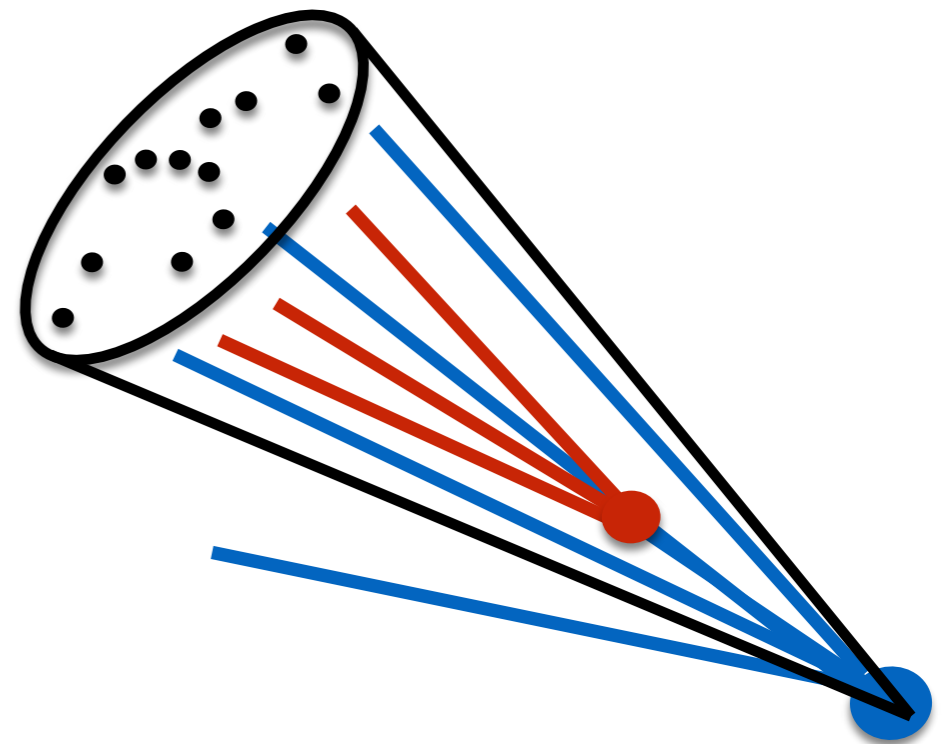


flavor-tagging in ATLAS

Chris Pollard

on behalf of the ATLAS collaboration

2019 05 02

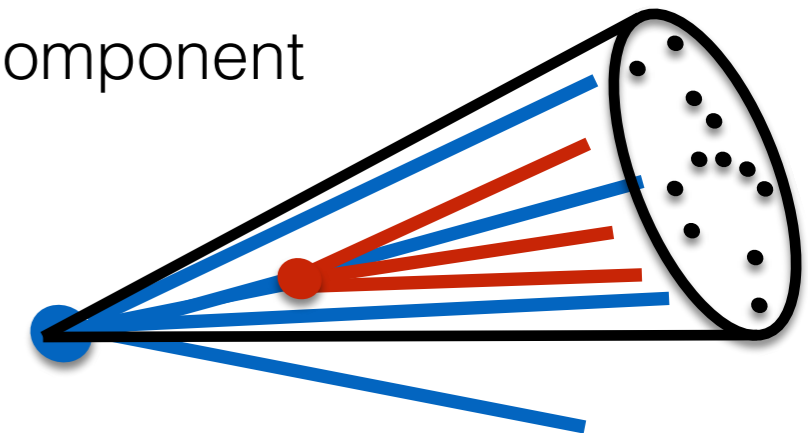


goals

- give a broad overview of flavor-tagging work in ATLAS, especially highlighting the main taggers and some recent results
- topics:
 - algorithm inputs and their simulation
 - mainline algorithms currently in use
 - performance in simulation and data
 - specialized taggers
- obviously I have to leave out some topics and details...
- ... so all public results are available here:
<https://twiki.cern.ch/twiki/bin/view/AtlasPublic/FlavourTaggingPublicResultsCollisionData>

algorithm inputs

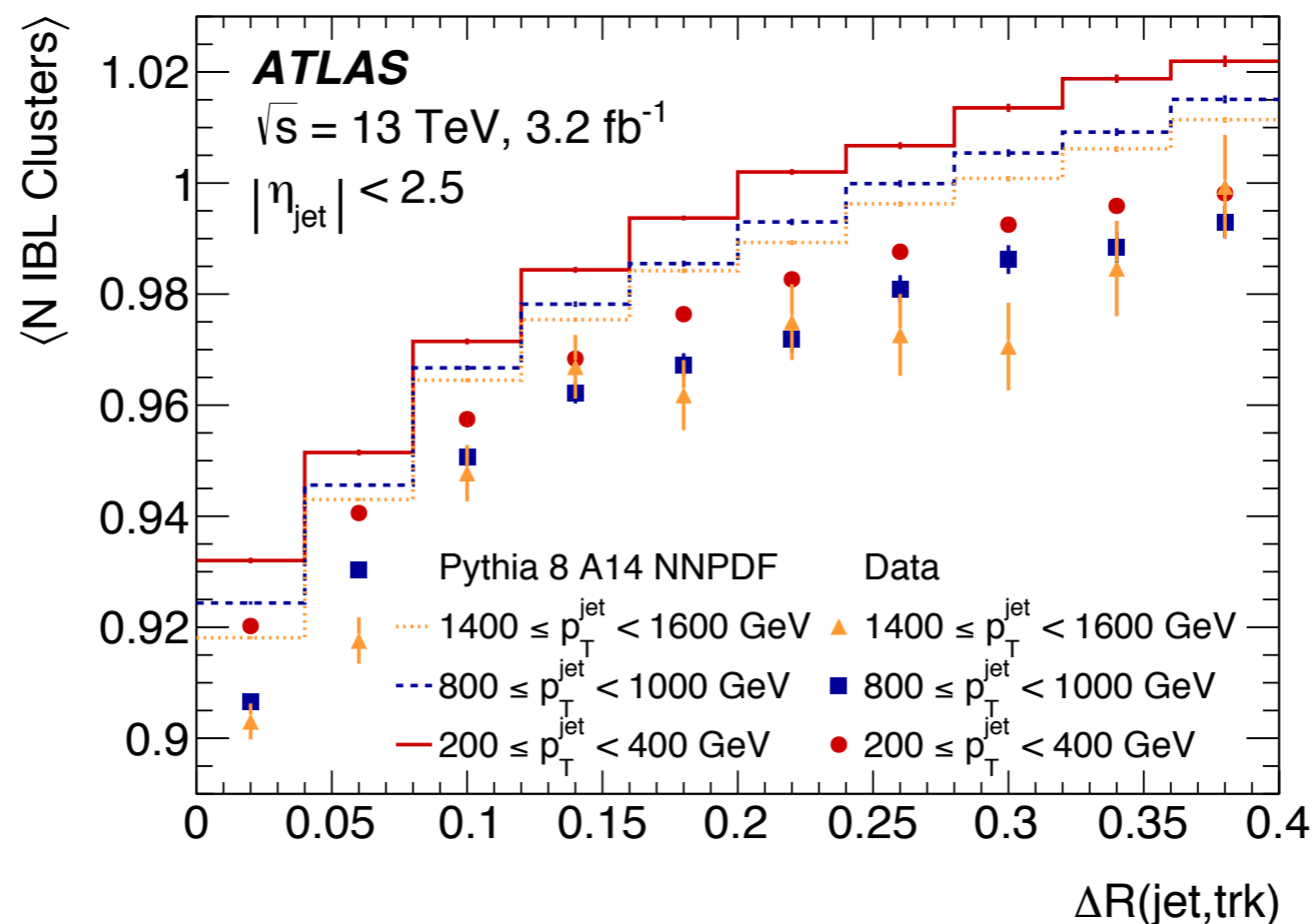
- our primary b -taggers take as inputs **inner-detector (ID) tracks** and **jets**.
- several jet collections have been studied for b -tagging, but currently we support
 - "**EMTopo**" jets **built from topological clusters**
 - clusters calibrated based on electromagnetic component
 - anti-kt, $R = 0.4$
 - variable-radius (**VR**) jets **built from ID tracks**
 - anti-kt, $\rho = 30$ GeV, min $R = 0.02$
 - good performance at low- p_T and condensed environments
- ID tracks are **associated** to a jet based on a **p_T -dependent association cone**:
 - $p_T(\text{jet}) = 20$ GeV : **$\Delta R < 0.45$**
 - $p_T(\text{jet}) \rightarrow \text{infinity}$: **$\Delta R < 0.24$**



modeling and performance of tracking inputs

PERF-2015-08

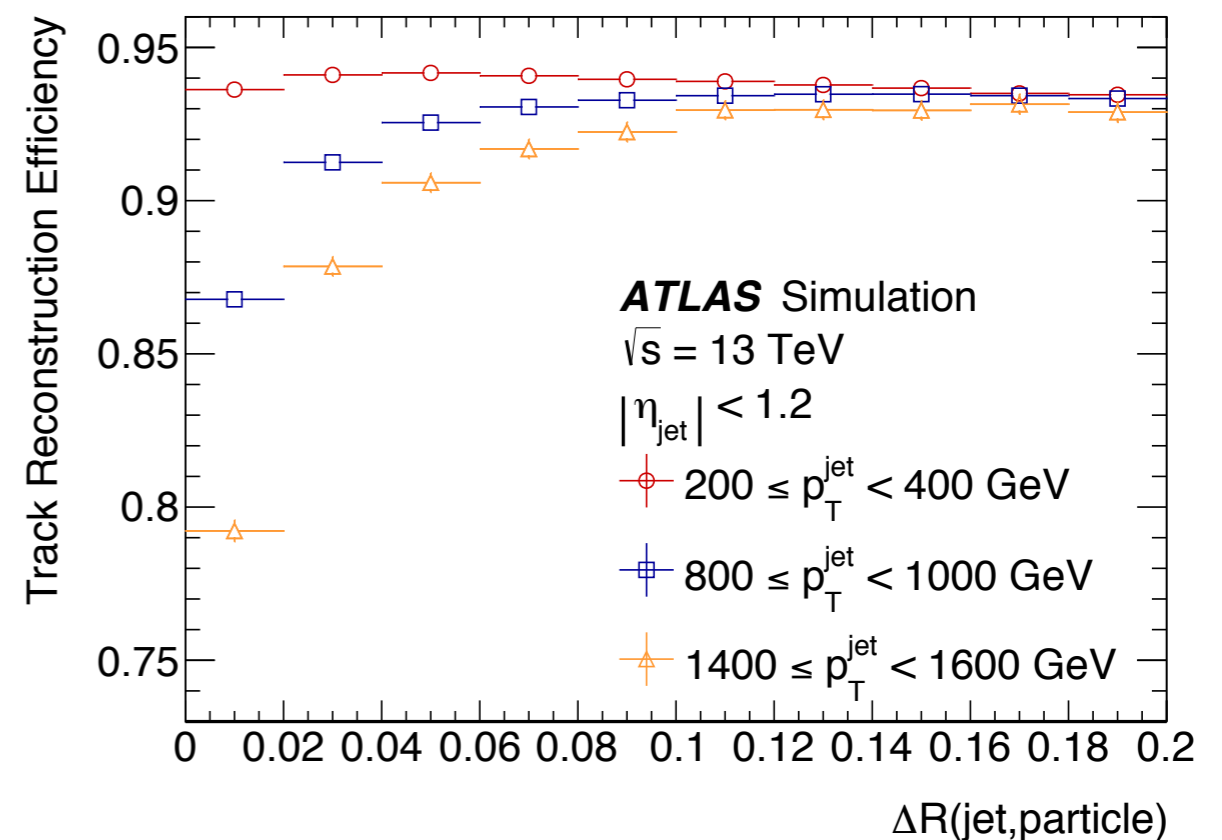
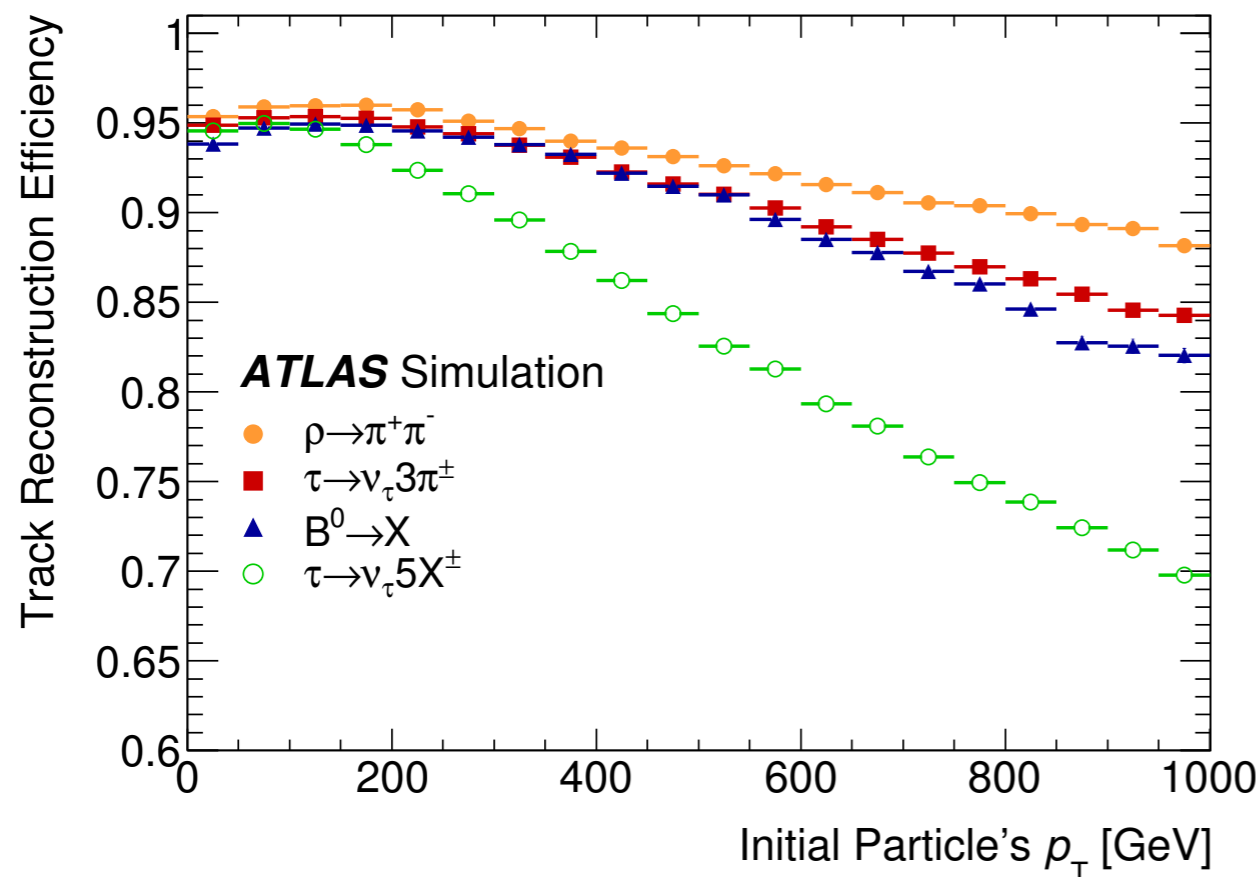
- to give an idea of expected **performance of tracking within jets**, there's a very nice PUB note from 2015.
- in general we see reasonable (but **certainly not perfect**) descriptions of low-level tracking inputs to flavor tagging.



