ATLAS EXPERIMENT

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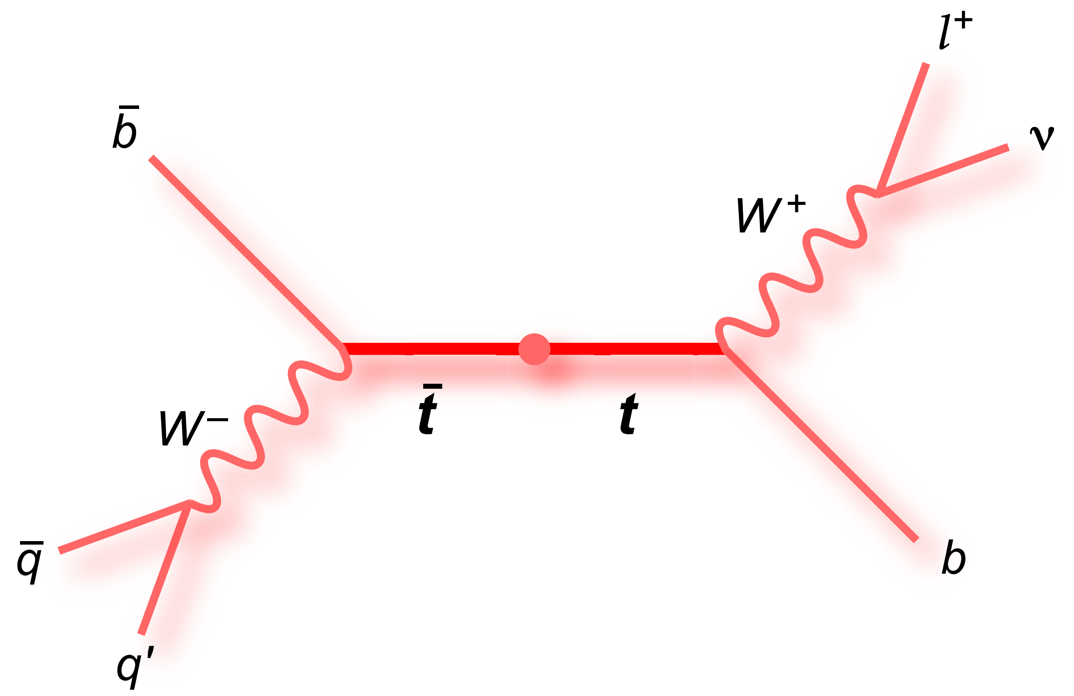
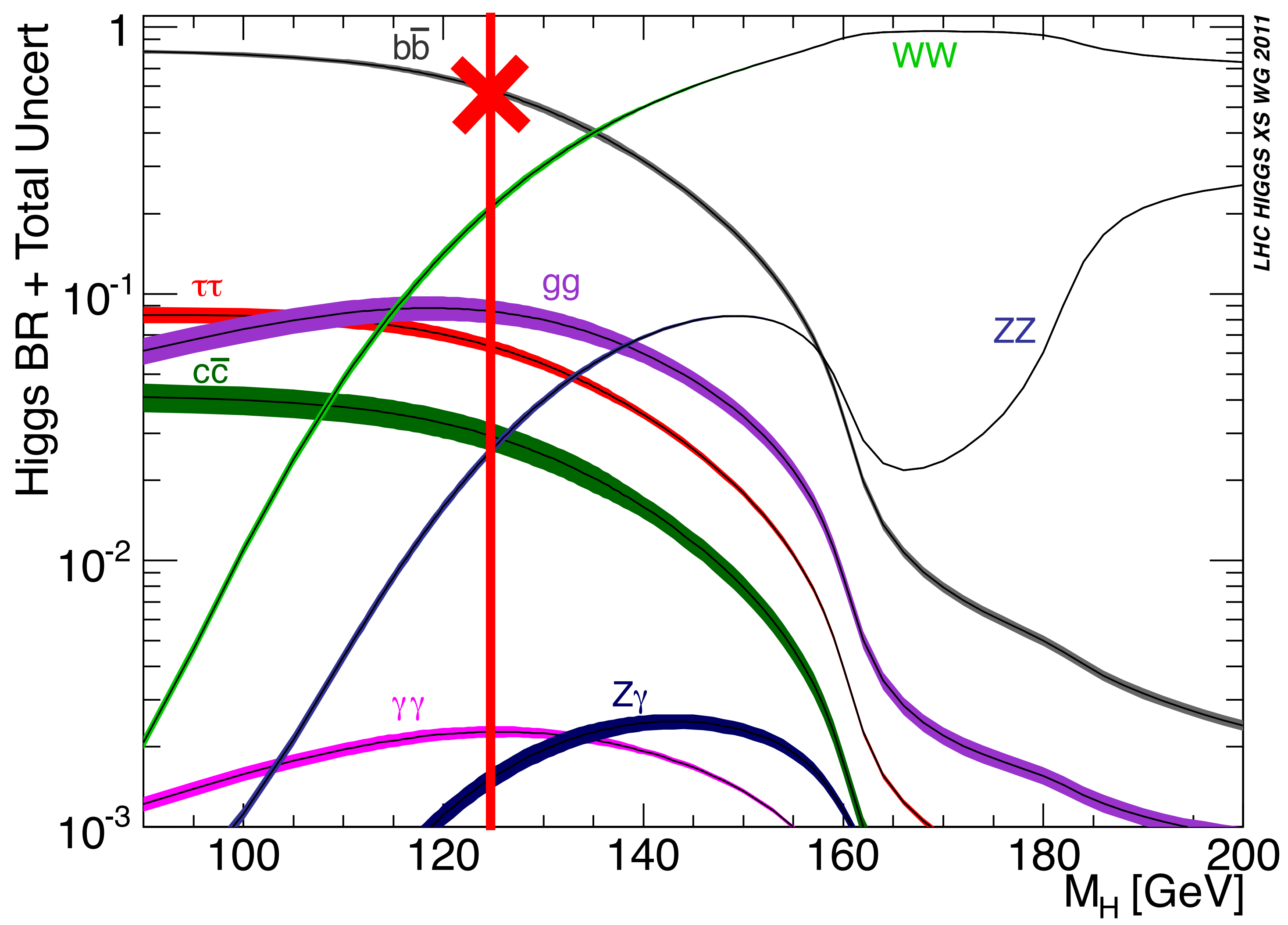
JET FLAVOR TAGGING IN ATLAS AND ITS APPLICATION IN ANALYSES

