In-situ techniques and ML for jets in the ATLAS experiment

Javier Aparisi o.b.o. IFIC's Large-R jet calibration team

3rd red LHC Workshop

May 7, 2019

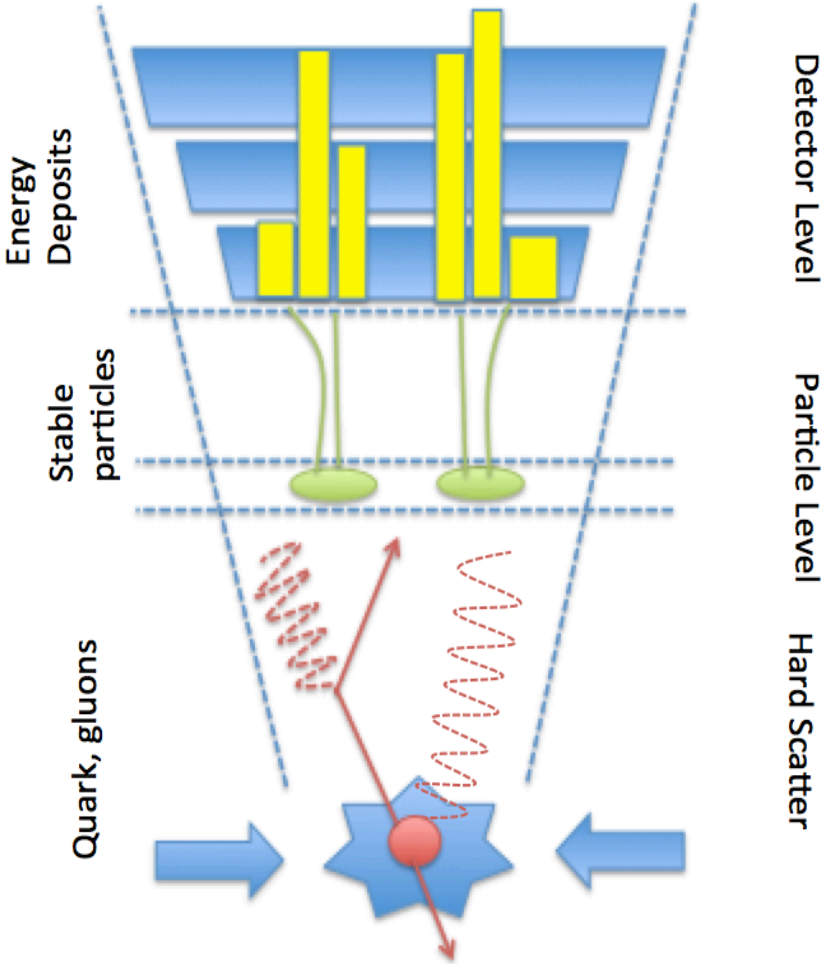
ATLAS EXPERIMENT

CSIC
CONSEJO SUPERIOR DE INVESTIGACIONES CIENTÍFICAS

UNIVERSITAT DE VALÈNCIA

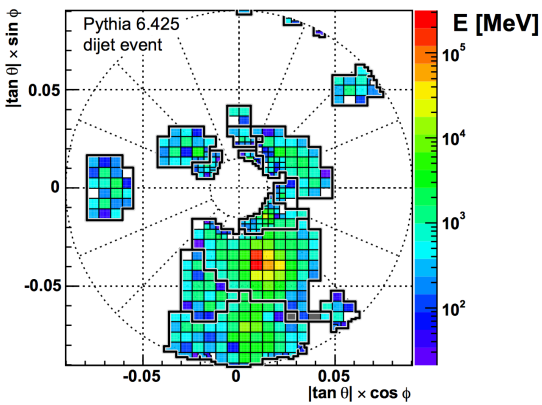
1. Large-R jets and ML in ATLAS

- The decay products of massive particles such as Higgs, Top, W or Z bosons become collimated and can be captured in a single large-R jet.
- Many searches and measurements use these jets, so their sensitivity depends on how well we understand them.
- We will review some fields where ML methods are being applied already within the jet calibration and reconstruction chain
- It's interesting to see how ML and the in-situ techniques can complement each other. We will draw some ideas about this!

