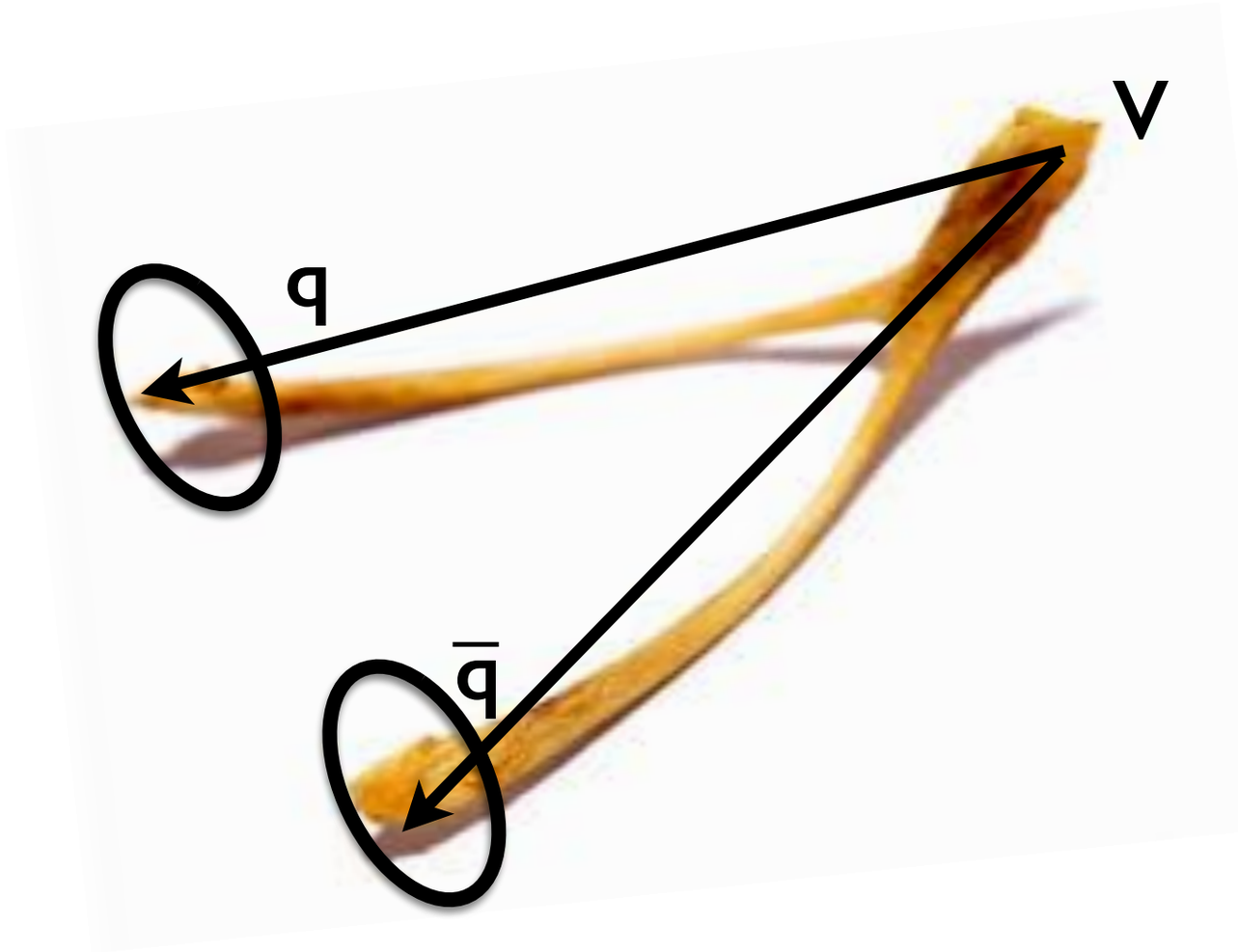
W/Z tagging techniques

Cristina Mantilla Suarez (Johns Hopkins)

Jet Substructure "Planning for the Future" Event
November 30th, 2016

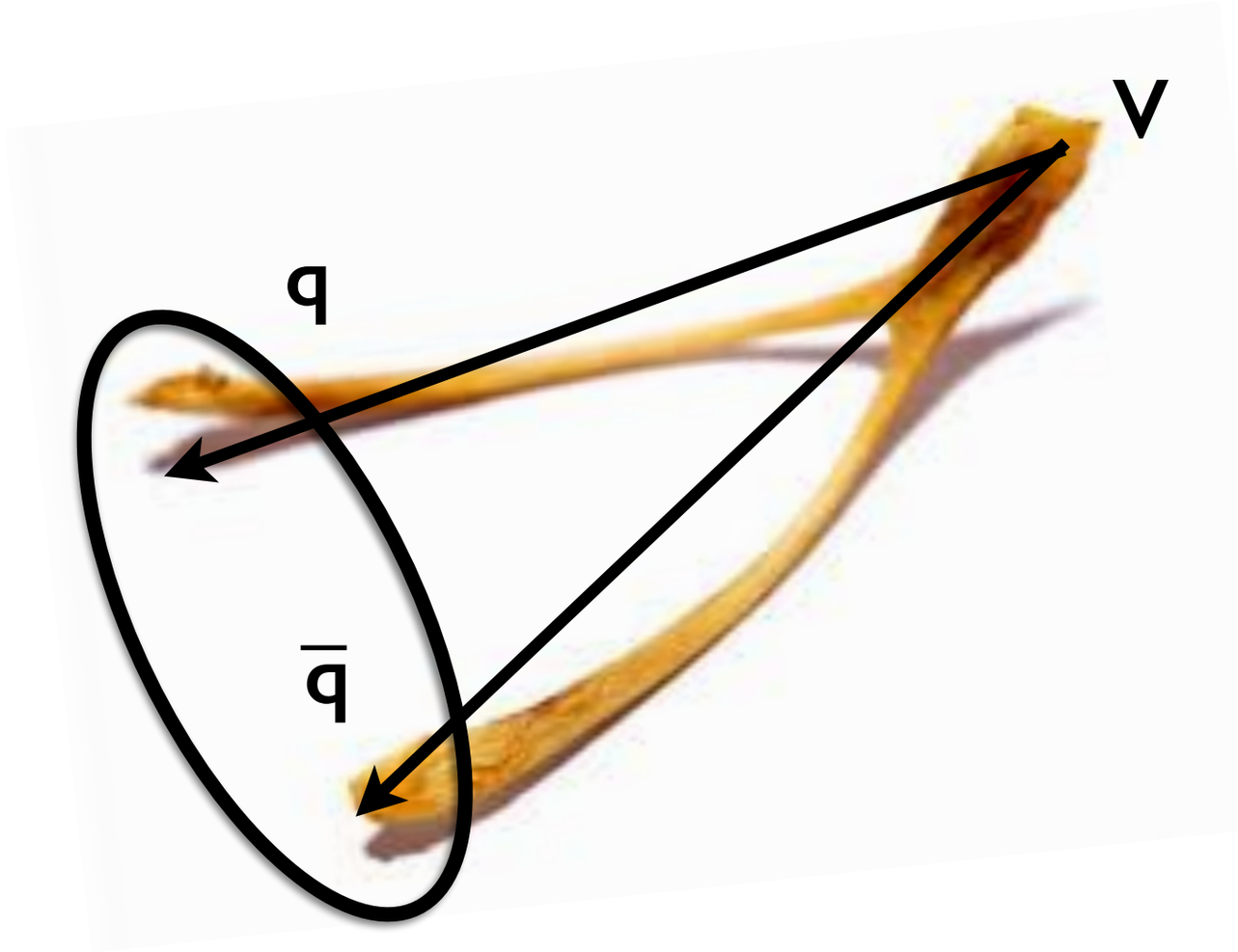
The wish-bone

- Tagging W/Z:



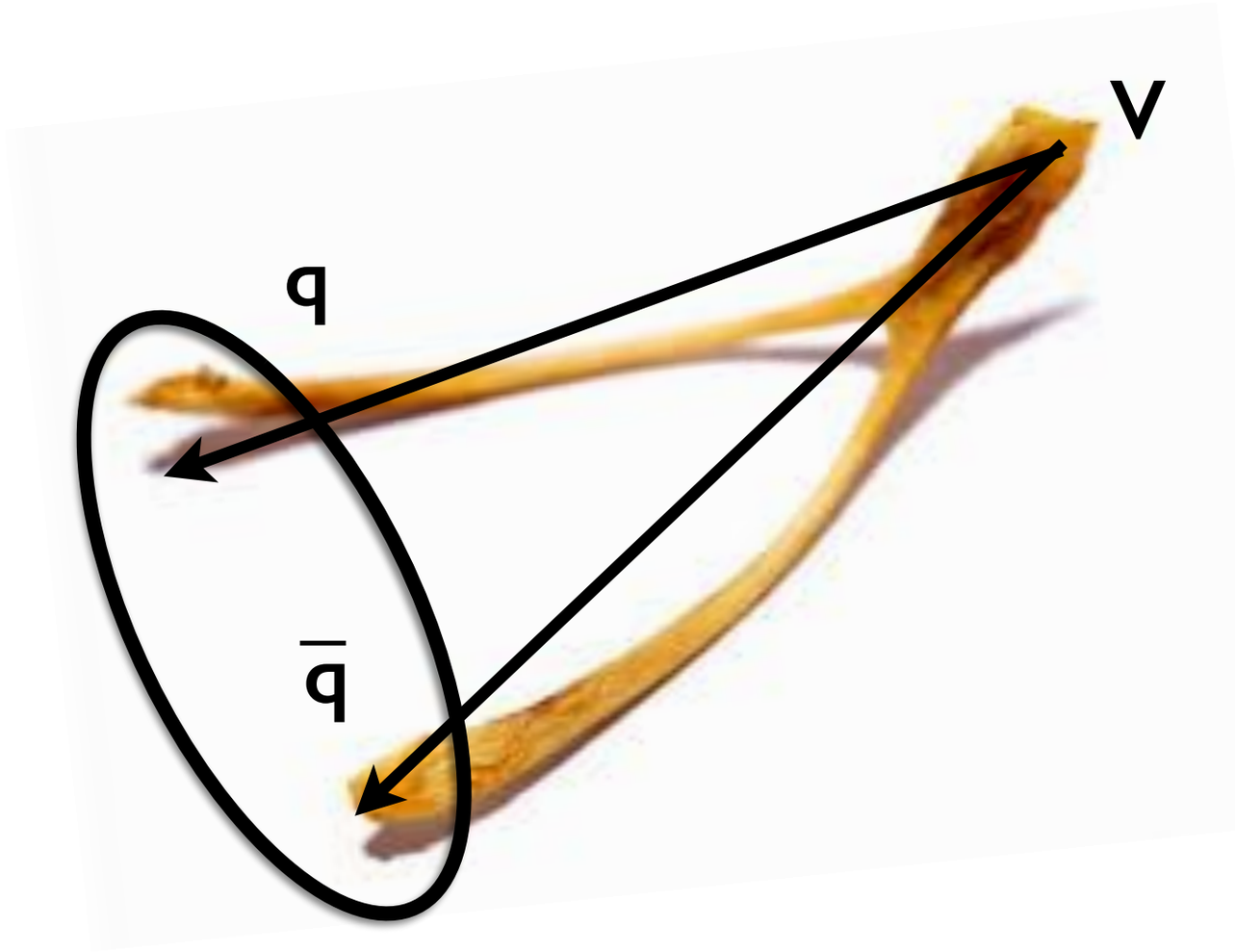
The boosted wish-bone

- Tagging W/Z:
  - Jet mass and Grooming techniques
  - Substructure observables
  - New techniques



The boosted wish-bone

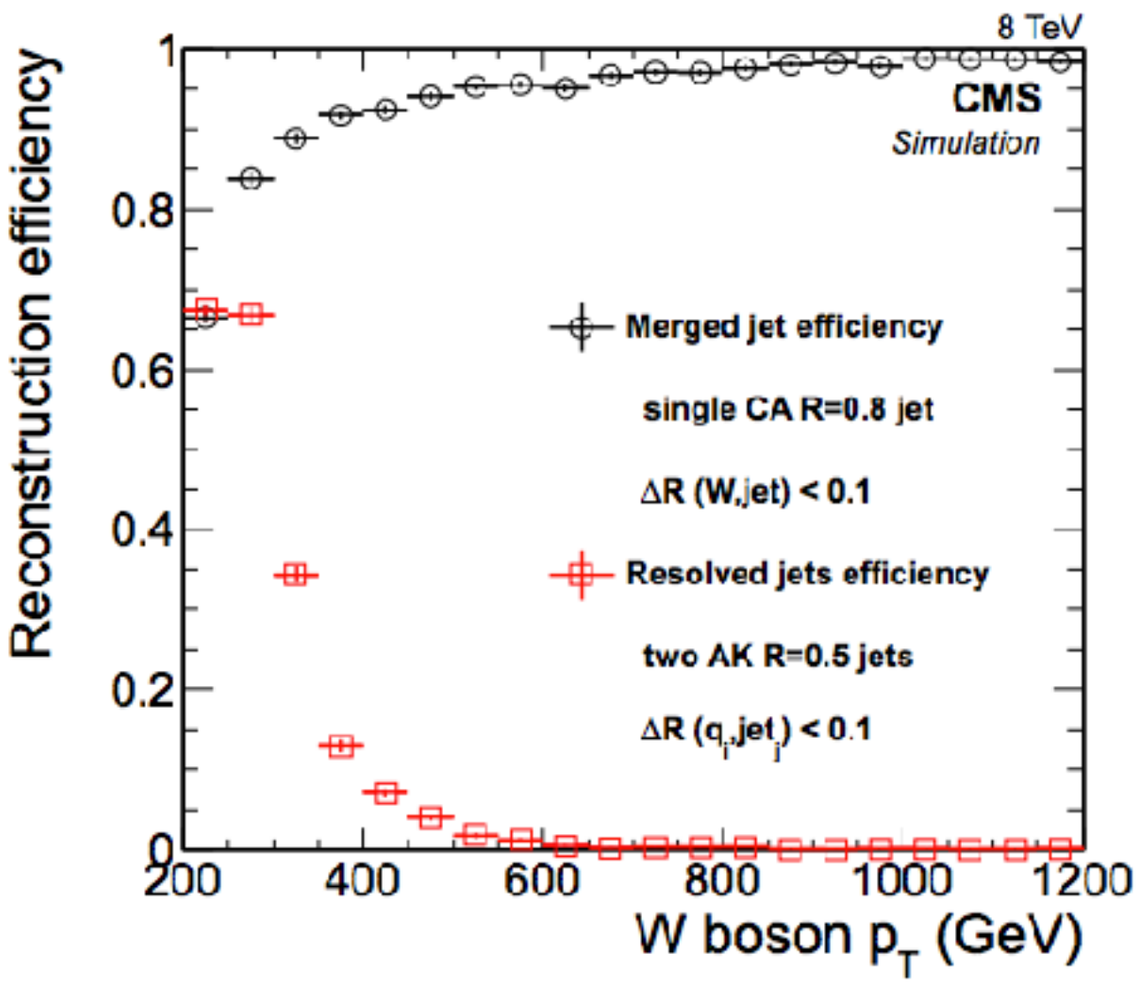
- Tagging W/Z:
  - Jet mass and Grooming techniques
  - Substructure observables
  - New techniques
- Performance at 13 TeV
- Summary and Outlook

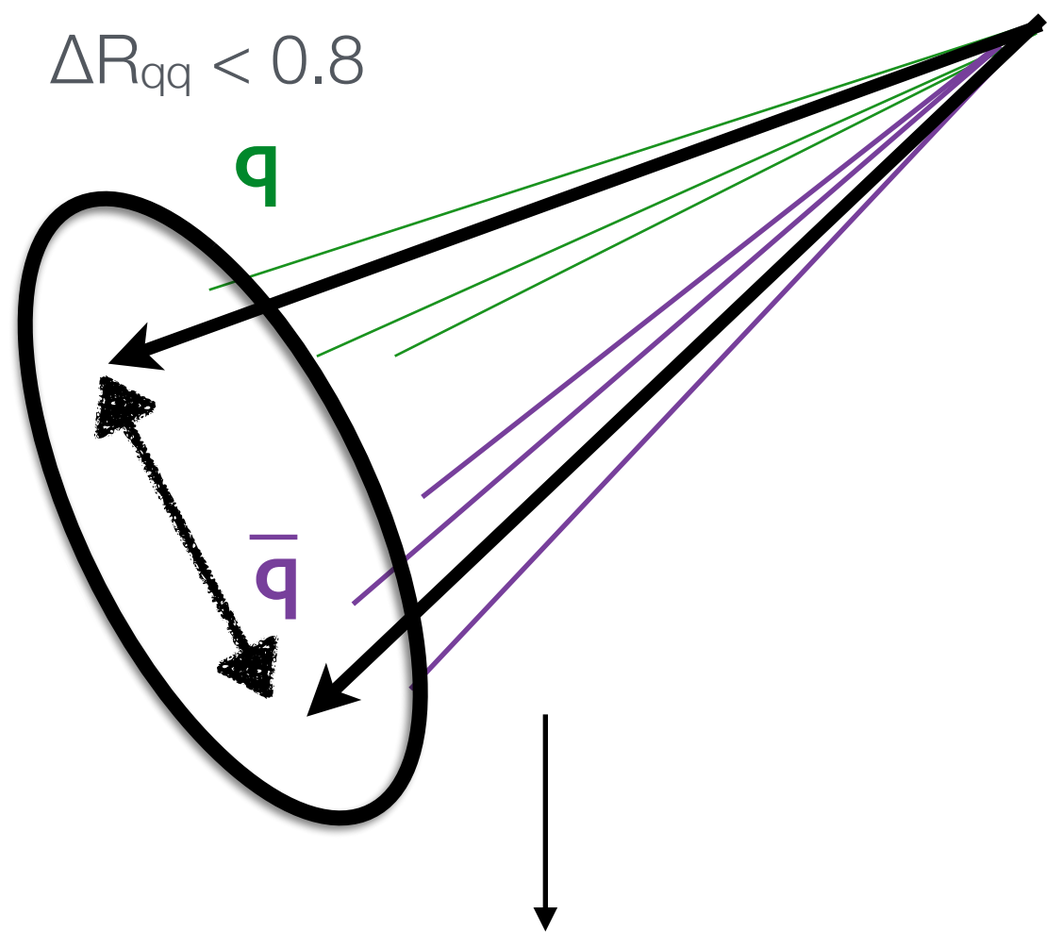


W/Z boosted topologies

Vector bosons with **pT>200 GeV** merged into single R = 0.8 jet

CMS-JME-13-006





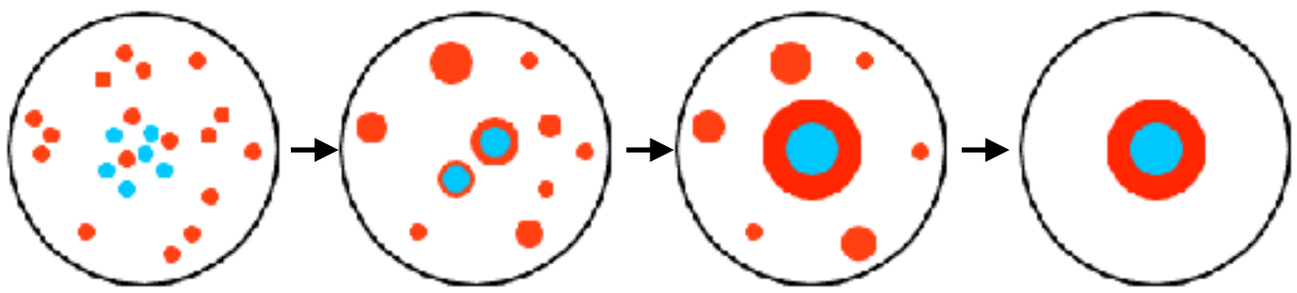
Challenge: Jet mass
Jet substructure

Mass observables

Tagging observables: Pruned Jet mass

Pruning

- Recluster jet. Removes soft, wide-angle constituents [2,3]