modeling and performance of tracking inputs

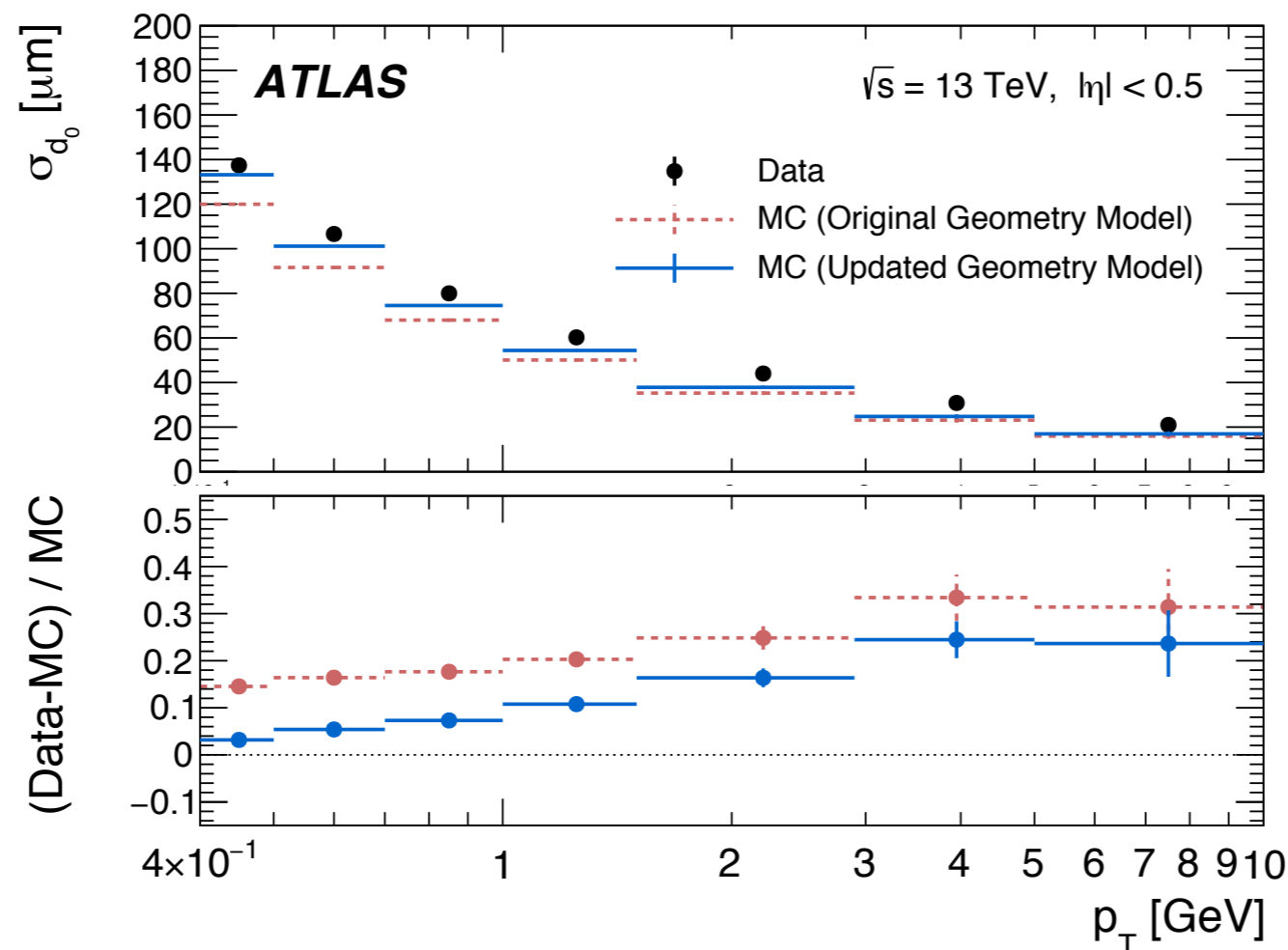
PERF-2015-08

- our current track reconstruction procedure has some limitations in extreme kinematic regions inside jets
- this is quite an interesting area to invest in improvements -> especially toward Run III



modeling and performance of tracking inputs

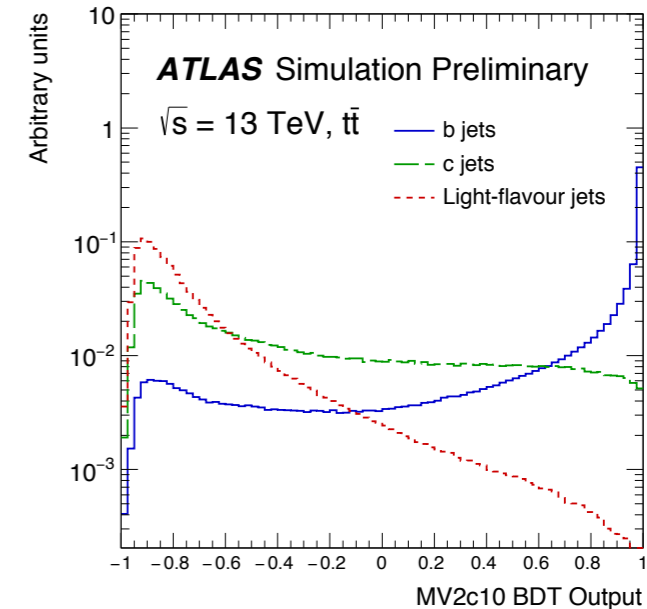
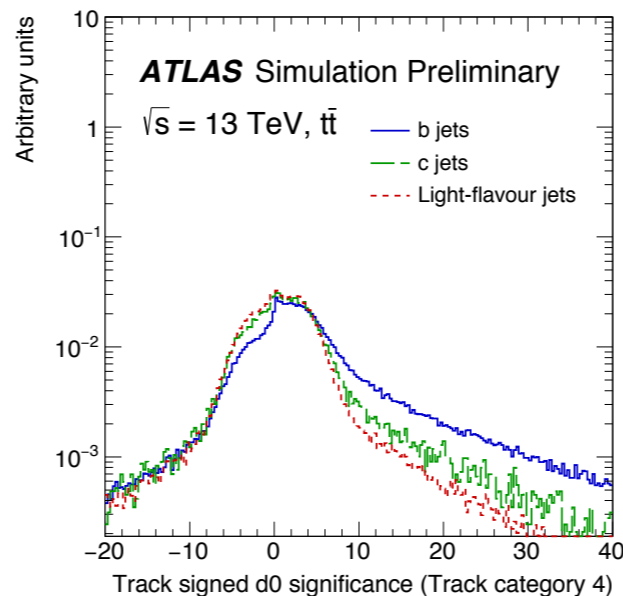
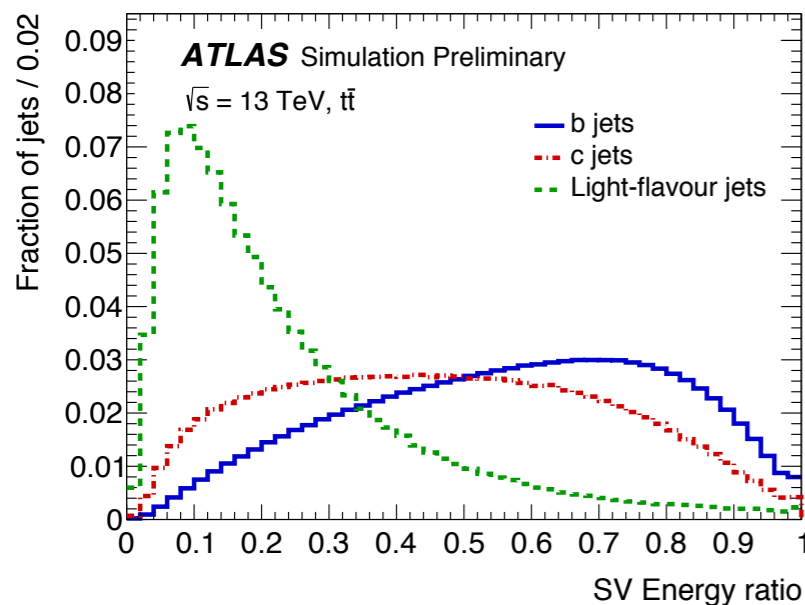
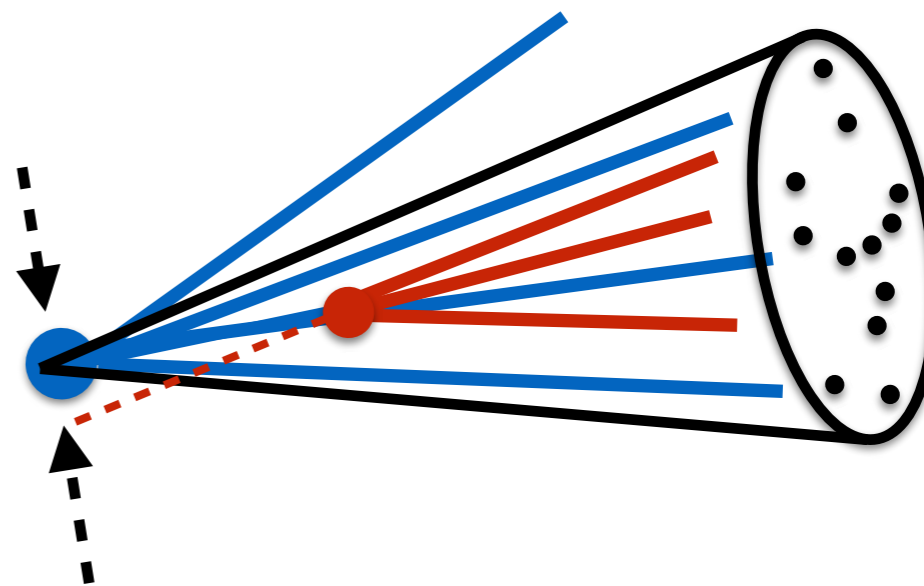
- a lot of effort has gone into **improving the simulation of the inner tracker** (including the IBL)
- **significant improvements in material description** leading up to 2017 data taking
- many of our tagging efficiency **SFs move closer to unity** after these updates



PERF-2015-07

algorithms overview

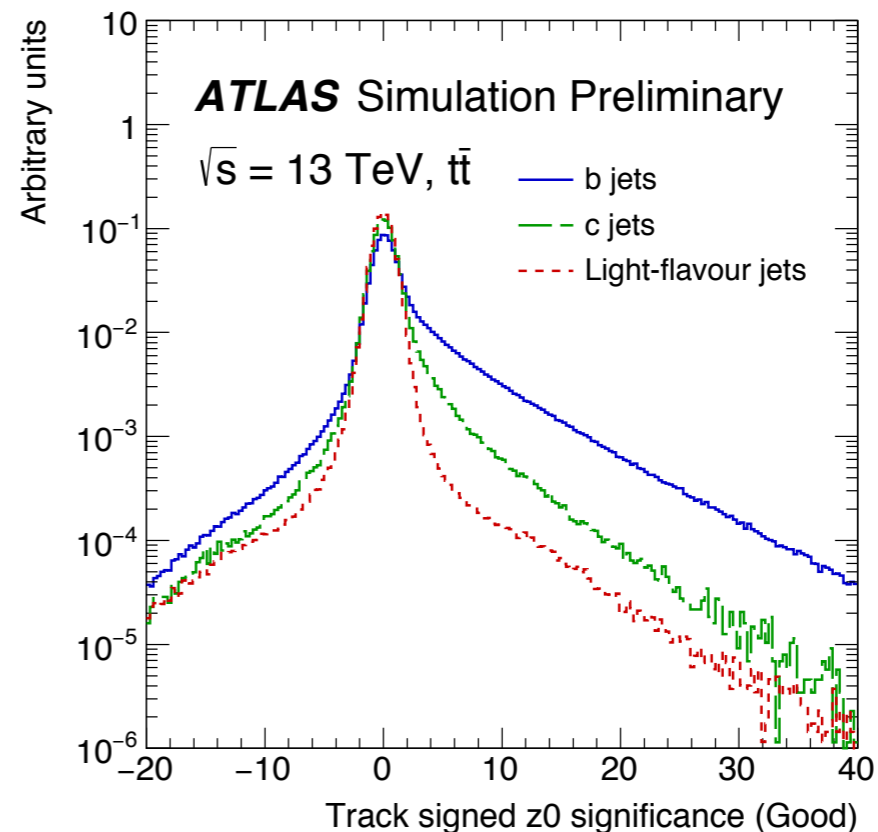
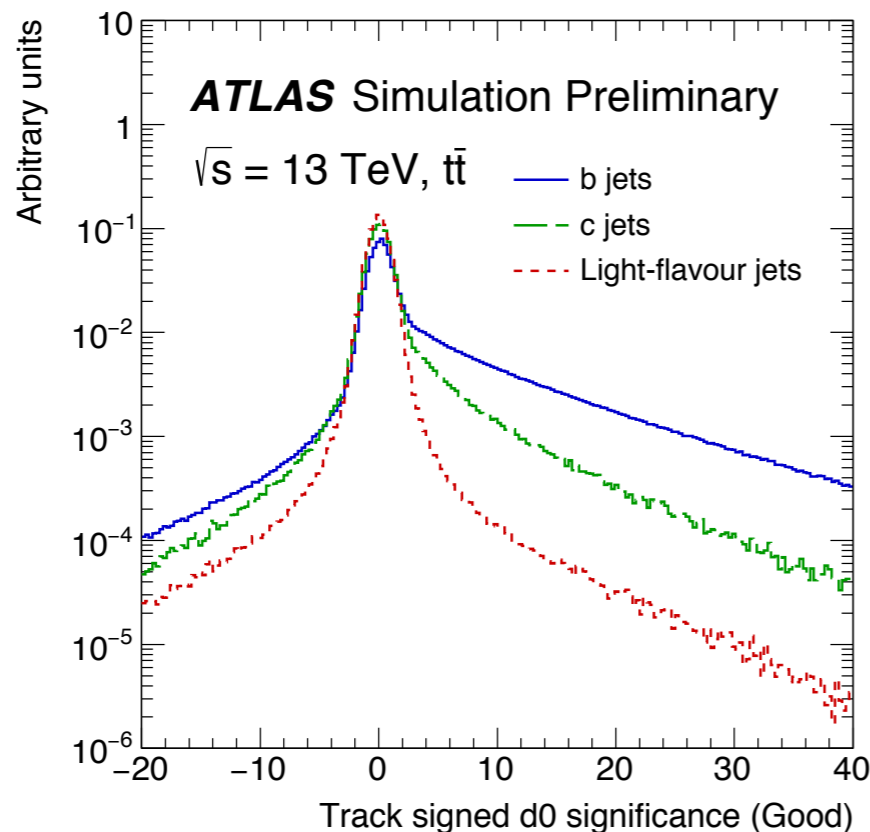
- **low-level tagging algorithms** take advantage of heavy hadrons' lifetimes, masses, and decay products
 - **track impact parameter (IP) significance**
 - **secondary** and **tertiary vertices**
 - **soft-leptons**
- **high-level taggers:**
 - feed observables from low-level taggers into **BDT** or **NN**
 - optimize on simulated **$t\bar{t}$** and **$Z' \rightarrow qq$** events



low-level taggers: IPTag

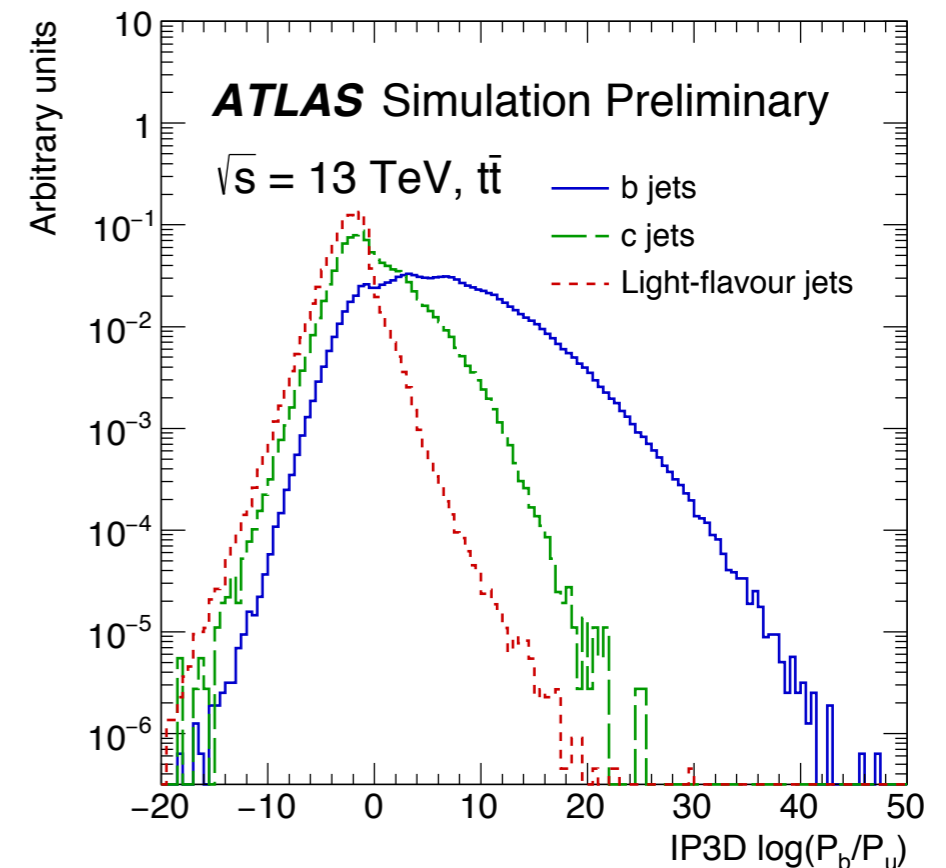
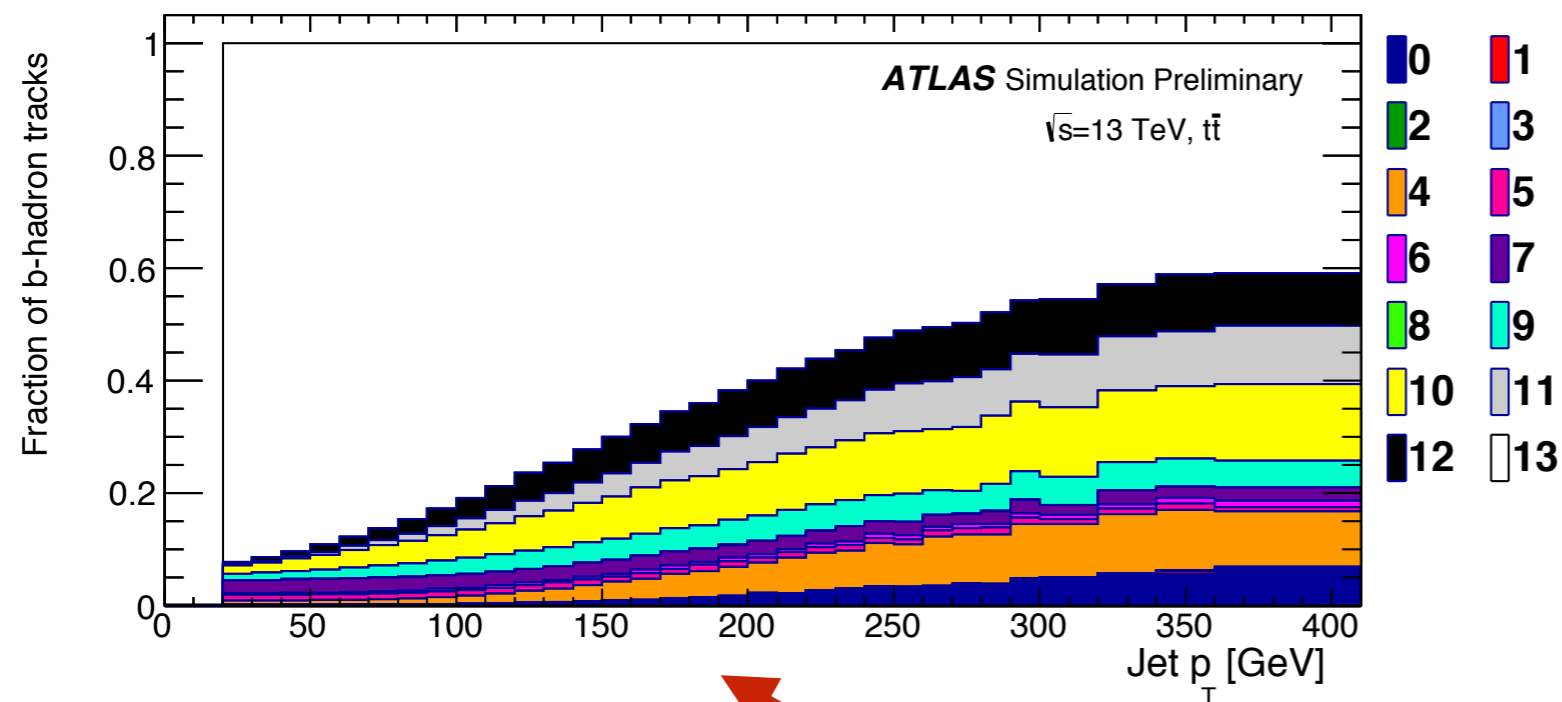
ATL-PHYS-PUB-2016-012