INTRODUCTION

- Many new physics model final states, top quark decays, H->bb decay have at least one jet containing a b-hadron (b-jets) in the final state
- Important for ATLAS analysis program to reliably identify b-jets:
  - High b-identification efficiency at high rejection of jets from c, s, u, d quarks and gluons
  - Reliable description of performance in simulation

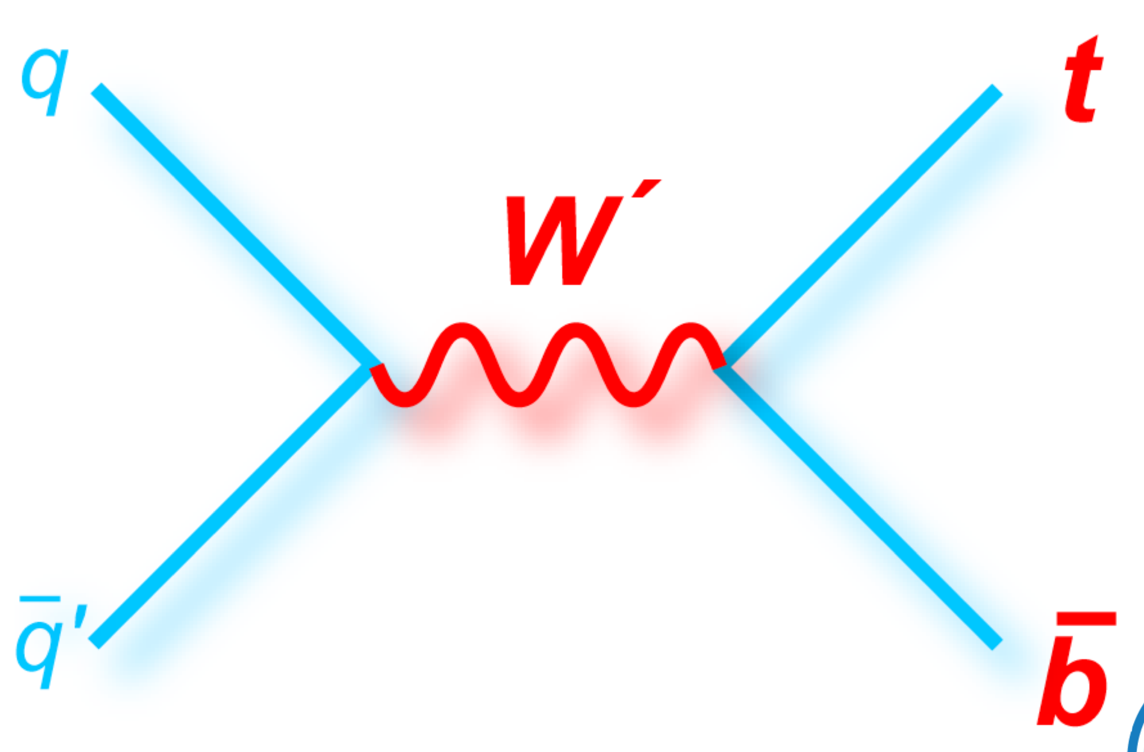
ttbar decay





Higgs branching ratio as function of the Higgs mass

Potential new heavy resonance

