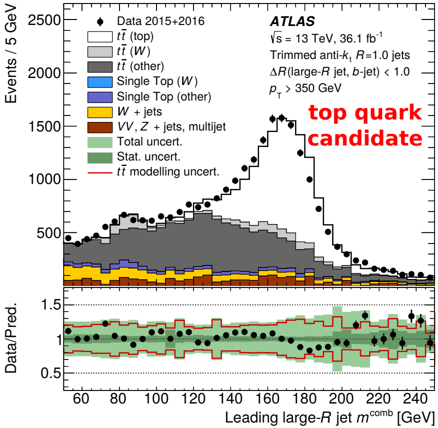


# Scale factor extraction regions

Both: JETM-2018-03

- The selected W- and top-candidate pre-tag mass distributions show high signal purity
  - Fit three templates: $t\bar{t}$ signal process, $t\bar{t}$ background processes, and non-$t\bar{t}$ backgrounds

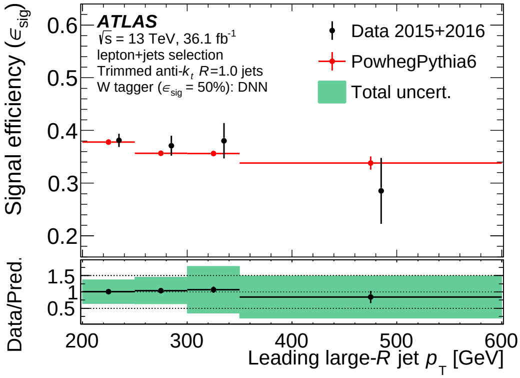


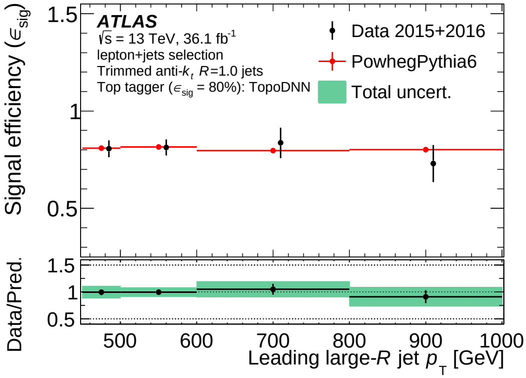



# Resulting signal scale factors ($p_T$ sliced)

Both: JETM-2018-03

- Data and simulation agree within data statistical uncertainties, even for complex taggers
  - Shown for the W-tagging DNN and the top-tagging topocluster-based DNN
  - Agreement also stable against large range of pileup (not shown here)

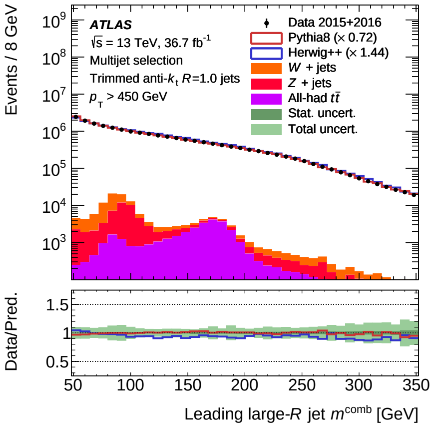


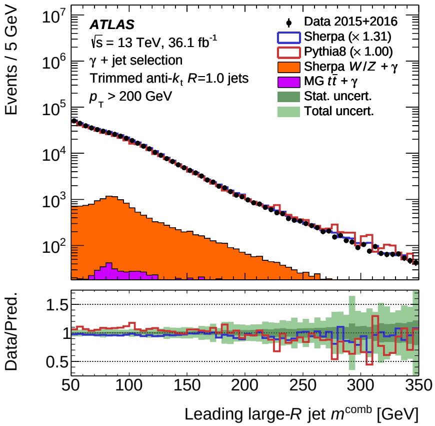



# Extracting background scale factors

Both: JETM-2018-03

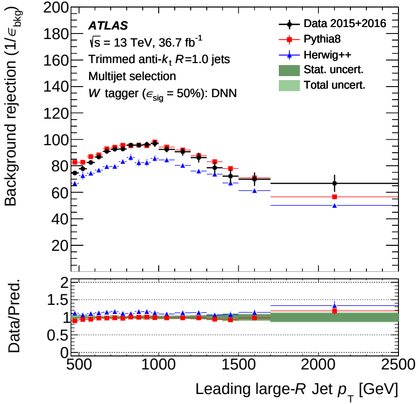
- Study performance of taggers in background samples: QCD multijets and $\gamma$+jets
  - Comparing allows for studying modelling differences between tagging gluons and light quarks

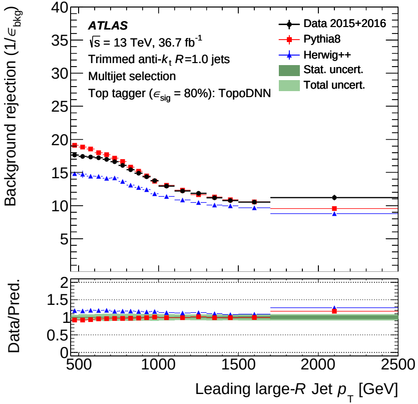


# Resulting background scale factors

- As before, these are for the W-tagging DNN and the top-tagging topocluster-based DNN
  - Multijet (below): W- and top-tagging both agree with Pythia8, disagree with Herwig++
  - $\gamma$+jet (backup): W-tagging agrees with Sherpa not Pythia8, top-tagging agrees with both