- for **IP2D** and **IP3D**, impact parameter significance templates are built from simulation for b -, c -, and light jets for tracks with
 - $p_T > 1$ GeV; $|d_0| < 1\text{mm}$ and $|z_0 \sin\theta| < 1.5\text{mm}$
- where the **IP significances** are defined as $d_0/\sigma(d_0)$ and $z_0 \sin\theta/\sigma(z_0 \sin\theta)$



low-level taggers: IPTag

ATL-PHYS-PUB-2016-012

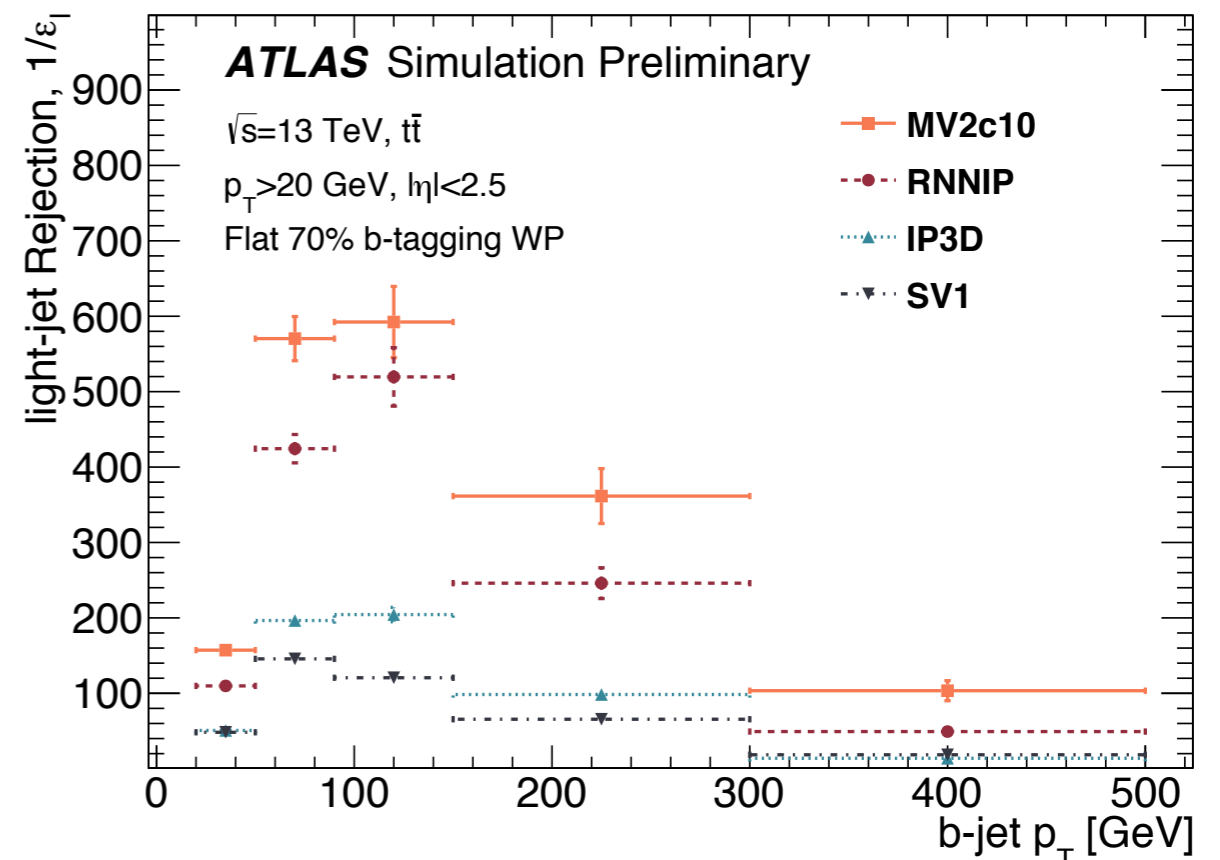
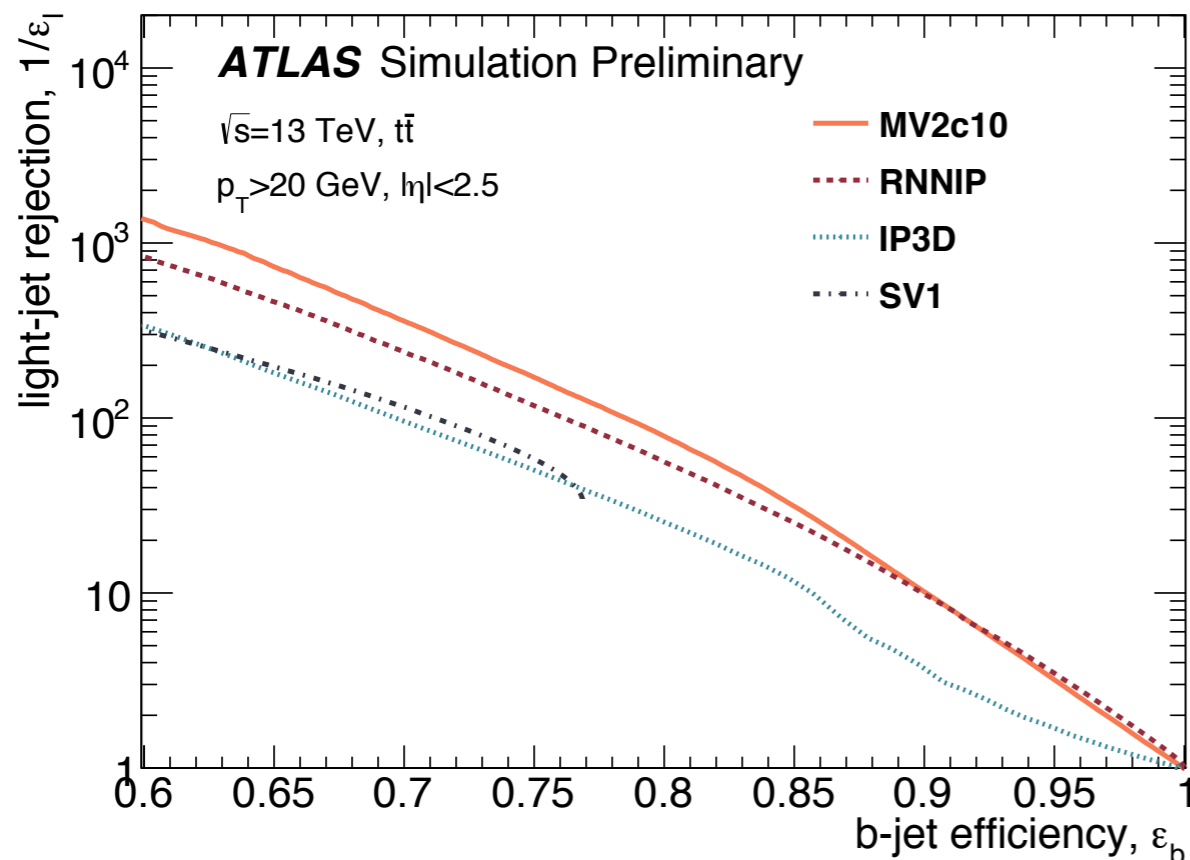


- tracks are further split into **14 categories by quality criteria** (number of IBL, B-layer, Pix, and Si hits; number of shared hits, etc).
- given the templates for each track category, a likelihood ratio is assigned to each track, and the sum of log-likelihood ratios is used as the discriminant.

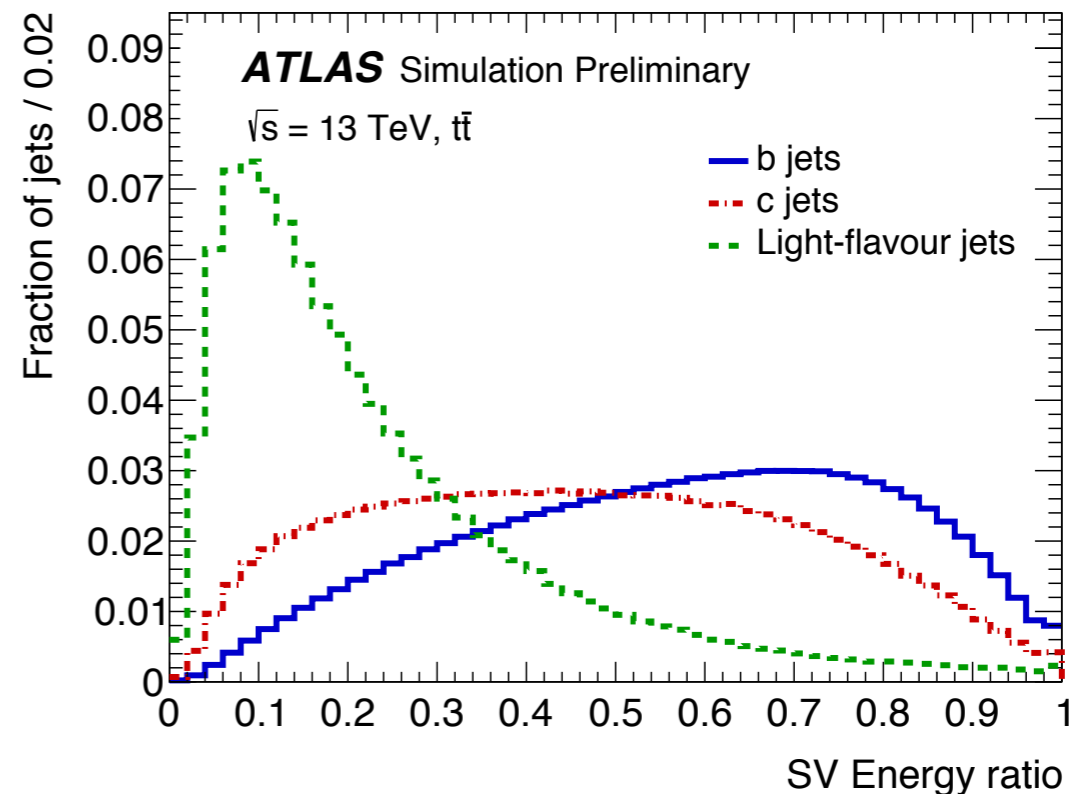
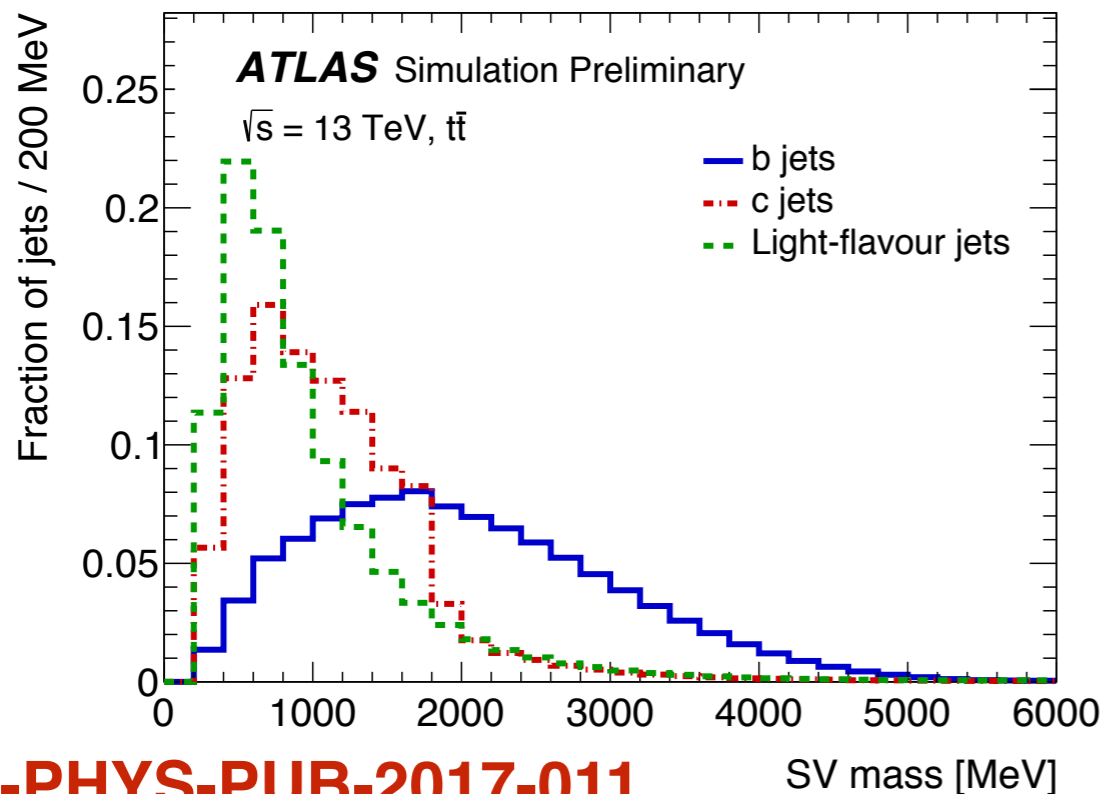
low-level taggers: RNNIP

ATL-PHYS-PUB-2017-003

- in the last few years a **new impact-parameter tagger** using **recurrent neural networks** (RNNs) has been developed
- the **same tracks** as IPTag, **including track quality categories**, are used as inputs.
- excellent performance w.r.t. IPTag is observed, **especially at high-pT**.
- **first physics results** using this low-level tagger should appear shortly.