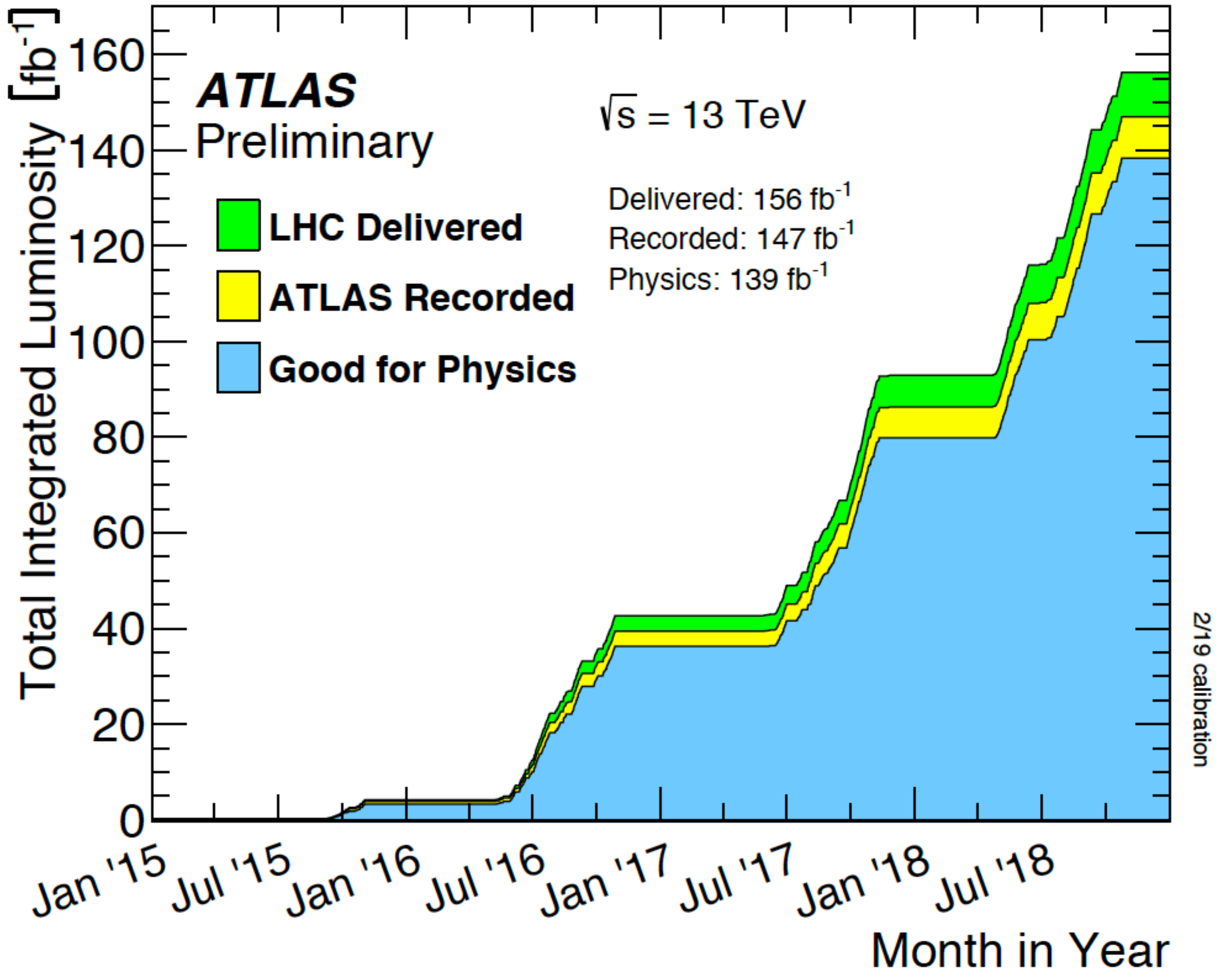


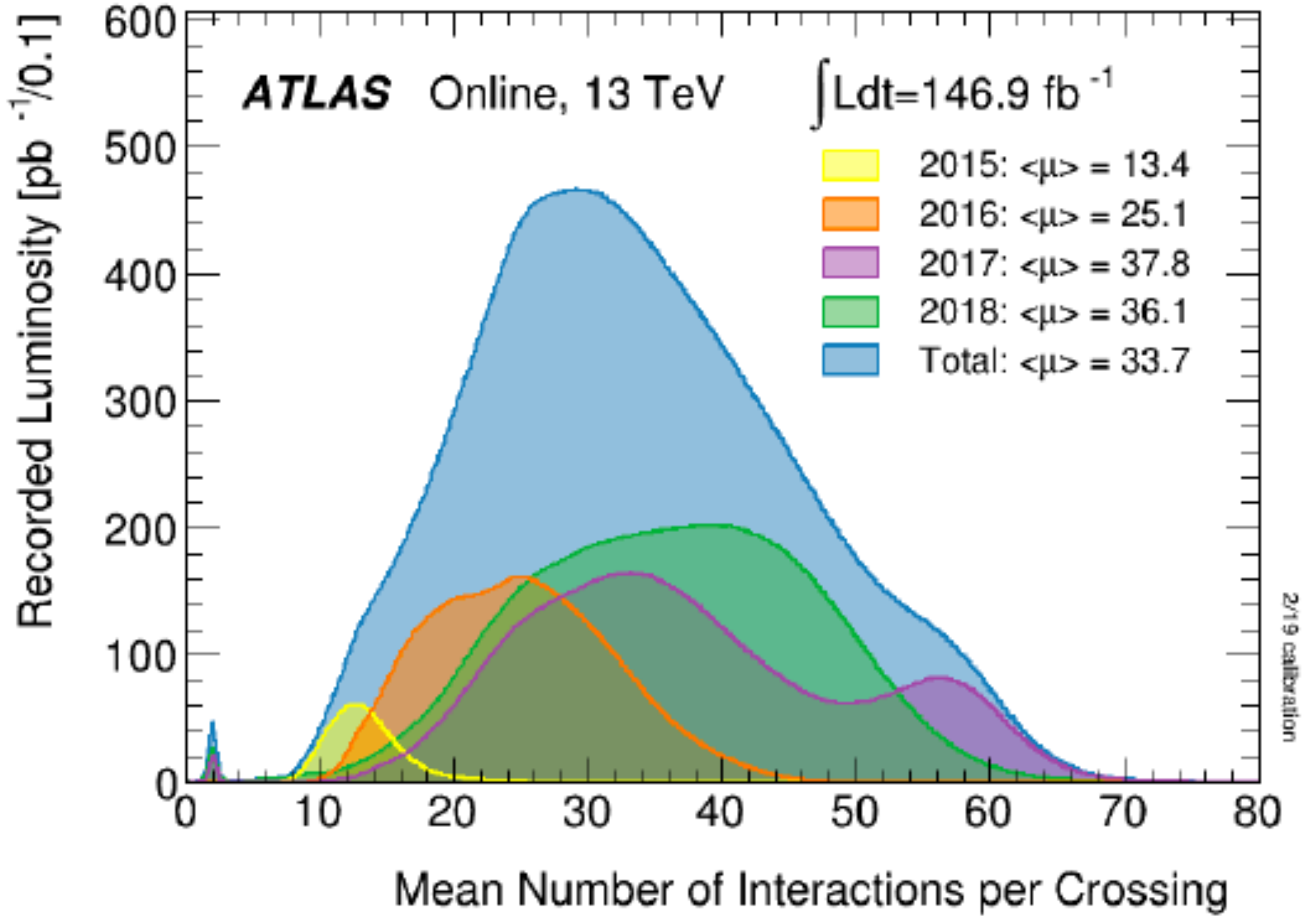
+ your favorite SUSY/ new physics model here

ATLAS EXPERIMENT

THE DATASET

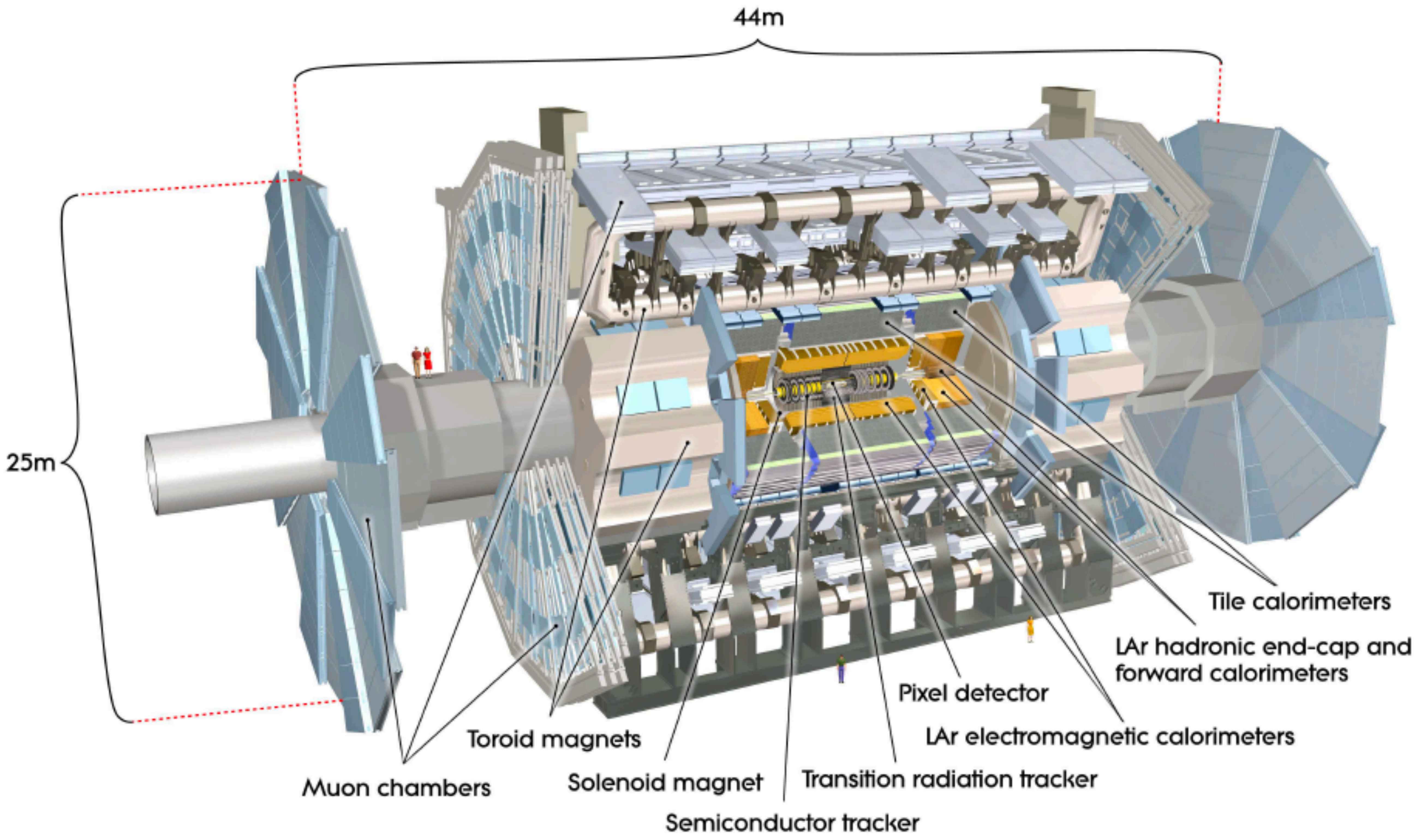
- Use ATLAS collision dataset recorded during **Run 2 of the LHC** (2015-2018) @center-of-mass energy $\sqrt{s}$=13TeV from proton-proton collisions
  - 156 fb-1 pp data delivered
  - 147 fb-1 recorded
  - **139 fb-1 "good for physics"** (preliminary uncertainty 1.7%)
- Peak luminosity: 2.1x10^{34} $cm^{-2}s^{-1}$
- Average number of interactions: 33.7