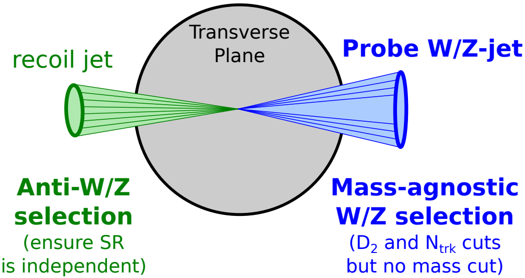


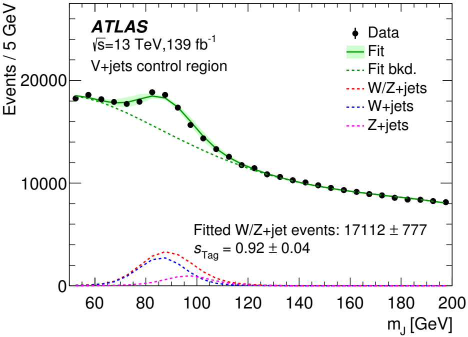



 Plot: HDBS-2018-31

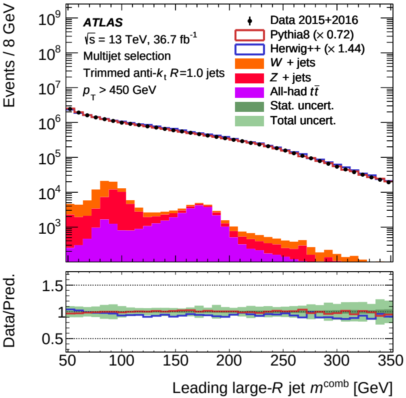
- Fully-hadronic di-boson resonance search uses V+jets events to evaluate tagger efficiency
  - Shown below for TCC jets and a 3-variable tagger; more details in Thursday's talk by E. Must
  - Similar approach using Z(→bb)+$\gamma$ events in Wednesday's talk by R. Jacobs
- Extends measurement to higher $p_{\mathrm{T}}$, but much harder as background dominates signal
  - Need to be careful: breaks down if signal and background peak at the same mass

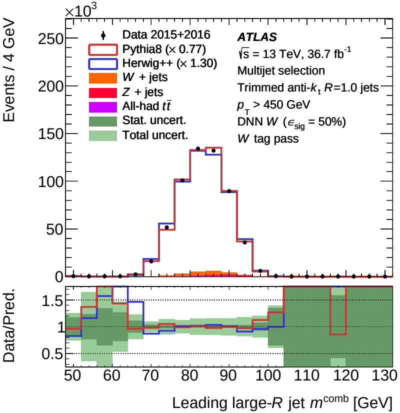
**V+jet(s) events, $p_T$ > 600 GeV**



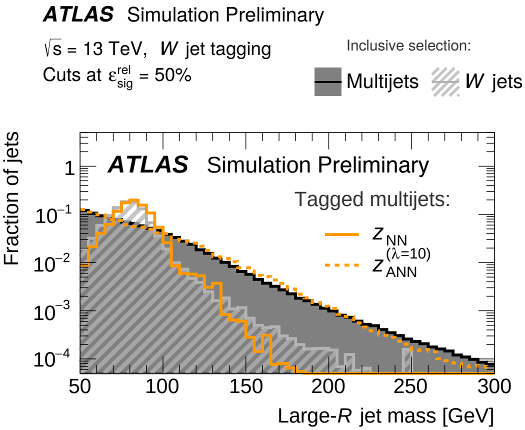



- ML taggers, whether BDT or DNN, quickly learn that the jet mass is very important
  - Very strongly shape the background mass distribution to look like signal
  - Becomes ∼impossible to extract signal efficiency in V+jets events with such ML taggers



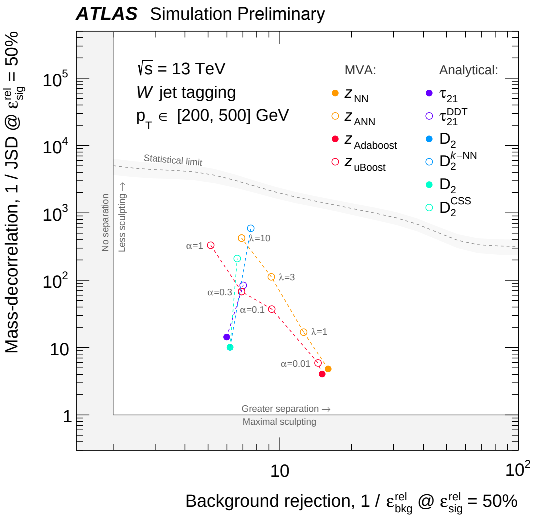



- This can be addressed using mass decorrelation strategies, such as Adversarial NNs
  - Significantly reduces the correlation and thus mass-sculpting



# Looking forward: mass decorrelation strategies

- Adversarial NNs parametrizes trade-off between tagging power (x-axis) and mass decorrelation (y-axis)
- Supports scale factor extraction in background-dominated regions
  - Final tagger can be mass+ANN selection, but will still lose some tagging performance



# Looking forward: revisiting the jet definition

New @ BOOST2019

Plot: PUB-2019-027

ATLAS EXPERIMENT

- Huge effort underway to revisit the jet definition; tagging is an important consideration
  - Below is the W-tagging background rejection for 50% signal efficiency, using mass+$D_2$
  - The current ATLAS jet definition is highlighted as a green box - clear potential gains!