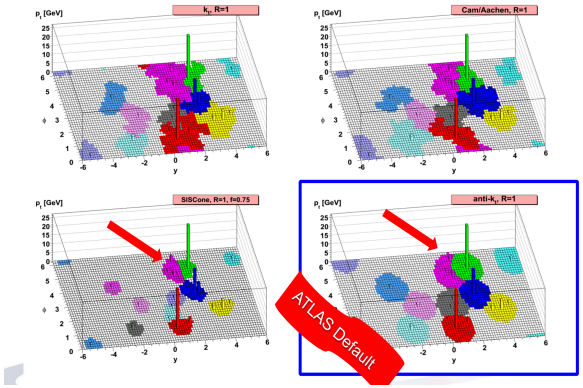


2. Large-R jets in the ATLAS experiment

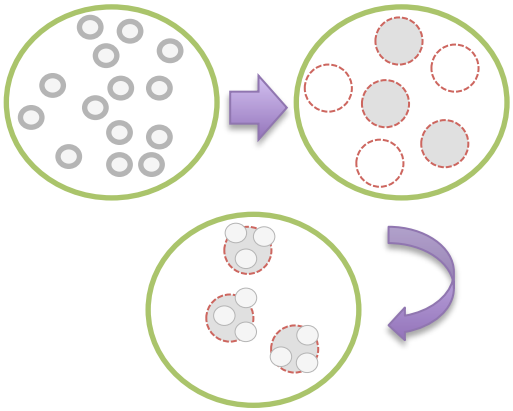
Inputs



Reconstruction

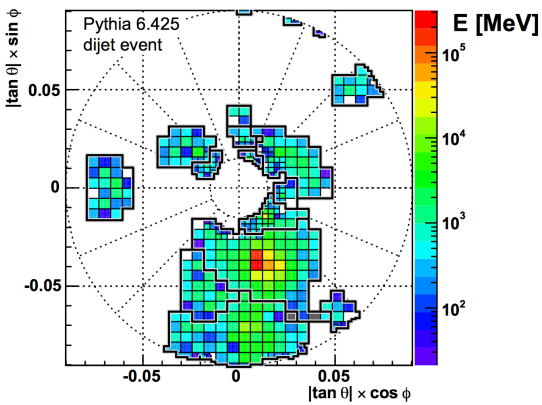


Grooming

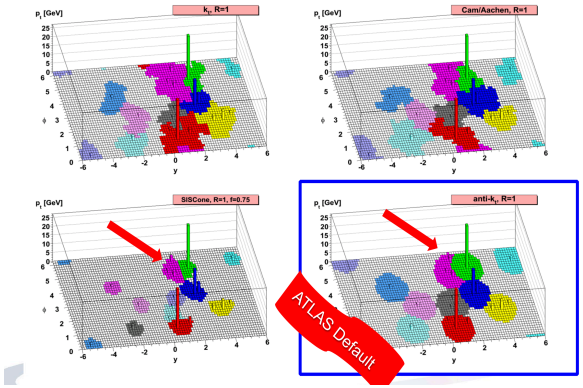


2. Large-R jets in the ATLAS experiment

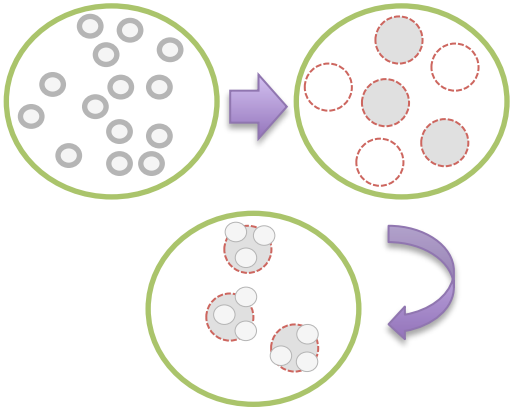
Inputs

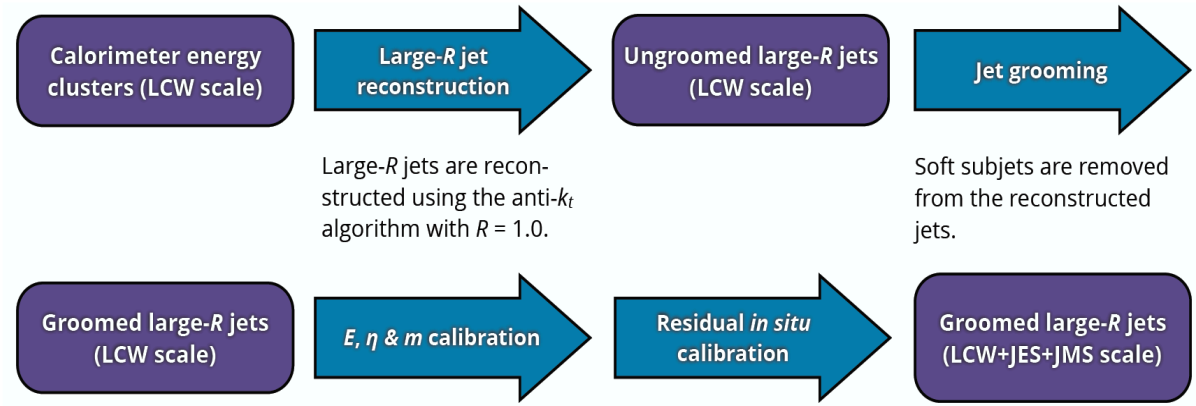


Reconstruction



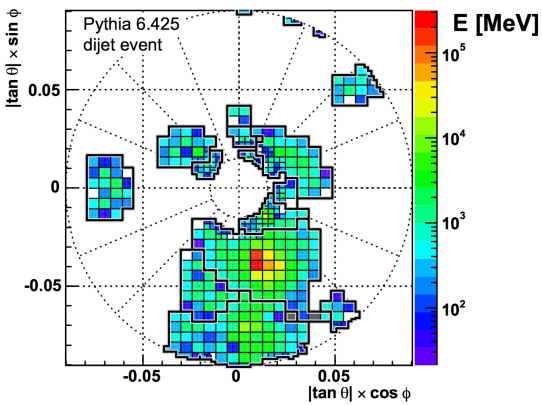
Grooming



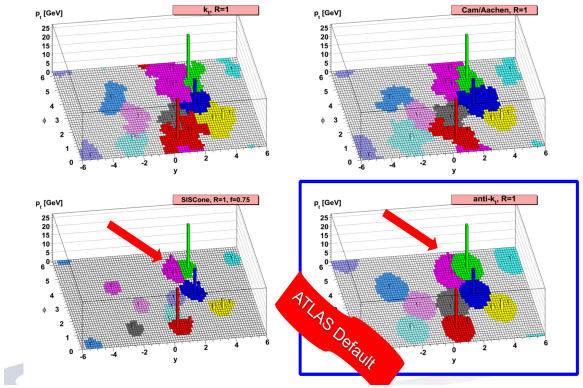


2. Large-R jets in the ATLAS experiment

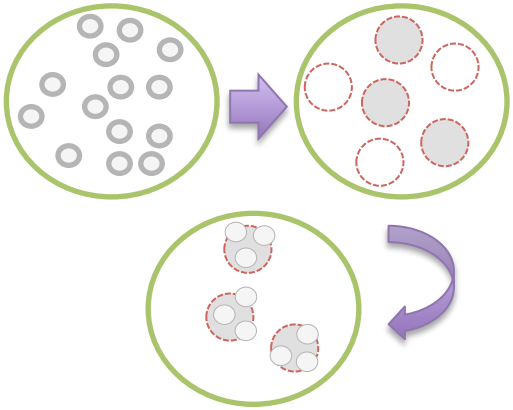
Inputs

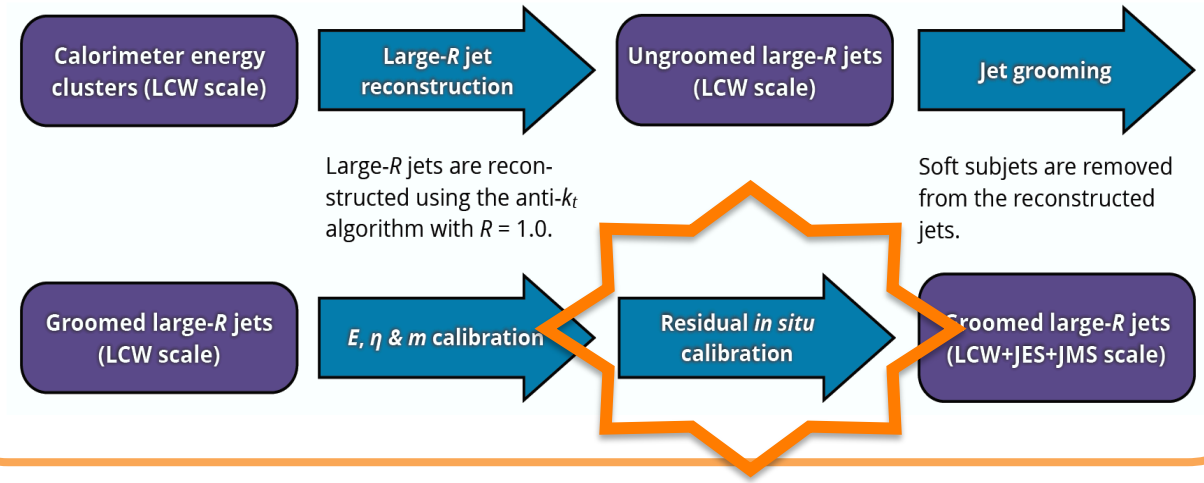


Reconstruction



Grooming





3. In-situ calibration of Large-R jets

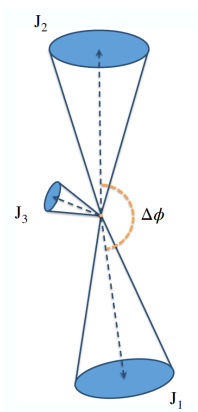
Eta Intercal.
From dijets

→

