

# Searches and techniques for boosted resonances (non-diboson) with the ATLAS detector

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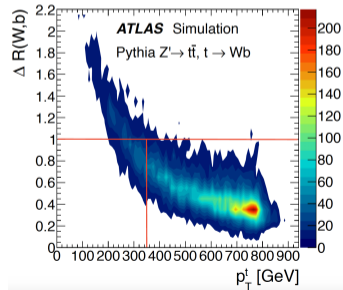
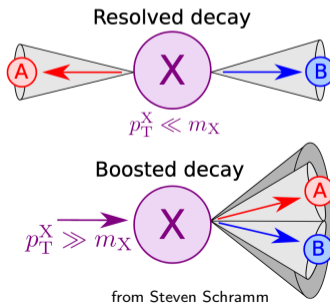
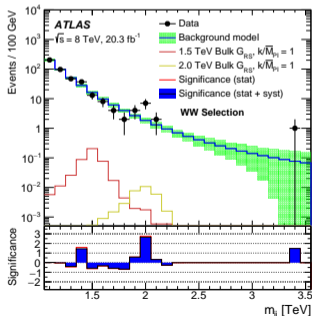
On behalf of the ATLAS Collaboration

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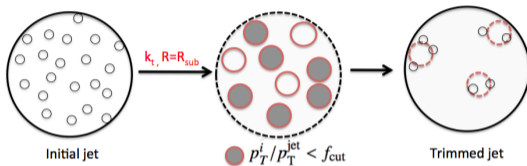


- Many theories for new physics predict the existence of new resonances (e.g.  $Z'$ ,  $W'$ )
  - Topcolor-assisted-technicolor, two-Higgs-doublet, warped extra dimensions, composite Higgs
  - Focus here on  $Z' \rightarrow t\bar{t}$  and  $W' \rightarrow tb$  resonances
- **Search strategy**
  - Hadronic decays have the highest branching ratios!
  - Search for resonant structure in invariant  $t\bar{t}$ ,  $tb$  mass distribution
  - Main challenge is the suppression of the dominant QCD background  $\rightarrow$  develop taggers



**1 Removal of soft, wide-angle radiation, pile-up effects**

- Constituent-level pile-up suppression: e.g. Constituent Subtraction, SoftKiller
- Grooming algorithm: e.g. trimming (Run-2 default up to now), Soft Drop (new default)