**ATLAS** Simulation Preliminary

$\sqrt{s}$ = 13 TeV, 68% mass window + $D_2$ $W$ tagger

Anti-$k_t$ $R$=1.0 jets, no JES or JMS calibration applied

300 GeV < $p_T^{true}$ < 500 GeV, $|\eta^{true}|$ < 1.2

Bkg. rejection factor ($1/\varepsilon_{Bkg.}$) @ 50% $\varepsilon_{Sig.}$ (colour scale 10–50)

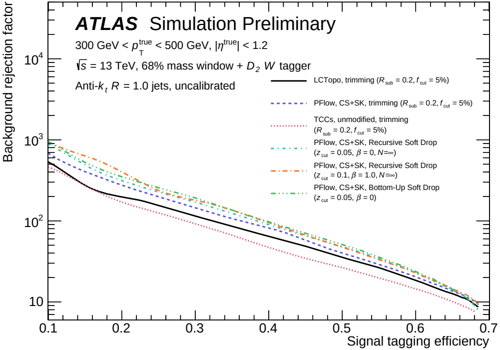
| Jet Grooming Method | | LCTopo Unmodified | LCTopo CS+SK | LCTopo VS+SK | PFlow Unmodified | PFlow CS+SK | PFlow VS+SK | PFlow PUPPI | TCC Unmodified | TCC CS+SK | TCC VS+SK |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Soft Drop | $z_{cut}$ = 0.1, β = 0.0 | 23.12 | 36.32 | 35.58 | 35.00 | 44.34 | 43.54 | 45.16 | 24.52 | 29.56 | 29.77 |
| Soft Drop | $z_{cut}$ = 0.1, β = 1.0 | 18.36 | 36.45 | 35.83 | 36.71 | 44.89 | 45.41 | 46.63 | 23.03 | 29.16 | 29.17 |
| Recursive Soft Drop | $z_{cut}$ = 0.05, β = 0.0, N = ∞ | 12.32 | 37.20 | 36.49 | 38.28 | 48.77 | 48.50 | 49.73 | 18.29 | 30.98 | 31.89 |
| Recursive Soft Drop | $z_{cut}$ = 0.1, β = 0.0, N = ∞ | 29.09 | 36.22 | 36.56 | 38.14 | 37.74 | 38.28 | 36.99 | 29.76 | 30.77 | 30.88 |
| Recursive Soft Drop | $z_{cut}$ = 0.05, β = 1.0, N = ∞ | 9.95 | 31.19 | 30.36 | 26.46 | 48.34 | 47.59 | 48.61 | 13.26 | 27.44 | 26.85 |
| Recursive Soft Drop | $z_{cut}$ = 0.1, β = 1.0, N = ∞ | 18.25 | 38.81 | 38.96 | 43.45 | 46.23 | 46.41 | 46.89 | 25.58 | 31.83 | 31.46 |
| Recursive Soft Drop | $z_{cut}$ = 0.05, β = 0.0, N = 3 | 11.96 | 36.49 | 35.93 | 35.25 | 48.15 | 48.04 | 47.28 | 17.22 | 31.32 | 30.62 |
| Recursive Soft Drop | $z_{cut}$ = 0.1, β = 0.0, N = 3 | 26.26 | 37.65 | 37.22 | 38.49 | 36.00 | 36.59 | 36.35 | 29.25 | 29.87 | 29.98 |
| Recursive Soft Drop | $z_{cut}$ = 0.05, β = 1.0, N = 3 | 9.82 | 31.03 | 30.31 | 25.59 | 47.96 | 47.53 | 48.46 | 13.09 | 27.00 | 26.44 |
| Recursive Soft Drop | $z_{cut}$ = 0.1, β = 1.0, N = 3 | 17.87 | 38.90 | 38.26 | 41.92 | 45.88 | 47.02 | 46.84 | 23.94 | 31.34 | 30.48 |
| Recursive Soft Drop | $z_{cut}$ = 0.05, β = 0.0, N = 5 | 11.72 | 37.03 | 36.09 | 35.69 | 48.40 | 47.63 | 48.57 | 18.29 | 31.27 | 31.65 |
| Recursive Soft Drop | $z_{cut}$ = 0.1, β = 0.0, N = 5 | 27.07 | 37.10 | 36.92 | 36.50 | 36.44 | 36.61 | 35.86 | 29.42 | 30.05 | 29.45 |
| Recursive Soft Drop | $z_{cut}$ = 0.05, β = 1.0, N = 5 | 9.79 | 31.11 | 30.30 | 26.15 | 48.33 | 47.62 | 48.99 | 13.00 | 27.11 | 26.37 |
| Recursive Soft Drop | $z_{cut}$ = 0.1, β = 1.0, N = 5 | 18.20 | 38.69 | 38.90 | 43.20 | 46.38 | 46.62 | 46.57 | 25.21 | 32.06 | 31.46 |
| Bottom-up Soft Drop | $z_{cut}$ = 0.05, β = 0.0 | 11.73 | 36.21 | 37.58 | 35.55 | 49.25 | 48.59 | 51.45 | 16.92 | 31.13 | 30.96 |
| Bottom-up Soft Drop | $z_{cut}$ = 0.1, β = 0.0 | 26.18 | 36.61 | 36.29 | 39.92 | 39.59 | 38.92 | 39.50 | 30.70 | 30.73 | 30.38 |
| Bottom-up Soft Drop | $z_{cut}$ = 0.05, β = 1.0 | 9.24 | 30.93 | 30.22 | 25.34 | 48.39 | 47.52 | 48.58 | 12.21 | 27.30 | 26.69 |
| Bottom-up Soft Drop | $z_{cut}$ = 0.1, β = 1.0 | 17.47 | 39.00 | 39.11 | 43.99 | 46.05 | 46.42 | 47.10 | 24.69 | 31.95 | 31.28 |
| Pruning | $R_{cut}$=0.15, $Z_{cut}$=0.25 | 33.92 | 34.49 | 35.02 | 40.63 | 37.45 | 37.51 | 37.66 | 28.85 | 28.87 | 28.59 |
| Trimming | $f_{cut}$=5%, $R_{sub}$=0.1 | 27.61 | 28.91 | 29.43 | 31.70 | 31.76 | 31.55 | 31.79 | 26.43 | 26.31 | 27.66 |
| Trimming | $f_{cut}$=9%, $R_{sub}$=0.1 | 26.35 | 27.35 | 26.69 | 30.98 | 31.87 | 31.95 | 31.53 | 27.96 | 29.07 | 28.15 |
| Trimming | $f_{cut}$=5%, $R_{sub}$=0.2 | 36.14 | 35.79 | 36.23 | 39.94 | 38.70 | 39.28 | 39.72 | 28.07 | 28.27 | 27.34 |
| Trimming | $f_{cut}$=9%, $R_{sub}$=0.2 | 30.87 | 31.97 | 32.05 | 35.52 | 37.01 | 36.91 | 35.94 | 26.98 | 28.22 | 27.11 |