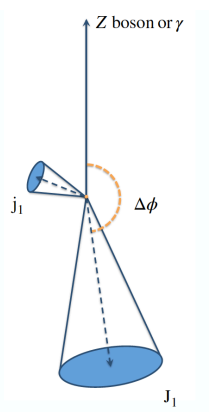
JES from Z/
gamma + jet

→

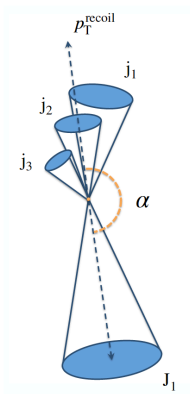
JMS from ttbar
and tracks



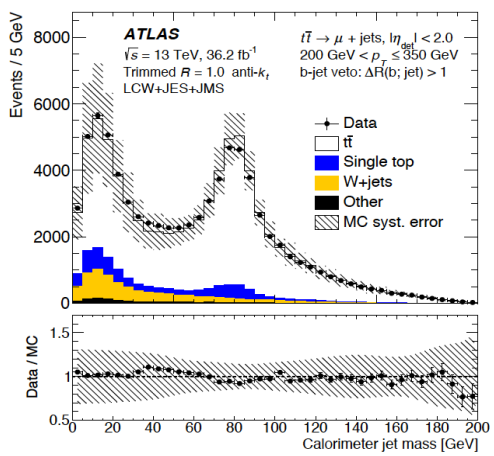
(a) dijet event

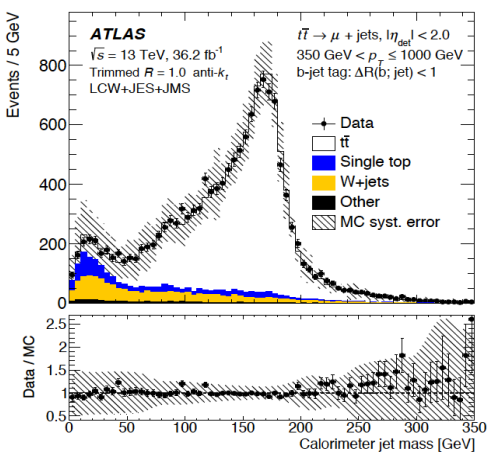


(b) Z+jet or γ+jet event

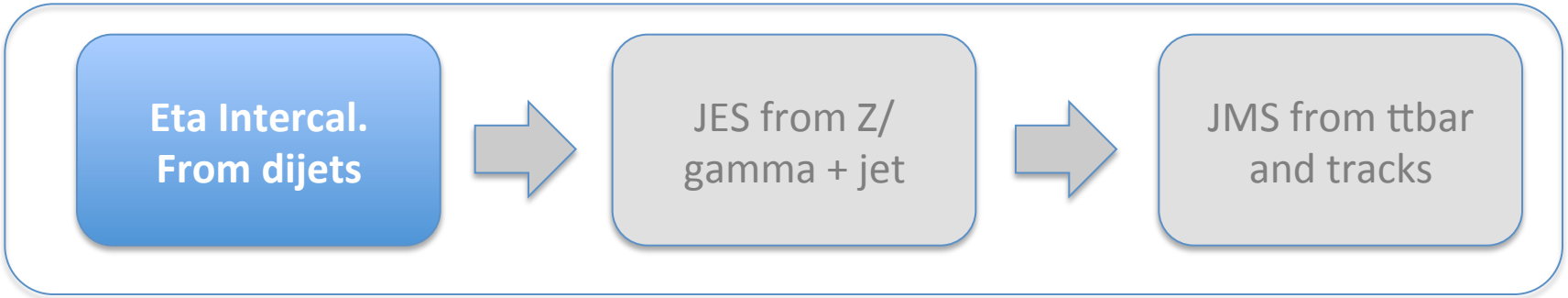


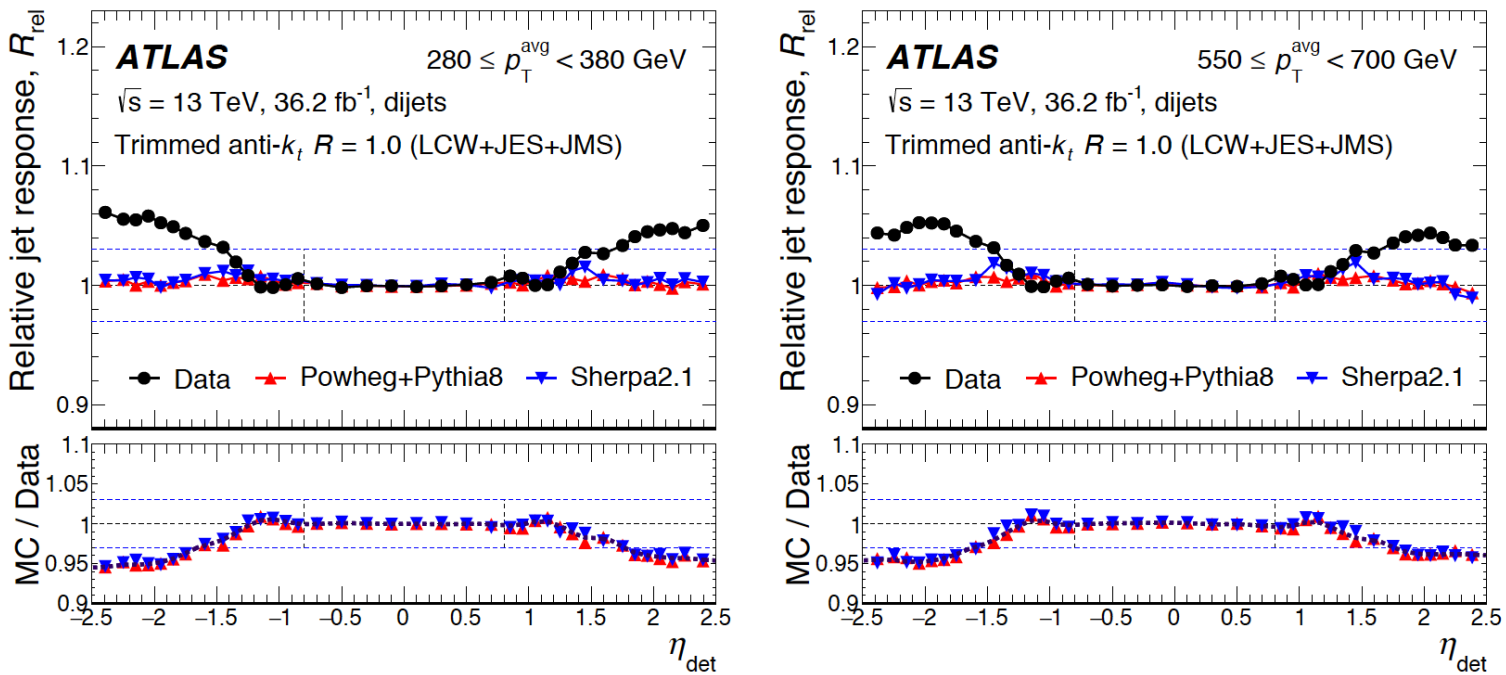
(c) multijet event



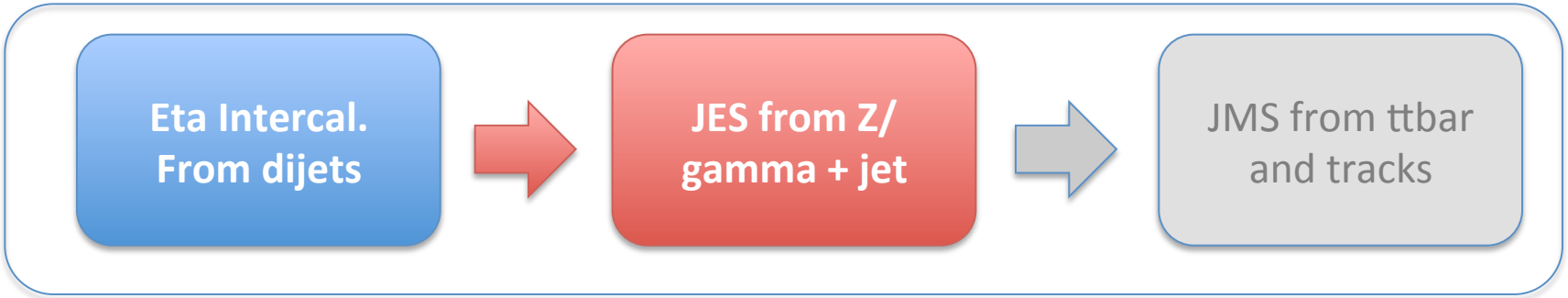


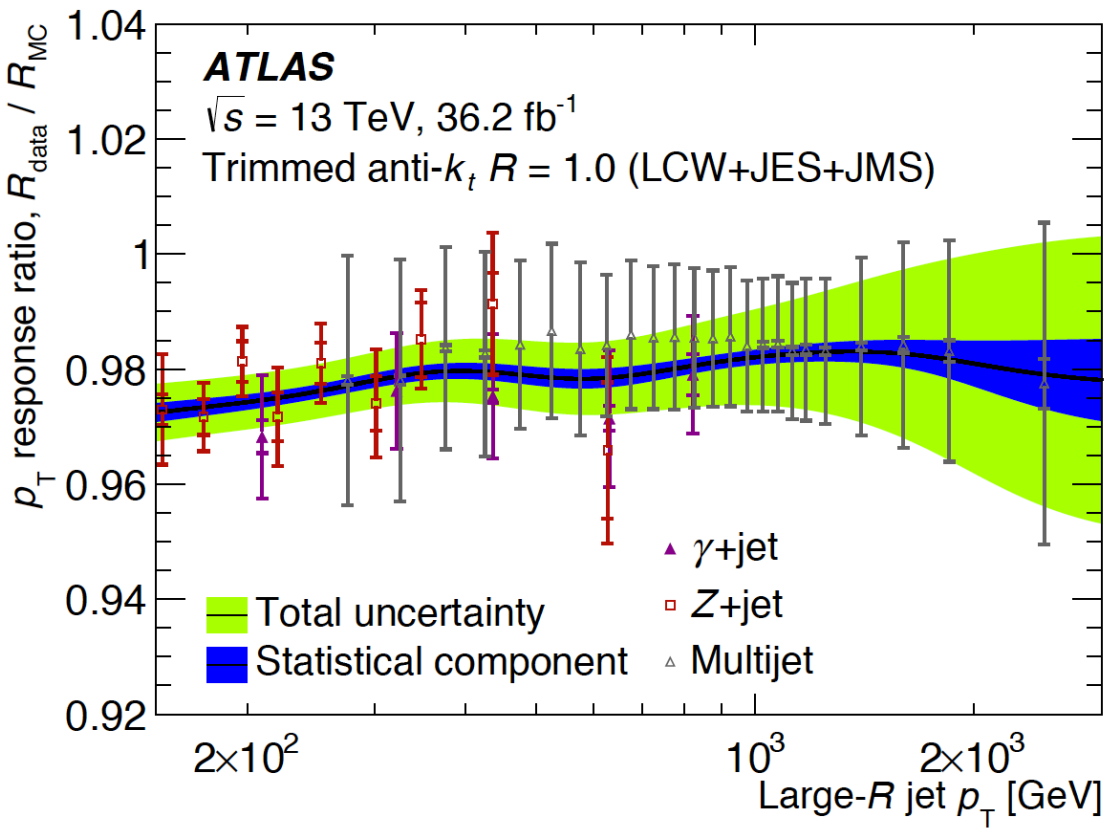
3. In-situ calibration of Large-R jets



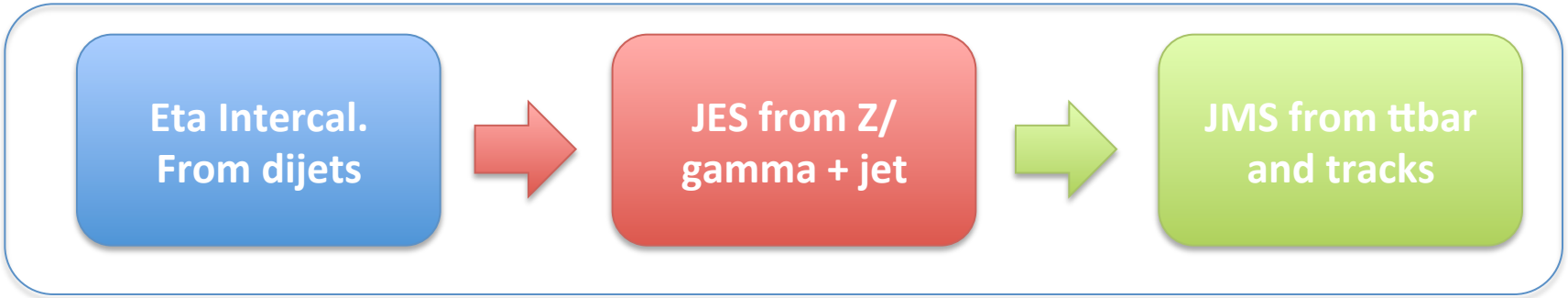


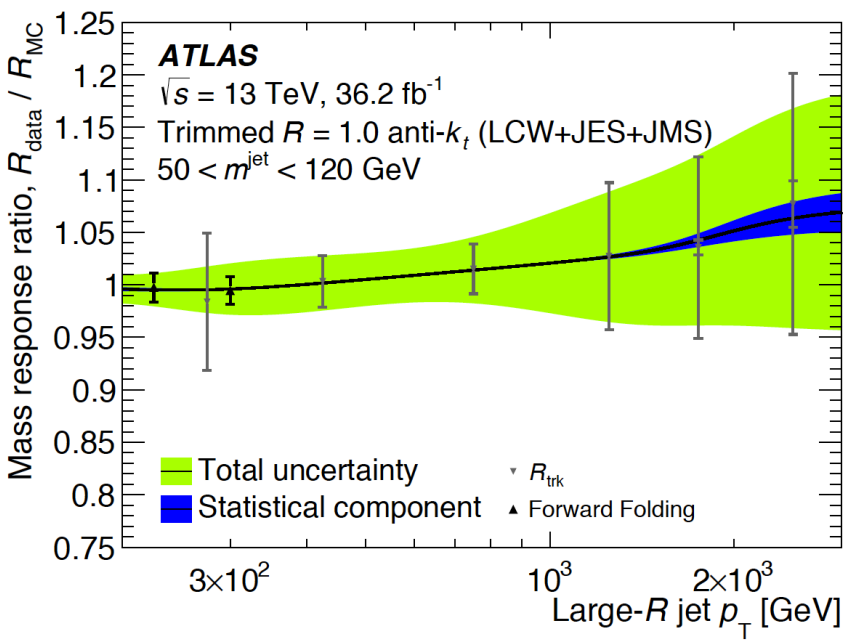
3. In-situ calibration of Large-R jets

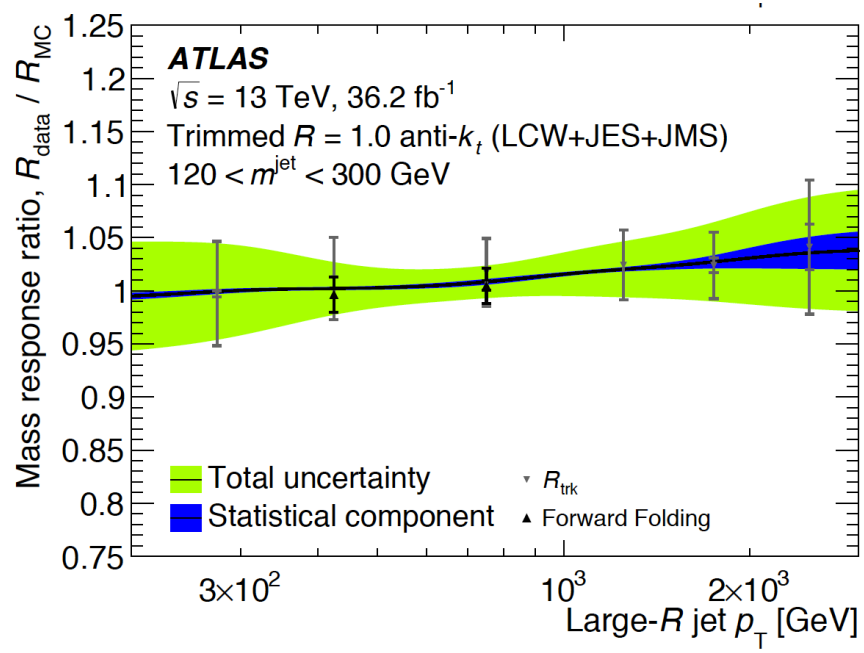




3. In-situ calibration of Large-R jets







3. In-situ calibration of Large-R jets

- In-situ calibration allows us to validate the relative JES and JMS!!!