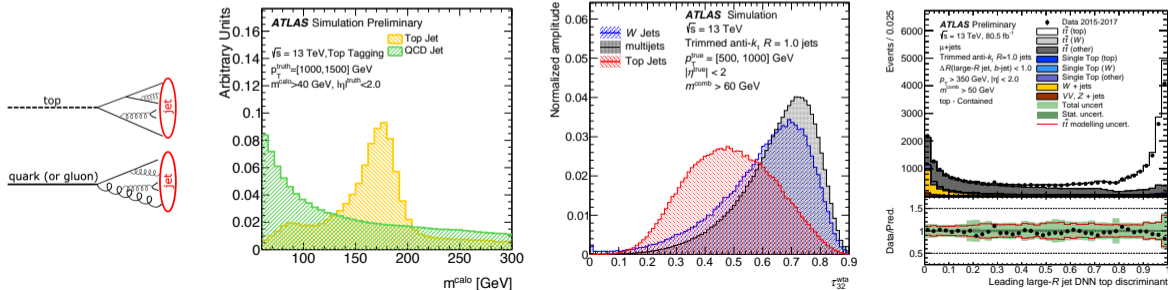


## 1 Removal of soft, wide-angle radiation, pile-up effects

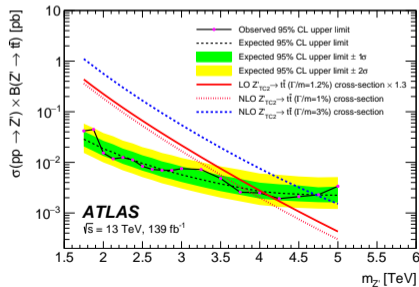
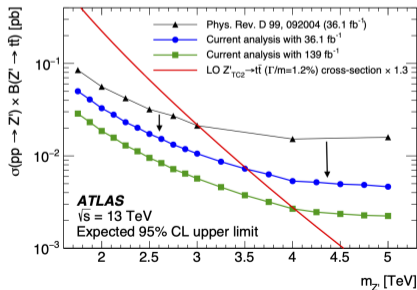
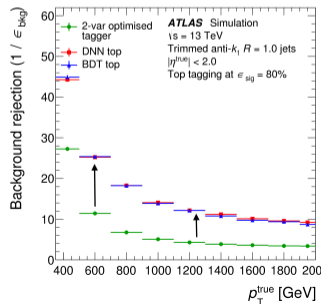
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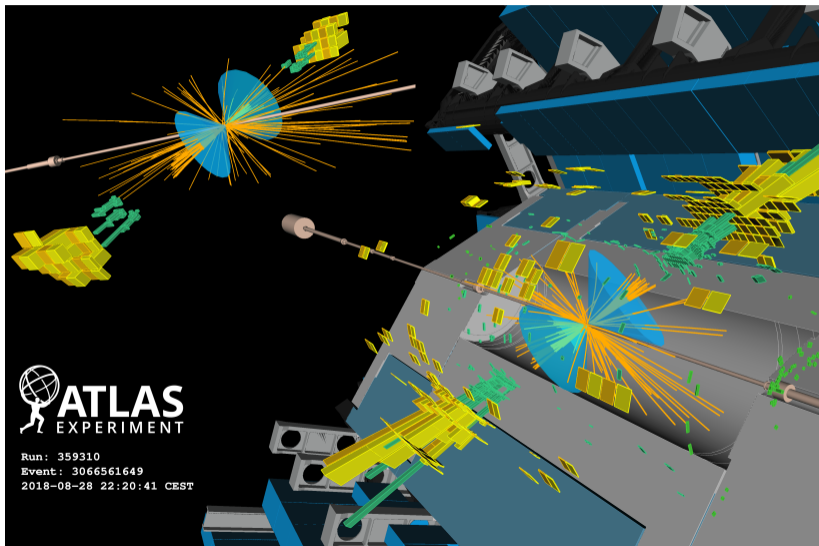
## 2 Jet substructure variables / taggers

- Study the internal structure of the jet to distinguish e.g. top jets from q/g-initiated jets
- Simple taggers: cut on jet mass + one other substructure variable (e.g.  $N$ -subjettiness)
- Complex taggers: Deep Neural Networks (DNN) trained on various substructure variables
- Taggers are calibrated in data via scale factors (SF) using  $t\bar{t}$ , multijet and  $\gamma$ +jet events

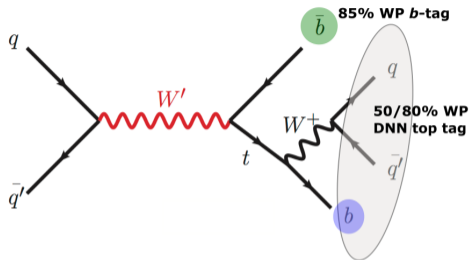


- Search performed using full Run-2 dataset ( $139 \text{ fb}^{-1}$ )
- DNN tagger used to identify boosted top quark decays @ 80% signal efficiency +  $b$ -tagged variable- $R$  track jet (77% WP)
- Data-driven background estimation using fit function
- Largest systematic uncertainties from tagging SFs (and  $b$ -tagging)
  - Dominated by generator differences when calibrating efficiency in MC to data





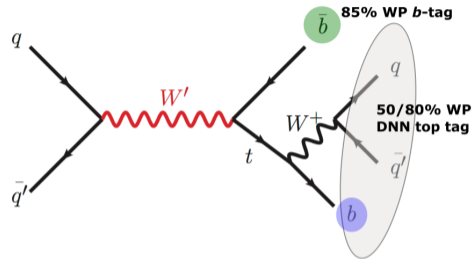
- Search for  $W' \rightarrow t\bar{b} \rightarrow q\bar{q}'b\bar{b}$  using  $139 \text{ fb}^{-1}$
- Searches done separately for left- and right-handed gauge bosons
- Here: only results for right-handed  $W'$
- See poster by [Kuan-Yu Lin](#) for more details!



## Signal regions

- SR1: 50% top tag, 1  $b$ -jet with  $\Delta R(\text{top}, b\text{-jet}) < 1.0$  and one add.  $b$ -jet
- SR2: 80% but not 50% top tag, 1  $b$ -jet with  $\Delta R(\text{top}, b\text{-jet}) < 1.0$ , one add.  $b$ -jet
- SR3: 50% top tag, 0  $b$ -jet with  $\Delta R(\text{top}, b\text{-jet}) < 1.0$  and one add.  $b$ -jet

- Discriminating variable:  $tb$  invariant mass
- $t\bar{t}$  background taken from simulation
- Data-driven multijet background estimate
- Various regions defined based on top tagging decision and  $b$ -jet requirements