Initial jet $\Delta R_{ij} < d_{cut}$ or $z > z_{cut}$ Pruned jet

$$z = \frac{min(p_{T1}, p_{T2})}{p_{T1} + p_{T2}}$$

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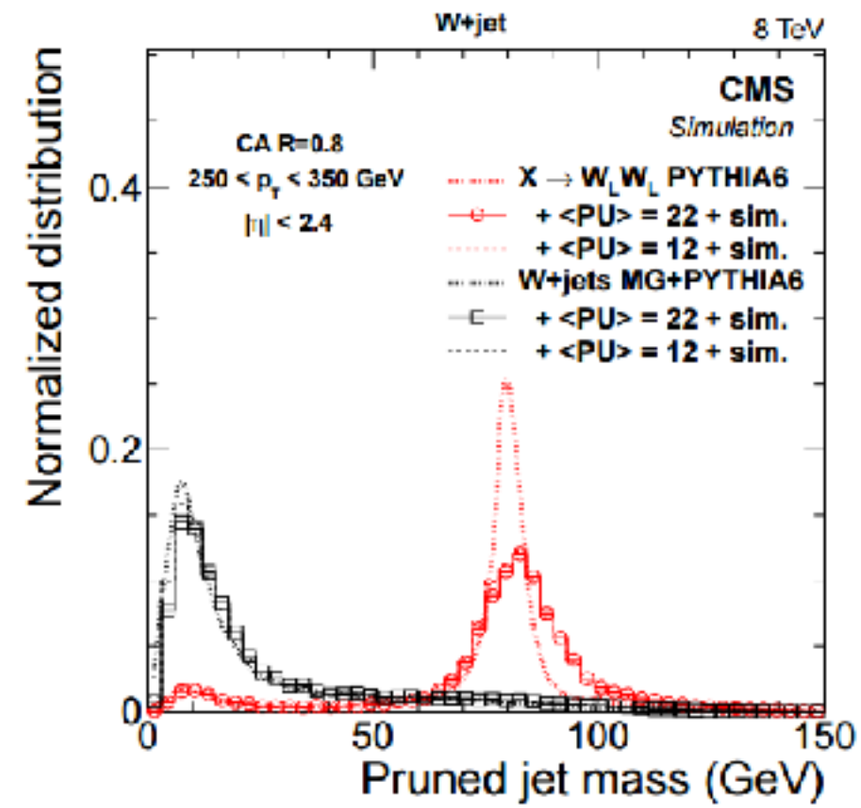


CMS: d_{cut} =0.5, z_{cut} =0.1

[2] https://arxiv.org/abs/0912.0033 Ellis et. al.
[3] https://arxiv.org/abs/1110.5333 Walsh et. al.

Tagging observables: SoftDrop Jet mass

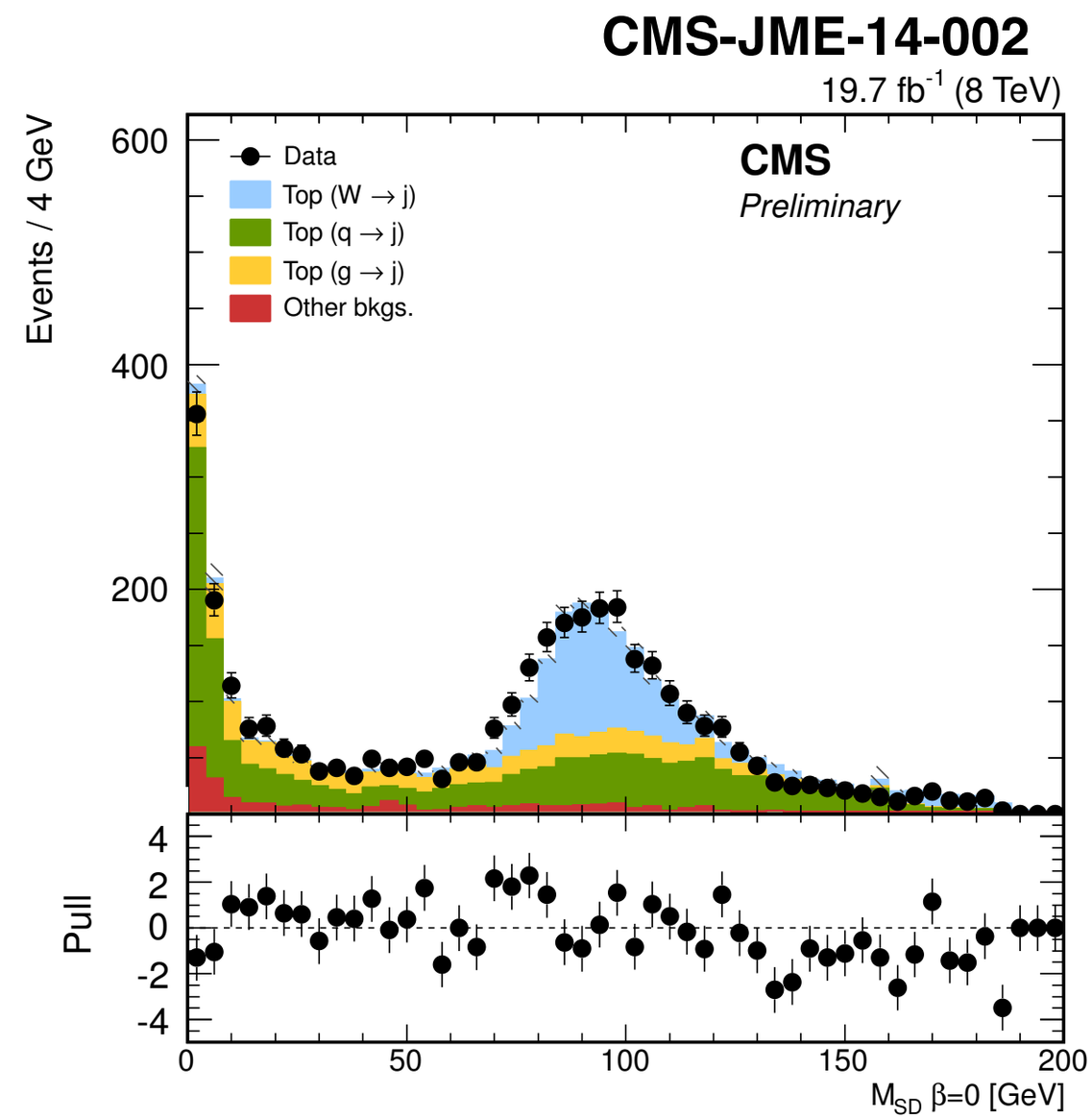
Softdrop (mMDT)

- Reverse order
  - De-cluster final jet
  - At each step remove soft and wide-angle contributions: [4]
    require:

$$\frac{min(p_{T1}, p_{T2})}{p_{T1} + p_{T2}} > z_{cut} \left(\frac{\Delta R_{12}}{R_0} \right)^{\beta}$$

Primarly aimed to separate W-jets from q/g
Does not fully reject PU and UE

CMS: PUPPI + Softdrop
$R_0 = 0.8$, $\beta = 0$, $z_{cut} = 0.1$



[4] https://arxiv.org/abs/1402.2657 Larkoski et. al.

Tagging observables: Trimmed Jet mass

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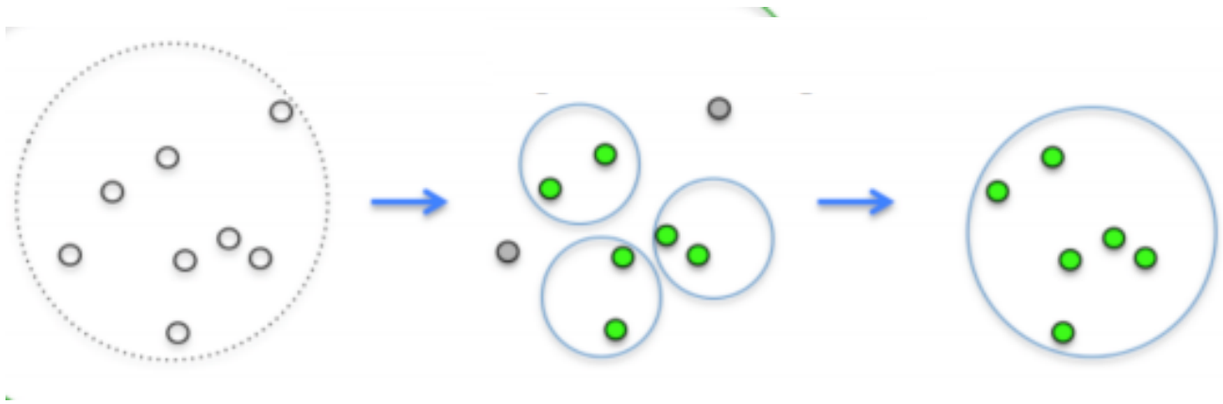
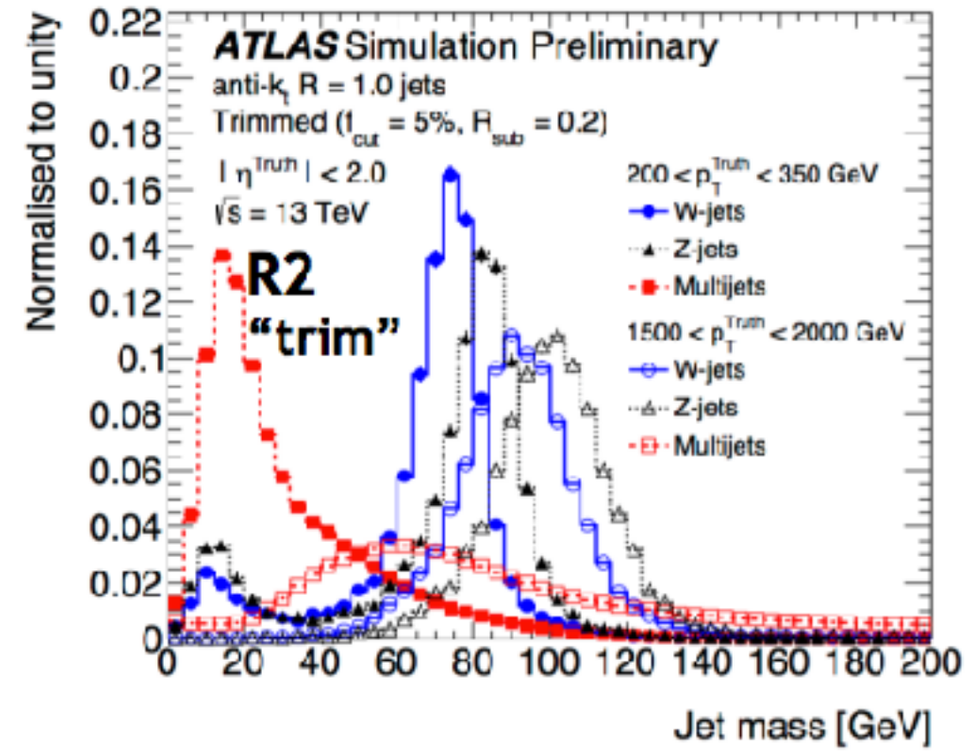
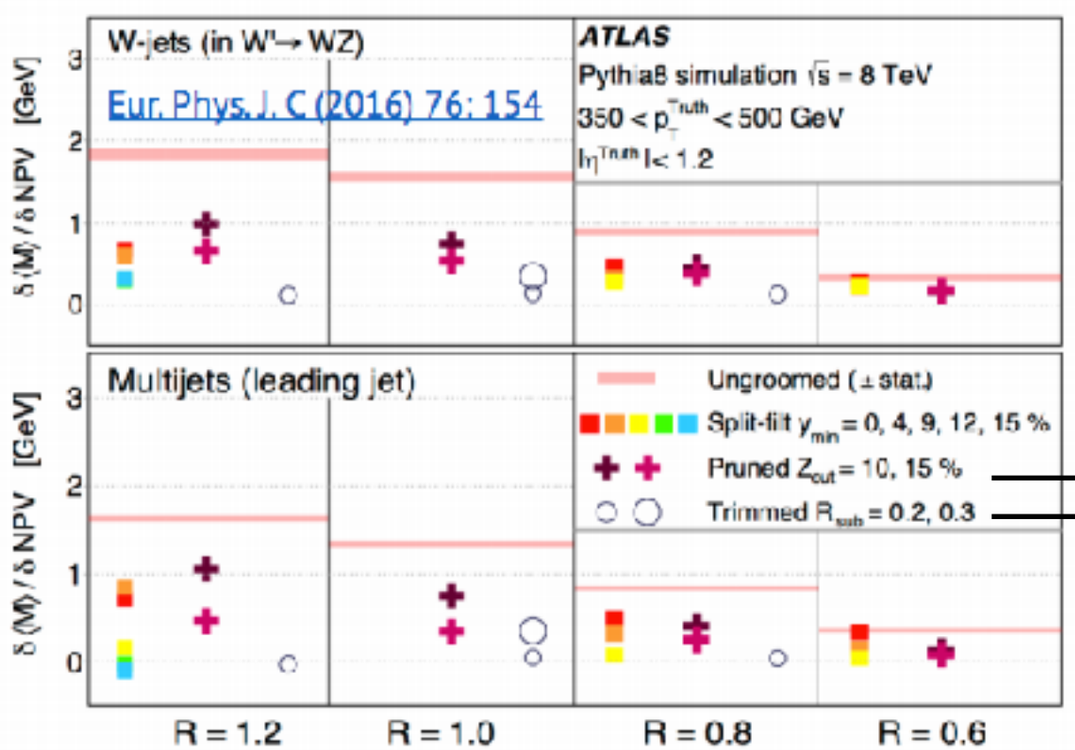
Trimming/Filtering





- Require $p_{T1}/ p_{Tjet} > f_{cut}$ and $N_{subjets} > N_{min}$



Pruned: W/Z tagging at Pt~500 GeV

ATLAS: R2 ("trim") AntiKt, R=1.0 trimmed, R_{subjet}= 0.2, f_{cut} = 5%

Reduced bkg and PU stability

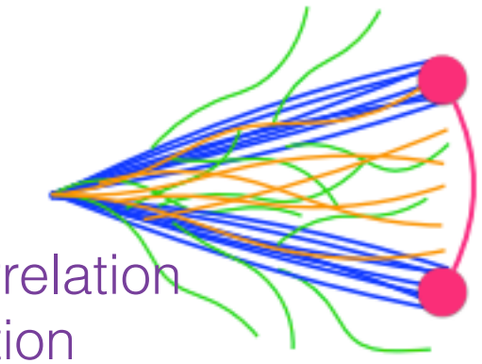
reduced pileup dependence after grooming: Each value of δ⟨M⟩/δNPV is the slope of a straight line fit of ⟨M⟩ versus NPV