low-level taggers: SV1



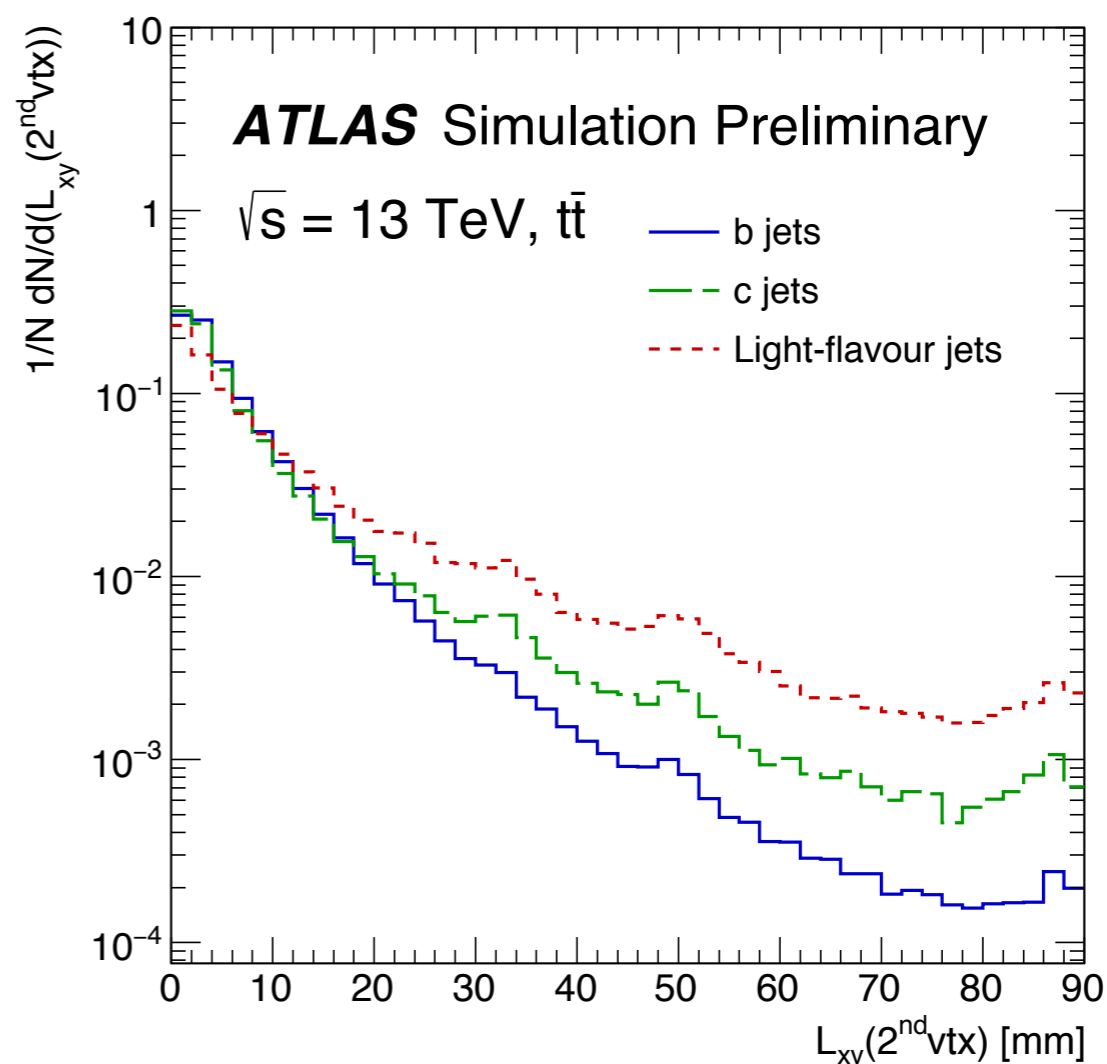
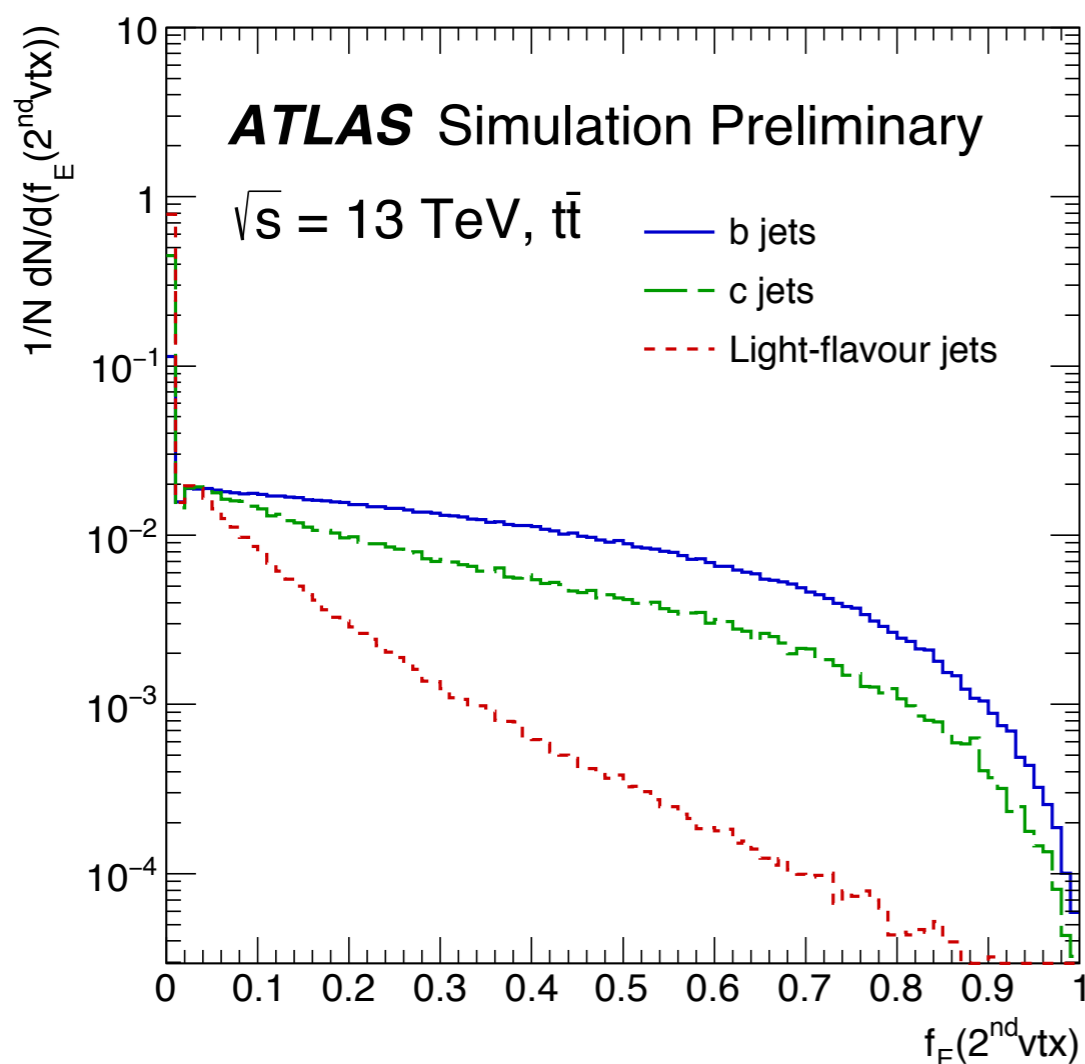
ATL-PHYS-PUB-2017-011

- **SV1** uses the **single-secondary-vertex-finding** (SSVF) algorithm to identify jets with secondary vertices consistent with a *b*-hadron decay.
- in short, all tracks associated to a jet are allowed to form **2-track vertices** which are then **iteratively merged** until one secondary vertex (SV) remains
- χ^2 and SV mass requirements are imposed in particular to **remove K_s , Λ_0 , and photon conversions**.
- after an acceptable secondary vertex is found, discriminating observables like **SV mass, SV energy fraction, decay length significance** are constructed.

low-level taggers: JetFitter

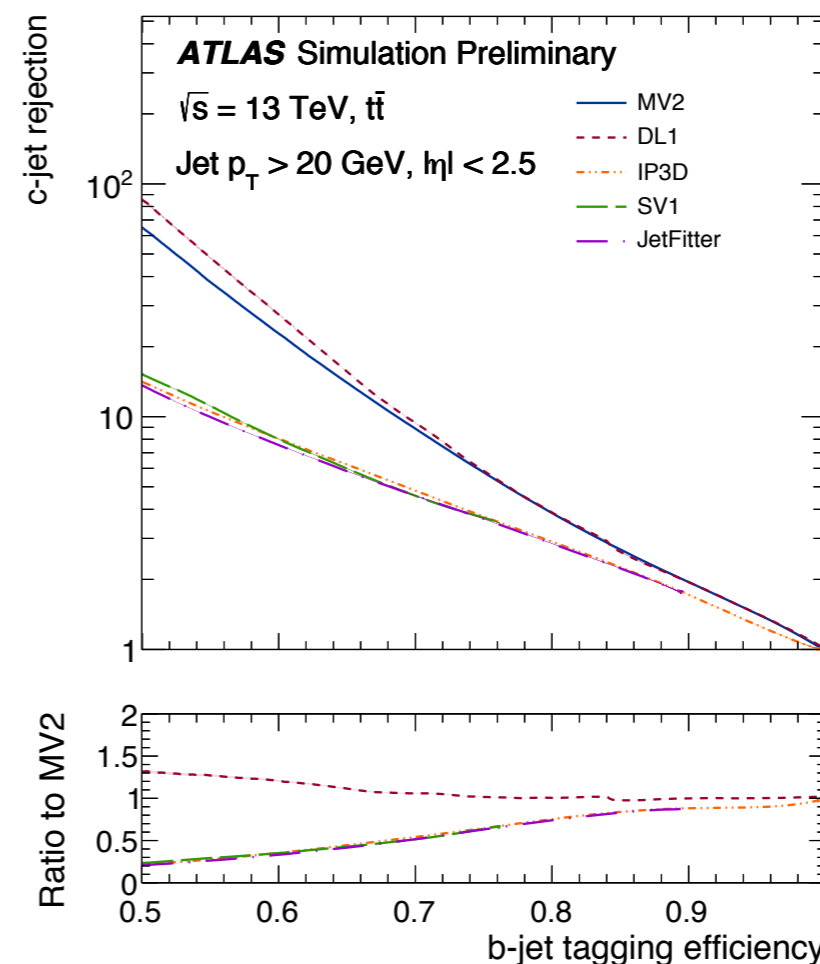
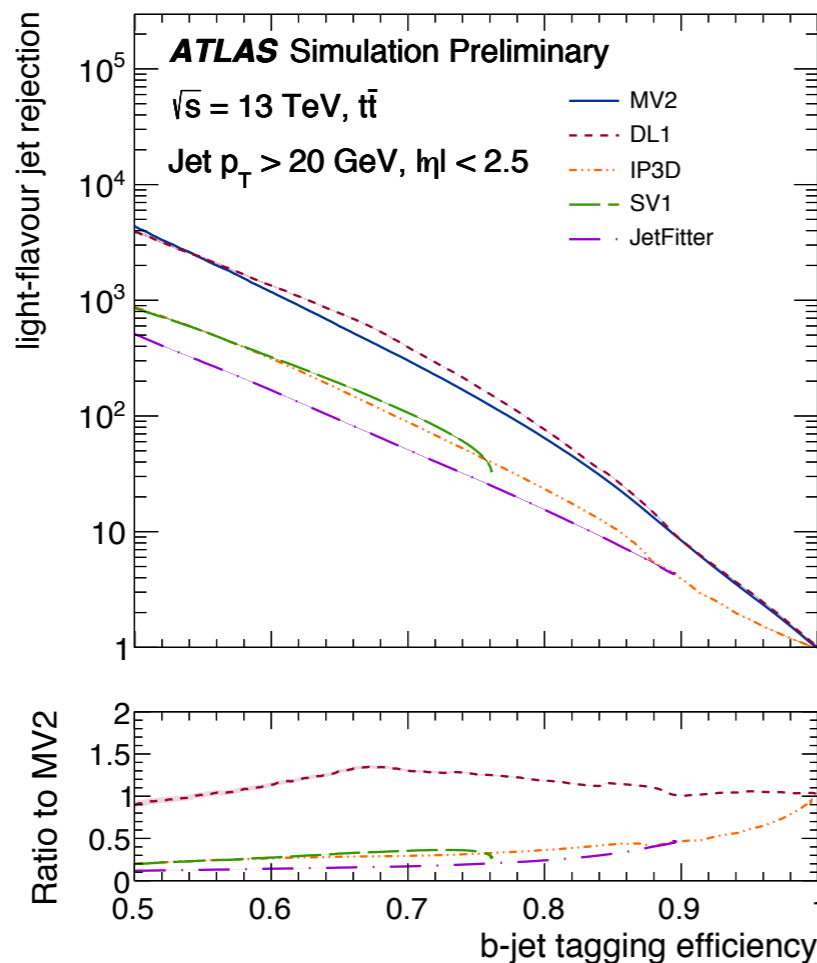
ATL-PHYS-PUB-2018-025

similar to SV1, after secondary and tertiary vertices are constructed, discriminating observables are calculated for use in high-level taggers



high-level taggers

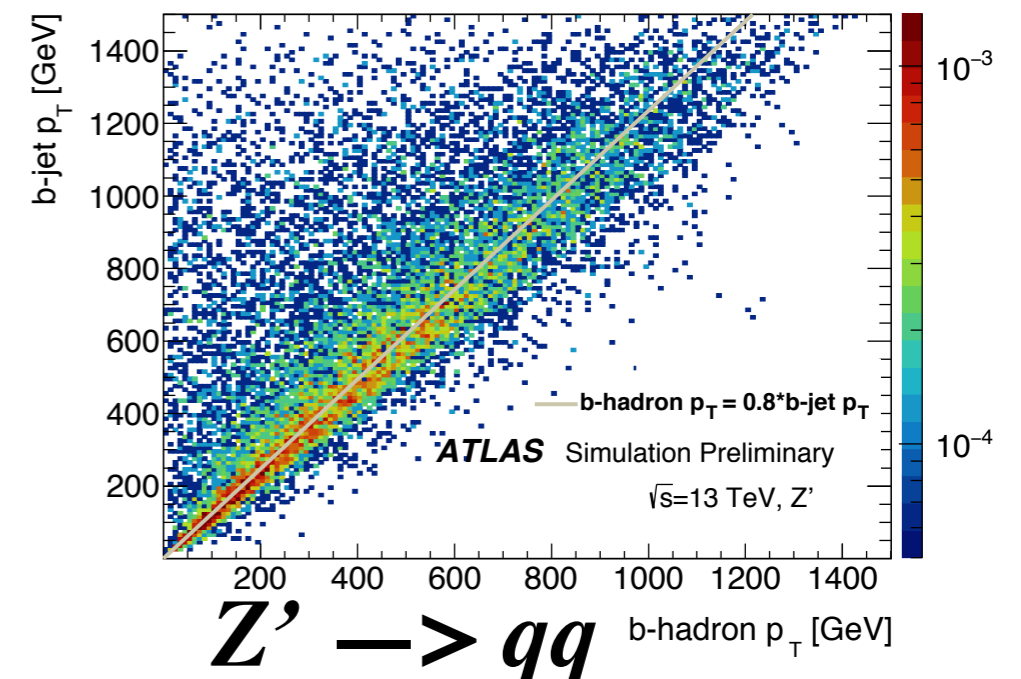
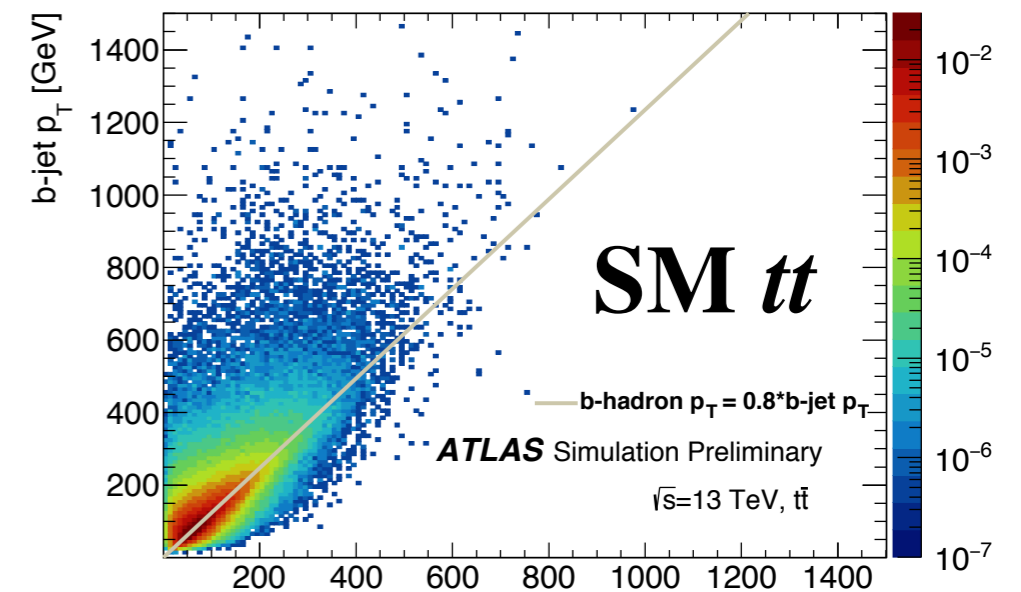
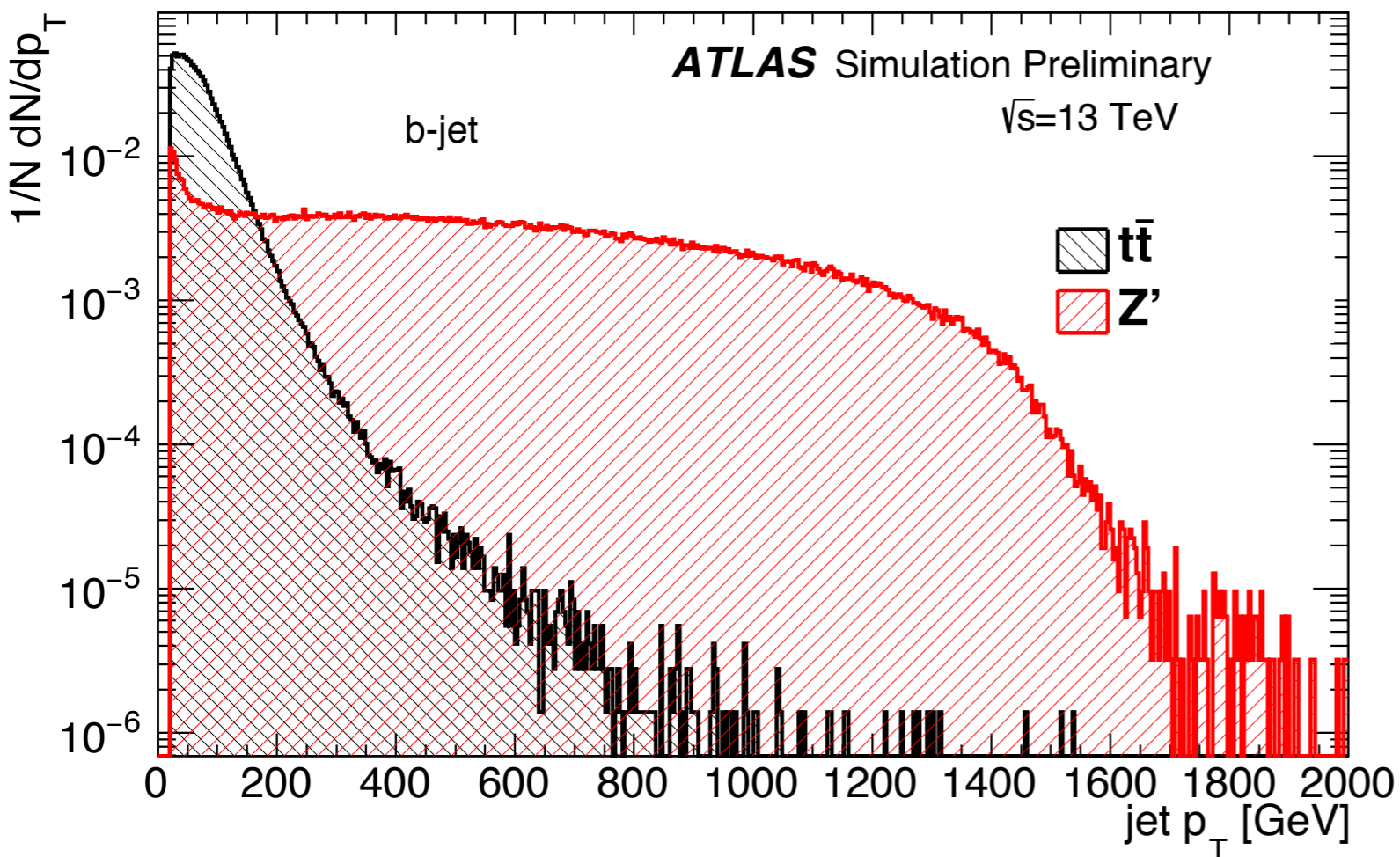
- we currently use **two families** of high-level taggers: **MV2 (BDT)** and **DL1 (deep neural network)**...
- ... that take **discriminating observables from the low-level taggers** as inputs.
- as expected, significant gains are achieved by **taking advantage of correlations** between the outputs of the low-level taggers.