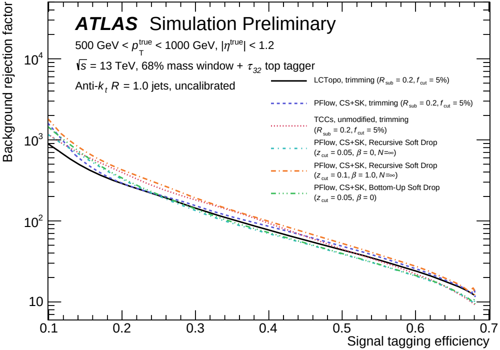
# Alternative jet definition tagging performance

**New @ BOOST2019**

Both: PUB-2019-027

- Tagging performance is not the only important metric for picking a jet definition
  - A few options that work well in all metrics are shown below
- Improvements possible compared to the current definition (solid black line)
  - PFO jets provide best performance in this kinematic range (TCC best at high $p_{\mathrm{T}}$, in backup)



# Summary

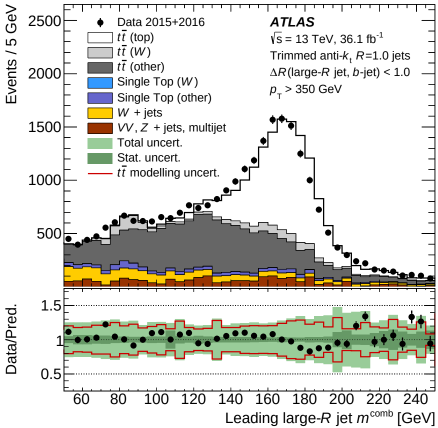
- W/Z/top taggers are becoming increasingly complex
  - Historically two-variable taggers, increasingly moving towards ML-based taggers
- ML tagging efficiencies are extracted in dedicated regions
  - Semi-leptonic $t\bar{t}$ used for top-jets and low $p_{\mathrm{T}}$ W-jets
  - V+jets used for high $p_{\mathrm{T}}$ W/Z-jets, as long as there is no peak-like mass shaping
  - QCD multijets and $\gamma$+jets used for background efficiencies
- The jet definition strongly influences the jet tagging potential
  - Studying improved jet inputs, constituent-level pileup mitigation, and grooming algorithms
  - Promising initial signs of tagging performance improvements to follow

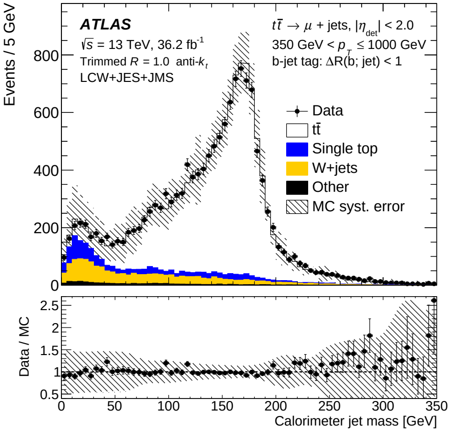
# Backup Material

# Mass calibration and the top peak

Left: JETM-2018-03
Right: JETM-2018-02

- In the scale factor pre-tag plot, there is a clear jet mass scale shift
- This is fixed by application of the *in situ* calibration, see C. Wanotayaroj's talk for details