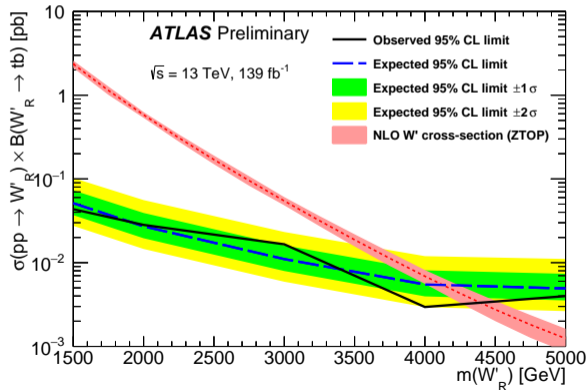
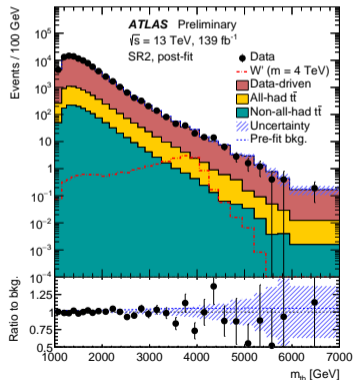


Top tagging	0 small- $R$ $b$ -tags	1 small- $R$ $b$ -tag
50% WP	<b>B</b>	<b>A: Signal Region 1</b>
80% WP	<b>D</b>	<b>C: Signal Region 2</b>
Loose tag	<b>F</b>	<b>E</b>

$$N_{\text{SR1, SR2}}^{\text{bkg}}(i) = \left( N_{B,D}^{\text{data}}(i) - N_{B,D}^{t\bar{t}}(i) \right) \frac{N_E(i)}{N_F(i)}$$

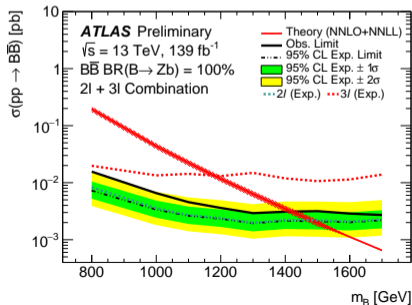
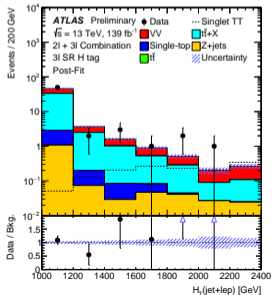


- Good agreement is observed between the data and prediction without any significant excess
- Limits set on  $\sigma \times \text{BR}$  excluding right-handed  $W'$  with masses  $< 4.4 \text{ TeV}$
- Previous limits on right-handed  $W'$ :
  - CMS excluded  $m_{W'} < 3.4 \text{ TeV}$  (all-had) using  $137 \text{ fb}^{-1}$ : [2104.04831](#)
  - ATLAS excluded  $m_{W'} < 3.25 \text{ TeV}$  (all-had. + lepton+jets) using  $36.1 \text{ fb}^{-1}$ : [1807.10473](#).



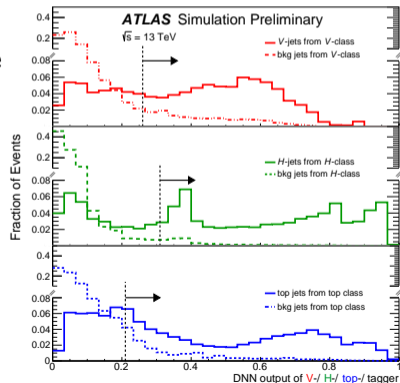
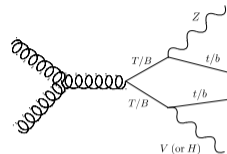
# Search for pair-production of vector-like quarks

- Large- $R$  reclustered (RC) jets used to identify  $V/H$ , top
  - Reclustered jets: small- $R$  jet input to jet clustering
- Multi-Class Boosted Object Tagger (MCBOT)
  - DNN trained with 18 inputs variables to identify jet origin
    - $p_T$ , mass, RC constituents (i.e.  $N_{\text{small-}R}$ ) + 4-vector,  $b$ -tagging score of three leading  $p_T$  RC constituents
  - Simultaneous identification of  $V/H$ /top jets
  - In case of ambiguities, choose tag with highest DNN score