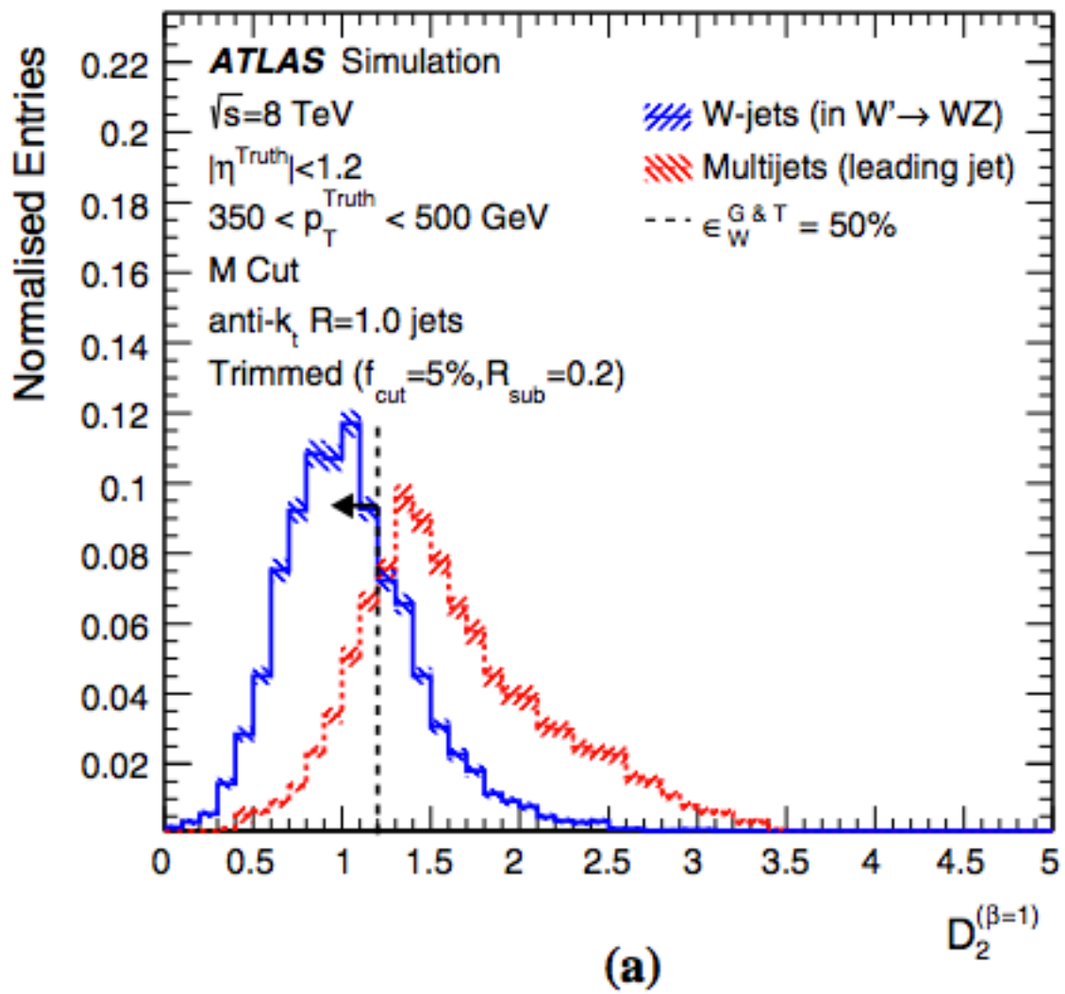
Substructure observables

Tagging observables: Jet substructure D_2

D_2

- Related to ratio of 3- and 2-point correlation functions [5]





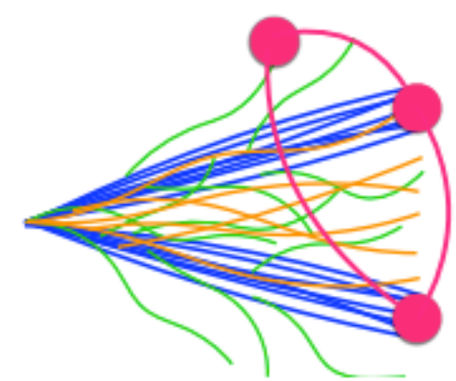
For a N prong jet, strong N-correlation but weak (N + 1)-point correlation

$$e_2^\beta = \sum_{i<j\in J} z_i z_j \times (\Delta R_{ij})^\beta$$

$$e_3^\beta = \sum_{i<j<k\in J} z_i z_j z_k \times (\Delta R_{ij} \cdot \Delta R_{jk} \cdot \Delta R_{ik})^\beta$$

↑

Jet J with constituents i,j,k



For 2 prong:

$$D_2^\beta = \frac{e_3^\beta}{(e_2^\beta)^3} \qquad C_2^{(\beta)} = \frac{e_3^{(\beta)}}{(e_2^{(\beta)})^2}$$

[5] J. High Energ. Phys. (2014) 2014: 9. Larkoski et. al.
Cartoons from Ian Moult's BOOST 2016 talk

Performances in Data: R_2 + smoothed D_2 (pT)

D_2 smoothed

Applies a cut based on the jet pT using a 4th-order polynomial formula fit to define a smoothed selection to get flat signal efficiency

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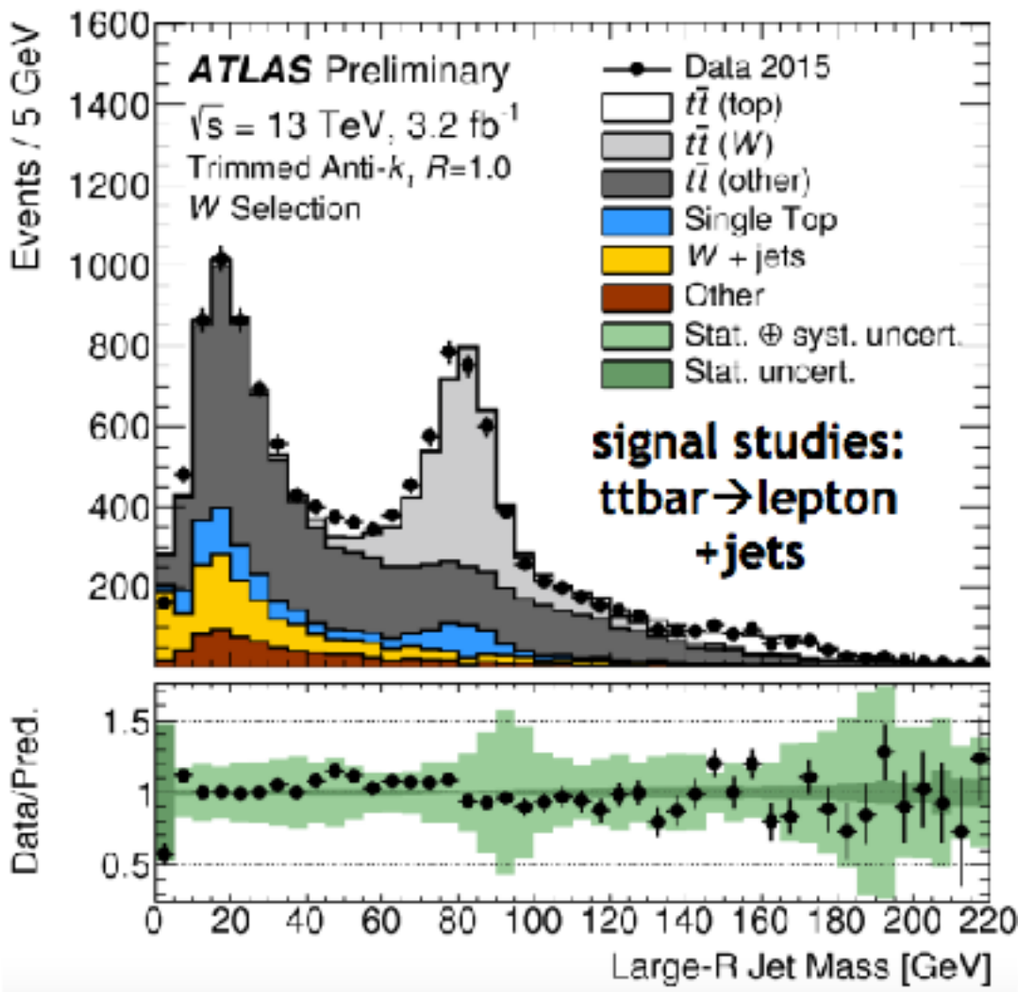

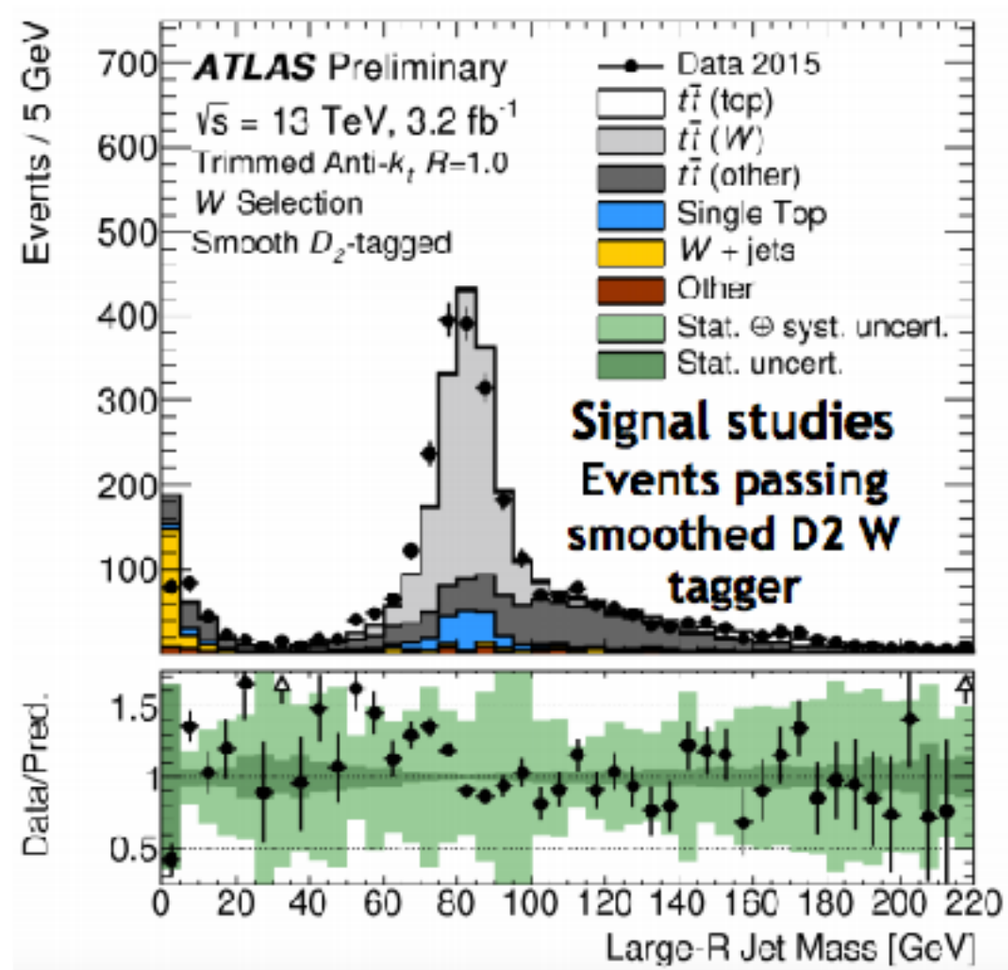

Mass calibration: Down to 5%

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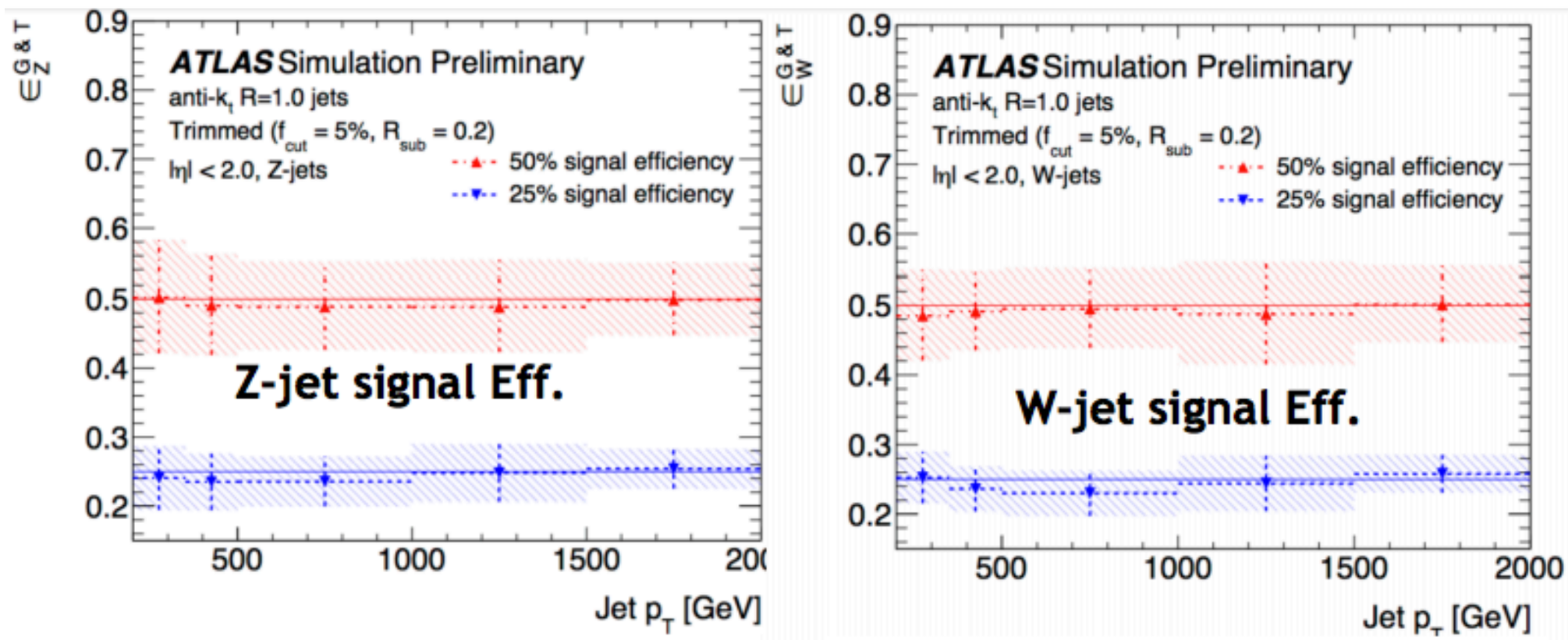


Tagging observables: Jet substructure τ_2/τ_1

N-subjettiness[6]

- Measures the degree to which a jet can be considered as composed of N-subjets.

Distance between momentum of constituent k w.r.t momentum of rest-frame subjet N

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

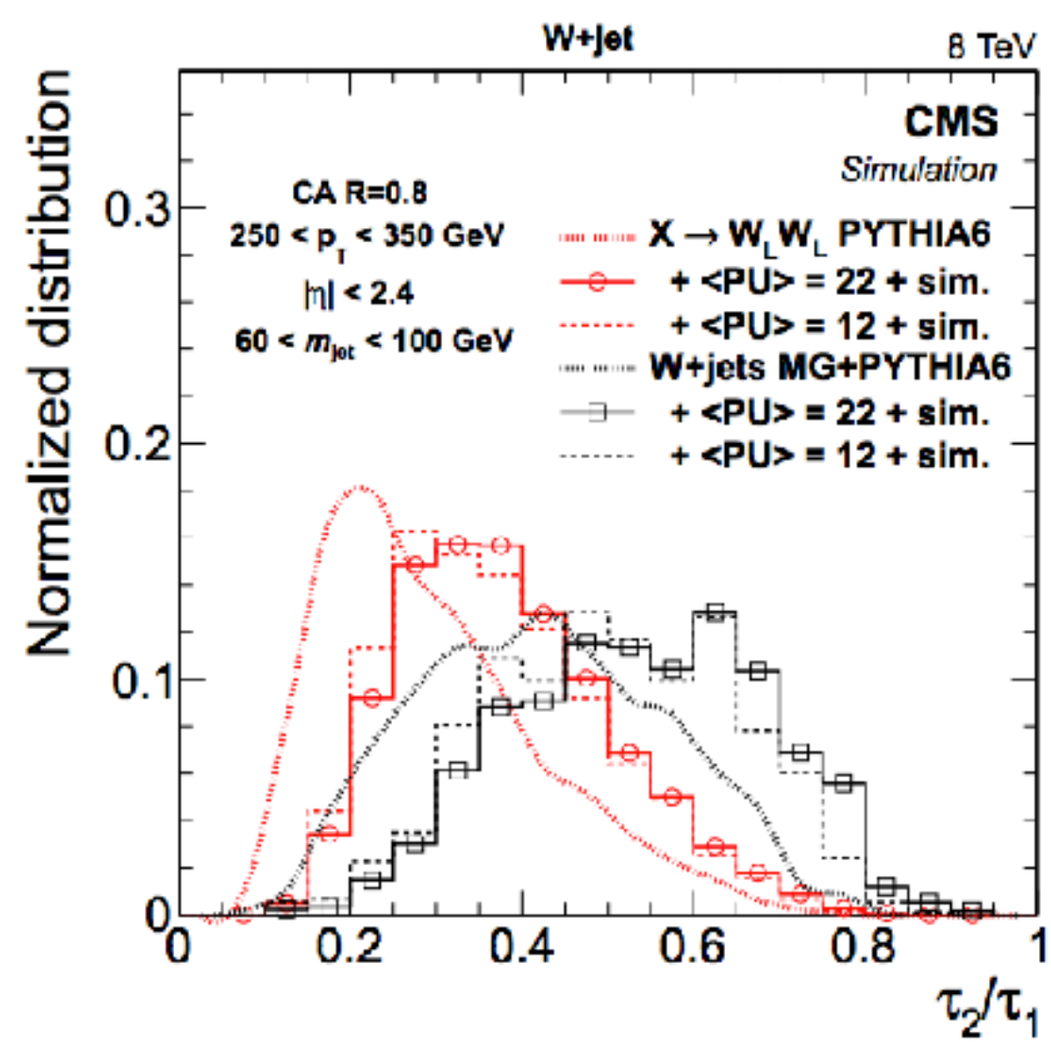
Each constituent assigned to nearest subjet

Small τ_N indicates compatibility with N axes

- For 2-prong substructure we define a discriminant ratio:

τ_2/τ_1 or **τ_{21}**

CMS-JME-13-006



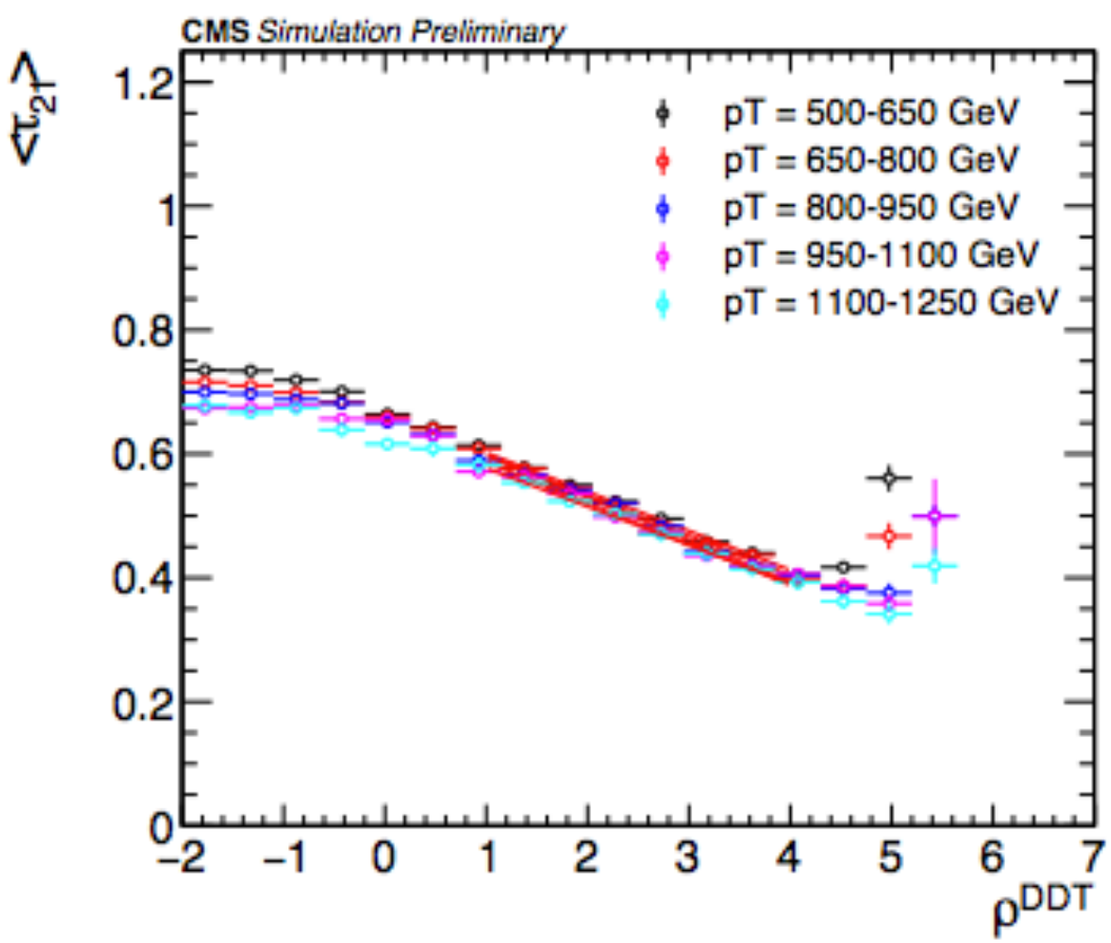
[6] https://arxiv.org/abs/1108.2701 Thaler et. al.