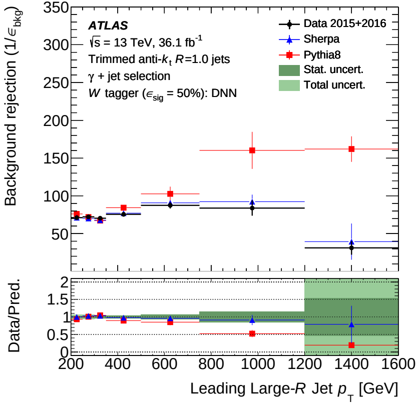


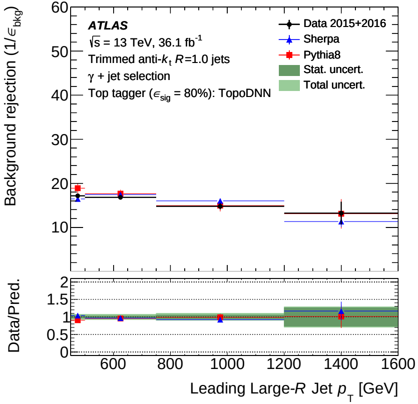



# Resulting background scale factors

Both: JETM-2018-03

- As before, these are for the W-tagging DNN and the top-tagging topocluster-based DNN
  - Multijet (body): W- and top-tagging both agree with Pythia8, disagree with Herwig++
  - $\gamma$+jet (below): W-tagging agrees with Sherpa not Pythia8, top-tagging agrees with both



# Looking forward: revisiting the jet definition

New @ BOOST2019

Plot: PUB-2019-027

ATLAS EXPERIMENT

- Huge effort underway to revisit the jet definition; tagging is an important consideration
  - Below is the W-tagging background rejection for 50% signal efficiency, using mass+$D_2$

**ATLAS** Simulation Preliminary
$\sqrt{s}$ = 13 TeV, 68% mass window + $D_2$ $W$ tagger

Anti-$k_t$ $R$=1.0 jets, no JES or JMS calibration applied
1000 GeV < $p_T^{true}$ < 1500 GeV, $|\eta^{true}|$ < 1.2

Bkg. rejection factor ($1/\varepsilon_{Bkg.}$) @ 50% $\varepsilon_{Sig.}$ (colour scale 30–110)

| Jet Grooming Method | | LCTopo Unmodified | LCTopo CS+SK | LCTopo VS+SK | PFlow Unmodified | PFlow CS+SK | PFlow VS+SK | PFlow PUPPI | TCC Unmodified | TCC CS+SK | TCC VS+SK |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Soft Drop | $z_{cut}$ = 0.1, β = 0.0 | 42.52 | 42.38 | 42.61 | 50.99 | 50.92 | 49.68 | 49.29 | 64.25 | 81.84 | 62.55 |
| | $z_{cut}$ = 0.1, β = 1.0 | 58.19 | 57.39 | 57.15 | 76.30 | 73.63 | 73.68 | 72.41 | 78.21 | 99.39 | 75.30 |
| Recursive Soft Drop | $z_{cut}$ = 0.05, β = 0.0, N = ∞ | 53.03 | 51.26 | 51.39 | 59.31 | 58.65 | 58.66 | 58.54 | 62.73 | 79.42 | 59.97 |
| | $z_{cut}$ = 0.1, β = 0.0, N = ∞ | 38.36 | 36.82 | 36.72 | 38.39 | 39.43 | 39.62 | 38.87 | 43.78 | 55.09 | 42.54 |
| | $z_{cut}$ = 0.05, β = 1.0, N = ∞ | 53.56 | 62.74 | 62.97 | 86.75 | 86.22 | 86.31 | 85.27 | 94.43 | 111.17 | 87.44 |
| | $z_{cut}$ = 0.1, β = 1.0, N = ∞ | 58.44 | 56.99 | 56.81 | 75.14 | 73.23 | 72.98 | 73.18 | 77.44 | 96.95 | 74.56 |