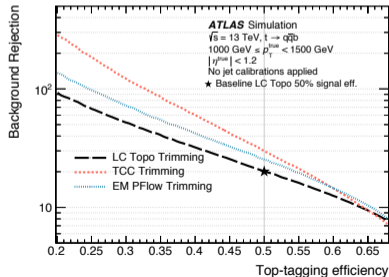
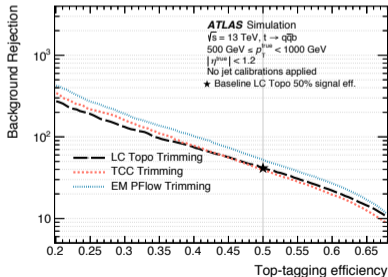
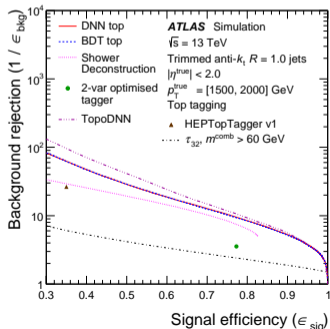


# ATLAS-CONF-2021-024

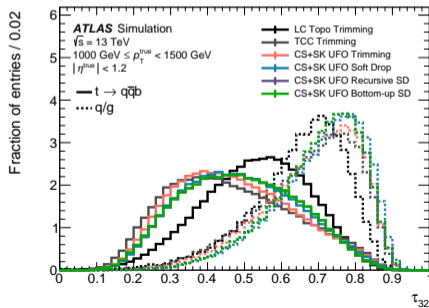
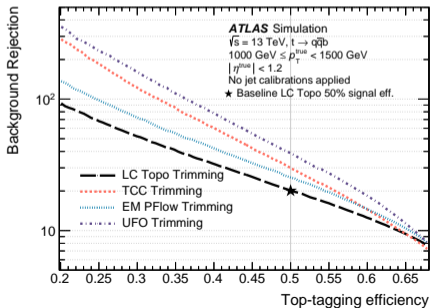
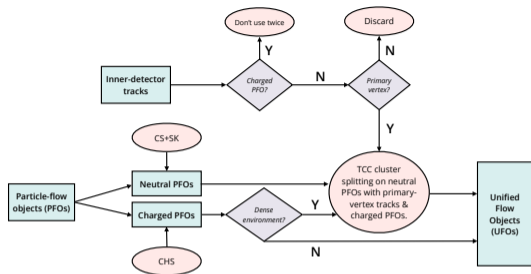
- See also Mesut's talk later



- 1 Develop more sophisticated taggers, e.g. use jet constituents as input
- 2 Develop new, more advanced jet definitions
  - Most analyses in ATLAS use large- $R$  jets reconstructed only from calorimeter info
    - At high  $p_T$ , full decay sometimes reconstructed within one topological cluster
  - Different algorithms used to take advantage of inner detector tracks
    - Particle Flow (PFlow): takes advantage of excellent track  $p_T$  resolution at low  $p_T$
    - Track-CaloClusters (TCC): uses tracks angular information at high  $p_T$  + cluster splitting

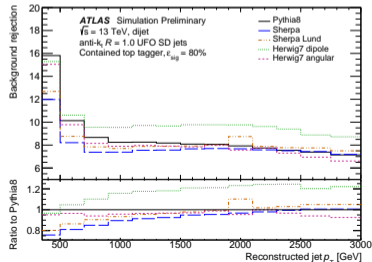
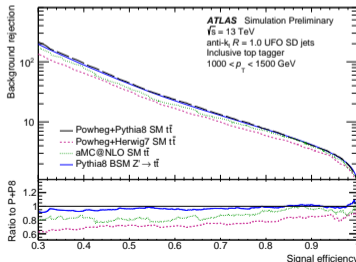
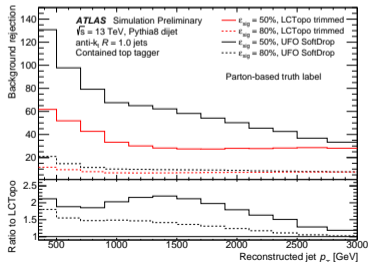


- New input type developed that takes advantage of PFlow and TCC algorithm
- UFOs outperform other inputs over broad range
- ATLAS re-optimised the choice of grooming algorithm using various metrics: tagging perf., mass resolution, pile-up dependence



- DNN top tagger was re-optimised for new UFO jet collection
  - $R = 1.0$  UFO jets (with const. pile-up suppression (CS+SK)) + Soft Drop ( $\beta = 1, z_{\text{cut}} = 0.1$ )
- Input variables:  $\tau_1, \tau_2, \tau_3, \tau_4, \sqrt{d_{12}}, \sqrt{d_{23}}, \text{ECF}_1, \text{ECF}_2, \text{ECF}_3, C_2, D_2, L_2, L_3, Q_W, T_M$
- Two taggers developed for inclusive tops and contained tops at 50/80% sig. eff.
- Performance compared for new UFO taggers with respect to previous LCTopo taggers
  - When applied to the same signal events, UFO taggers outperform LCTopo taggers
- Generator differences are one of the main uncertainties in the calibration of boosted taggers

!!!NEW!!!