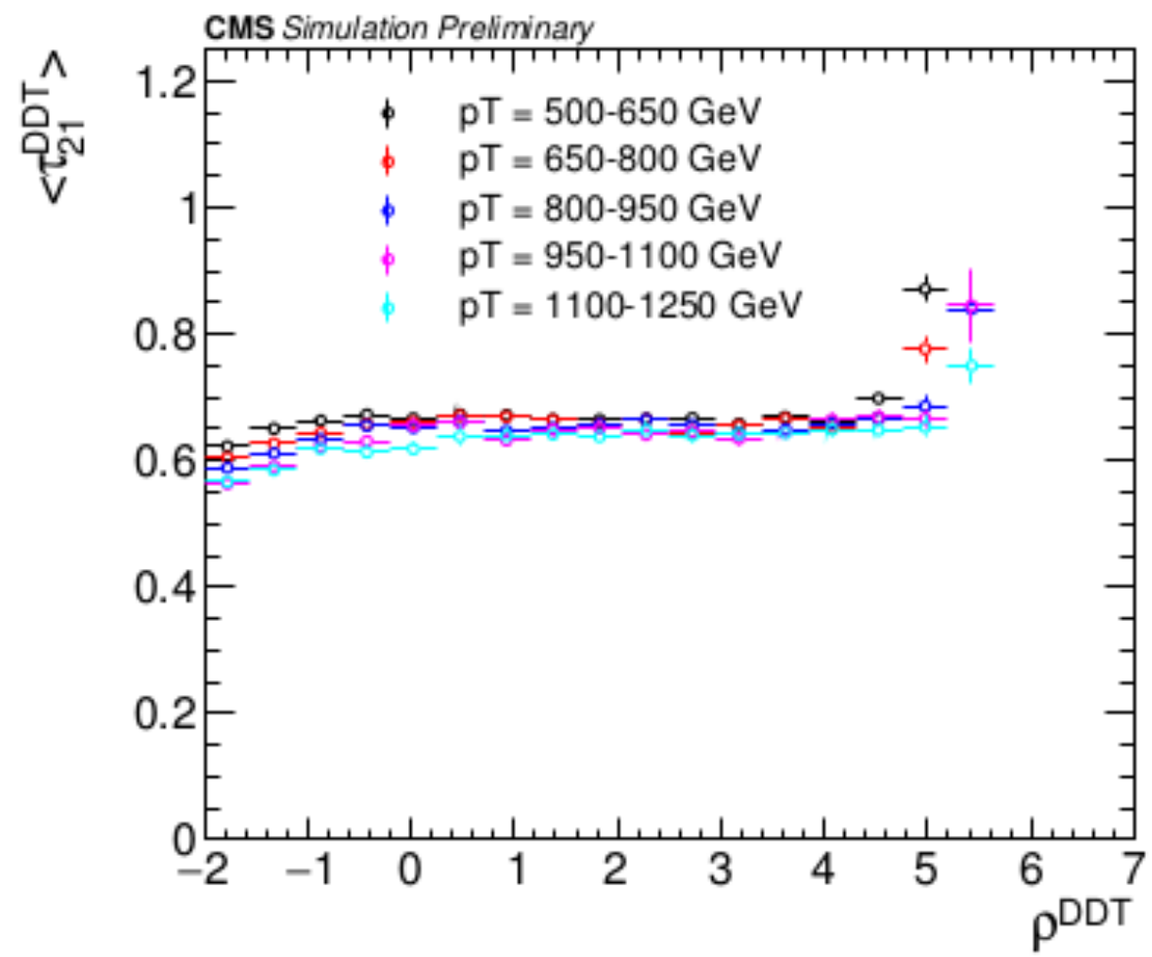
Tagging observables: Jet substructure $\tau_2/\tau_1^{(DDT)}$

Designing De-correlated Taggers (DDT) [7]

- Explore τ_2/τ_1 kinematic dependence
- Use QCD scaling variable $\rho^{DDT} = \log(m_{SD}^2/pT/\mu)$ to get rid of kinematic correlation:

CMS-EXO-16-030





Fit the linear dependence → **Apply transformation:**

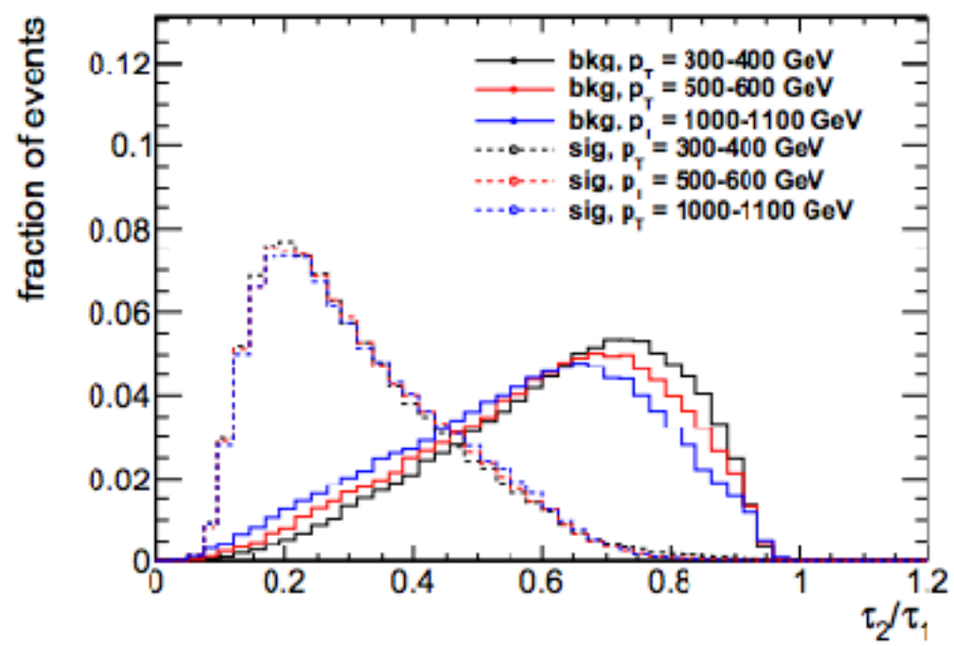
$$\tau_{21}^{DDT} = \tau_{21} + 0.063 \times \log(m_{SD}^2/pT/\mu)) < 0.38$$

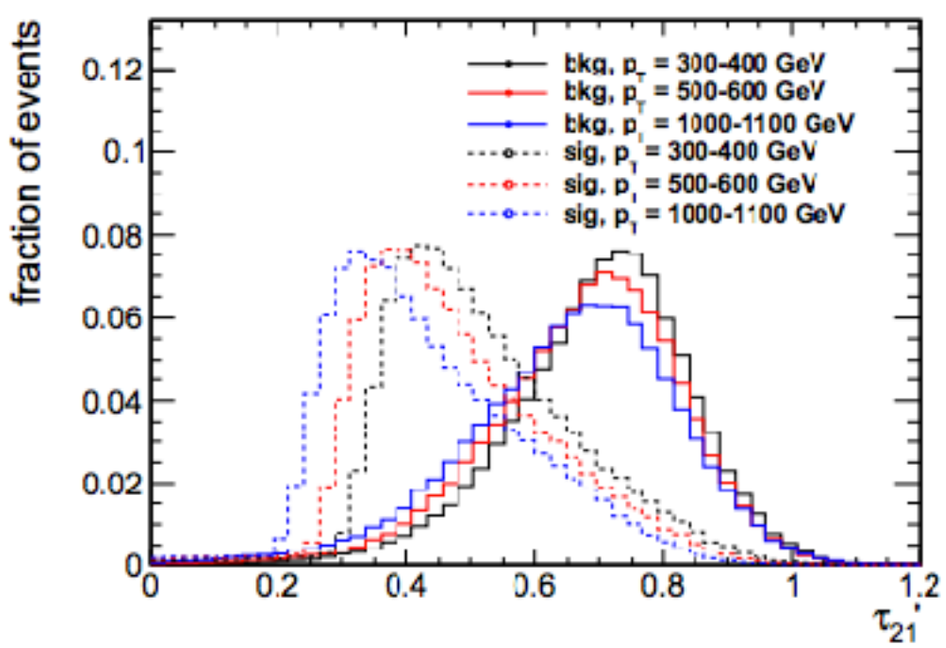
[7] https://arxiv.org/abs/1603.00027 P.Harris et. al.

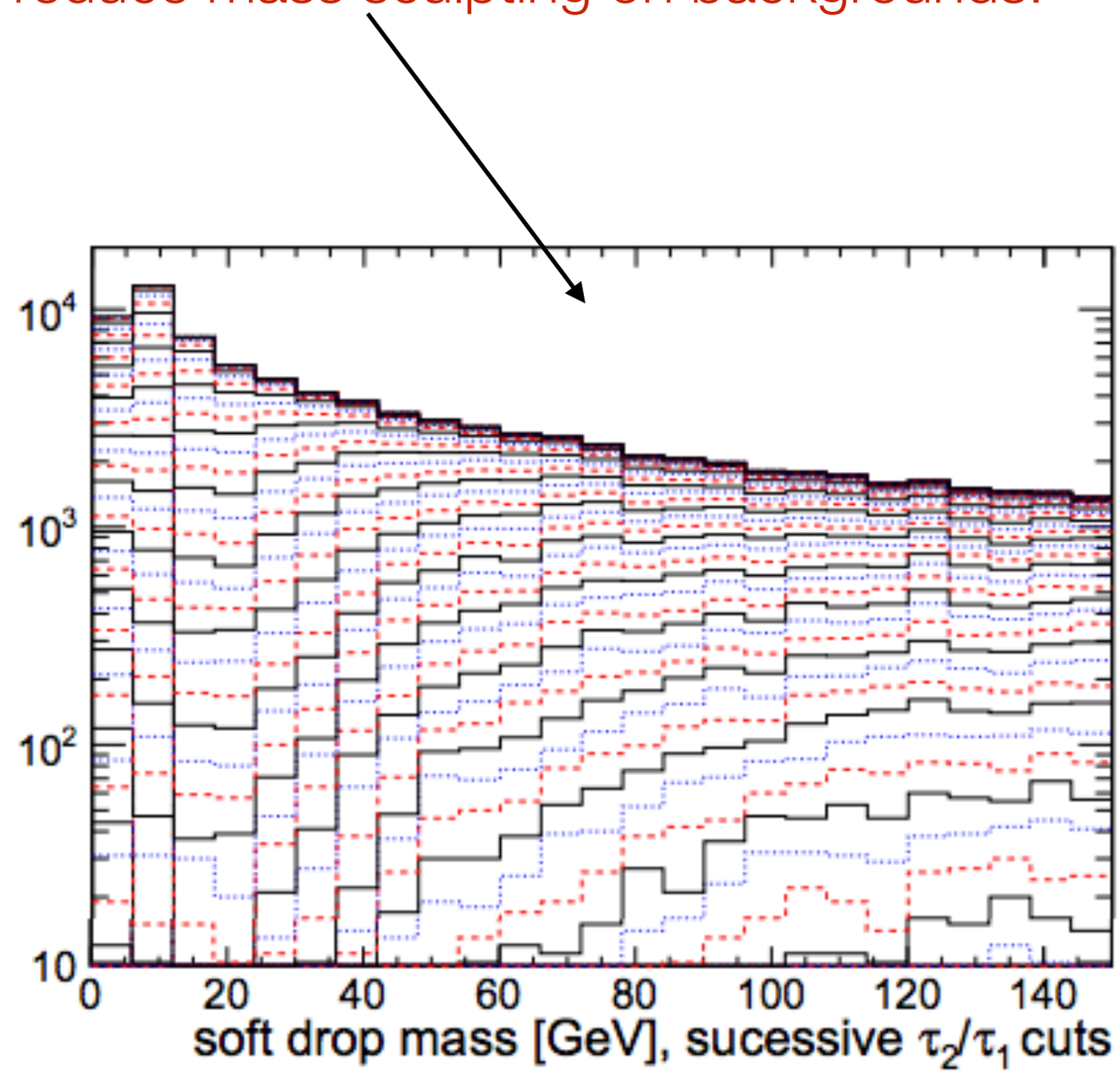
Tagging observables: Jet substructure

Designing De-correlated Taggers (DDT)

- Keeping same performance can reduce mass sculpting on backgrounds:







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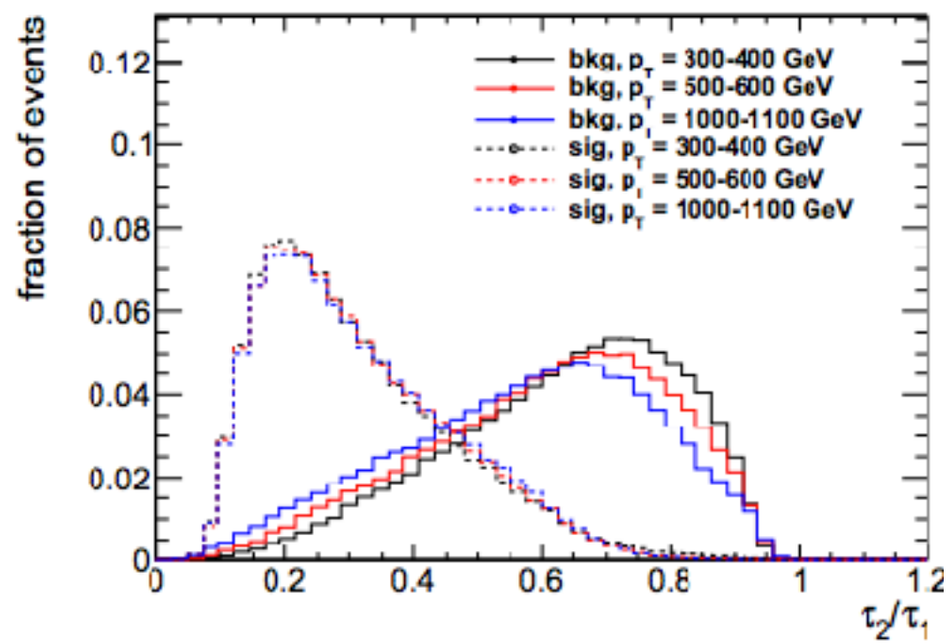
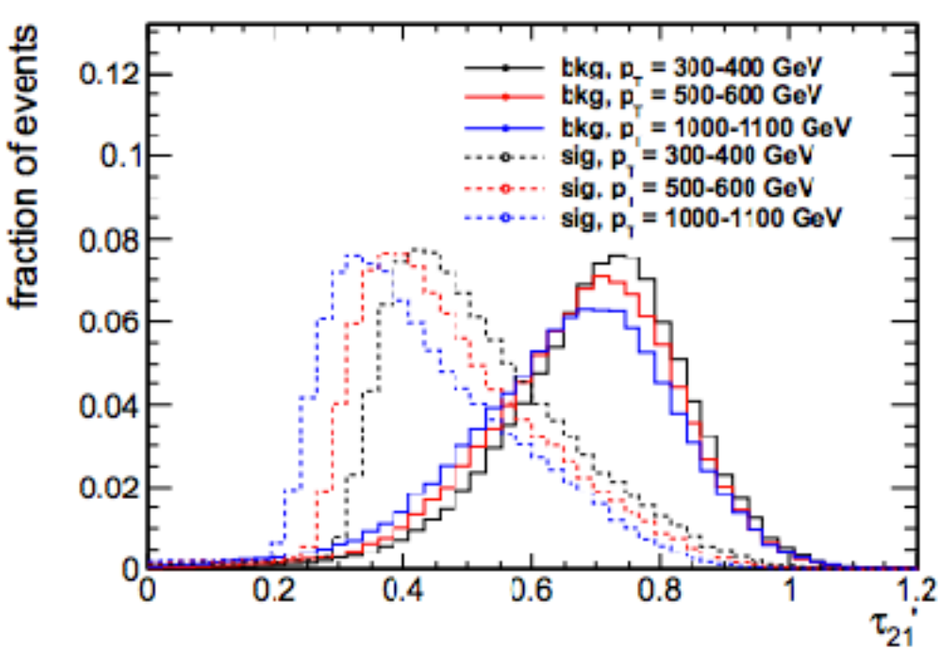
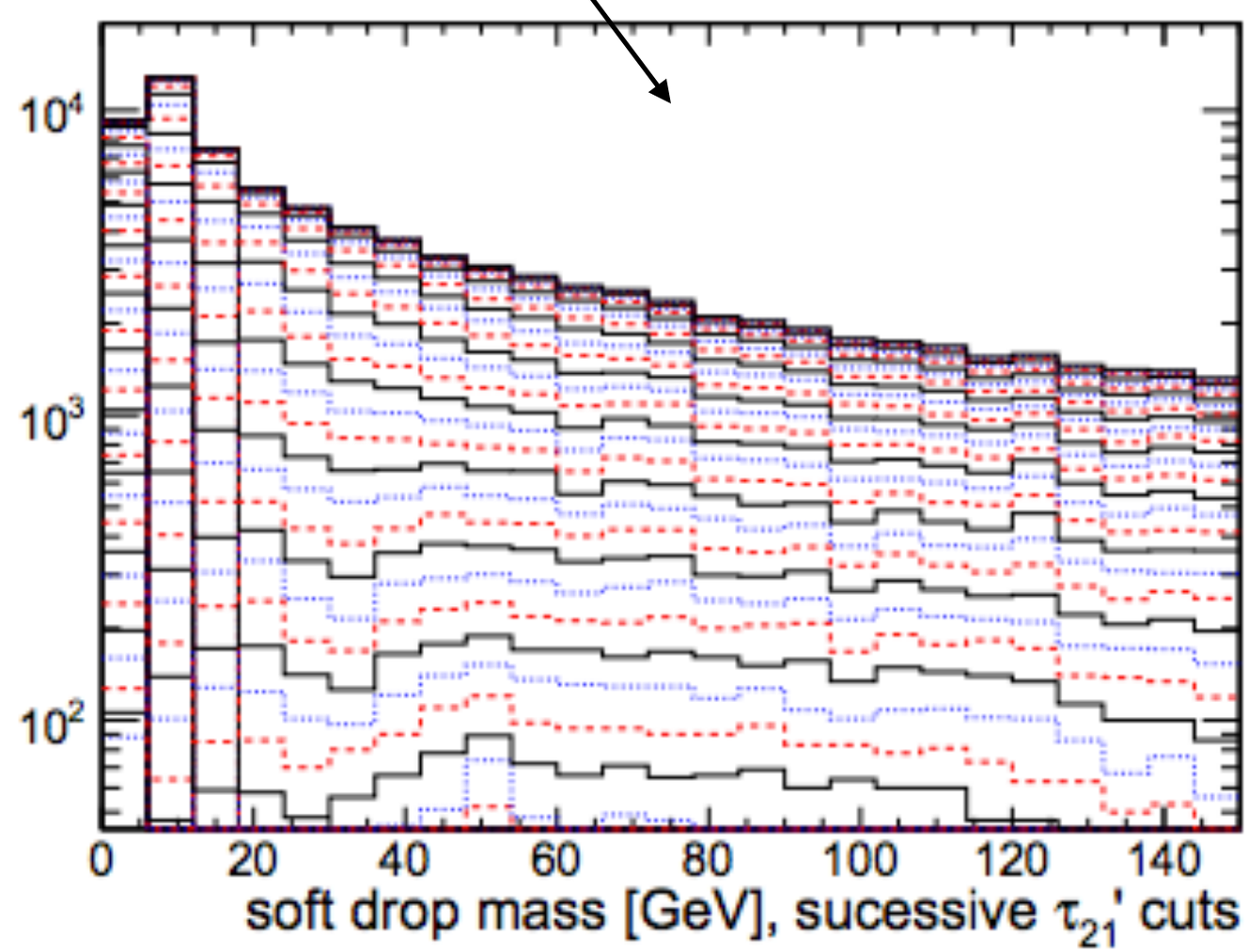
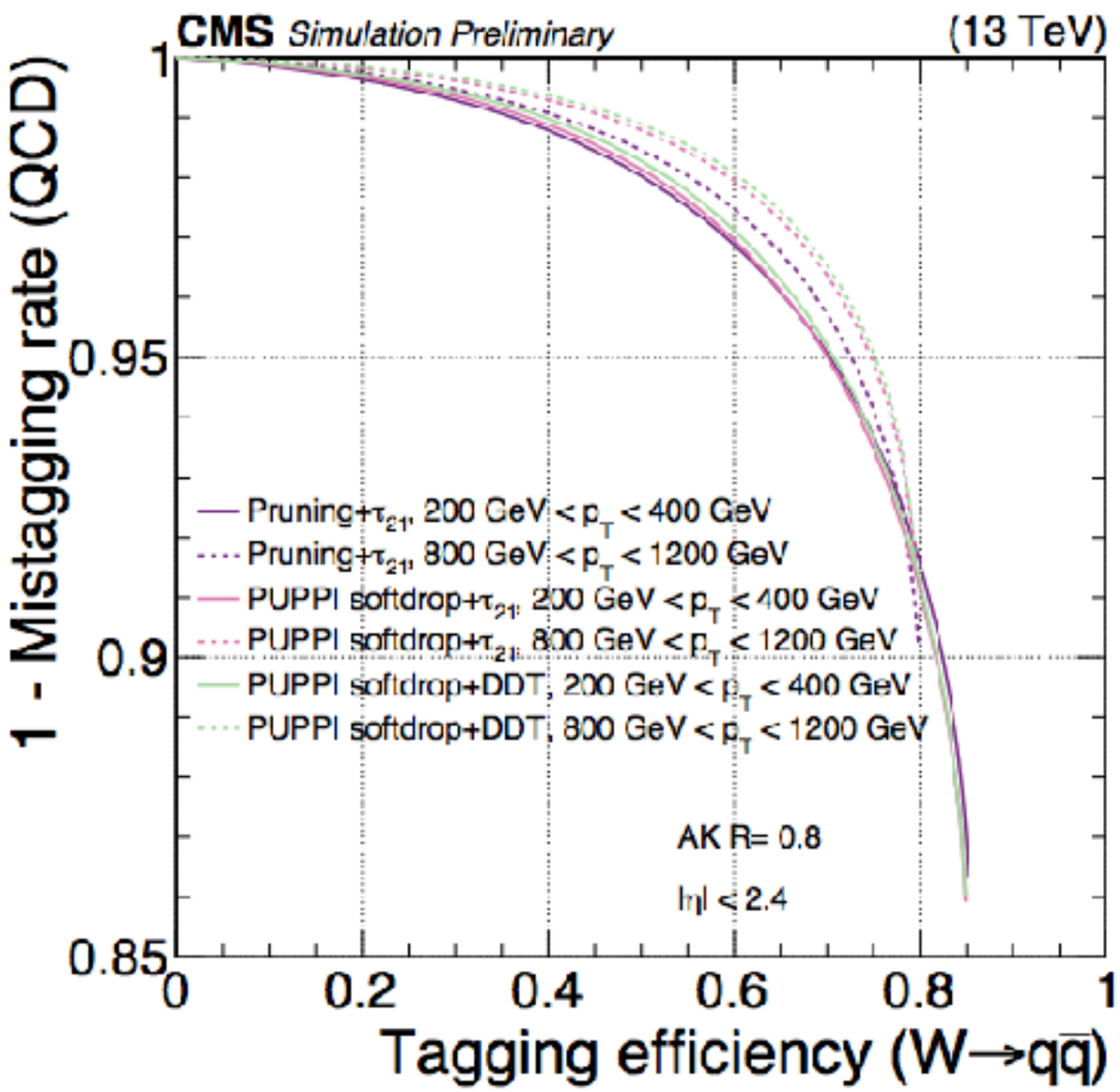


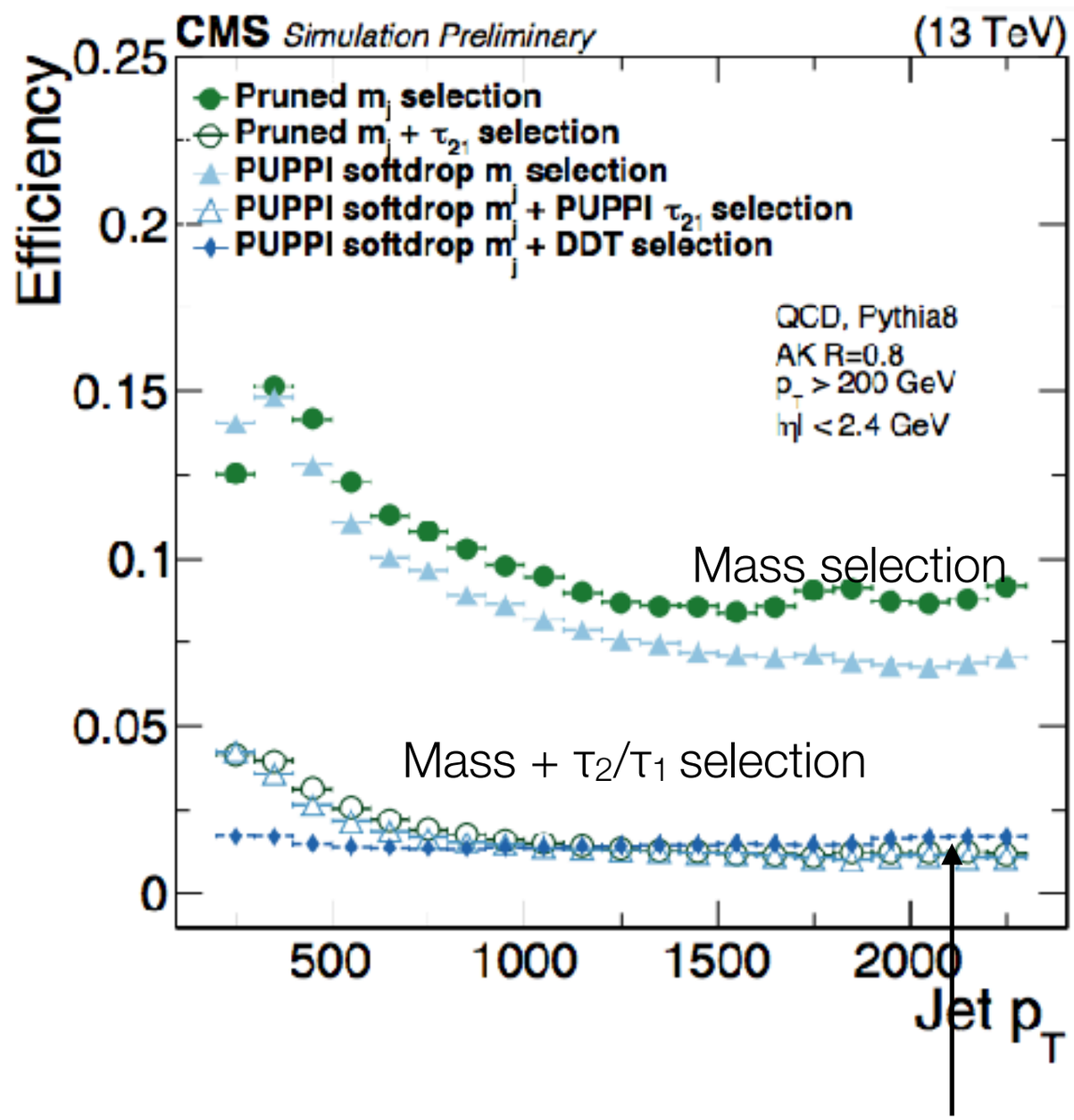




Performances in Simulation

CMS DP-2016/039



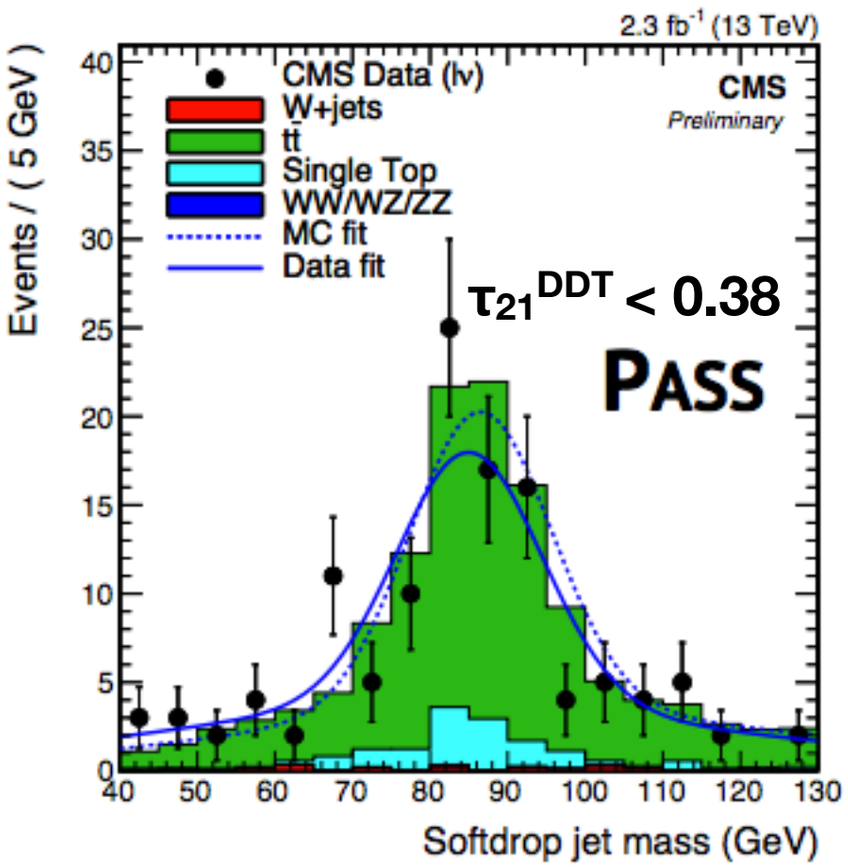


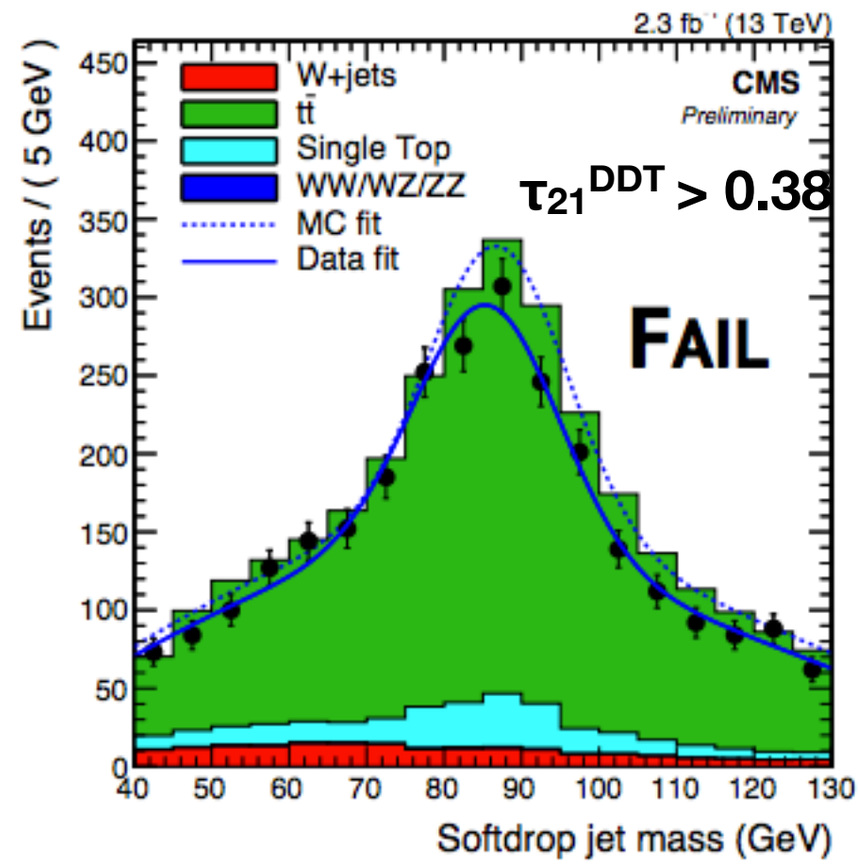
DDT: FLAT mistag rate vs jet pT

Performances in Data

CMS: Puppi + soft drop + DDT

- Semileptonic tt control region used to extract W-tagger data/MC scale factors
- Perform a simultaneous fit on jet mass in pass/fail regions to get τ_{21}^{DDT} efficiency in data and MC