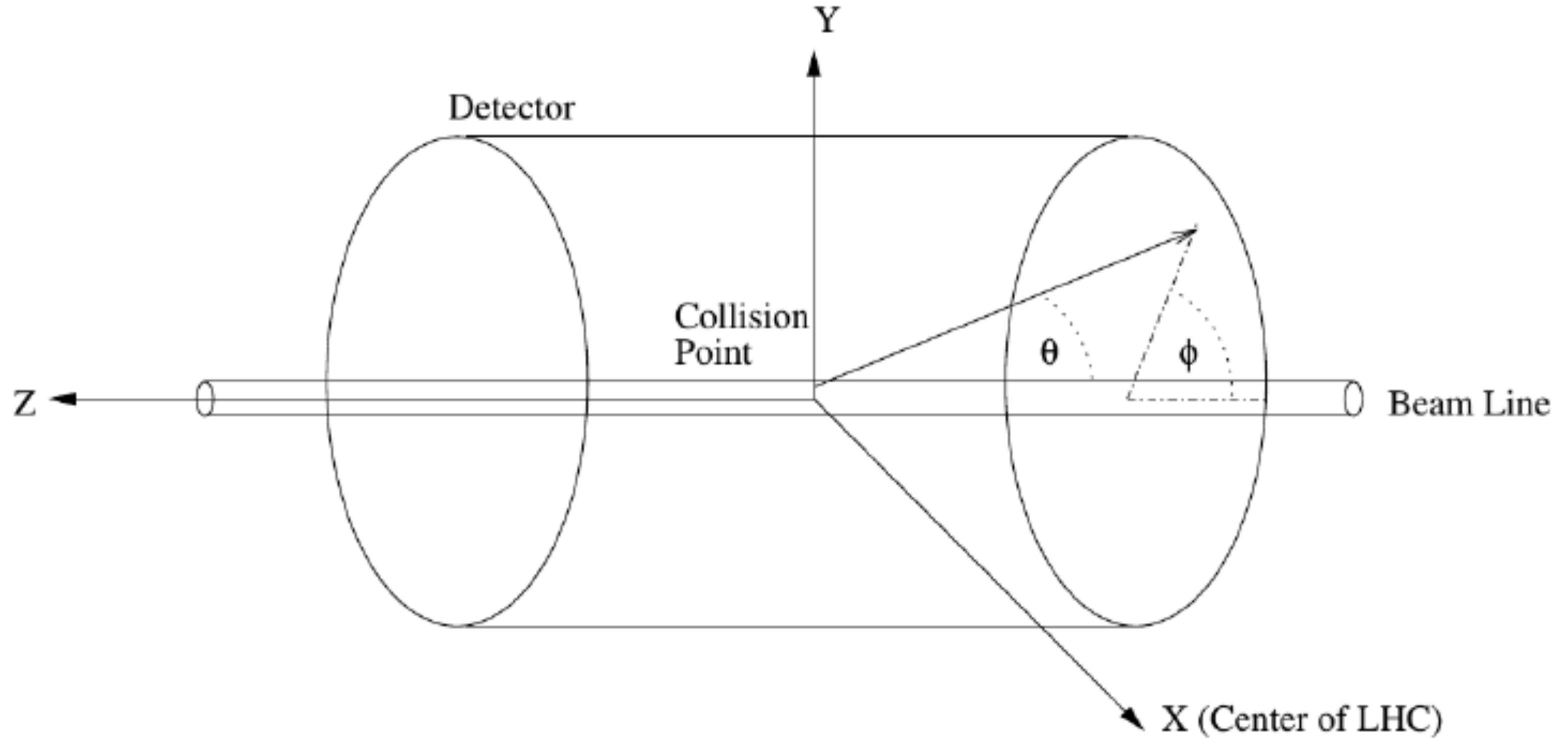


THE ATLAS DETECTOR

- Covers ~full solid angle
- Four main subsystems
  - **Inner detector tracker (ID) → charged particle track detection**
  - **Electromagnetic & hadronic calorimeter** → clusters from electromagnetic or hadronic interactions
  - **muon spectrometer**
- Before Run 2, "**Inner B-layer**" was added in the ID
  - Provides a tracking layer 3.3cm from the interaction point
  - Important for b-jet identification