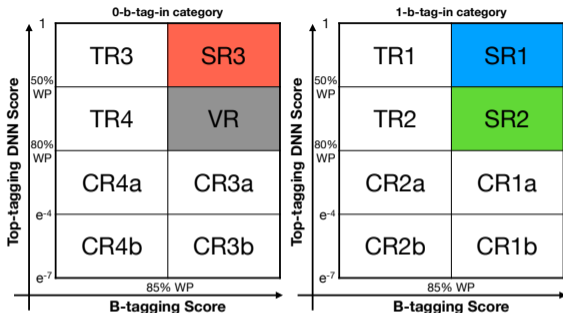
## Summary

- Many exciting searches for new physics have been performed
  - Focussed here only on final states involving hadronically-decaying top quarks
  - New impressive limits set on right-handed  $W'$  gauge bosons
  - Unfortunately no discover yet but we will keep increasing the sensitivity to smaller signal cross-sections by improving the performance of boosted top/W/Z/H taggers
- Analyses presented here use cutting-edge techniques for boosted top identification
- DNN taggers developed to identify single objects as well as multiclass object tagging
- New inputs developed for jet reconstruction that significantly enhance performance over broad range

# Backup

# Data-driven background estimation in $W' \rightarrow tb$ search

- VR: validation region
- TR: template region
- CR: control region
- SR: signal region



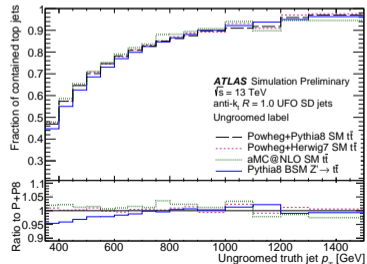
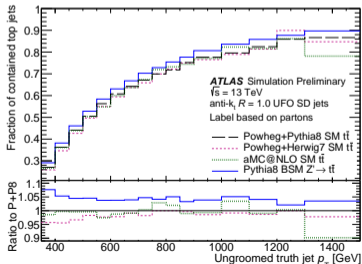
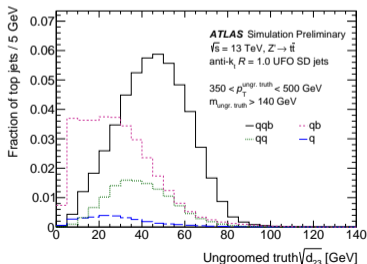
$$N_{\text{SR1,SR2}}^{\text{data-driven-background}}(i) = R_{\text{corr}}^1(i) \times (N_{\text{TR1,TR2}}^{\text{obs}}(i) - N_{\text{TR1,TR2}}^{\text{t}\bar{\text{t}}}(i)) \times \frac{N_{\text{CR1a}}^{\text{obs}}(i)}{N_{\text{CR2a}}^{\text{obs}}(i)}$$

↑
↑
↑

accounts for correlation between top tag and b-tagging
subtract  $t\bar{t}$  (taken from MC)
scale by yield from 0-tag to 1-tag region



- DNN top tagger was re-optimised for new UFO jet collection !!!NEW!!!
  - anti- $k_t$   $R = 1.0$  jets reconstructed from UFOs with constituent pile-up suppression (CS+SK)
  - Grooming algorithm: Soft Drop with  $\beta = 1$  and  $z_{\text{cut}} = 0.1$
- Input variables:  $\tau_1, \tau_2, \tau_3, \tau_4, \sqrt{d_{12}}, \sqrt{d_{23}}, \text{ECF}_1, \text{ECF}_2, \text{ECF}_3, C_2, D_2, L_2, L_3, Q_W, T_M$
- Two taggers developed for inclusive tops and contained tops
  - Contained tops: full top quark decay reconstructed within jets
    - Particle-level information used to define contained jets using mass and splitting scale
    - New labelling reduces generator dependence