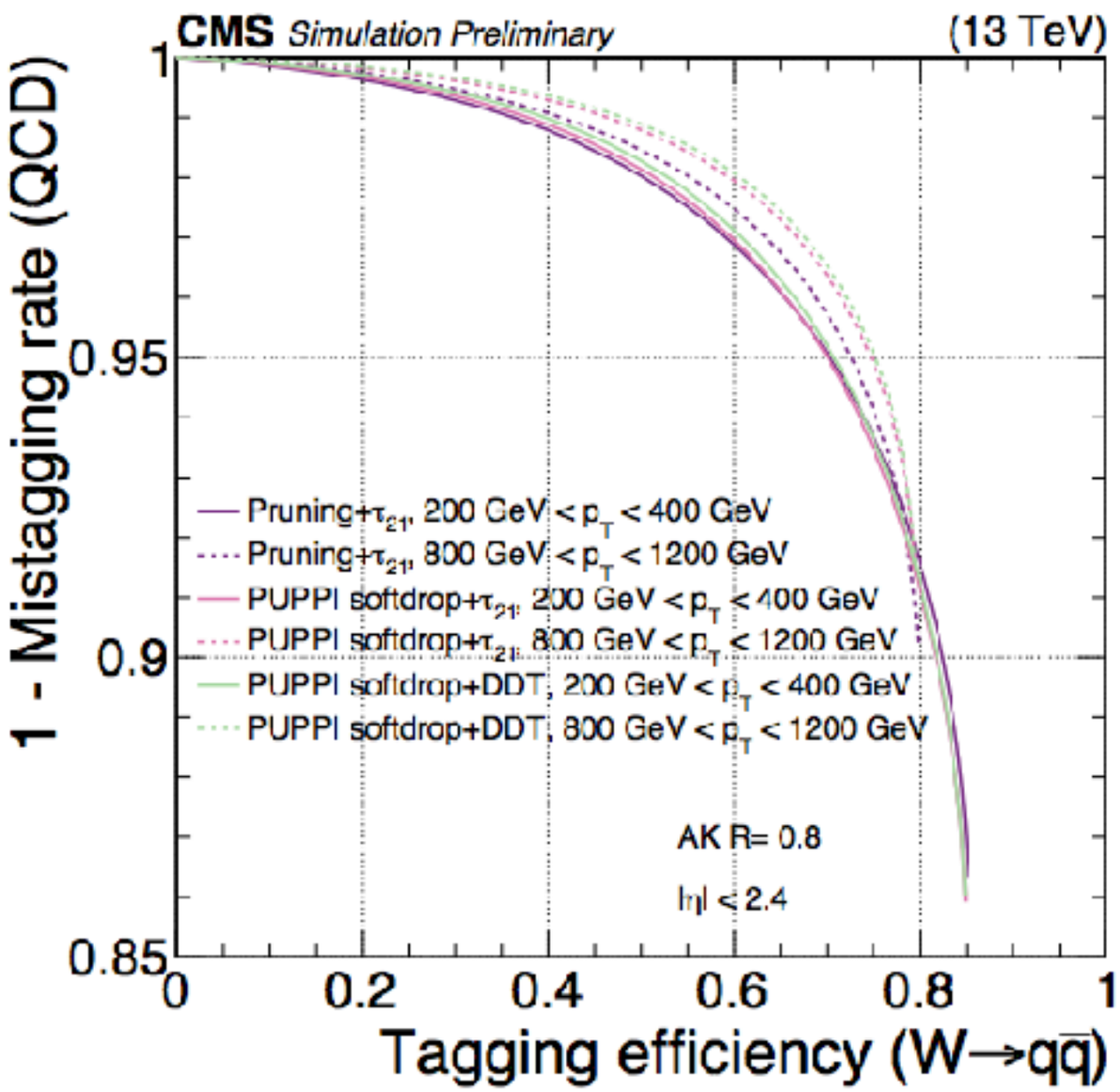
CMS-EXO-16-030

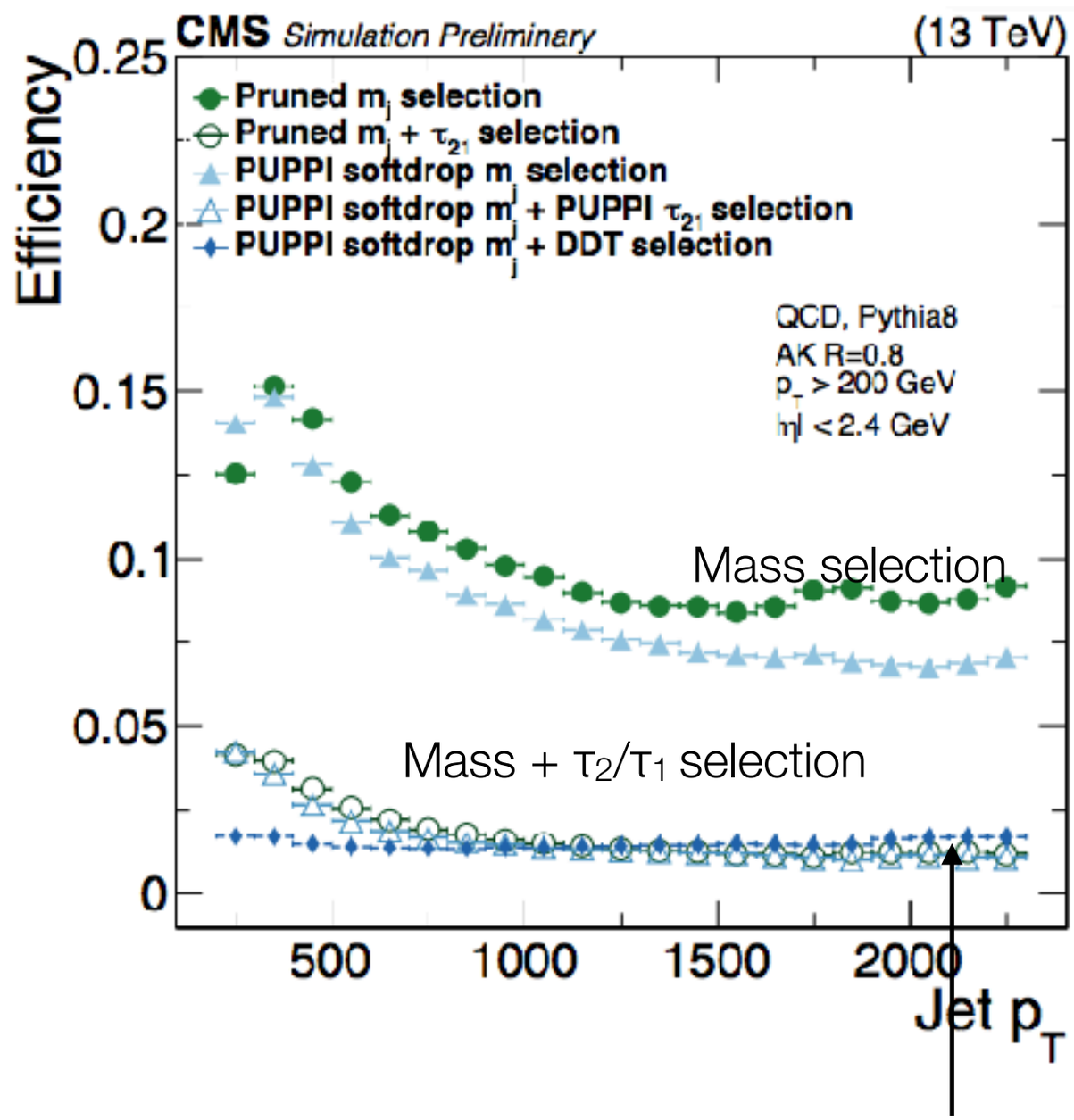
Mass calibration: Down to 1%

N-subjettiness scale factor: 0.95 ± 0.20
Jet mass peak correction: -0.59 ± 0.87 GeV
Jet mass resolution correction: 1.10 ± 0.12 GeV

Performances in Simulation

CMS DP-2016/039

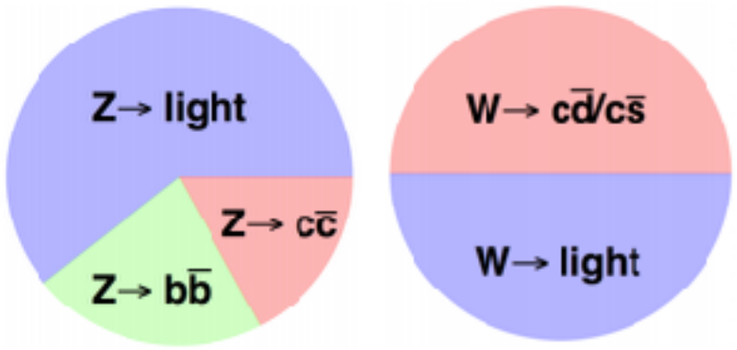


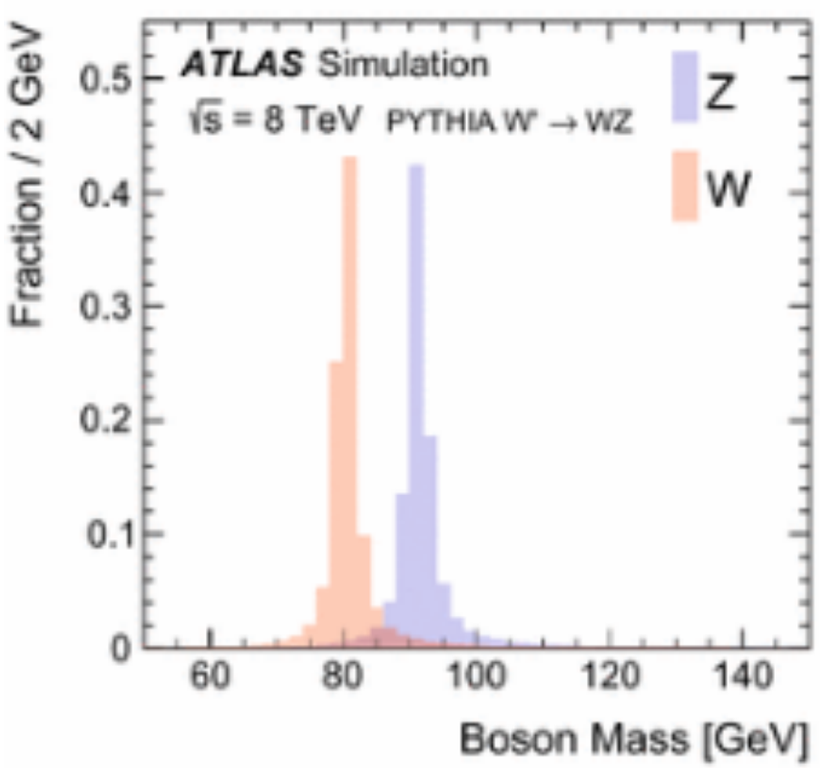


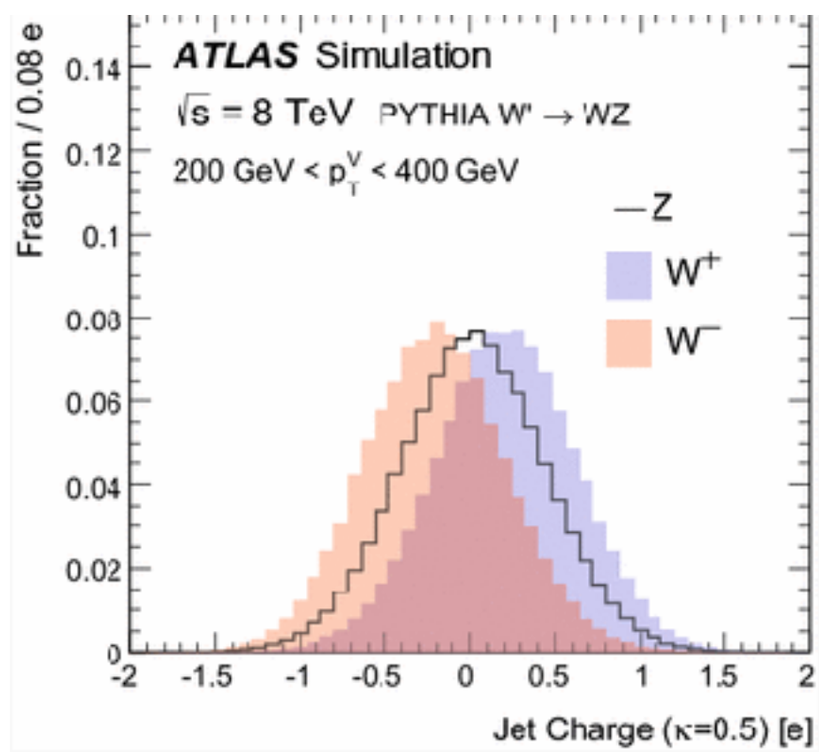
DDT: FLAT mistag rate vs jet pT

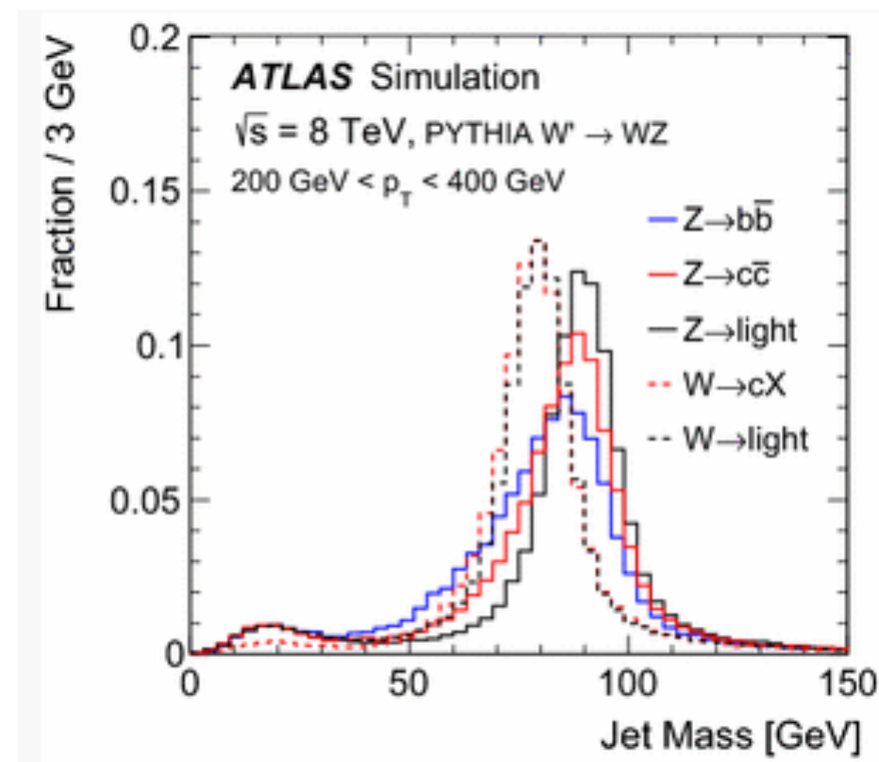
New ideas: Distinguishing W and Z

- Jet mass – V mass
- Jet charge – V charge
- B-tagging discriminant –heavy flavor decay V branching fractions









Eur. Phys. J. C (2016) 76: 238.

New ideas: Distinguishing W and Z

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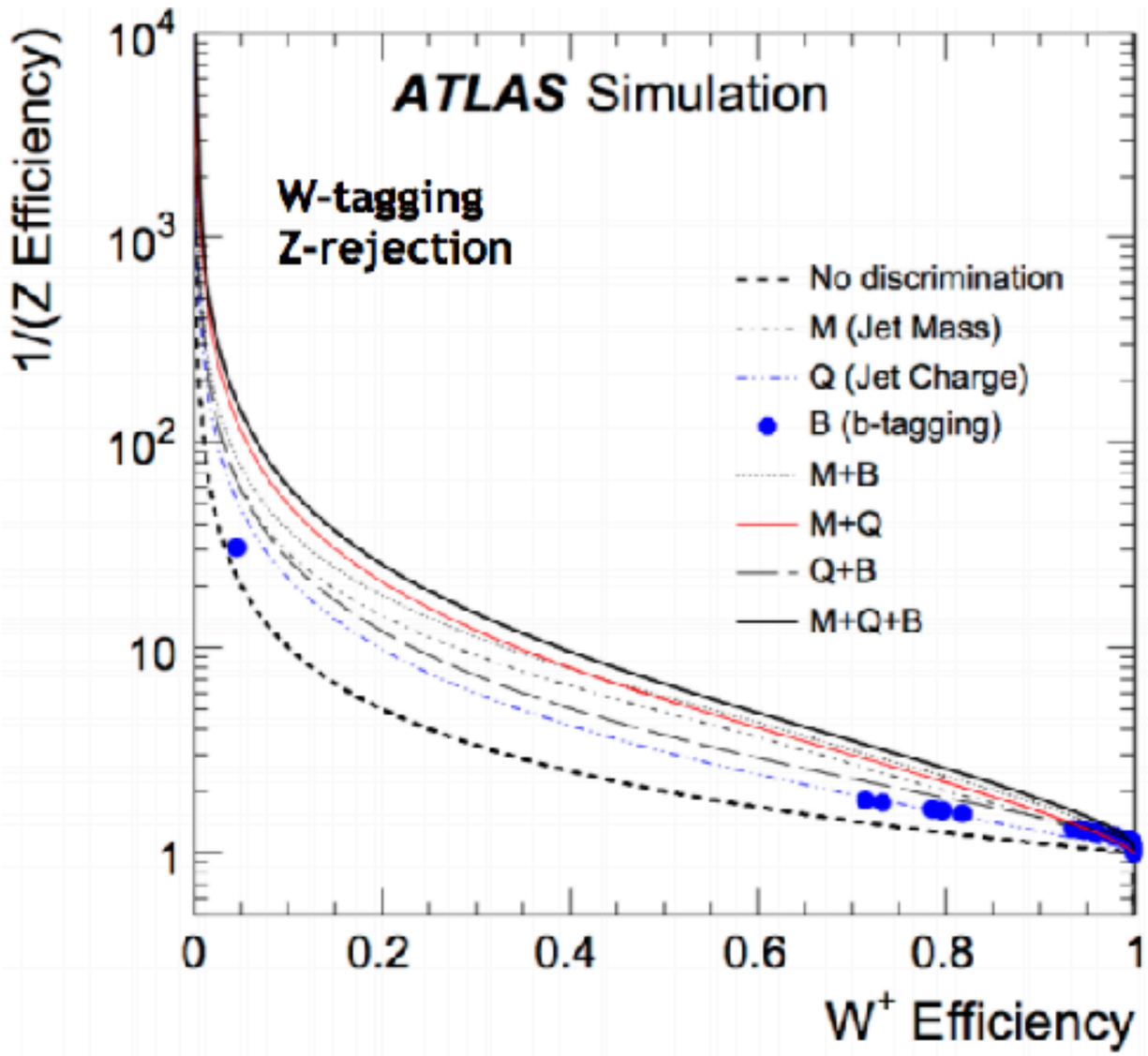
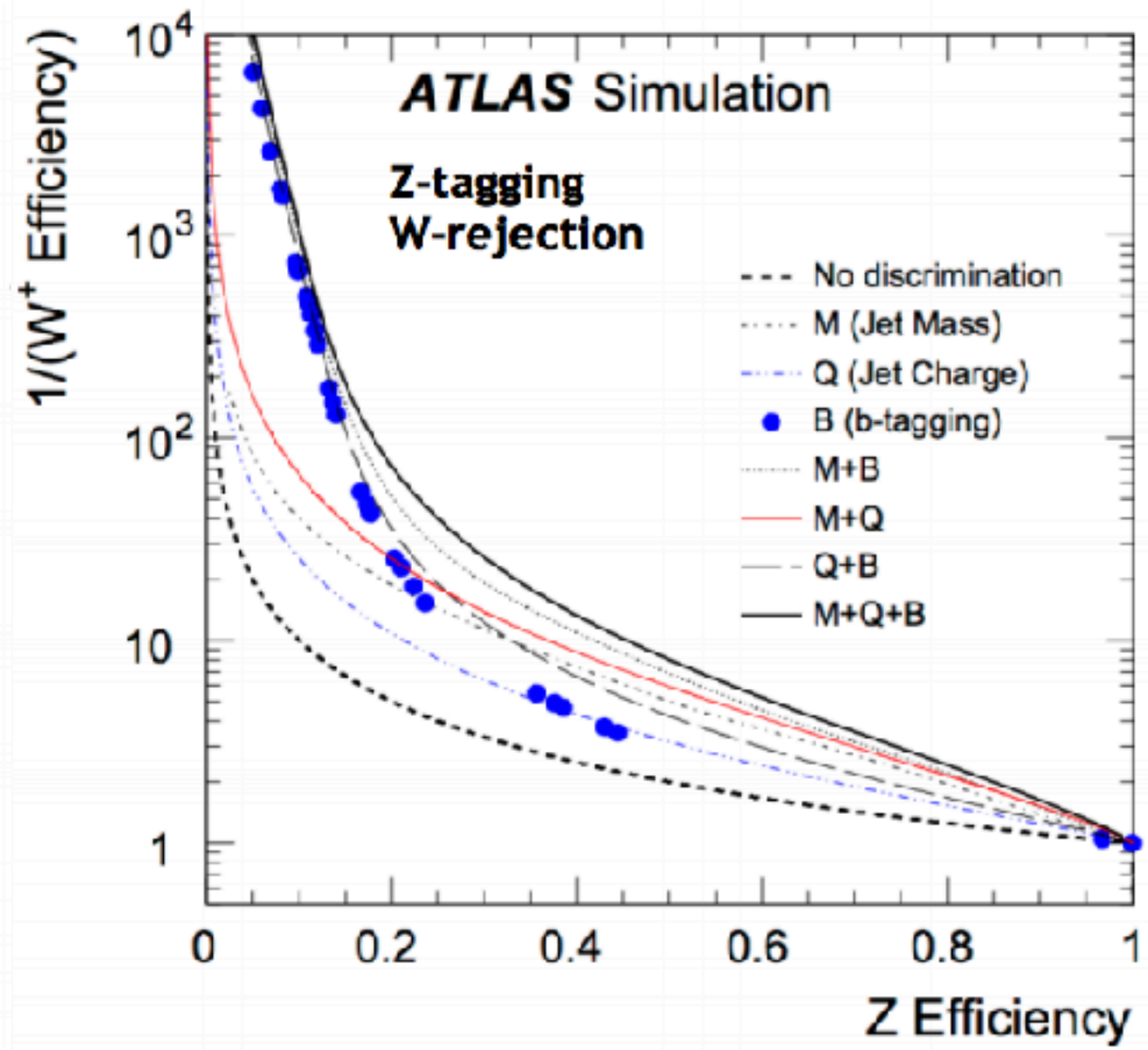