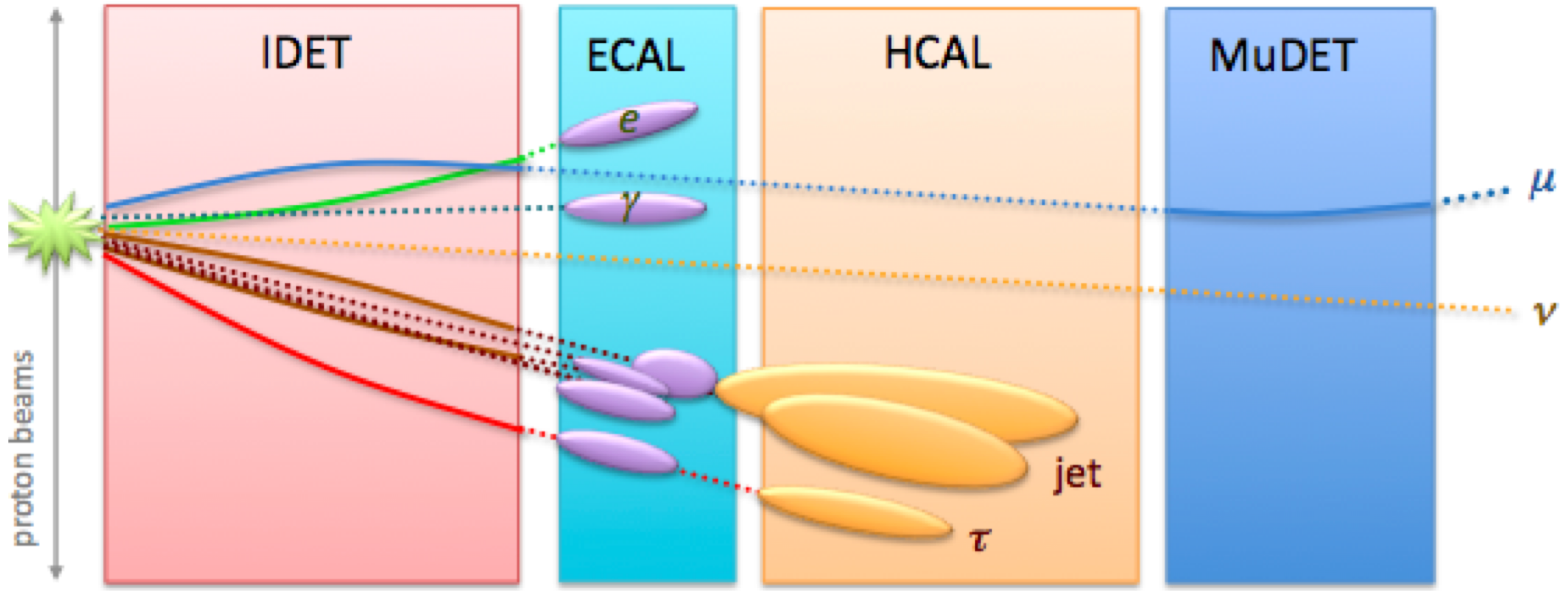


ATLAS coordinate system



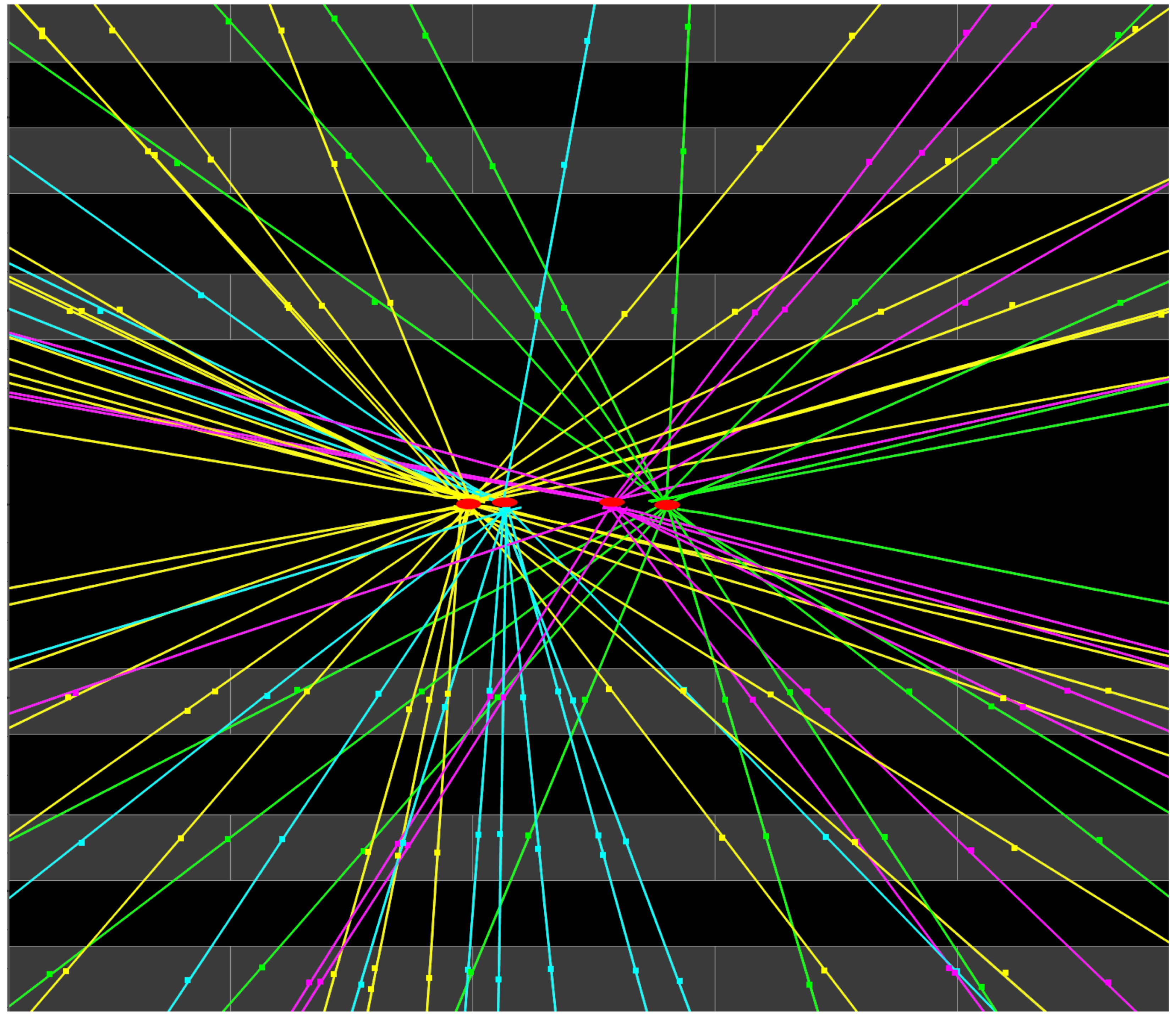
PARTICLE DETECTION IN ATLAS

- Collect information from all subsystems to reconstruct & identify particles coming out of the collision point
- Reconstruct electrons, muons, hadronic jets and photons
- Neutrinos are reconstructed from the missing energy in the transverse (x-y) direction