FTAG-2019-002

training inputs

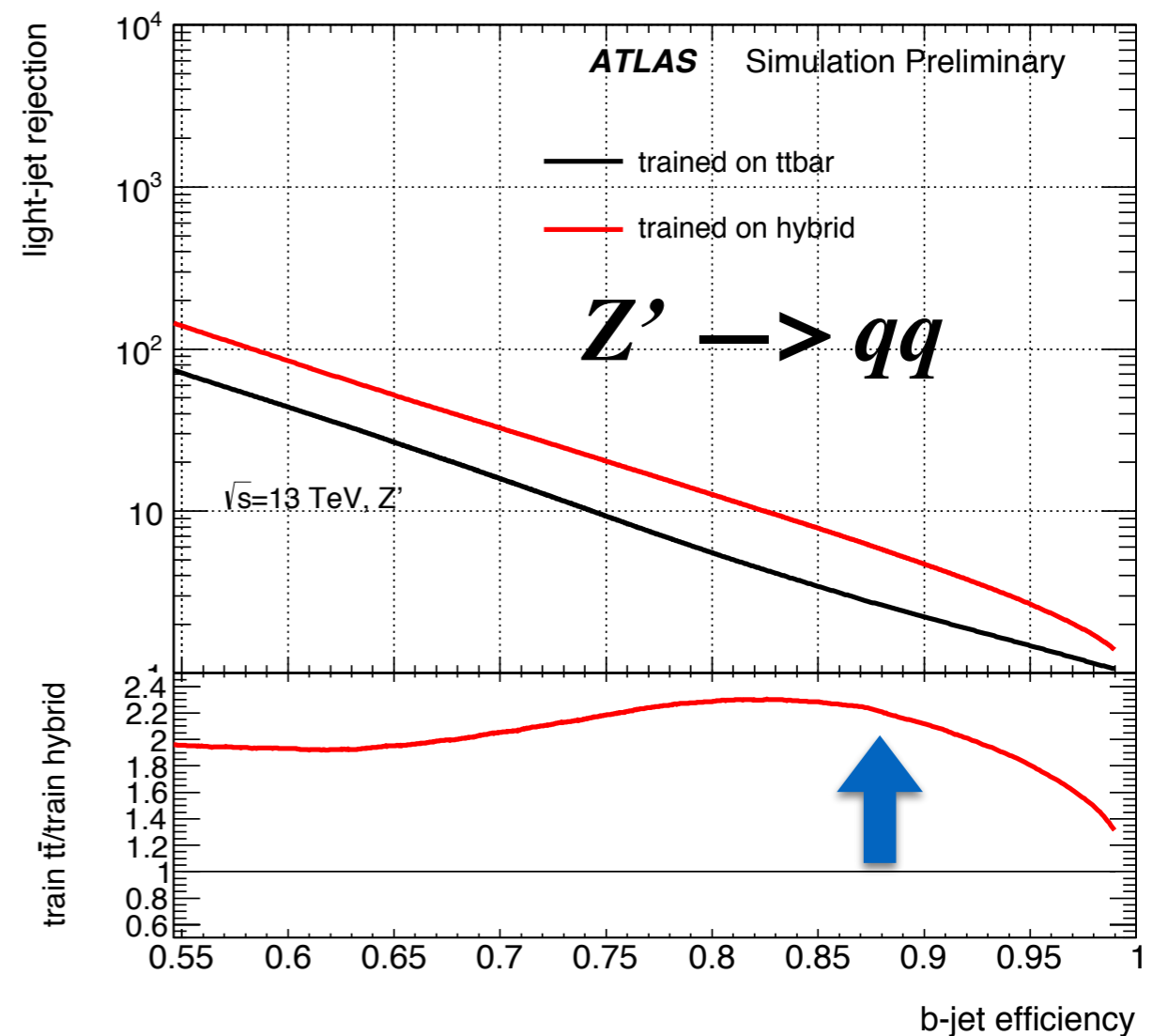
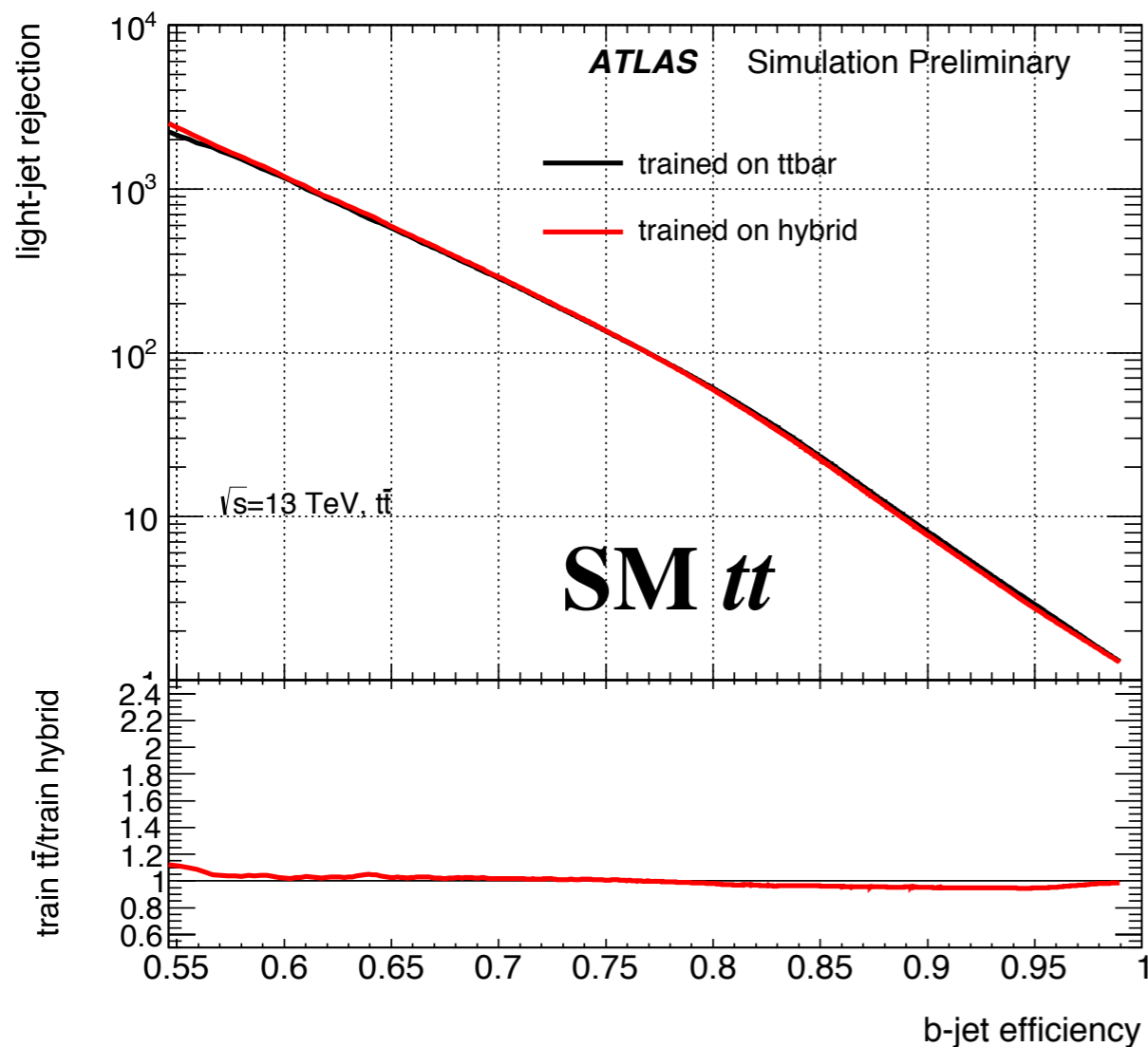
leading up to the 2017 data taking, we started training our taggers on a **hybrid** sample of jets **SM $t\bar{t}$** and **$Z' \rightarrow qq$** to better fill out the jet p_T distribution and have more representative b -fragmentation.



ATL-PHYS-PUB-2017-013

training inputs

this resulted in about a factor of **two** better light-jet rejection in most b -jet (from Z') efficiency ranges with the new training.



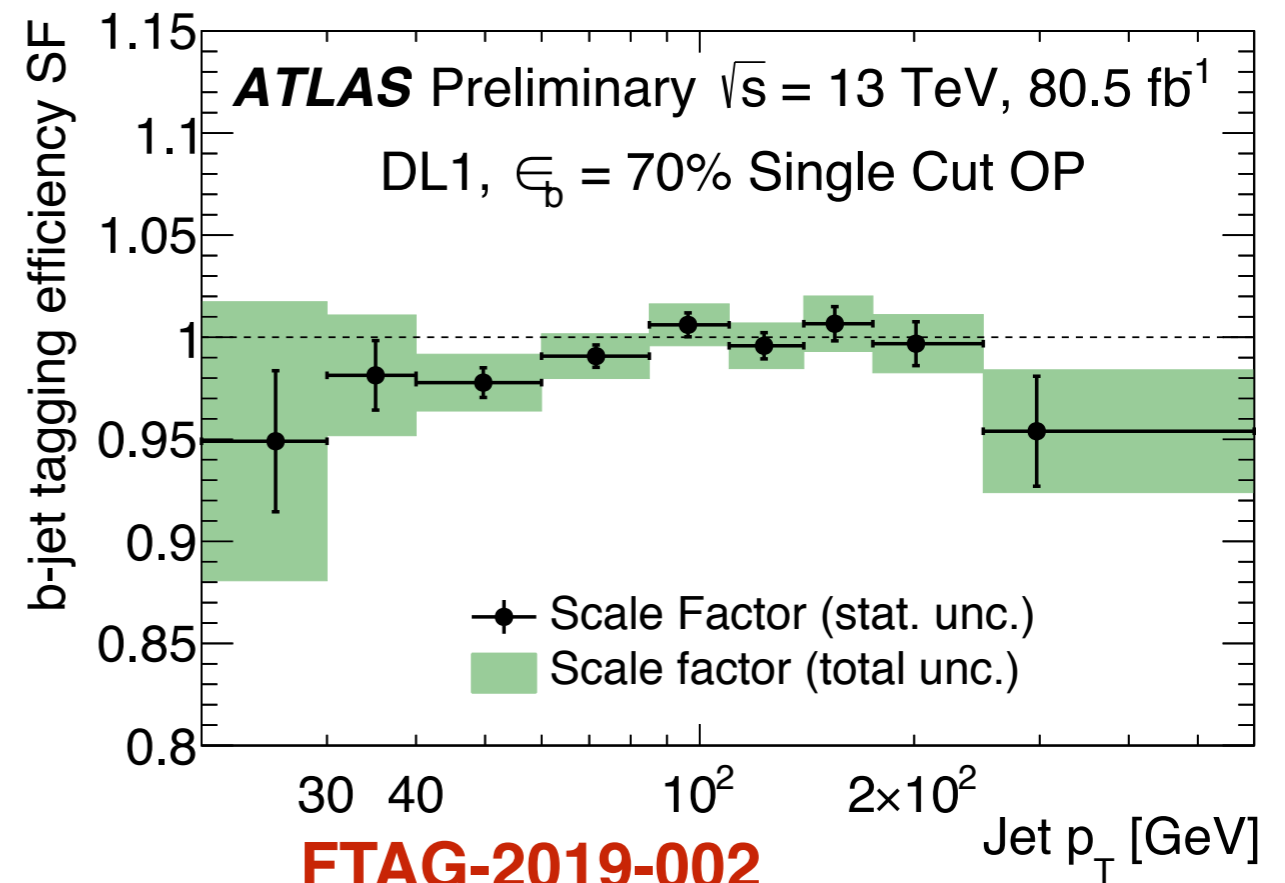
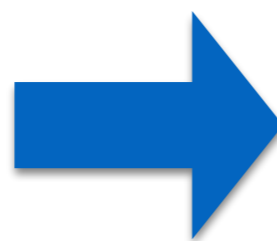
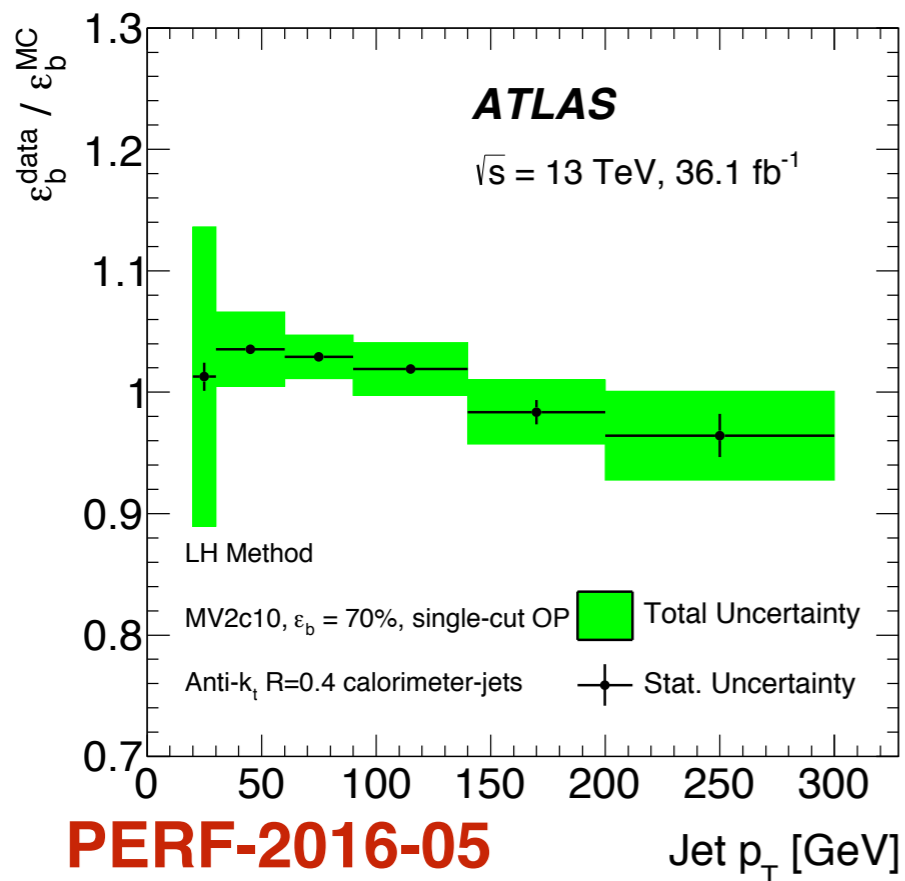
ATL-PHYS-PUB-2017-013