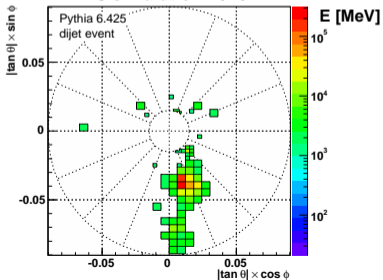
# Inputs to jet reconstruction - Topoclusters

- Group of topologically connected cells based on their significance

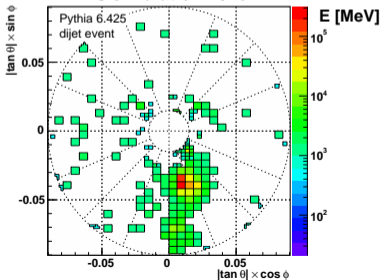
$$\zeta_{\text{cell}}^{\text{EM}} = \frac{E_{\text{cell}}^{\text{EM}}}{\sigma_{\text{noise, cell}}^{\text{EM}}} = \frac{E_{\text{cell}}^{\text{EM}}}{\sqrt{(\sigma_{\text{noise}}^{\text{electronic}})^2 + (\sigma_{\text{noise}}^{\text{pile-up}})^2}}$$

- Limitations: high  $p_{\text{T}}$  objects can be reconstructed within one topocluster

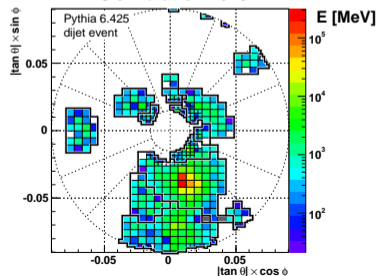
ATLAS simulation 2010



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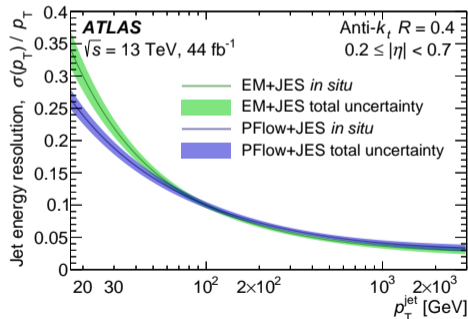
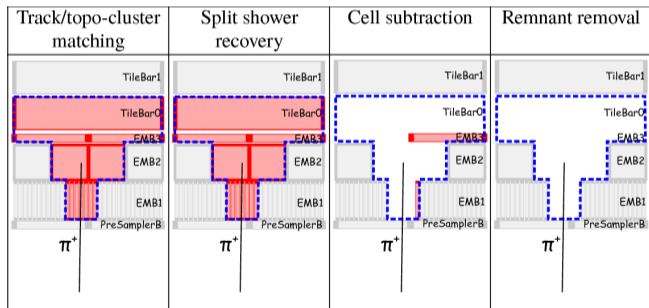


ATLAS simulation 2010



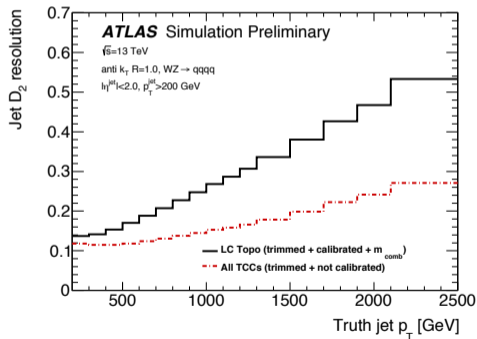
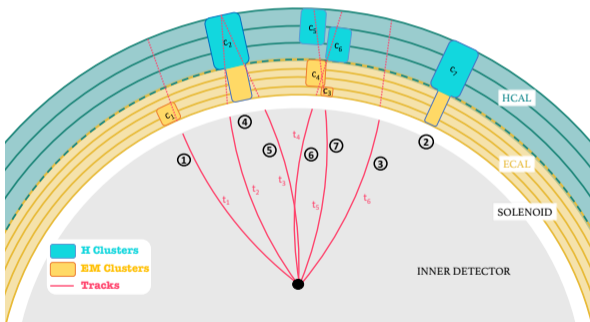
# Inputs to jet reconstruction - Particle Flow

- Benefits from better  $p_T$  resolution of tracks at low  $p_T$
- Match tracks to clusters and subtract energy of charged particle cell-by-cell
- We slowly switch off Particle Flow at higher momenta