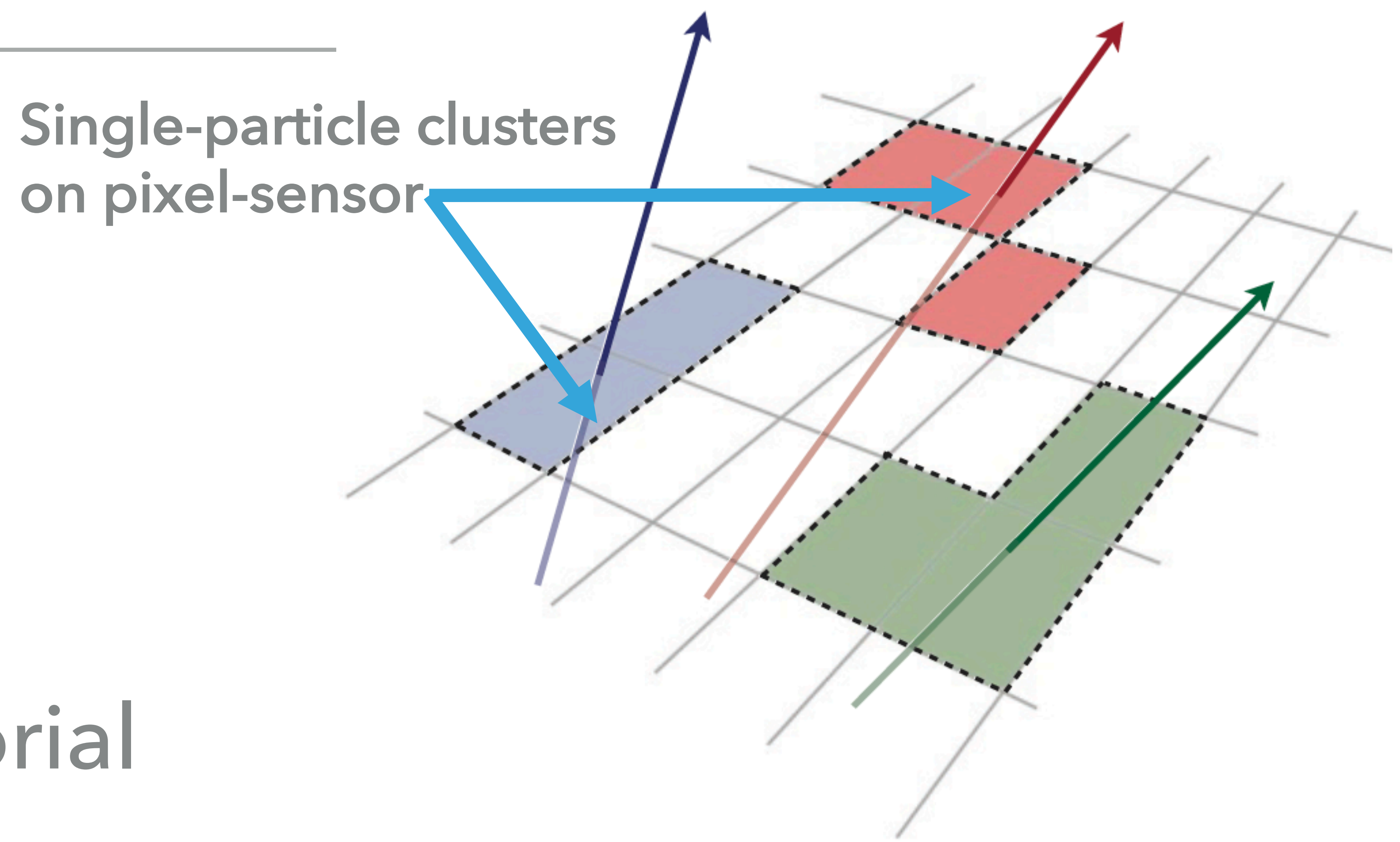


TRACK RECONSTRUCTION IN ATLAS AND ITS IMPORTANCE FOR FLAVOR TAGGING

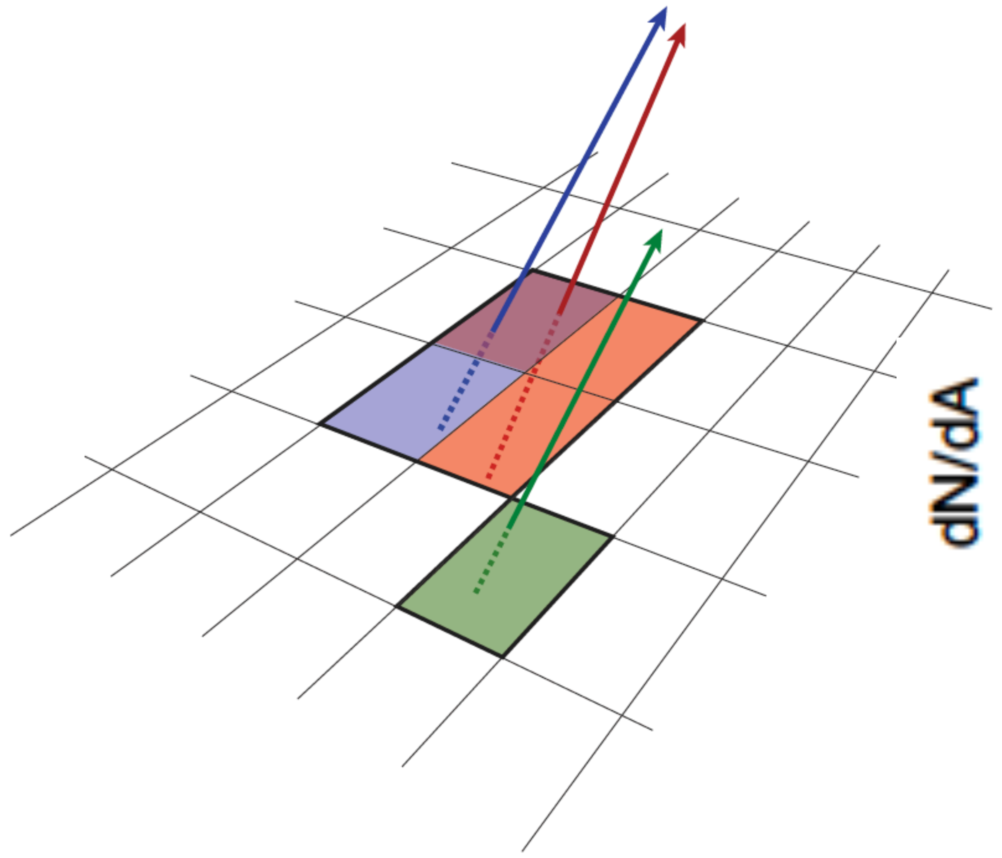
- Efficient track reconstruction and a precise measurement of track quantities and vertices is a key point to flavor tagging
  - Flavour tagging relies fully on the tracks assigned to a hadronic jets
  - A reconstructed primary vertex (interaction point of collision) defines the reference point for many flavor tagging quantities
- Tracks are assigned to jets using the angular distance between the track momenta and the jet axis