calibrations

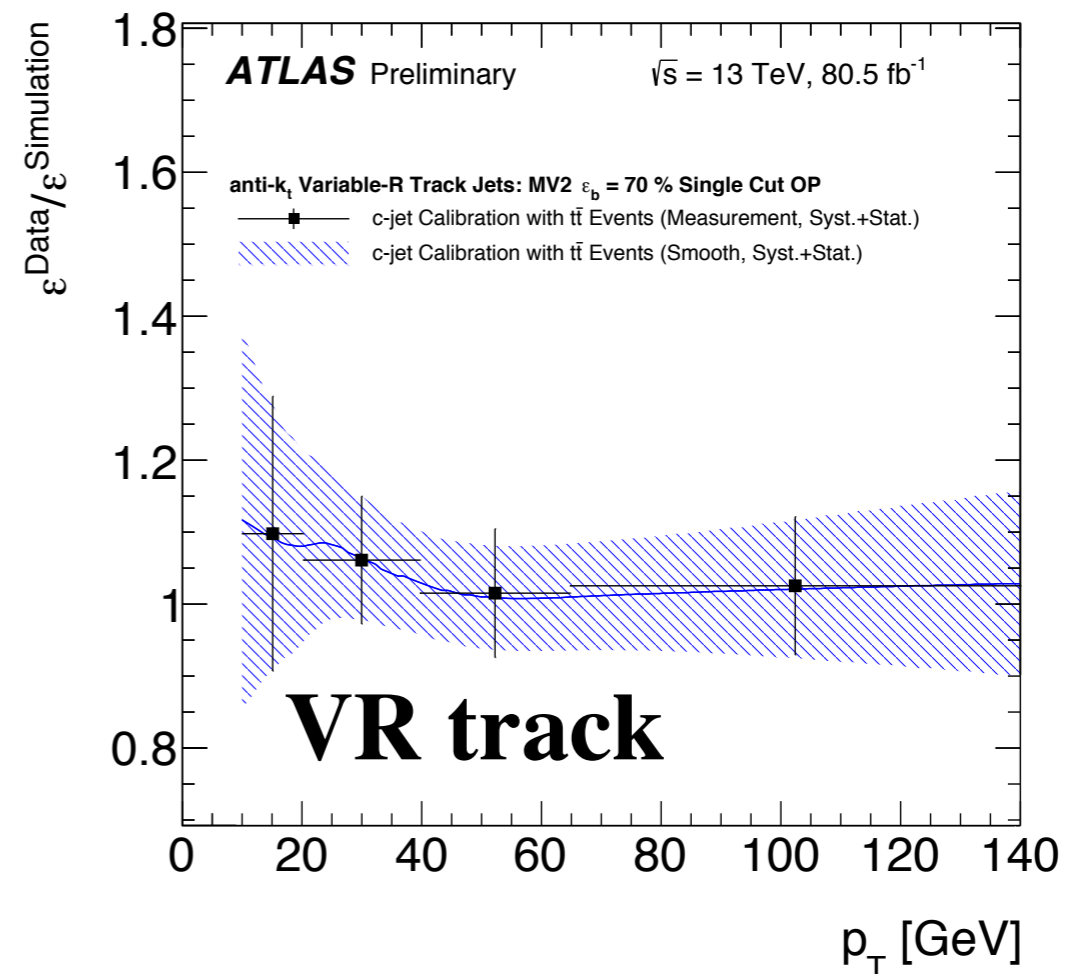
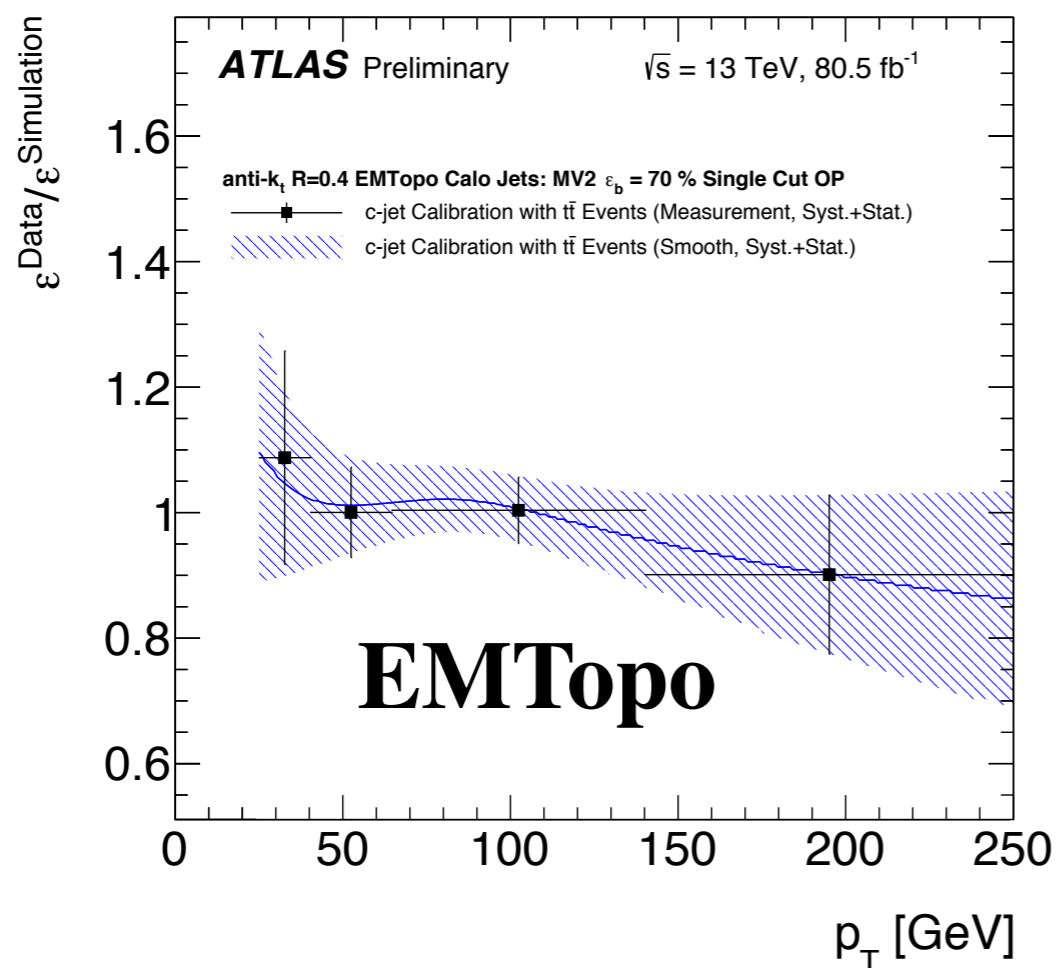
- we provide "standard" **calibrations as a function of jet p_T** separately for **b -, c -, and light-jets**.
- here "calibration" means we **measure in data** the probability of a jet passing a cut on the high-level **discriminant output distribution** and **correct the simulation to reflect this** with scale factors.
- we calibrate four operating points, corresponding to **60, 70, 77, and 85% b -jet efficiency working points** in the training sample.

b-jet calibrations

- the primary *b*-jet calibrations are carried out in ***tt* -> *eμbb* events** using a **likelihood fit** over the two jets.
- calibrations for both **VR track jets** and **EMTopo jets**.
- in the past large **uncertainties from light-jet background predictions** in *tt* events, somewhat **mitigated now by data-driven constraints**.



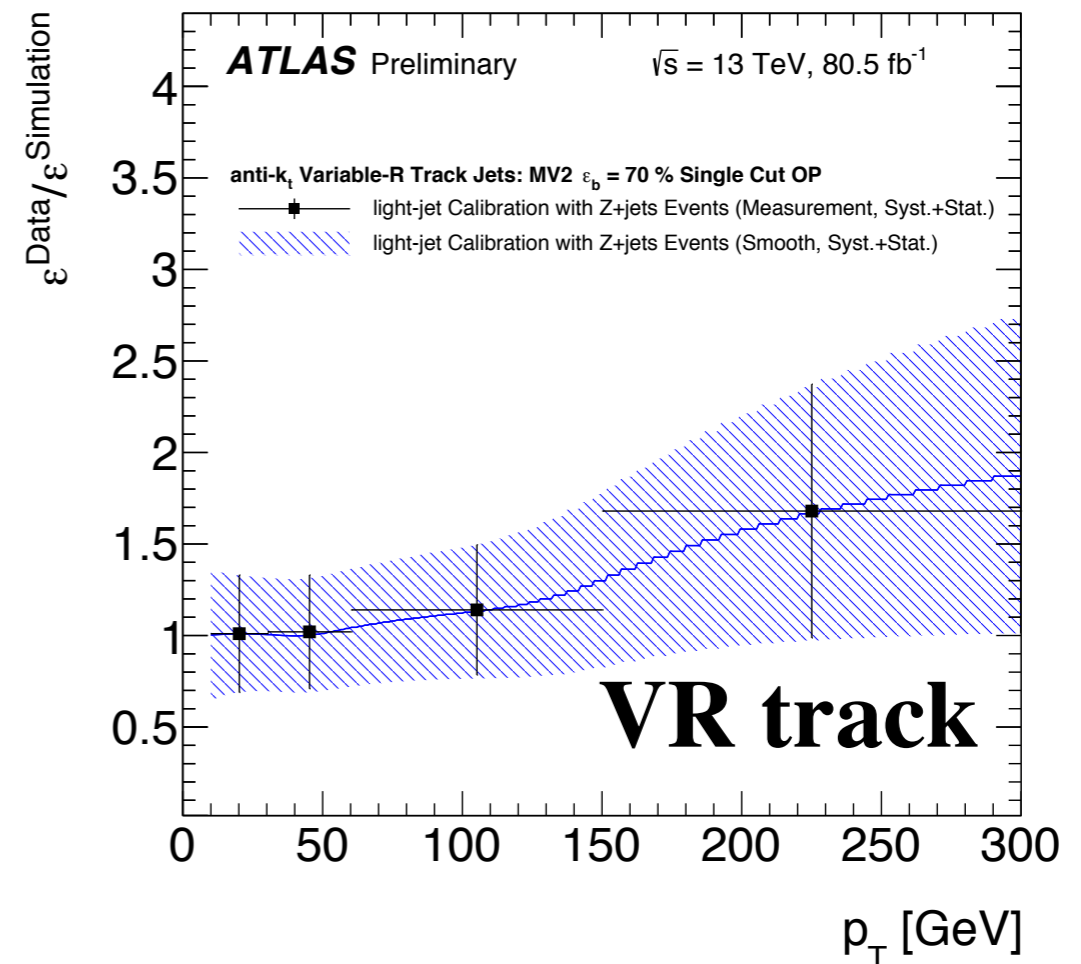
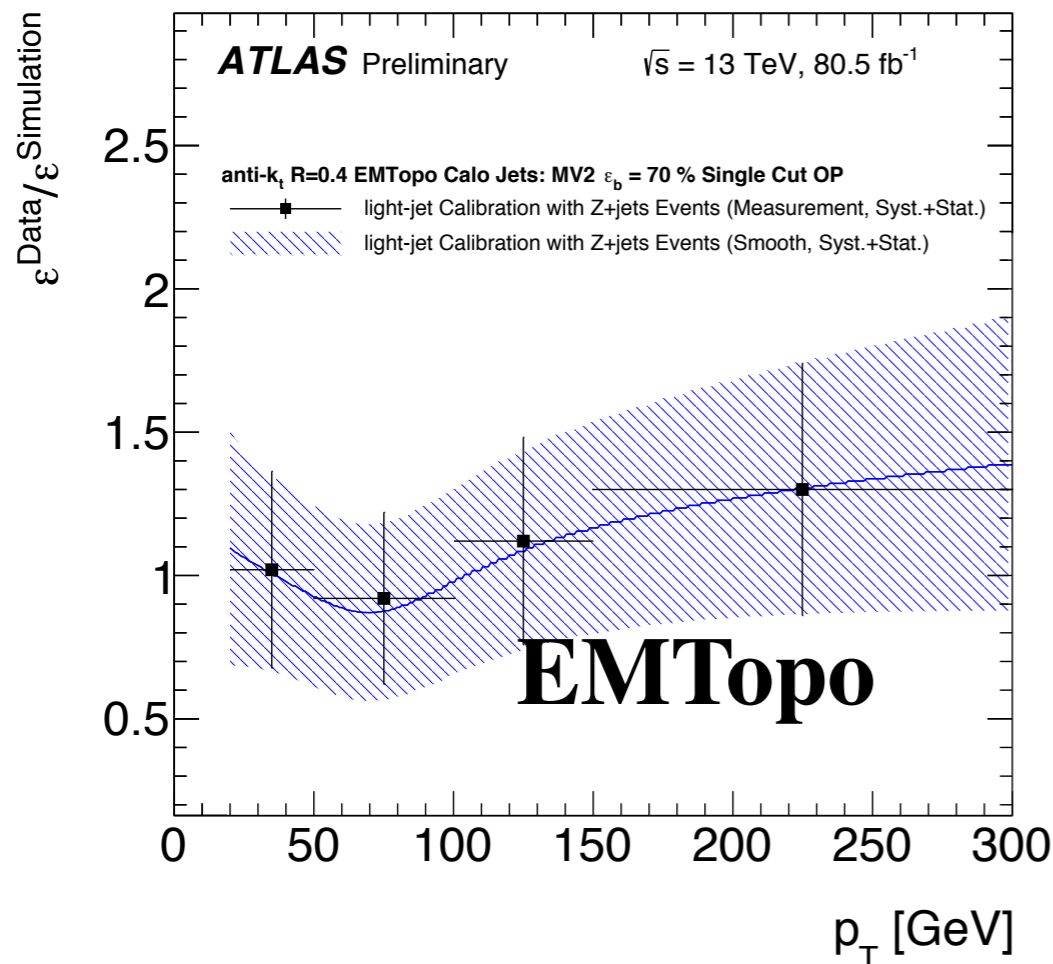
c-jet calibrations



- the primary c -jet calibrations are currently carried out in $tt \rightarrow \ell vcqbb$ **events** using KLFilter to determine the hadronic W decay products.
- calibrations for both **VR track jets and EMTopo jets**.
- largest **uncertainties from tt modeling**.