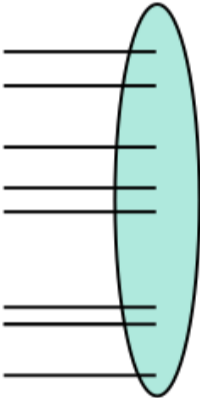


# Inputs to jet reconstruction - TCC

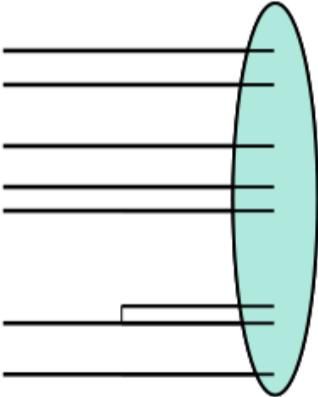
- Boosted object can be reconstructed within one cluster at high  $p_T$
- Split cluster using tracking information (excellent angular resolution)



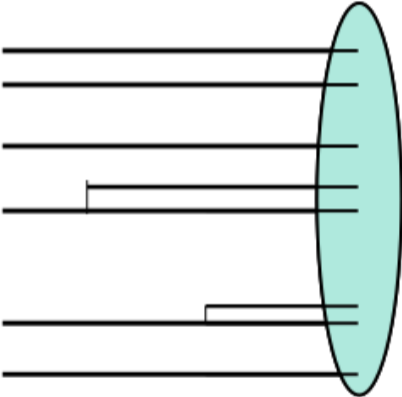
# Cambridge-Aachen illustration



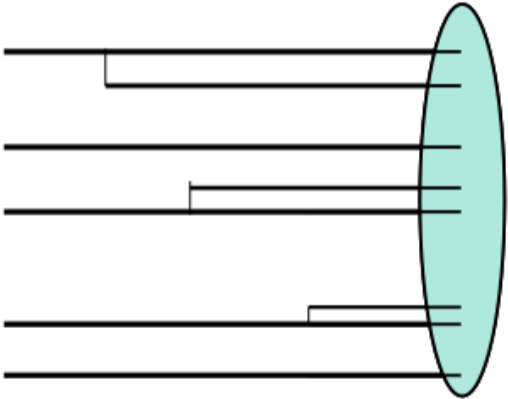
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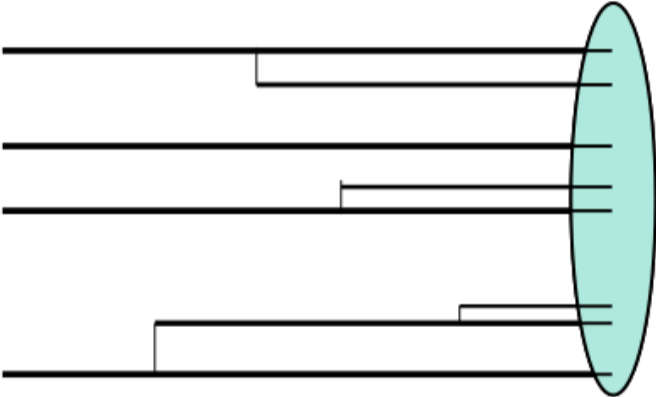


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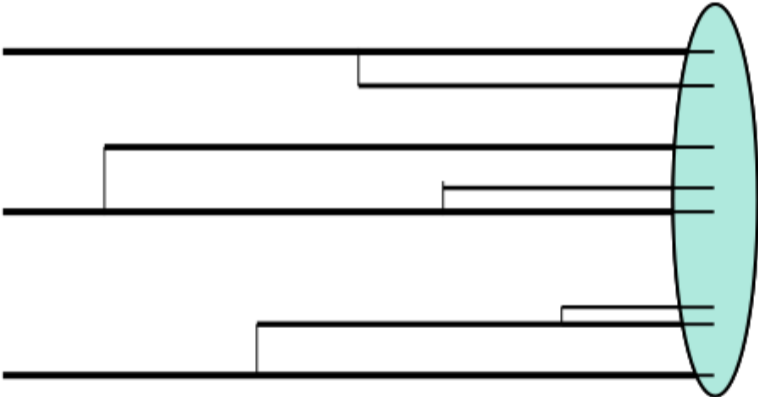