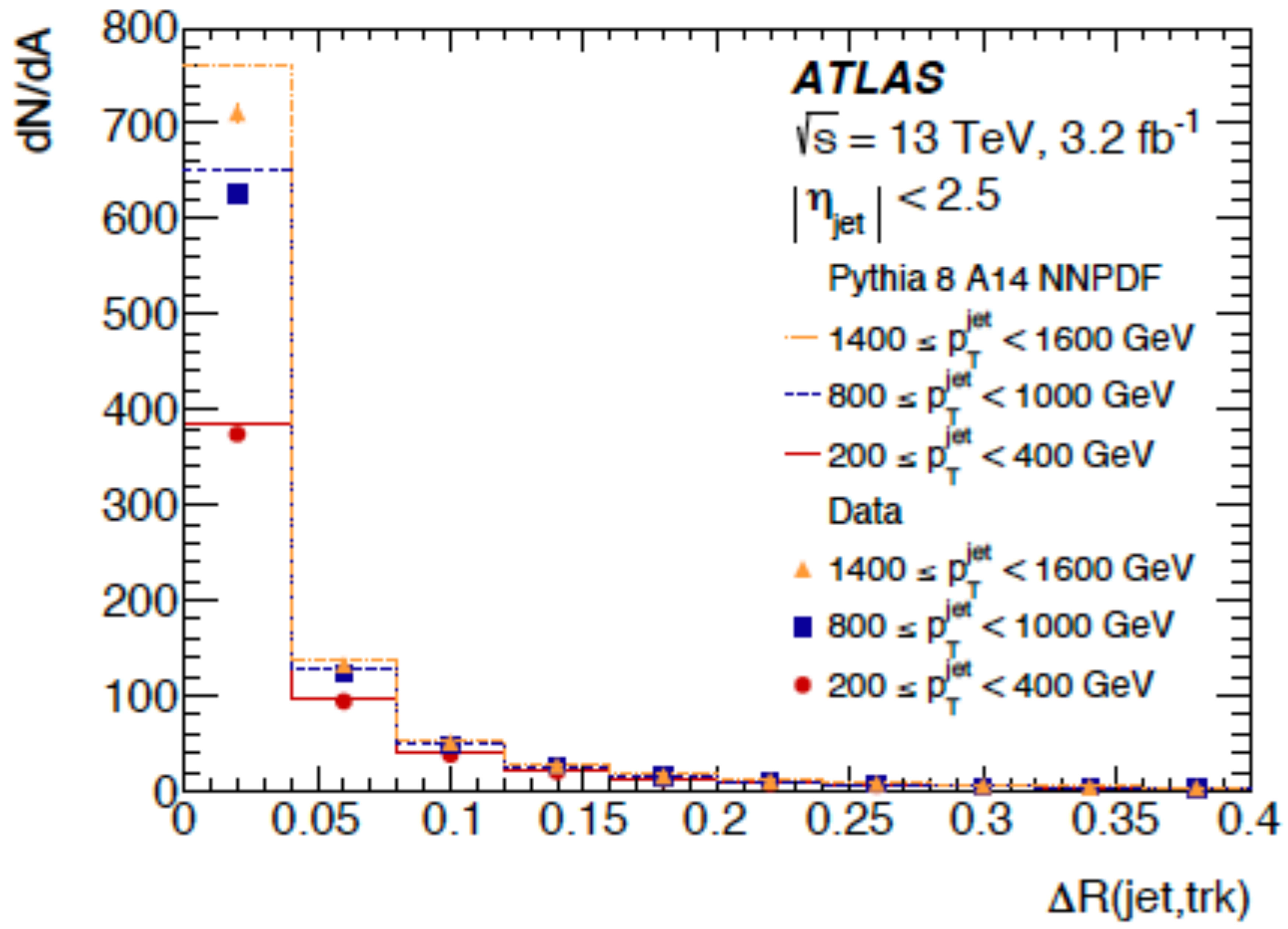
TRACK RECONSTRUCTION IN ATLAS



- Create clusters from raw hits in the inner detector
- Iterative track-candidate finding algorithm using track seeds formed by >= 3 clusters
- Pattern-recognition approach building first combinatorial candidates + stringent ambiguity solver



- Challenging in busy environments like energetic hadronic jets
  - Majority of jet tracks are in jet core
  - This may lead to tracking inefficiencies
- Algorithm can also resolve overlapping clusters of energy deposits ("merged clusters")