FTAG-2019-003

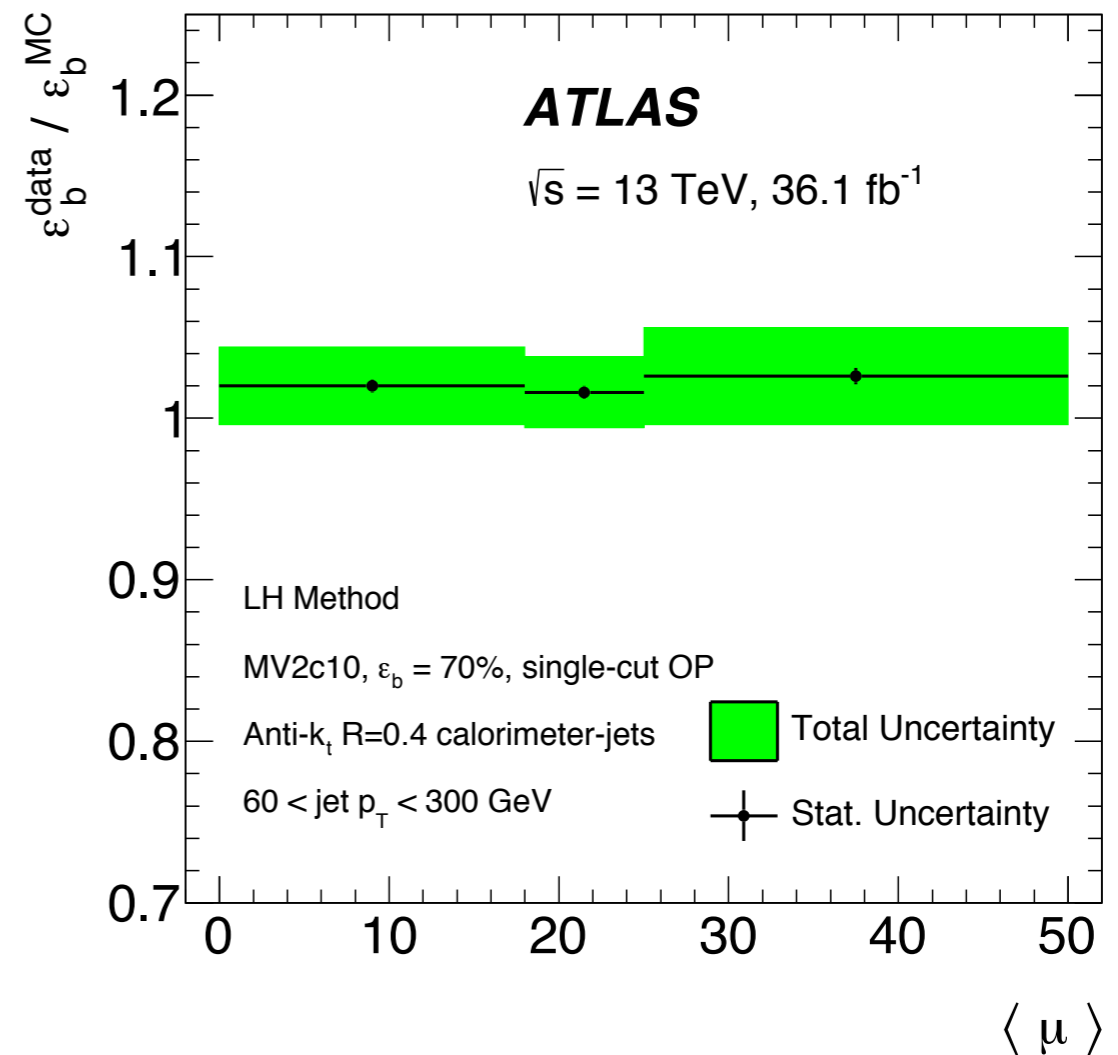
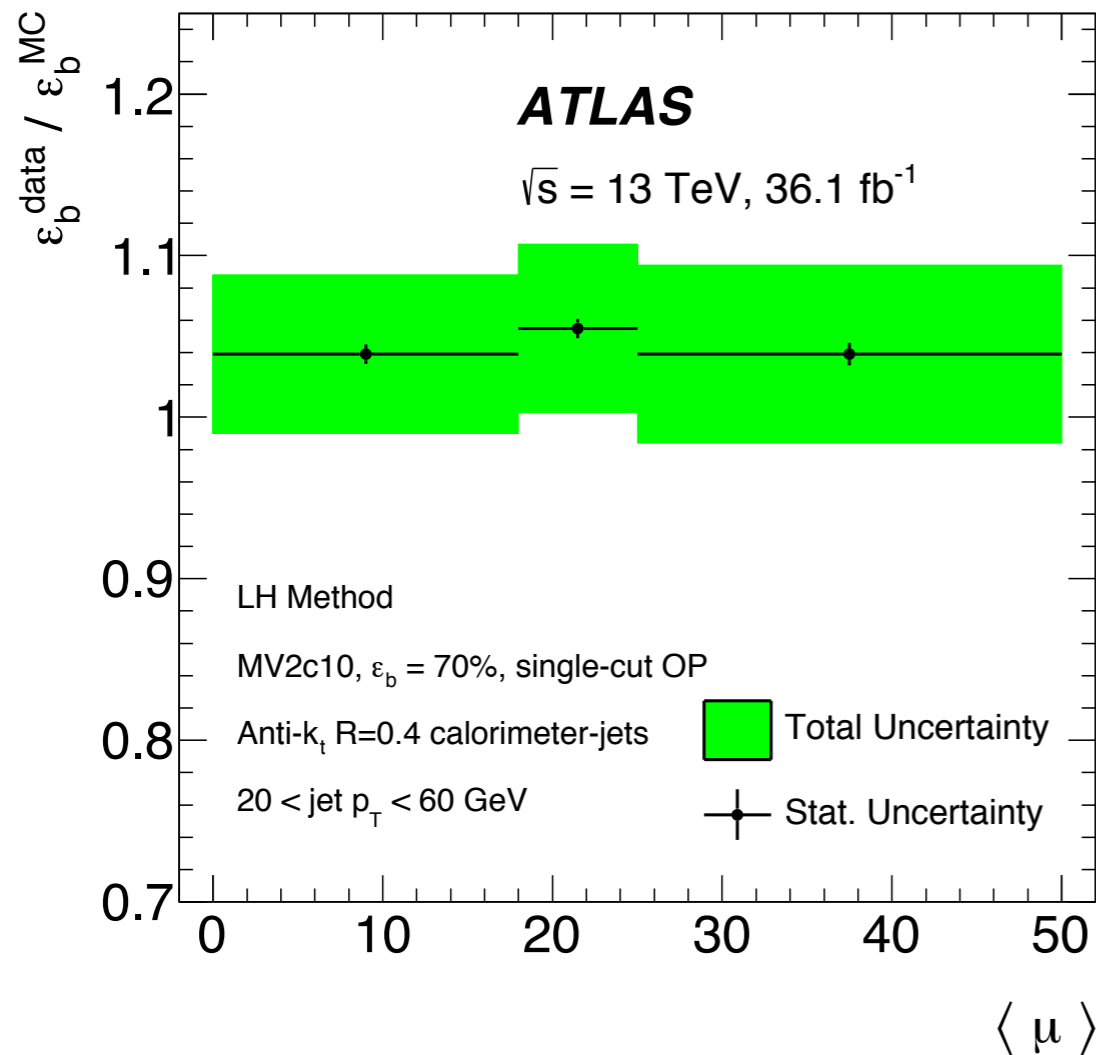
light-jet calibrations



- light jet mistag-rate calibrations have **always been challenging**, in part because it's difficult to know the **flavor-fractions before tagging**.
- we have moved to performing the **data-based negative tag calibration in Z+jets events**, where we have measurements to help us constrain these fractions.
- **bottom-up propagation of uncertainties** similar to those outlined in **ATLAS-CONF-2018-006** continue to be studied.

FTAG-2019-003

a word on pileup



scale factors so far **do not depend strongly on $\langle \mu \rangle$** , but we are keeping a close eye on this, especially for mistag rates.

PERF-2016-05

specialized taggers

we have several ongoing efforts to provide **non-standard taggers** for particular classes of physics analyses

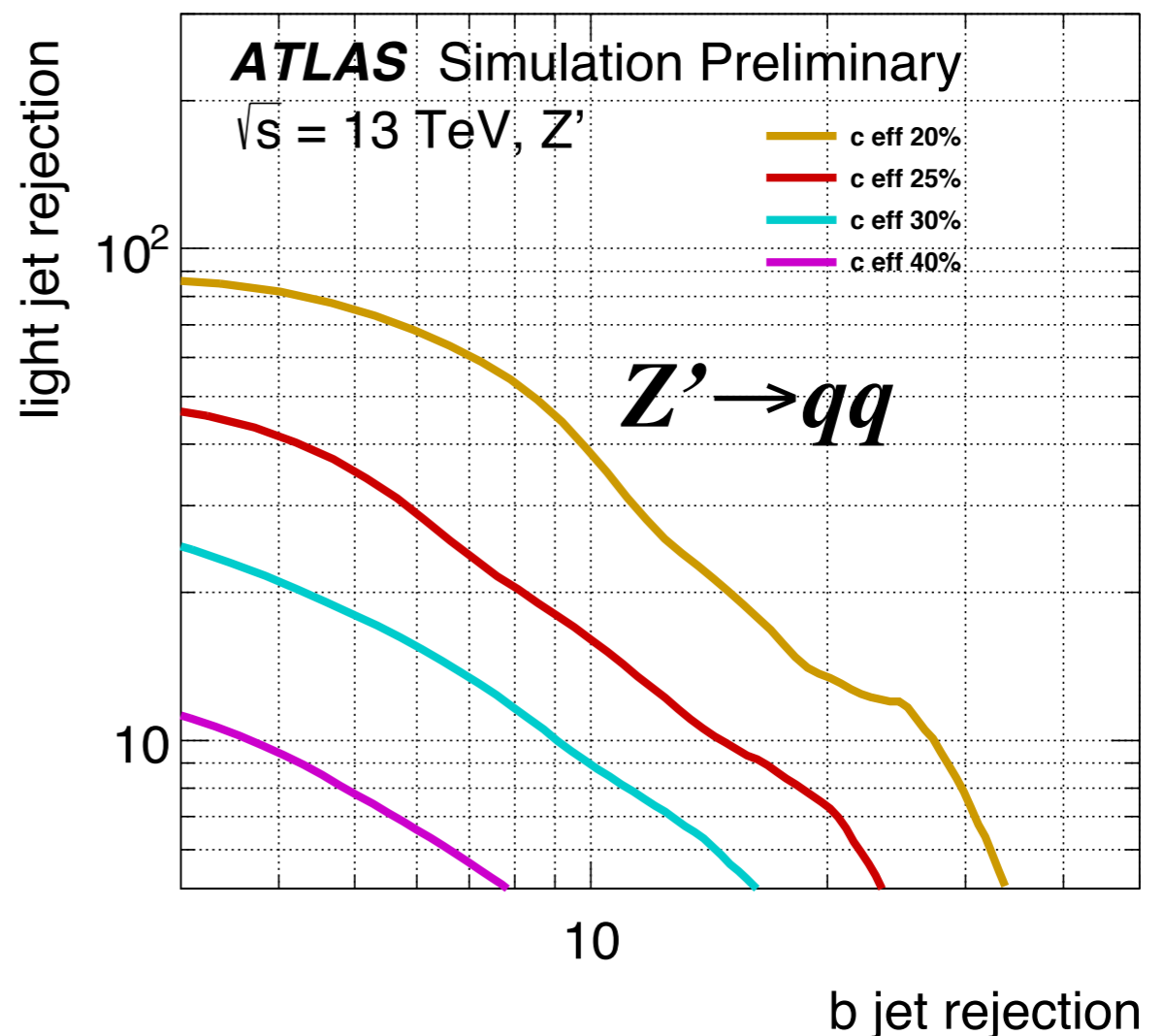
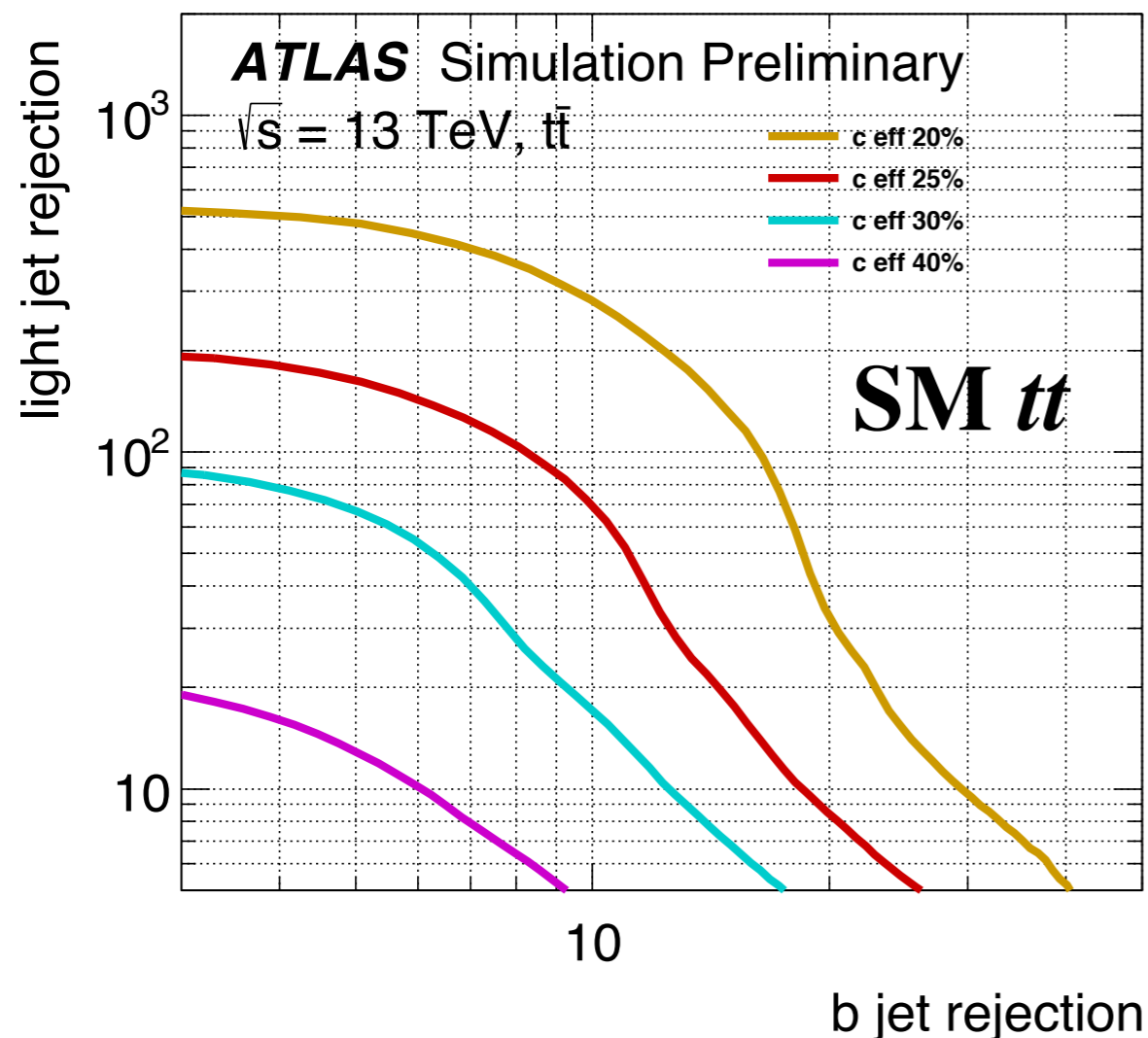
I'll highlight **$X \rightarrow bb$** tagging and **charm tagging** with a few slides.

charm taggers

several **charm taggers** have been optimized using the DL1 framework, but adding a few additional variables, especially related to JetFitter.

the results look quite promising, and **calibrations are underway** using similar techniques as for the *b*-tagger calibrations.