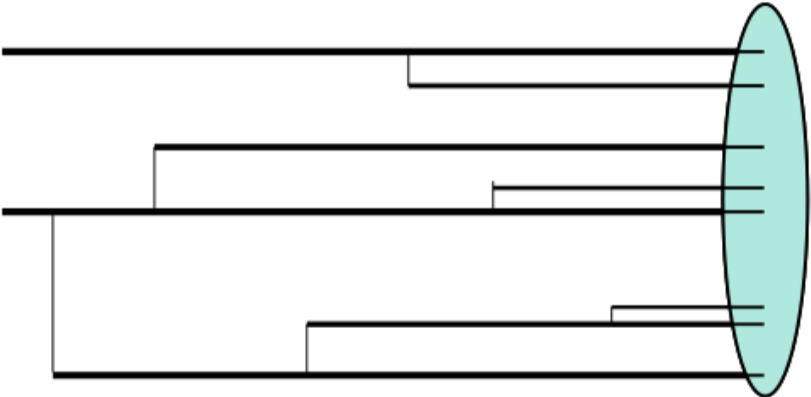
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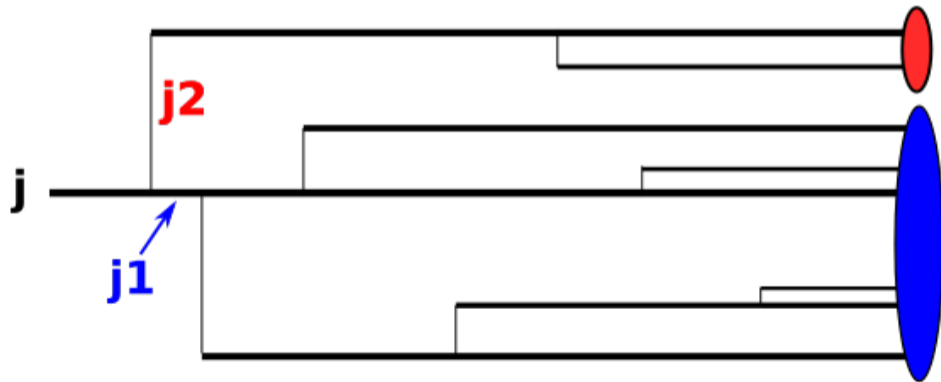


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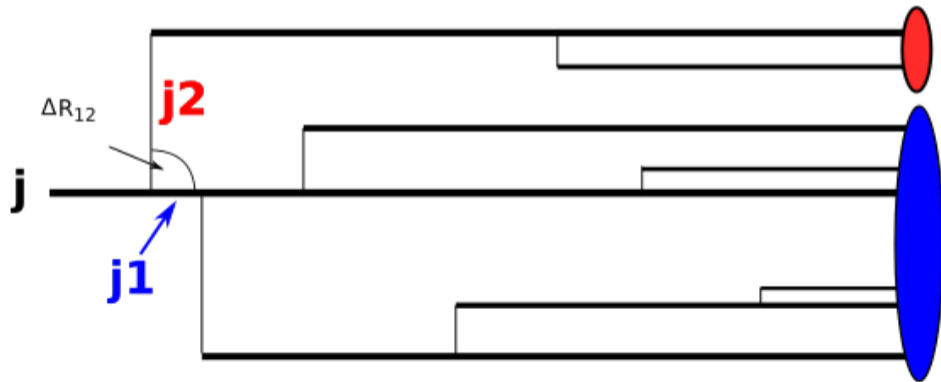
## Soft Drop algorithm at work

$$\frac{\min(p_{T,1}, p_{T,2})}{p_{T,1} + p_{T,2}} > z_{\text{cut}} \left( \frac{\Delta R_{12}}{R_0} \right)^\beta$$



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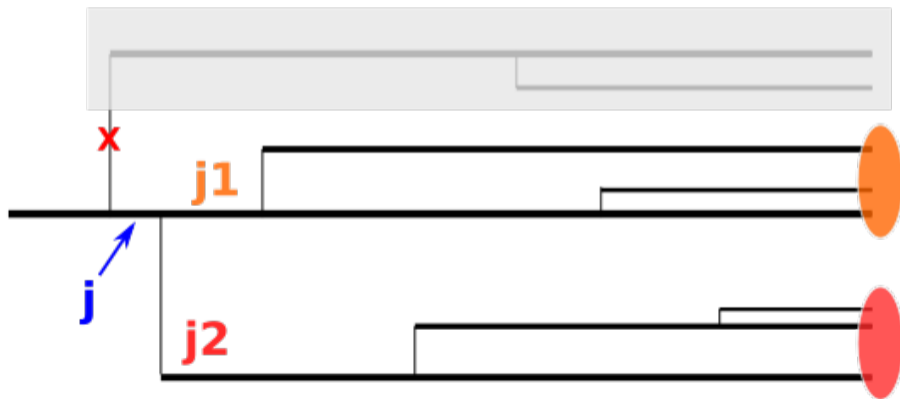
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