| | $z_{cut}$ = 0.05, β = 0.0, N = 3 | 52.68 | 51.33 | 50.87 | 62.80 | 61.38 | 61.44 | 59.62 | 64.42 | 81.01 | 63.57 |
| | $z_{cut}$ = 0.1, β = 0.0, N = 3 | 39.50 | 36.78 | 37.25 | 42.66 | 41.68 | 41.90 | 41.28 | 46.17 | 58.75 | 45.34 |
| | $z_{cut}$ = 0.05, β = 1.0, N = 3 | 53.64 | 63.57 | 63.45 | 86.63 | 86.27 | 86.37 | 85.38 | 94.52 | 111.26 | 87.47 |
| | $z_{cut}$ = 0.1, β = 1.0, N = 3 | 58.55 | 56.97 | 57.06 | 75.03 | 73.26 | 73.11 | 73.41 | 77.60 | 97.09 | 74.57 |
| | $z_{cut}$ = 0.05, β = 0.0, N = 5 | 53.05 | 51.83 | 51.83 | 62.20 | 60.79 | 60.90 | 60.20 | 65.62 | 79.37 | 62.57 |
| | $z_{cut}$ = 0.1, β = 0.0, N = 5 | 37.04 | 36.89 | 36.81 | 42.12 | 40.72 | 40.90 | 40.20 | 44.36 | 57.00 | 43.51 |
| | $z_{cut}$ = 0.05, β = 1.0, N = 5 | 53.56 | 62.74 | 62.97 | 86.65 | 86.16 | 86.26 | 85.21 | 94.39 | 111.18 | 87.44 |
| | $z_{cut}$ = 0.1, β = 1.0, N = 5 | 58.41 | 56.99 | 56.81 | 75.09 | 72.81 | 73.44 | 73.08 | 77.41 | 97.01 | 74.59 |
| Bottom-up Soft Drop | $z_{cut}$ = 0.05, β = 0.0 | 54.01 | 51.49 | 51.31 | 62.34 | 60.67 | 60.76 | 60.46 | 63.35 | 81.05 | 60.85 |
| | $z_{cut}$ = 0.1, β = 0.0 | 37.70 | 38.18 | 38.16 | 41.34 | 40.58 | 40.56 | 40.01 | 45.89 | 57.66 | 44.75 |
| | $z_{cut}$ = 0.05, β = 1.0 | 52.44 | 63.49 | 63.48 | 86.86 | 86.20 | 86.23 | 85.37 | 94.30 | 111.09 | 87.44 |
| | $z_{cut}$ = 0.1, β = 1.0 | 58.74 | 57.20 | 56.97 | 75.55 | 73.35 | 73.16 | 73.61 | 77.98 | 97.08 | 74.54 |
| Pruning | $R_{cut}$=0.15, $Z_{cut}$=0.25 | 36.89 | 31.78 | 31.80 | 44.68 | 39.15 | 39.27 | 39.11 | 54.00 | 59.85 | 48.18 |
| Trimming | $f_{cut}$=5%, $R_{sub}$=0.1 | 36.90 | 38.70 | 38.55 | 48.66 | 47.83 | 47.83 | 47.10 | 59.65 | 76.24 | 59.84 |
| | $f_{cut}$=9%, $R_{sub}$=0.1 | 29.30 | 29.82 | 30.20 | 39.21 | 39.24 | 39.24 | 38.50 | 51.75 | 64.59 | 51.43 |
| | $f_{cut}$=5%, $R_{sub}$=0.2 | 51.85 | 55.15 | 54.98 | 76.93 | 79.49 | 79.49 | 74.86 | 82.73 | 103.82 | 79.74 |
| | $f_{cut}$=9%, $R_{sub}$=0.2 | 46.51 | 49.47 | 49.40 | 68.84 | 71.67 | 71.71 | 67.16 | 74.76 | 93.30 | 72.44 |