  → How well the MC models a given observable?

- Matter of fact that after in-situ JES, rel JMS comes to 1
  → In-situ JES: between 0.97 and 0.98 over pT range: 150 – 2000 GeV
  → In-situ JMS: compatible to 1 over full range: 200 – 2000 GeV

- Systematic control
  → In-situ JES: 1-2% across the entire pt range!!
  → In-situ JMS: from 2 to 10% at very high pT!

3. In-situ calibration of Large-R jets

- In-situ calibration allows us to validate the relative JES and JMS!!!
  → How well the MC models a given observable?

- Matter of fact that after in-situ JES, rel JMS comes to 1
  → In-situ JES: between 0.97 and 0.98 over pT range: 150 – 2000 GeV
  → In-situ JMS: compatible to 1 over full range: 200 – 2000 GeV

- Systematic control
  → In-situ JES: 1-2% across the entire pt range!!
  → In-situ JMS: from 2 to 10% at very high pT!

All this is telling us that despite the MC-based calibration, there are still some deviations between data and MC that must be corrected !!!
The MC is not PERFECT!!

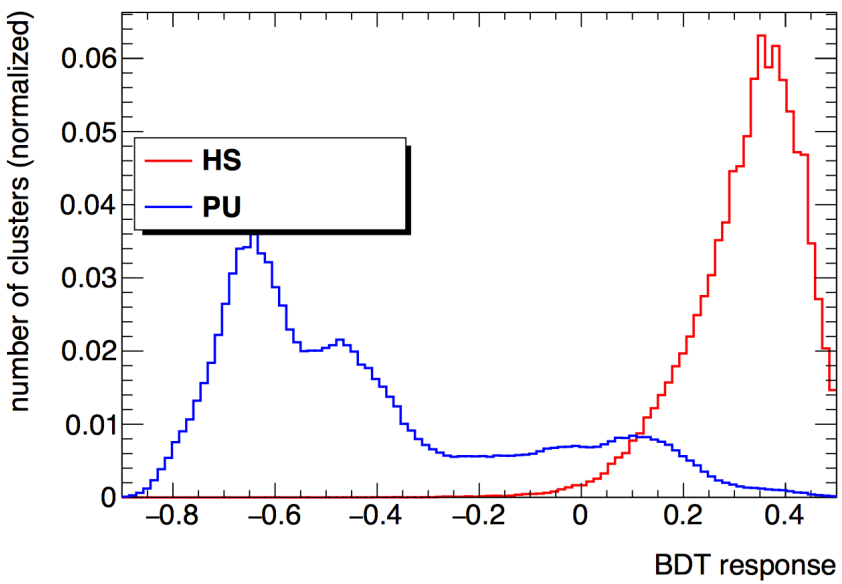
4. ML studies in PU suppression

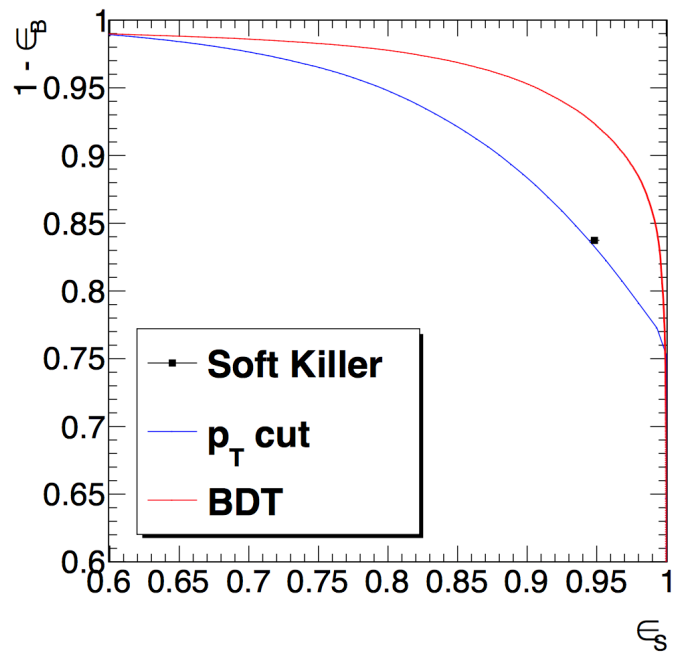
There is room for improvement!! Are the topo-clusters the most suited objects for jet sub-structure studies? Alternatives:

→ PFLOW: algorythm that connects clusters and tracks. So it's possible to link clusters with the hard scatter vertex. Also it profits from the high resolution of the tracker at high pT, crucial for jet substructure studies

ML techniques to distinguish between PU and signal in neutral topoclusters!!