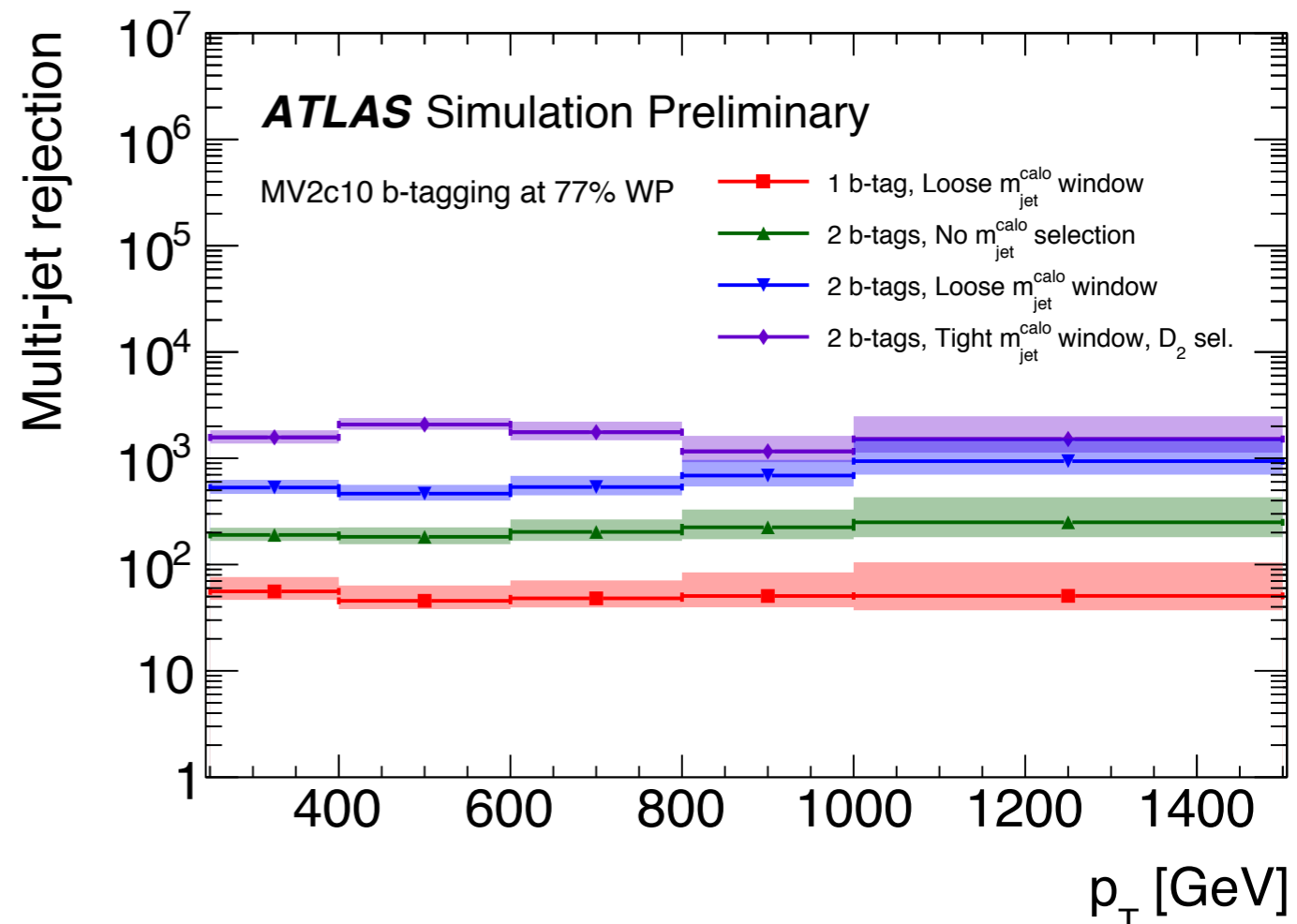
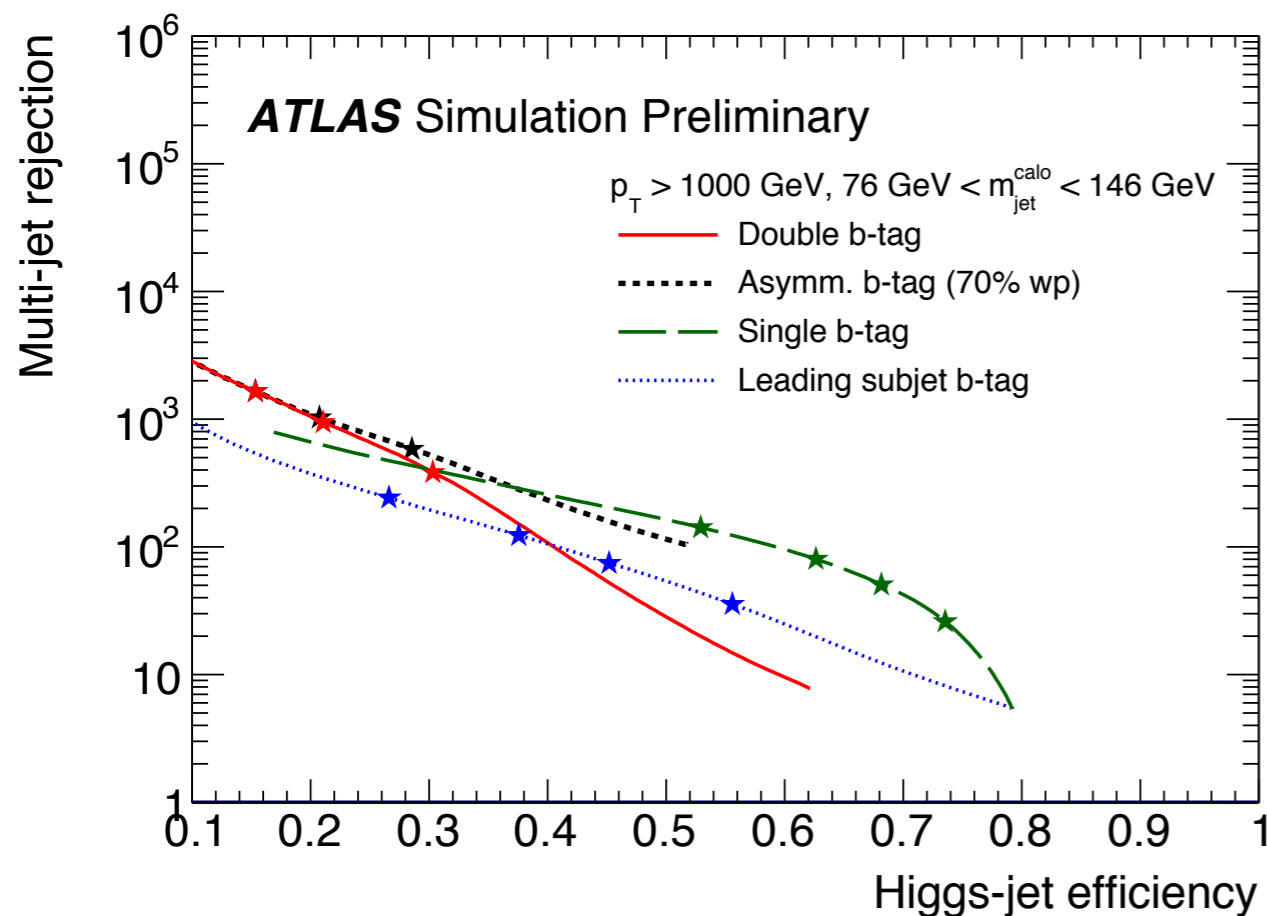
ATL-PHYS-PUB-2017-013



$X \rightarrow bb$ tagging

$Z/H/X \rightarrow bb$ reconstruction techniques available for analyses: combination of **b -tagging** and **jet substructure** for discrimination, targeting color singlet signals

here large- R ($R = 1.0$) calorimeter jets are used to identify candidates, and small- R ($R = 0.2$) track jets are used for b -tagging

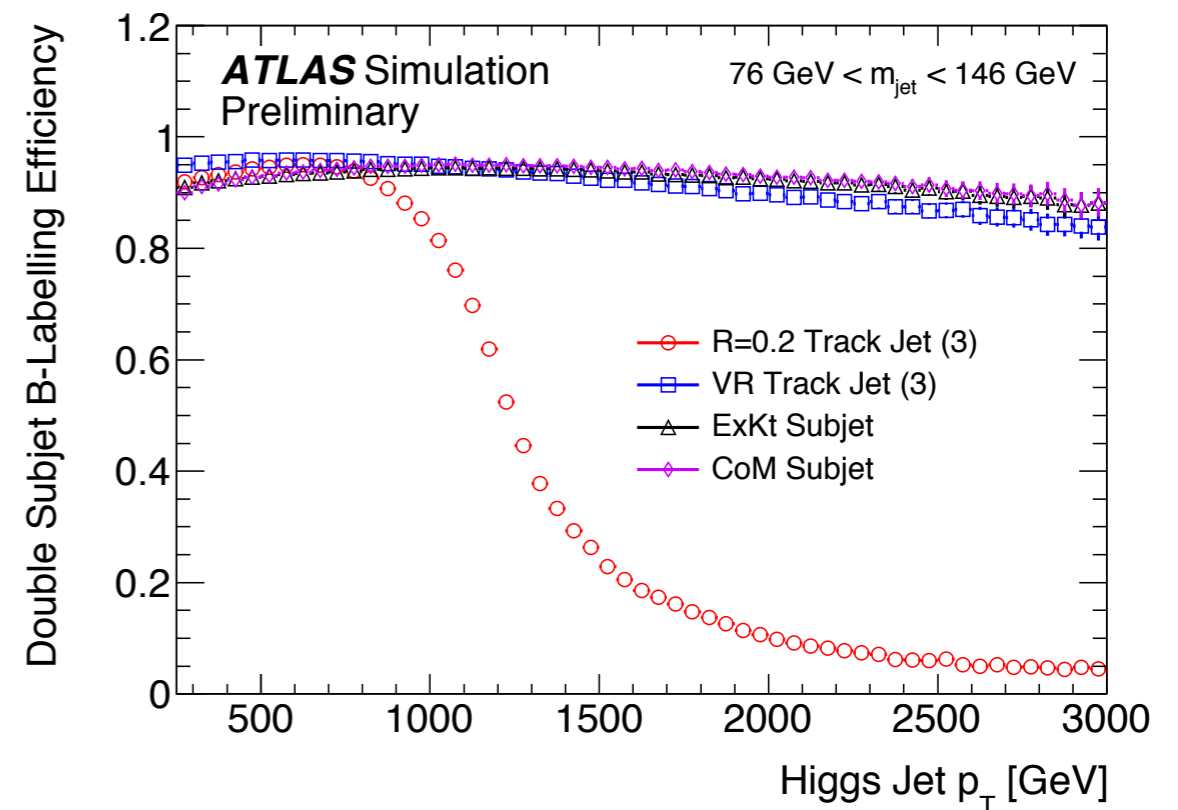
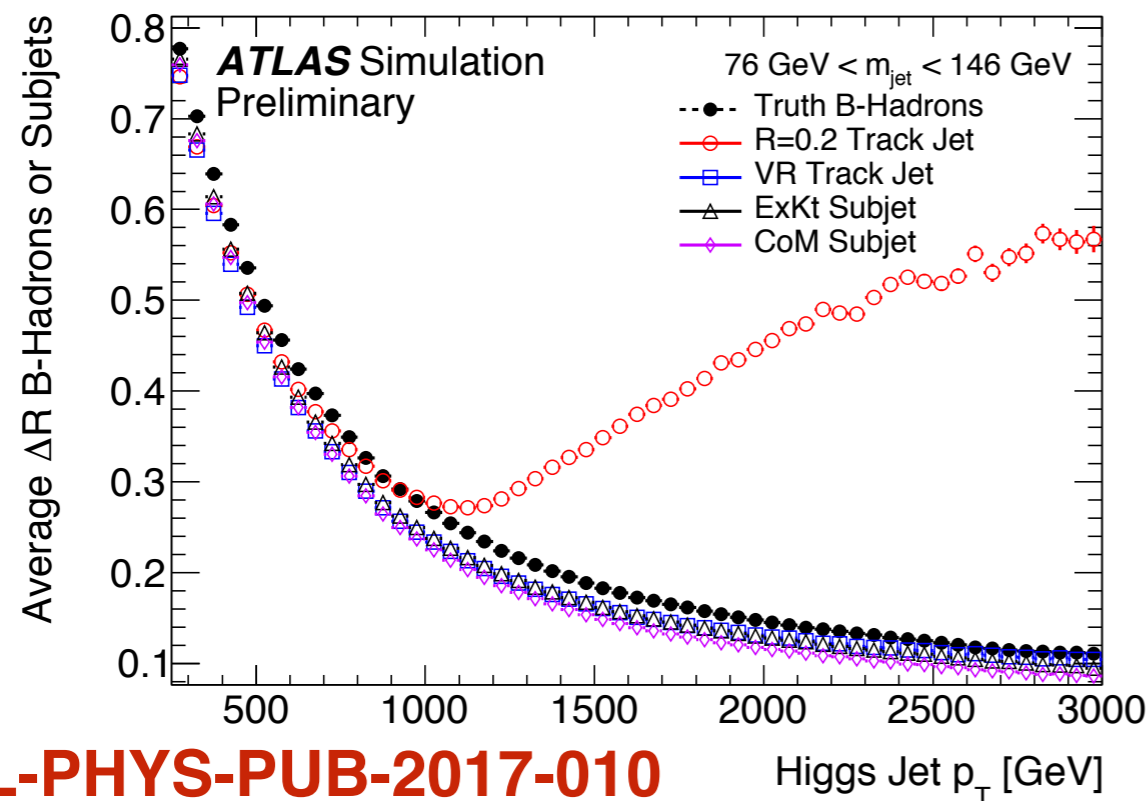


ATLAS-CONF-2016-039

"advanced" $X \rightarrow bb$ tagging

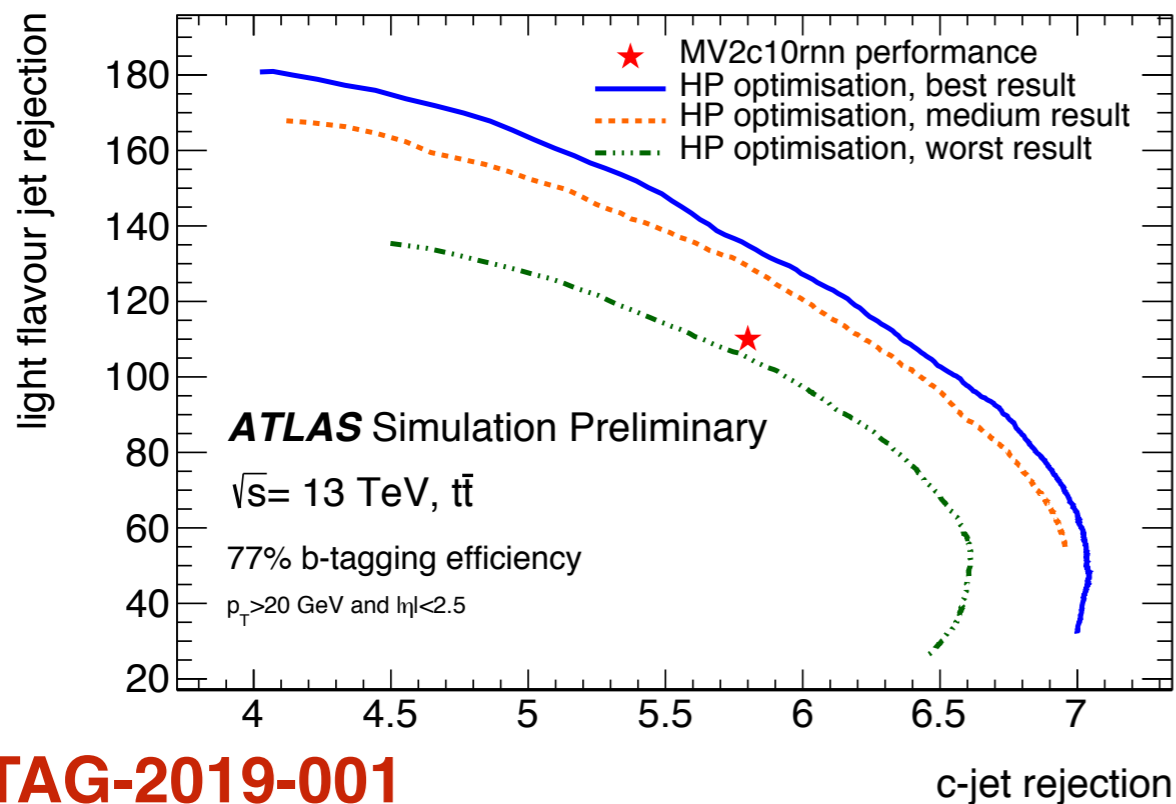
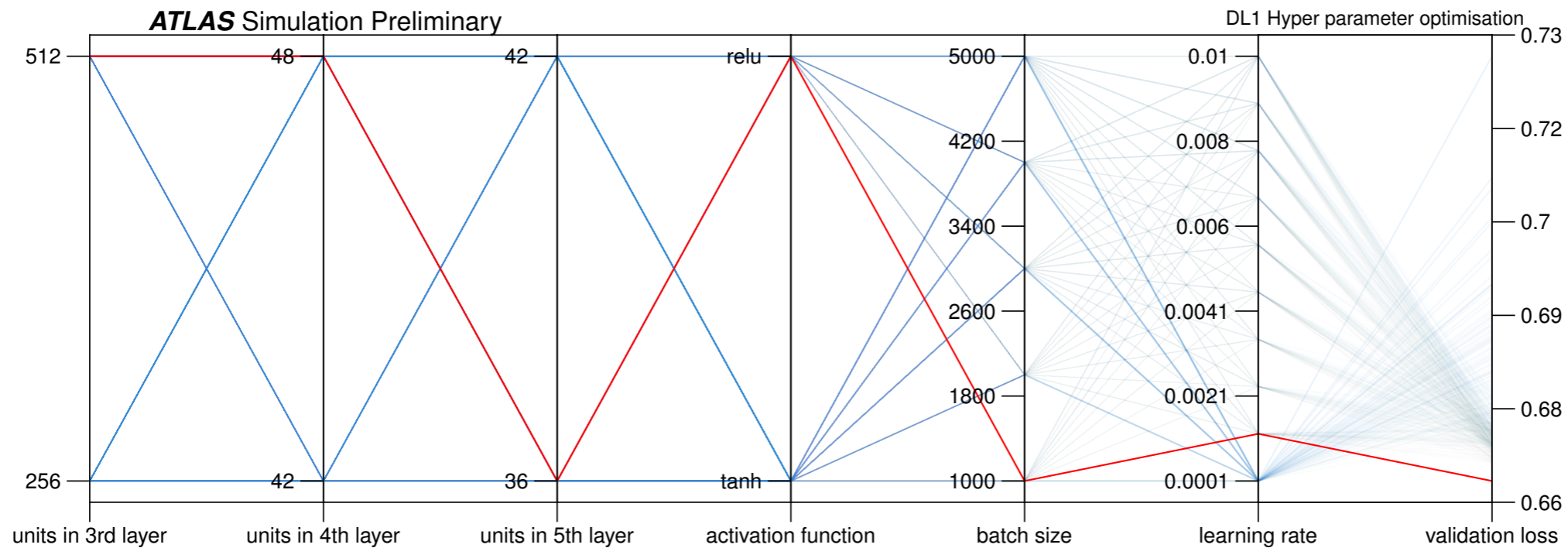
more sophisticated $Z/H/X \rightarrow bb$ reconstruction techniques being developed and calibrated (VR track jets already in use!)

- center-of-mass (CoM) tagging: boost into resonance rest frame (using reconstructed large- R jet kinematics), perform track-to-jet association, then apply b -tagging
- exclusive-kt subjet tagging: apply kt clustering on large- R jet constituents, associate tracks to final two kt subjets, and apply b -tagging



ATL-PHYS-PUB-2017-010

technical developments



there have also been some nice developments on the **hardware/software side of things**:

- **DL1 hyperparameter scans are now performed on GPUs distributed over the LHC grid**
- this opens up some nice possibilities for **more performant taggers, better validation**, etc in a **reasonable amount of time!**

conclusion

- ATLAS has a set of **very performant *b*-taggers** using primarily inner-detector tracking information seeded by **calorimeter or track jets**.
- there are **many ongoing efforts** to
 - improve performance of input tracks and jets
 - use tracking information more effectively for flavor discrimination
 - develop new low-level taggers
 - improve the way we train high-level taggers
 - provide more precise calibrations
 - foster development of novel taggers for specialized use cases
 - and many more...
- **thanks for your attention!**