Jet Constituent Type

# Looking forward: revisiting the jet definition

New @ BOOST2019

Plot: PUB-2019-027

ATLAS EXPERIMENT

- Huge effort underway to revisit the jet definition; tagging is an important consideration
  - Below is the top-tagging background rejection for 50% signal efficiency, using mass+$\tau_{32}$

**ATLAS** Simulation Preliminary
$\sqrt{s}$ = 13 TeV, 68% mass window + $\tau_{32}$ top tagger
Anti-$k_t$ $R$=1.0 jets, no JES or JMS calibration applied
500 GeV < $p_T^{true}$ < 1000 GeV, $|\eta^{true}|$ < 1.2

Bkg. rejection factor ($1/\varepsilon_{Bkg.}$) @ 50% $\varepsilon_{Sig.}$

| Jet Grooming Method | | LCTopo Unmodified | LCTopo CS+SK | LCTopo VS+SK | PFlow Unmodified | PFlow CS+SK | PFlow VS+SK | PFlow PUPPI | TCC Unmodified | TCC CS+SK | TCC VS+SK |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Soft Drop | $z_{cut}$ = 0.1, β = 0.0 | 50.61 | 49.98 | 51.84 | 69.66 | 89.08 | 84.51 | 83.18 | 59.25 | 60.80 | 58.74 |
| Soft Drop | $z_{cut}$ = 0.1, β = 1.0 | 60.89 | 69.07 | 69.62 | 77.77 | 100.27 | 101.12 | 90.89 | 64.83 | 70.03 | 68.09 |
| Recursive Soft Drop | $z_{cut}$ = 0.05, β = 0.0, N = ∞ | 31.12 | 43.06 | 43.54 | 51.69 | 51.95 | 51.54 | 51.61 | 45.73 | 44.09 | 43.51 |
| Recursive Soft Drop | $z_{cut}$ = 0.1, β = 0.0, N = ∞ | 28.27 | 29.76 | 28.91 | 34.14 | 31.87 | 31.60 | 34.18 | 39.40 | 38.02 | 37.51 |
| Recursive Soft Drop | $z_{cut}$ = 0.05, β = 1.0, N = ∞ | 39.27 | 52.75 | 55.30 | 60.93 | 72.14 | 72.66 | 71.73 | 45.07 | 51.12 | 51.33 |
| Recursive Soft Drop | $z_{cut}$ = 0.1, β = 1.0, N = ∞ | 45.30 | 61.08 | 60.21 | 78.88 | 78.35 | 77.77 | 79.43 | 57.84 | 56.03 | 55.27 |
| Recursive Soft Drop | $z_{cut}$ = 0.05, β = 0.0, N = 3 | 37.88 | 43.60 | 43.94 | 54.93 | 59.07 | 59.92 | 60.93 | 46.52 | 44.65 | 45.69 |
| Recursive Soft Drop | $z_{cut}$ = 0.1, β = 0.0, N = 3 | 27.16 | 30.61 | 30.42 | 39.84 | 36.59 | 36.78 | 38.31 | 39.51 | 40.31 | 37.53 |
| Recursive Soft Drop | $z_{cut}$ = 0.05, β = 1.0, N = 3 | 40.71 | 52.13 | 54.70 | 59.81 | 71.55 | 72.61 | 71.30 | 47.25 | 51.47 | 51.82 |
| Recursive Soft Drop | $z_{cut}$ = 0.1, β = 1.0, N = 3 | 48.52 | 58.88 | 58.39 | 75.80 | 79.36 | 78.41 | 81.75 | 55.63 | 57.46 | 57.09 |
| Recursive Soft Drop | $z_{cut}$ = 0.05, β = 0.0, N = 5 | 35.03 | 44.37 | 43.21 | 55.18 | 54.80 | 54.88 | 58.03 | 46.58 | 45.70 | 44.08 |
| Recursive Soft Drop | $z_{cut}$ = 0.1, β = 0.0, N = 5 | 27.86 | 28.90 | 28.66 | 37.24 | 35.34 | 34.27 | 35.42 | 40.02 | 39.92 | 39.43 |
| Recursive Soft Drop | $z_{cut}$ = 0.05, β = 1.0, N = 5 | 40.62 | 53.37 | 53.14 | 59.28 | 71.77 | 72.93 | 71.62 | 45.87 | 51.18 | 51.62 |
| Recursive Soft Drop | $z_{cut}$ = 0.1, β = 1.0, N = 5 | 46.90 | 59.38 | 58.99 | 76.51 | 79.44 | 78.15 | 80.68 | 56.25 | 57.83 | 56.67 |
| Bottom-up Soft Drop | $z_{cut}$ = 0.05, β = 0.0 | 31.28 | 43.13 | 43.44 | 55.47 | 53.16 | 53.62 | 53.86 | 45.07 | 43.89 | 44.67 |
| Bottom-up Soft Drop | $z_{cut}$ = 0.1, β = 0.0 | 28.89 | 29.71 | 29.44 | 37.01 | 34.82 | 35.30 | 35.32 | 41.67 | 38.22 | 37.74 |
| Bottom-up Soft Drop | $z_{cut}$ = 0.05, β = 1.0 | 39.21 | 52.65 | 52.74 | 61.05 | 71.05 | 72.14 | 71.21 | 44.11 | 51.73 | 50.85 |
| Bottom-up Soft Drop | $z_{cut}$ = 0.1, β = 1.0 | 44.16 | 59.66 | 60.22 | 78.43 | 78.37 | 78.18 | 78.55 | 55.53 | 55.85 | 55.00 |
| Pruning | $R_{cut}$=0.15, $Z_{cut}$=0.25 | 28.44 | 20.76 | 21.96 | 39.31 | 34.68 | 34.74 | 36.59 | 27.40 | 21.18 | 19.91 |
| Trimming | $f_{cut}$=5%, $R_{sub}$=0.1 | 25.49 | 27.40 | 27.78 | 44.87 | 47.07 | 46.77 | 46.34 | 41.24 | 39.53 | 39.78 |
| Trimming | $f_{cut}$=9%, $R_{sub}$=0.1 | 14.55 | 19.01 | 17.50 | 35.64 | 35.98 | 35.64 | 34.21 | 22.13 | 28.68 | 27.19 |
| Trimming | $f_{cut}$=5%, $R_{sub}$=0.2 | 54.04 | 50.91 | 50.05 | 62.04 | 59.41 | 58.95 | 61.56 | 49.35 | 50.42 | 48.82 |
| Trimming | $f_{cut}$=9%, $R_{sub}$=0.2 | 49.91 | 46.23 | 47.02 | 64.96 | 62.11 | 62.08 | 66.41 | 42.49 | 40.39 | 39.22 |

Jet Constituent Type

# Looking forward: revisiting the jet definition

New @ BOOST2019

Plot: PUB-2019-027

ATLAS EXPERIMENT

- Huge effort underway to revisit the jet definition; tagging is an important consideration
  - Below is the top-tagging background rejection for 50% signal efficiency, using mass+$\tau_{32}$

**ATLAS** Simulation Preliminary
$\sqrt{s}$ = 13 TeV, 68% mass window + $\tau_{32}$ top tagger
Anti-$k_t$ $R$=1.0 jets, no JES or JMS calibration applied
1000 GeV < $p_T^{true}$ < 1500 GeV, $|\eta^{true}|$ < 1.2