ATLAS internal presentation

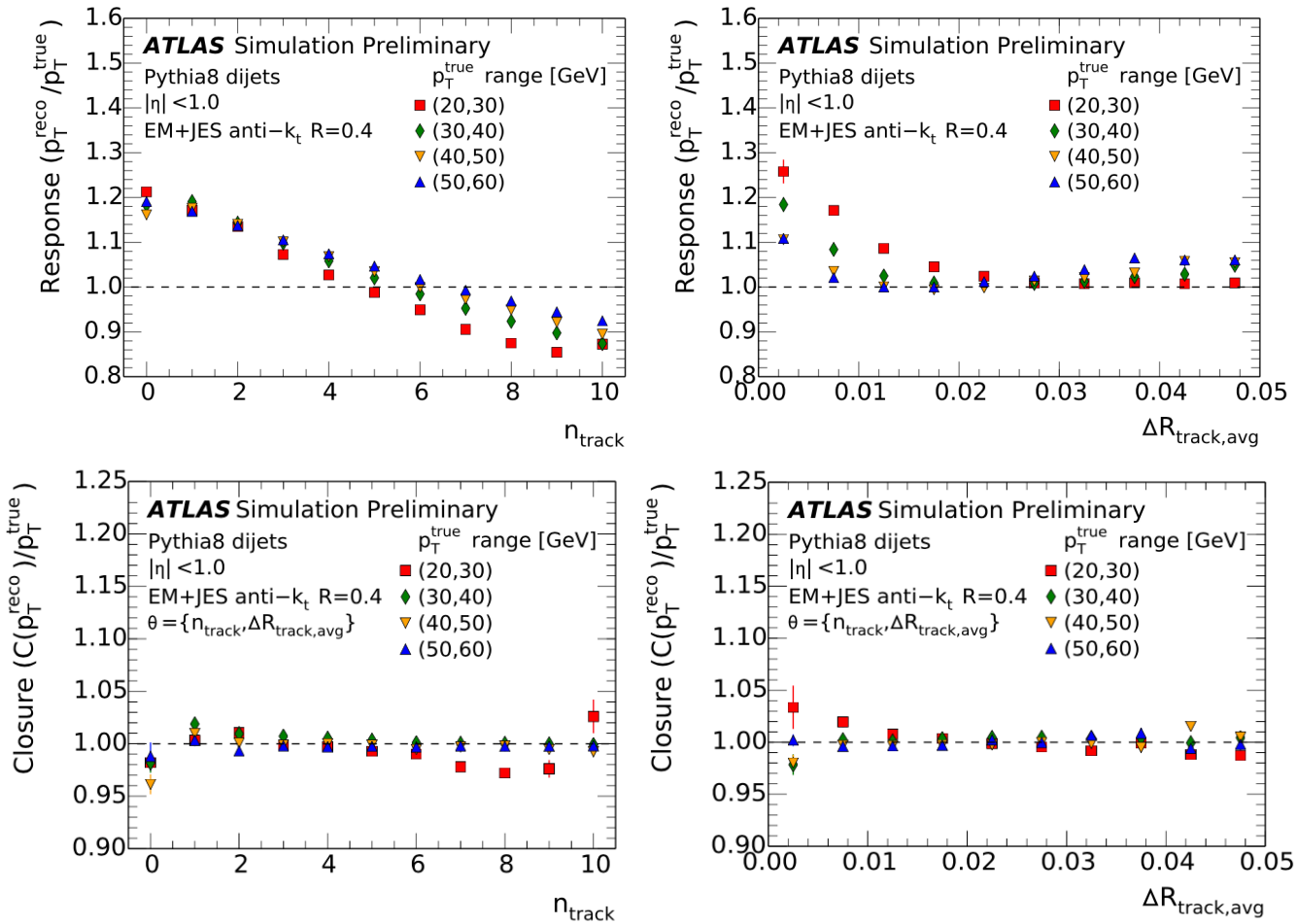




5. ML studies in the MC-based calibration

Two neural networks to learn correlations between new jet features and the correction of the reco jet pT given a true jet pT

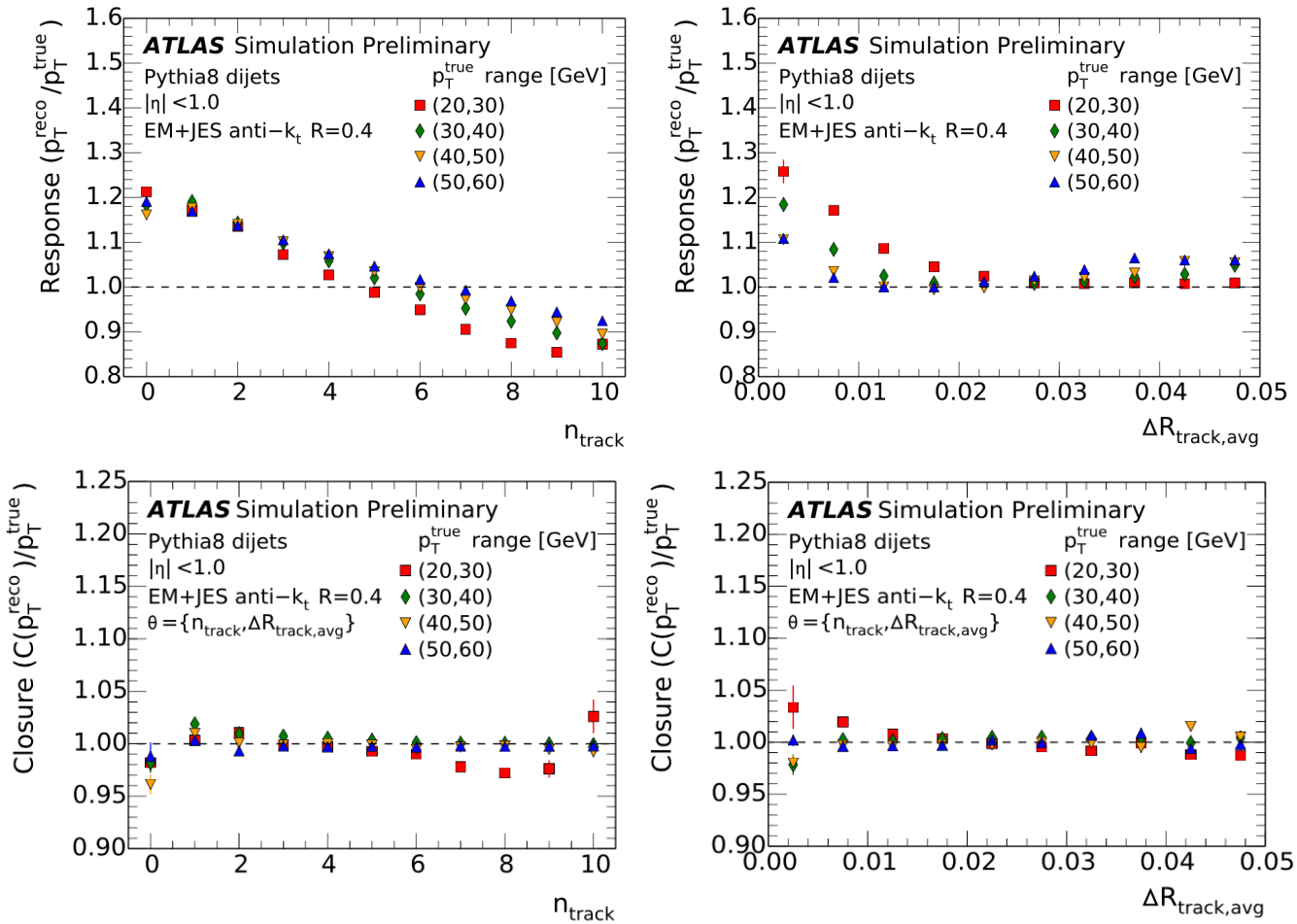
ATL_PHYS_PUB_2018_013



5. ML studies in the MC-based calibration

This can reduce any residual dependence on quark/gluon jet composition!!