At low Z-tagging efficiencies, large W rejection due to Z→bb tagging

Summary and Outlook

- Clearly Boosted W/Z tagging becomes more important with LHC Run II
- Use of novel W/Z tagging techniques allows great discrimination between signal and background in boosted topologies
  - Explored taggers that exhibit smooth behavior:

    Flat background efficiency: $\tau_2/\tau_1^{(DDT)}$ and Flat signal efficiency Smoothed D_2
  - CMS tagging baseline:

    Before Pruned mass + τ_2/τ_1 Now Soft Drop mass + Puppi + $\tau_2/\tau_1^{(DDT)}$
  - ATLAS tagging baseline:

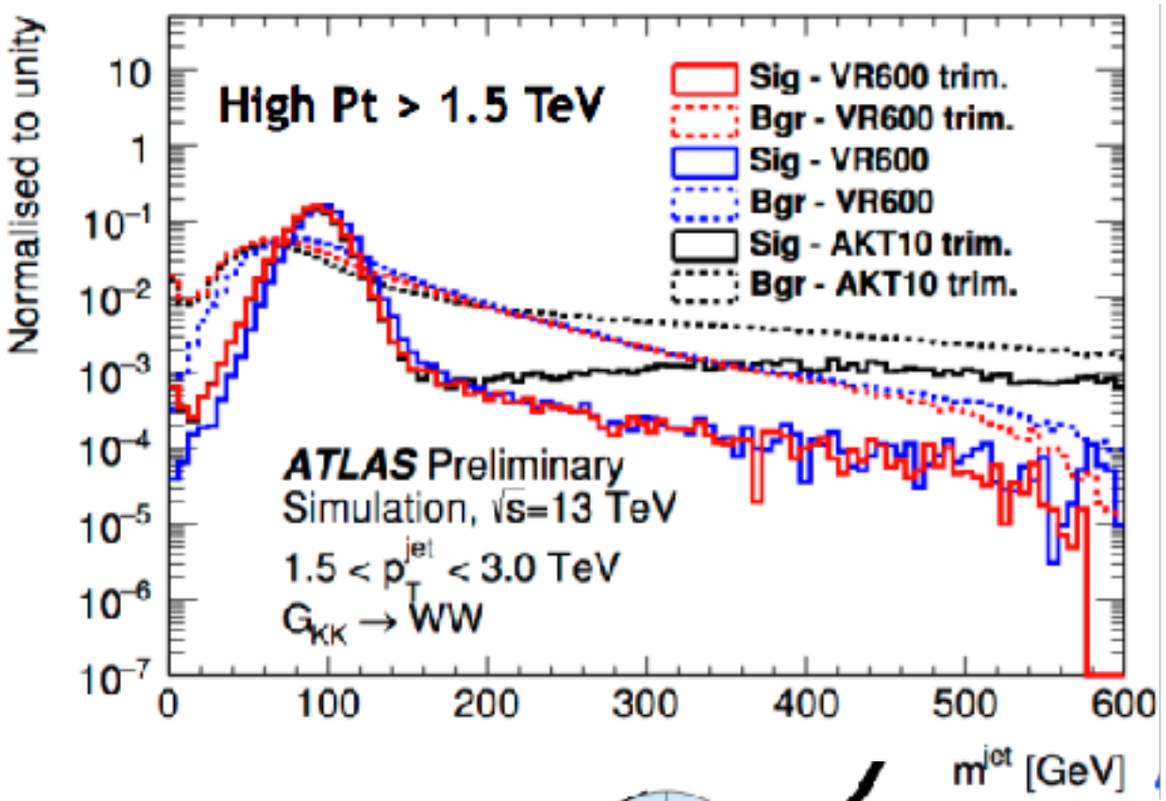
    Before Trimmed mass + $\sqrt{y_{12}}$ Now Trimmed Mass + Smoothed D_2
- Lots of ideas yet to explore!
  - Distinguish Z/W
  - Variable R-jets (Pt dependent jet radius) to define boosted objects
  - Explore kinematic dependence (High pT, low pT, mass and ρ) and reduce systematic uncertainties.

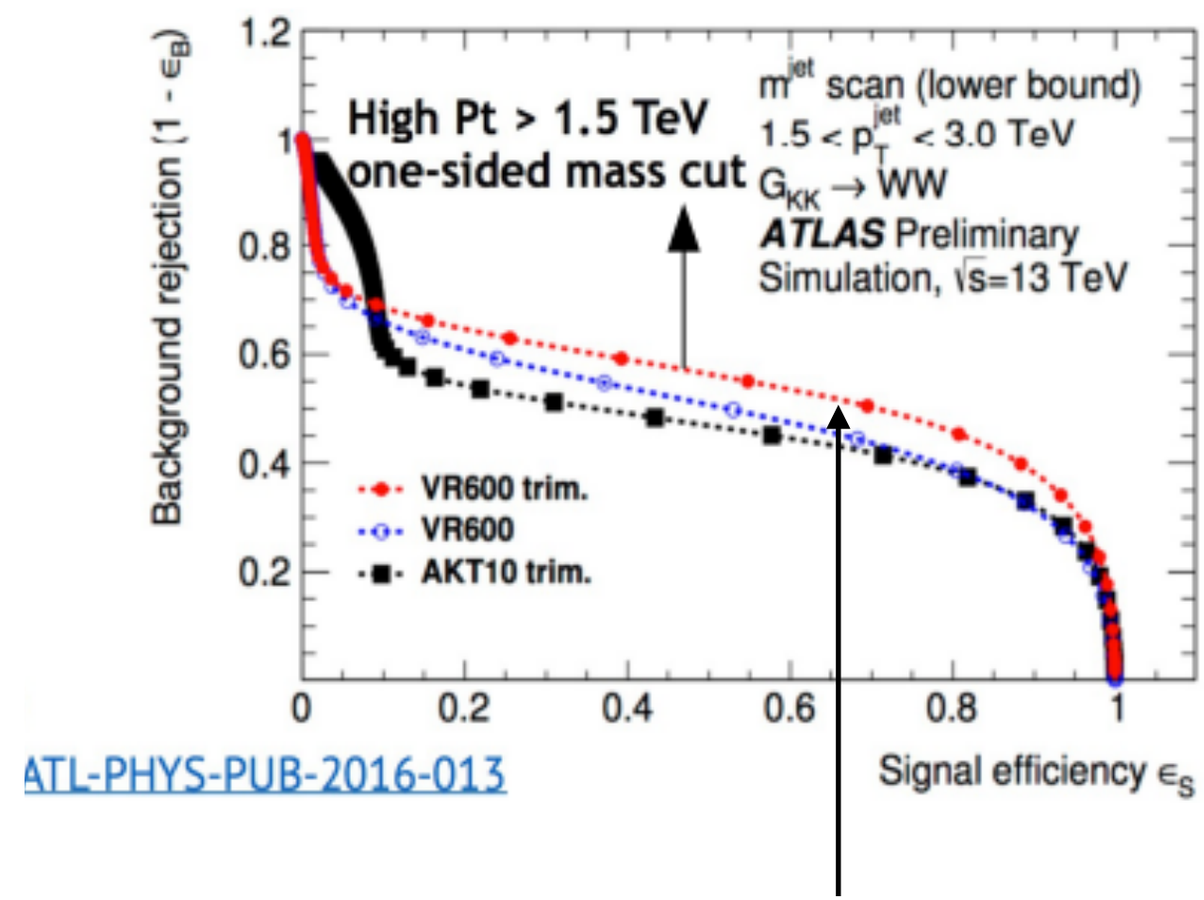
Backup

New ideas: Variable R jets

Variable R jets

- Can build Variable-R versions of the AntiKt (kt) and C/A algorithms $R_0 \longrightarrow R_{eff}(p_{T,i}) = \frac{\rho}{p_{T,i}}$.
- Size of a variable-R jet depends on its transverse momentum
  - separation between decay products of a heavy particle decreases with pT





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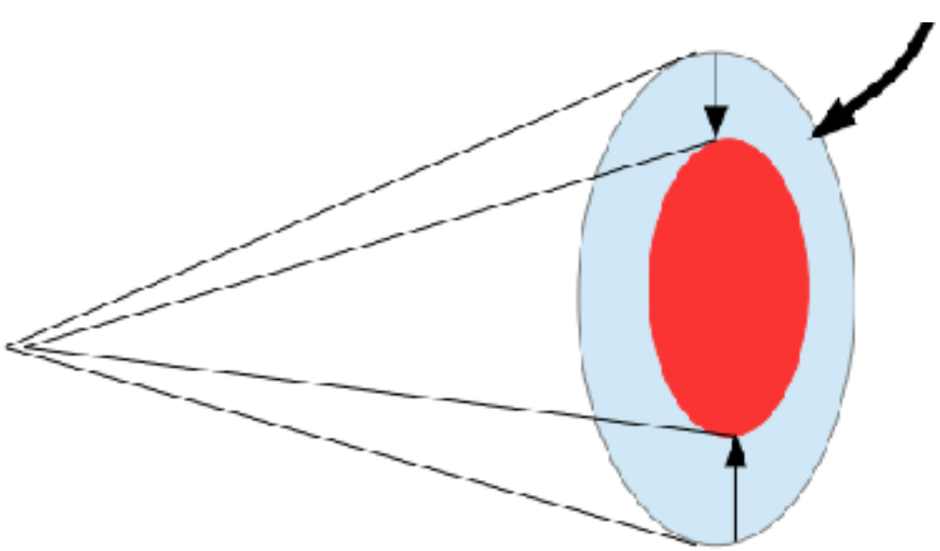
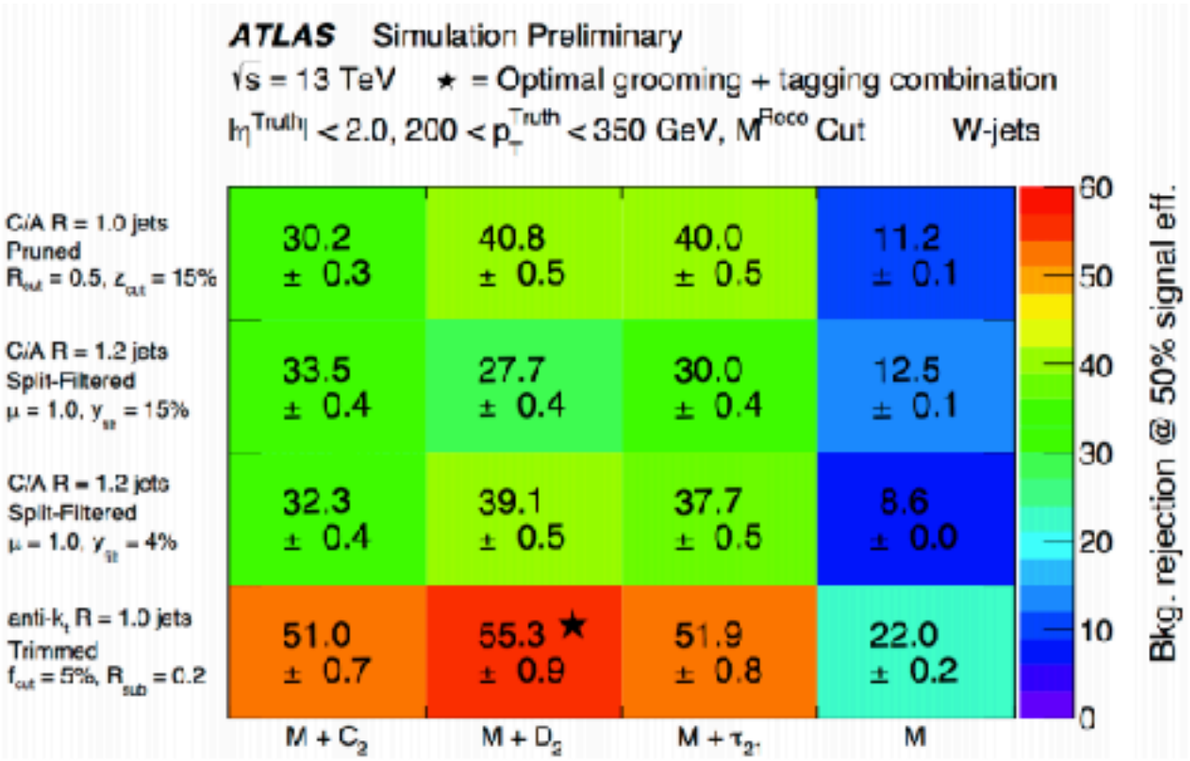
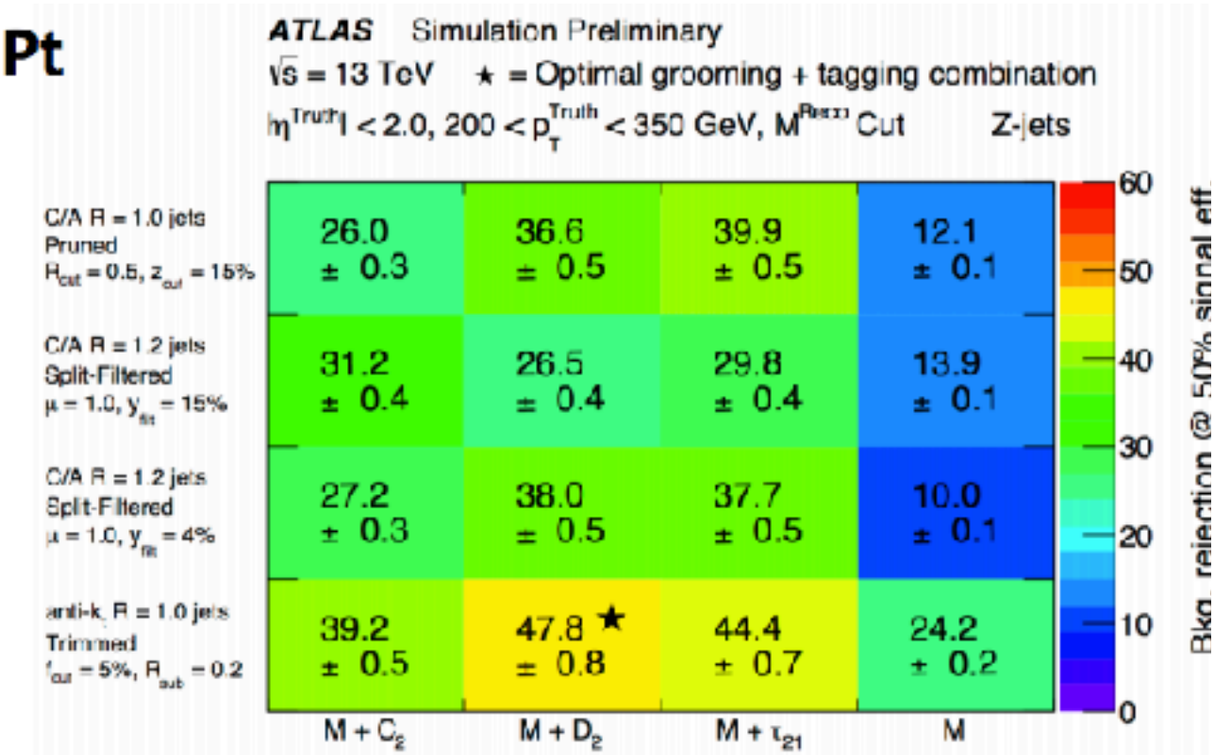