Bkg. rejection factor $(1/\varepsilon_{Bkg.})$ @ 50% $\varepsilon_{Sig.}$

| Jet Grooming Method | | LCTopo Unmodified | LCTopo CS+SK | LCTopo VS+SK | PFlow Unmodified | PFlow CS+SK | PFlow VS+SK | PFlow PUPPI | TCC Unmodified | TCC CS+SK | TCC VS+SK |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Soft Drop | $z_{cut}$ = 0.1, β = 0.0 | 13.69 | 12.63 | 12.60 | 19.77 | 18.71 | 18.83 | 19.68 | 20.79 | 20.12 | 20.02 |
| | $z_{cut}$ = 0.1, β = 1.0 | 26.31 | 26.21 | 26.15 | 33.66 | 32.49 | 32.59 | 33.43 | 38.28 | 39.91 | 37.19 |
| Recursive Soft Drop | $z_{cut}$ = 0.05, β = 0.0, N = ∞ | 14.47 | 14.87 | 14.93 | 16.68 | 16.35 | 16.34 | 16.48 | 29.09 | 28.86 | 28.19 |
| | $z_{cut}$ = 0.1, β = 0.0, N = ∞ | 9.18 | 8.74 | 8.81 | 8.99 | 8.77 | 8.83 | 8.78 | 16.80 | 17.09 | 15.99 |
| | $z_{cut}$ = 0.05, β = 1.0, N = ∞ | 15.32 | 21.81 | 21.78 | 25.92 | 26.95 | 26.65 | 26.65 | 29.50 | 34.31 | 32.75 |
| | $z_{cut}$ = 0.1, β = 1.0, N = ∞ | 23.98 | 24.11 | 24.18 | 29.43 | 28.40 | 28.74 | 28.91 | 37.04 | 37.63 | 36.28 |
| | $z_{cut}$ = 0.05, β = 0.0, N = 3 | 16.35 | 16.13 | 16.43 | 19.15 | 17.92 | 17.98 | 18.34 | 31.59 | 31.60 | 29.70 |
| | $z_{cut}$ = 0.1, β = 0.0, N = 3 | 9.27 | 8.93 | 8.91 | 9.44 | 9.38 | 9.37 | 9.27 | 18.09 | 17.11 | 16.33 |
| | $z_{cut}$ = 0.05, β = 1.0, N = 3 | 16.13 | 22.25 | 22.40 | 27.02 | 27.26 | 27.55 | 27.57 | 30.90 | 35.22 | 33.24 |
| | $z_{cut}$ = 0.1, β = 1.0, N = 3 | 24.95 | 24.22 | 24.15 | 30.38 | 29.56 | 29.58 | 30.00 | 37.56 | 38.77 | 35.70 |
| | $z_{cut}$ = 0.05, β = 0.0, N = 5 | 15.60 | 15.47 | 15.39 | 17.79 | 17.24 | 17.02 | 17.43 | 30.56 | 30.76 | 29.05 |
| | $z_{cut}$ = 0.1, β = 0.0, N = 5 | 9.10 | 8.85 | 8.87 | 9.07 | 9.00 | 8.99 | 8.87 | 17.41 | 17.78 | 16.04 |
| | $z_{cut}$ = 0.05, β = 1.0, N = 5 | 15.69 | 21.96 | 21.90 | 26.48 | 26.80 | 26.91 | 27.24 | 30.02 | 34.76 | 32.92 |
| | $z_{cut}$ = 0.1, β = 1.0, N = 5 | 24.15 | 24.36 | 24.41 | 30.02 | 28.85 | 29.00 | 29.90 | 38.62 | 37.95 | 36.46 |
| Bottom-up Soft Drop | $z_{cut}$ = 0.05, β = 0.0 | 14.13 | 14.87 | 14.92 | 16.57 | 16.72 | 16.82 | 16.69 | 28.91 | 28.95 | 28.12 |
| | $z_{cut}$ = 0.1, β = 0.0 | 9.23 | 9.03 | 9.10 | 9.30 | 9.18 | 9.21 | 9.39 | 18.19 | 17.98 | 16.58 |
| | $z_{cut}$ = 0.05, β = 1.0 | 14.88 | 21.82 | 21.72 | 25.40 | 26.99 | 26.55 | 26.49 | 28.96 | 34.27 | 32.81 |
| | $z_{cut}$ = 0.1, β = 1.0 | 24.01 | 23.96 | 23.91 | 29.40 | 28.92 | 29.18 | 28.77 | 36.92 | 38.74 | 36.03 |
| Pruning | $R_{cut}$=0.15, $Z_{cut}$=0.25 | 10.70 | 7.93 | 8.03 | 14.80 | 14.59 | 14.58 | 14.38 | 12.68 | 14.26 | 13.13 |
| Trimming | $f_{cut}$=5%, $R_{sub}$=0.1 | 12.36 | 12.49 | 12.55 | 18.84 | 18.75 | 18.74 | 18.70 | 27.37 | 29.74 | 27.13 |
| | $f_{cut}$=9%, $R_{sub}$=0.1 | 10.27 | 9.99 | 10.04 | 14.38 | 15.47 | 15.50 | 15.07 | 14.53 | 15.41 | 15.58 |
| | $f_{cut}$=5%, $R_{sub}$=0.2 | 22.30 | 21.07 | 21.26 | 27.21 | 26.82 | 26.74 | 27.23 | 32.99 | 35.35 | 32.25 |
| | $f_{cut}$=9%, $R_{sub}$=0.2 | 18.59 | 17.93 | 18.03 | 23.05 | 22.52 | 22.62 | 22.61 | 20.60 | 23.15 | 20.85 |

Jet Constituent Type

# Alternative jet definition tagging performance

**New @ BOOST2019**

Both: PUB-2019-027

- Tagging performance is not the only important metric for picking a jet definition
  - A few options that work well in all metrics are shown below
- Improvements possible compared to the current definition (solid black line)
  - TCC jets provide the best performance in this kinematic range (lower $p_T$ in body)