ATL_PHYS_PUB_2018_013



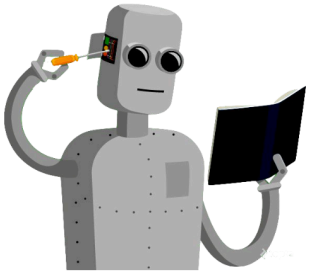
6. Taggers with ML techniques

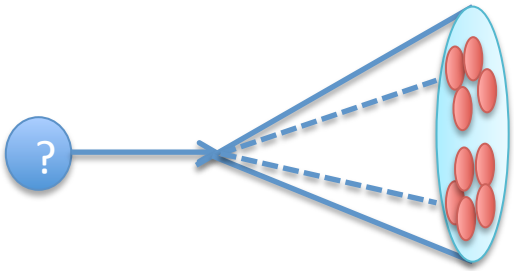
→ Distinguish between signal and background jets
→ ML-based taggers often rely on the MC simulation of sgn/bckg.
→ Substructure variables are crucial because their discrimination power!

Hot points:

- Is ML tagger learning physics or simple an artefact of the simulation?
- Can we check if variable for taggers is properly modelled by MC?
- Train tagger with MC, test with Data and MC samples... are the outputs compatible? In-situ techniques can speak about this!

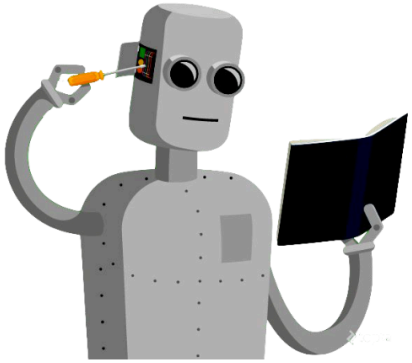
.... there are actually studies ongoing where taggers are trained with data! If interested, check out arXiv:1808.08979





7. Conclusions

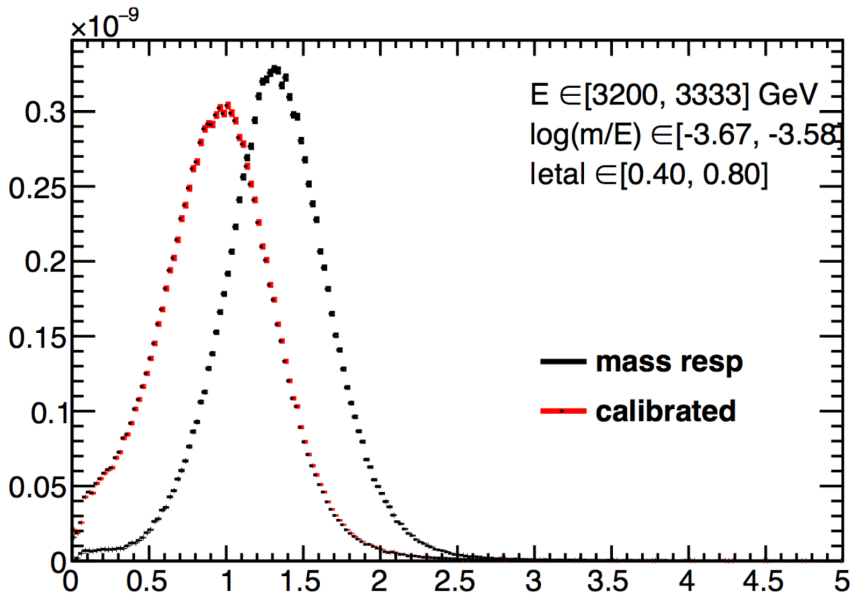
- In-situ techniques are crucial to figure out whether the MC models properly Data!
- There are many fields where ML turn out to be a really powerful and helpful tool!
- But let's make an efficient usage of these methods. Are we working with the most suited setup?
- In-situ techniques might also tell us if given tagger developed with ML approaches is actually learning from physics or just an artefact of the simulation



Back-up

5. ML studies in the MC-based calibration

Goal of MC-based calibration: ensure that certain average calibrated detector-level observable is the same as the corresponding particle-level on average. The avg. response, <Xreco / Xtrue> centered in 1



$$p_{T,reco}^{CAL} = f(p_T^{true}) \times p_T^{reco} \rightarrow p_{T,reco}^{CAL} = f^{-1}(p_T^{reco}) \times p_T^{reco}$$

5. ML studies in the MC-based calibration

Want to add new jet features:

$$if\ \theta \in \mathbb{R}^n\ then\ p_{T,reco}^{CAL} = f_{\theta n}^{-1}\left(\ldots f_{\theta 2}^{-1}\left(f_{\theta 1}^{-1}(p_T^{reco})\right)\ldots\right) \times p_T^{reco}$$

Too hard from a computational point of view. Let's use two neural networks:

1. Learn the average behavior of reco pT given true pT and theta:

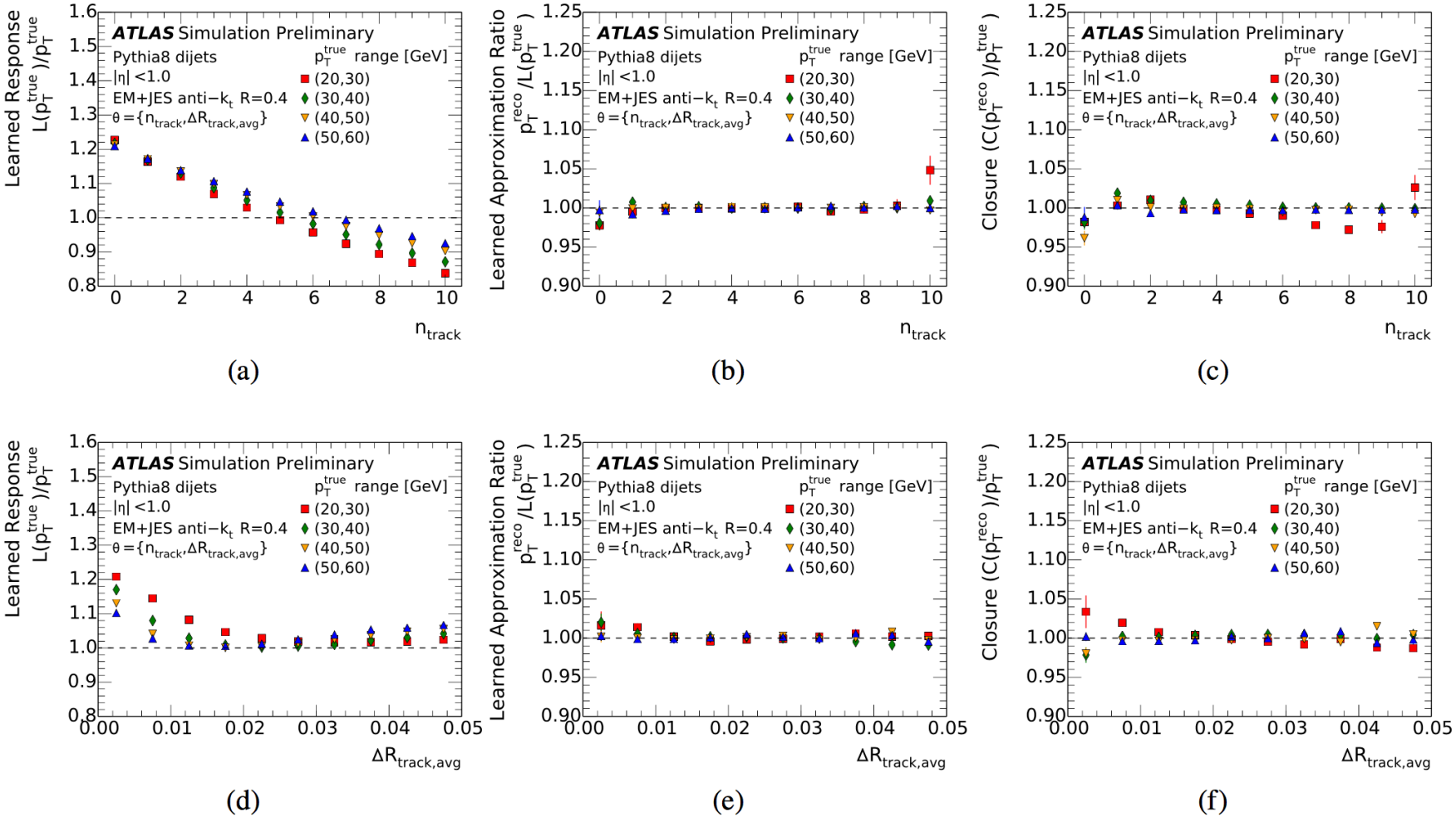
$$L(x,\theta)\ from\ f_\theta(x) = \langle\, p_T^{reco} \,|\, p_T^{true} = x, \theta \rangle$$

2. Learn to predict true pT given theta and L(x,theta). This is an approximation to the family of functions $f^{-1}_{theta}(x)$.

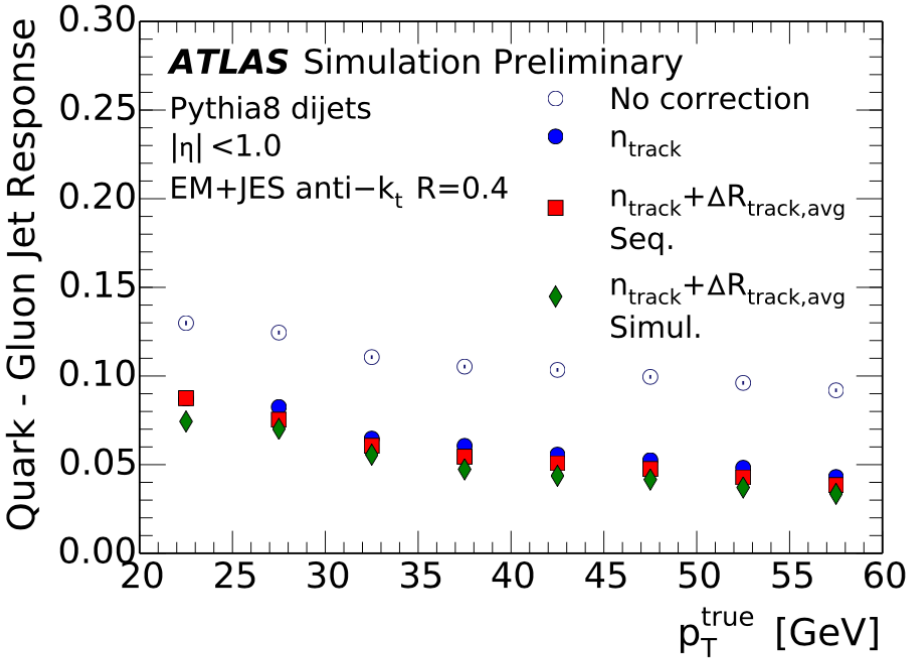
$$C\big(L(x,\theta)\big)\ to\ predict\ x\ given\ \theta\ and\ L(x,\theta)$$

$$p_{T,reco}^{CAL} = C(p_T^{reco},\theta) \times p_T^{reco}$$

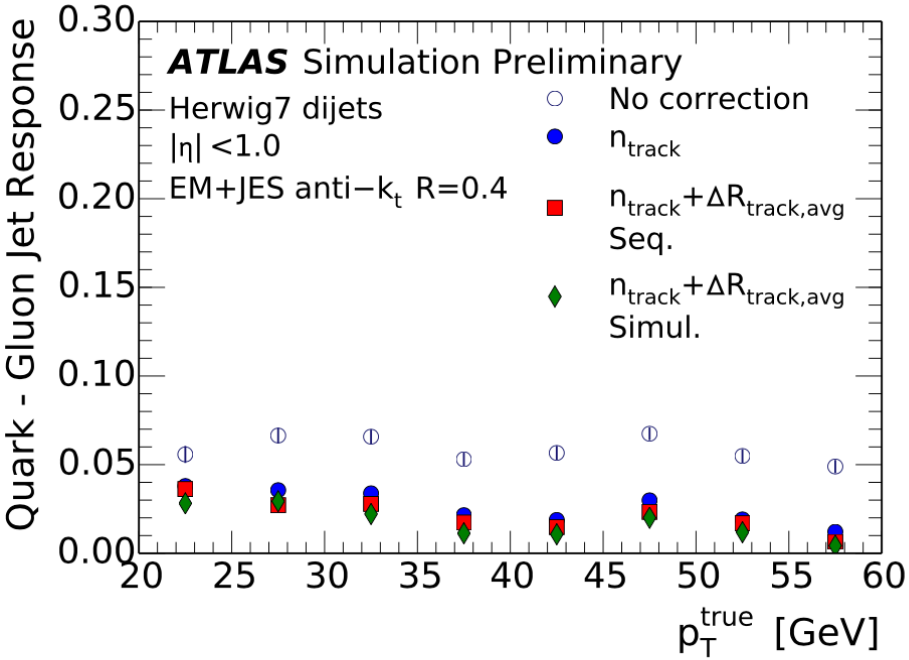
5. ML studies in the MC-based calibration



5. ML studies in the MC-based calibration



(a) Pythia 8



(b) Herwig 7

This can reduce any residual dependence on quark/gluon jet composition!!