At high pT shrinking the R helps

Tagging observables: Mass window + Jet substructure

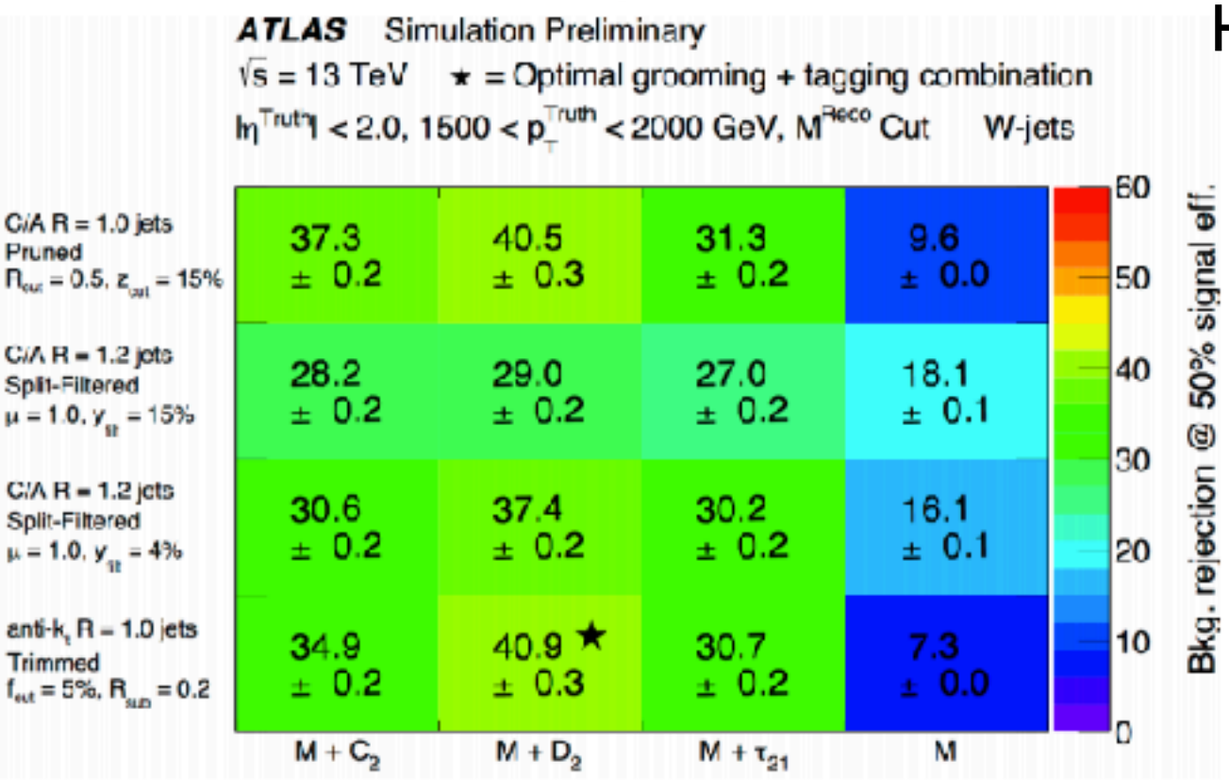
Low Pt

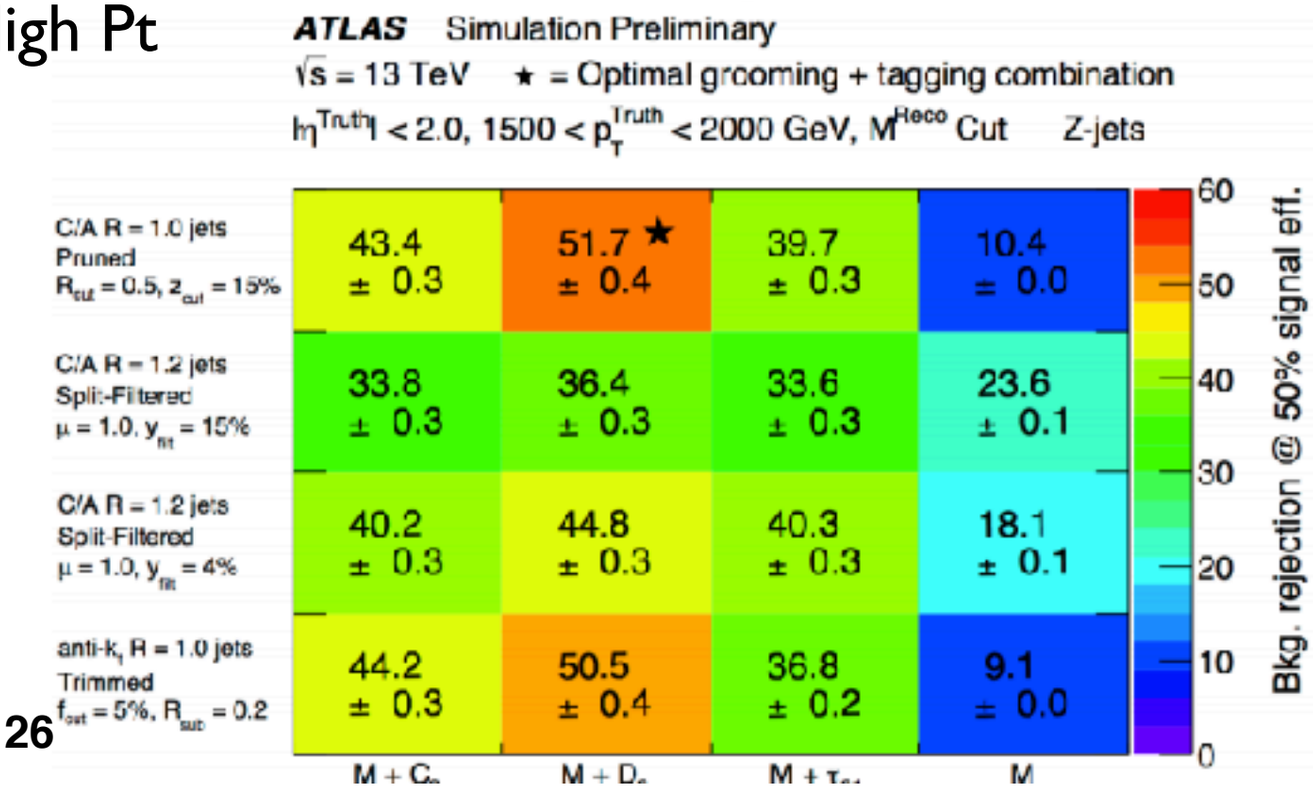




W-jets **Z-jets**

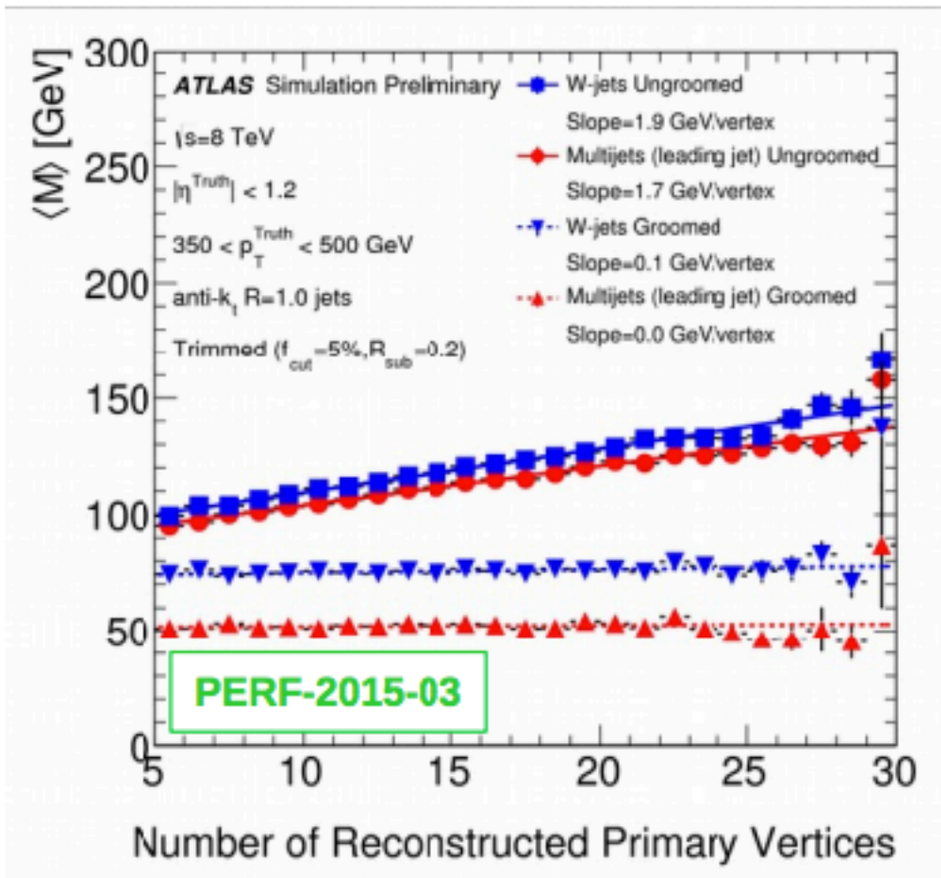
High Pt

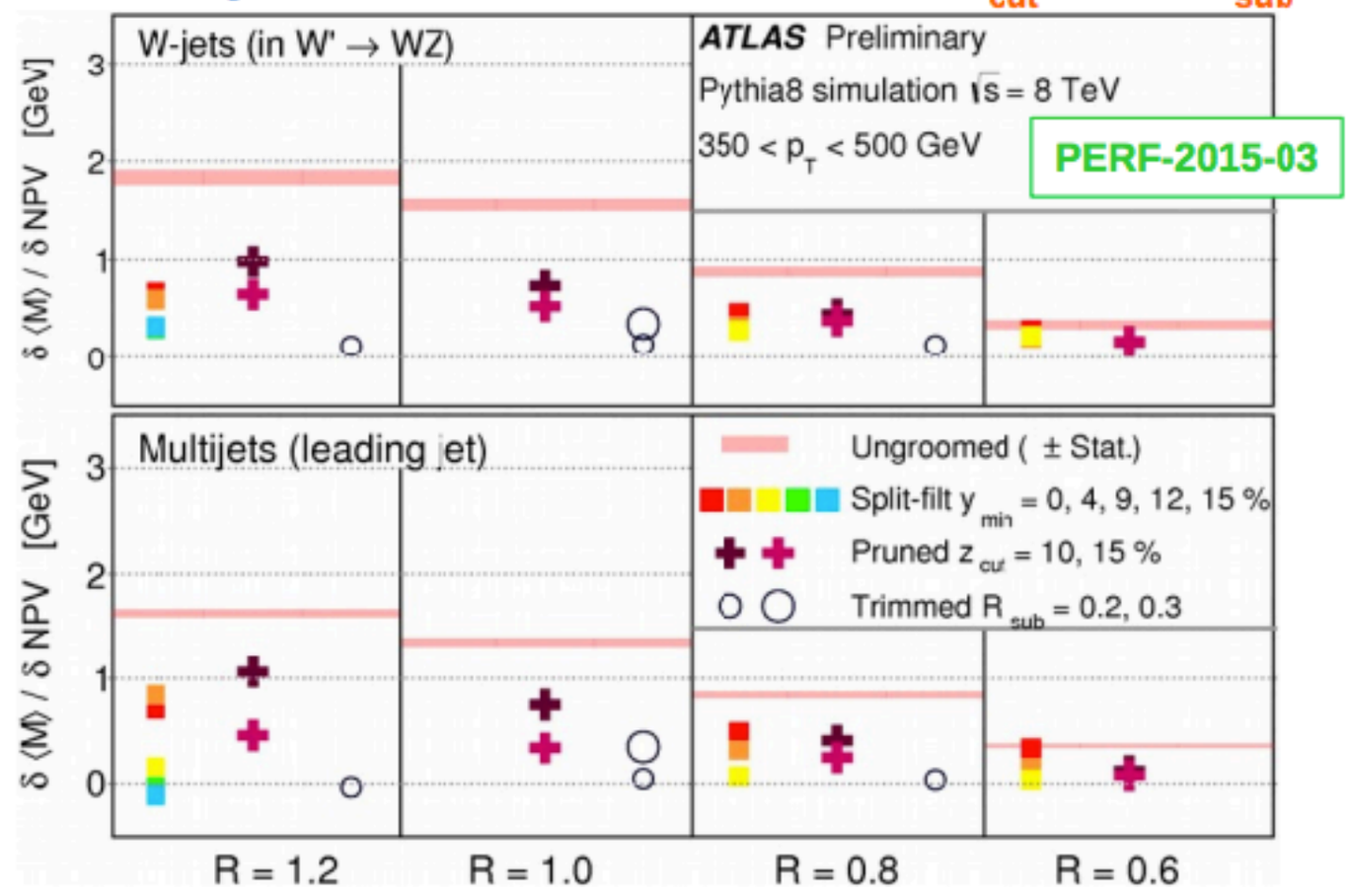




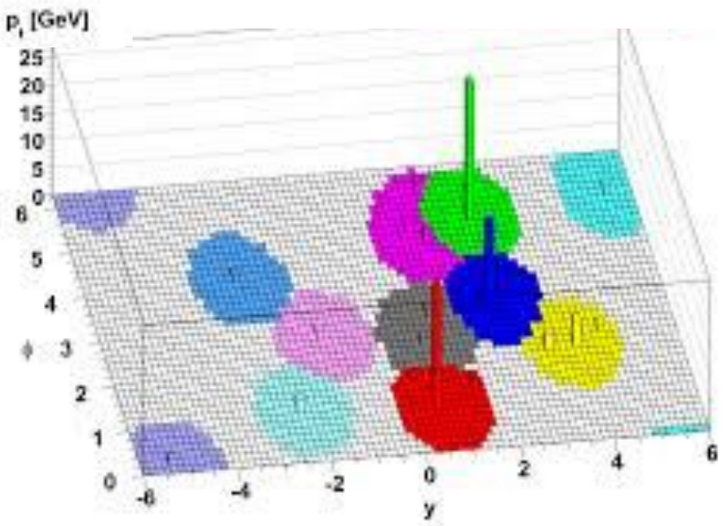
Jet grooming comparison

→ best grooming: low bkgd eff. + good P-U stability → **anti-kt R=1.0 trimmed f_{cut}=5%, R_{sub}=0.2**





Jet clustering



AK8 clustering + PUPPI

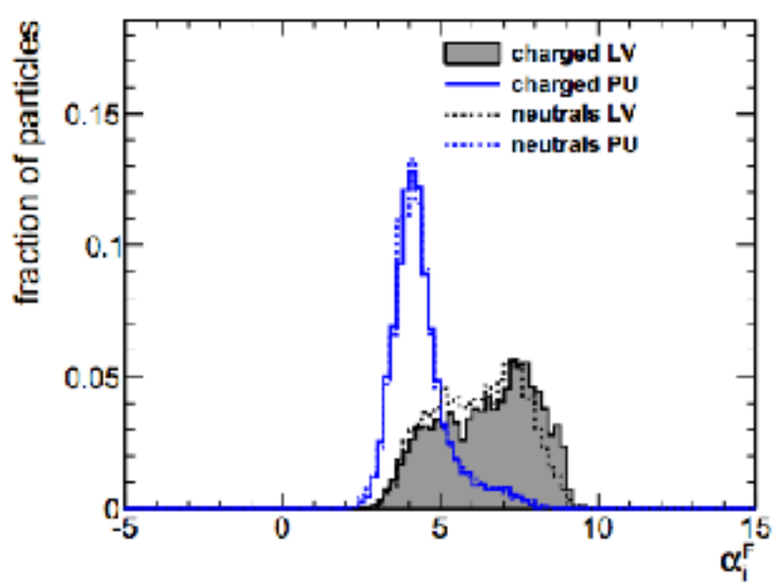
- PileUp per Particle Identification [1]
  - Takes as input PF particles (charged/neutral hadrons, photon, charged leptons)
  - Define α_i of each charged particle (i) using other particles (j) around it

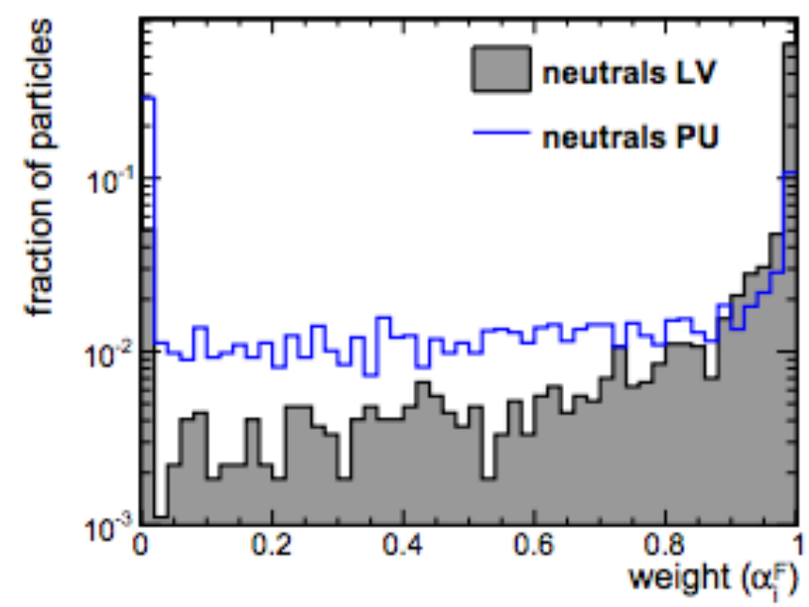
Step function to take into account only particles around it

$$\alpha_i = \log \sum_{j \in \text{event}} \frac{p_{Tj}}{\Delta R_{ij}} \Theta(R_{\min} \leq \Delta R_{ij} \leq R_0)$$

PT sum weighted with distance

- Transform the α distribution in a weight (1 for particle from LV, 0 for particles from PU)
- Jet reconstruction algorithm run on particles taking into account weight → PUPPI jet





[1] https://arxiv.org/abs/1407.6013 Bertolini et. al.

Performances in Simulation

CMS-JME-14-002