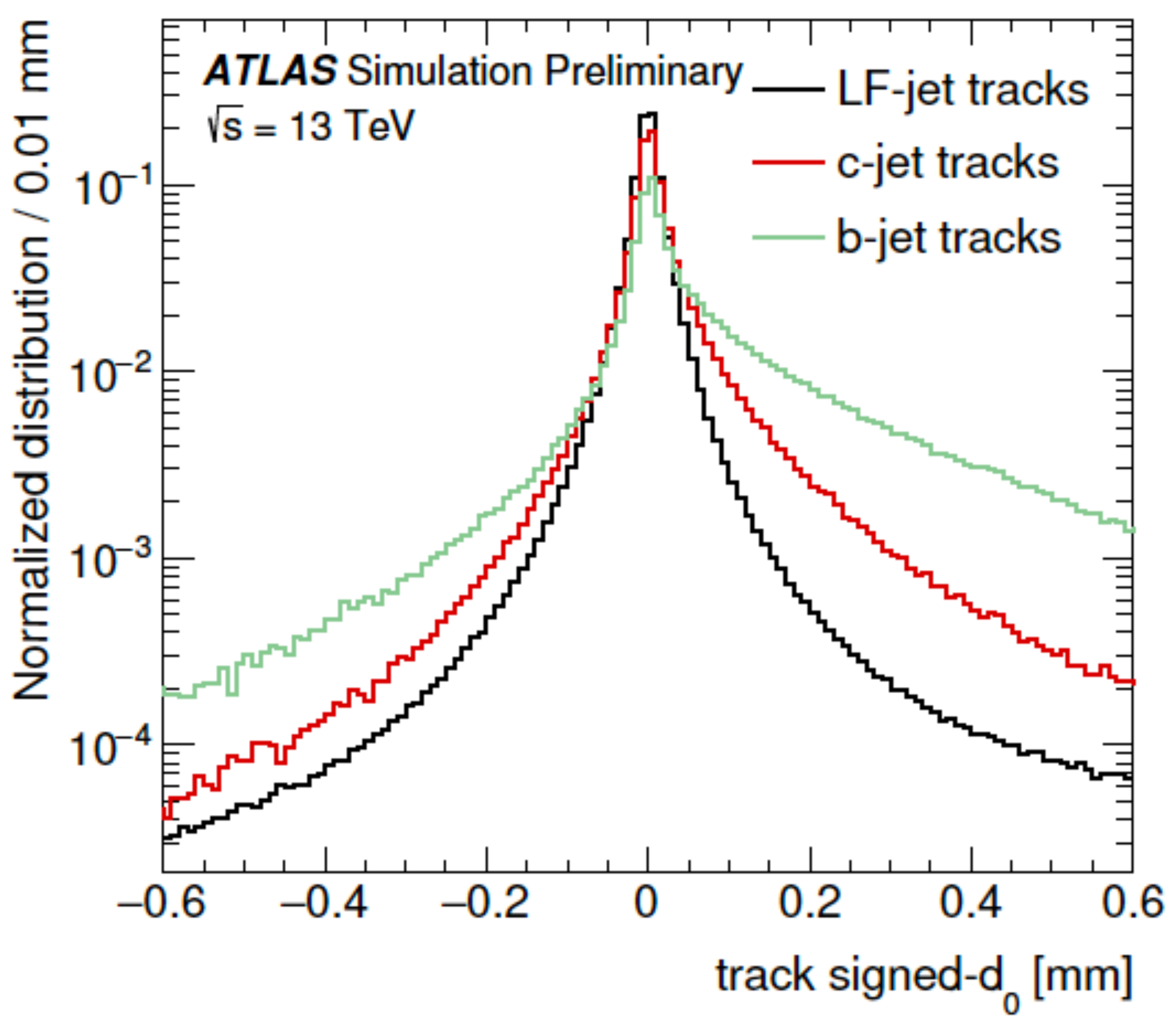


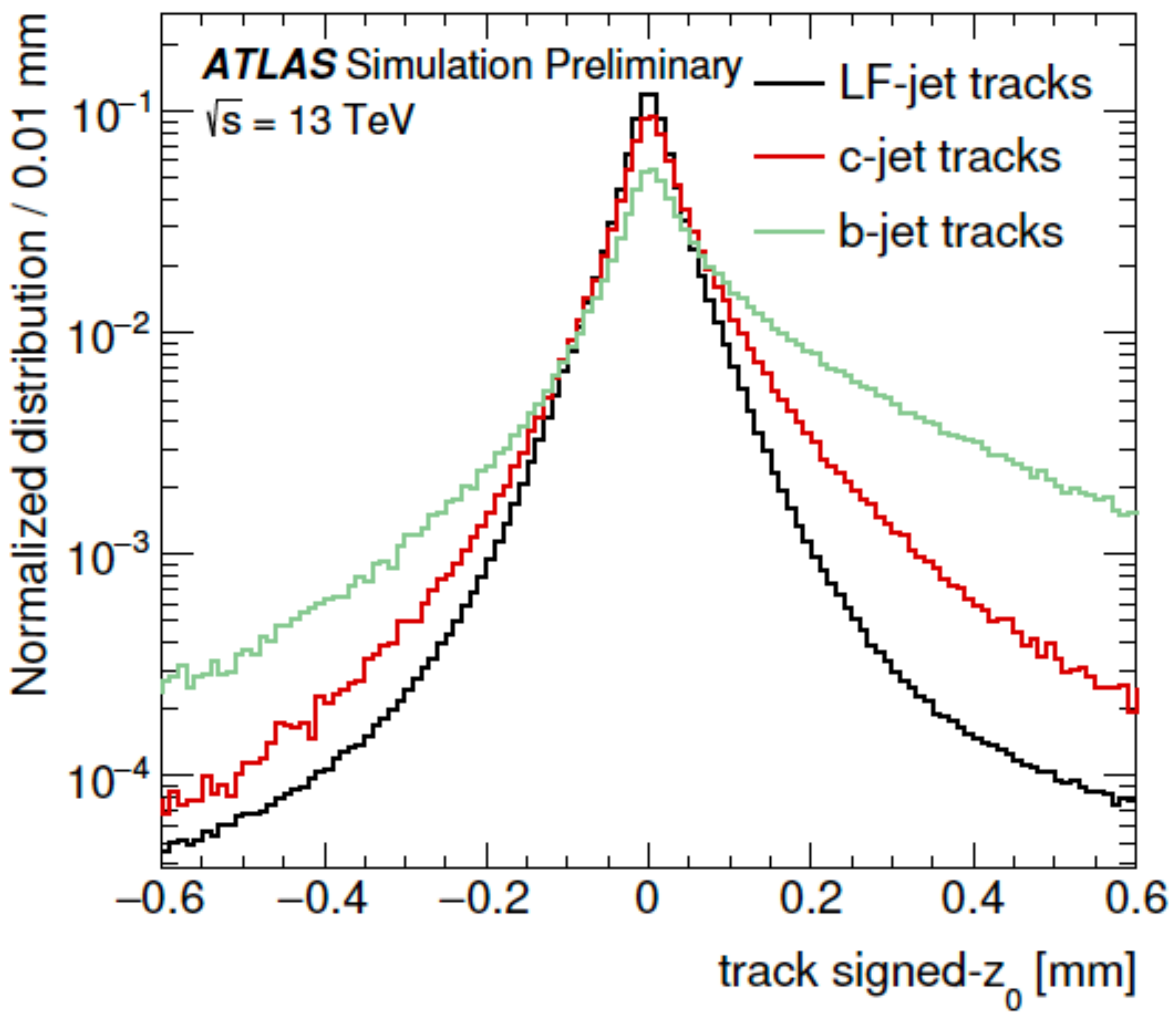
TRACKING: PERFORMANCE

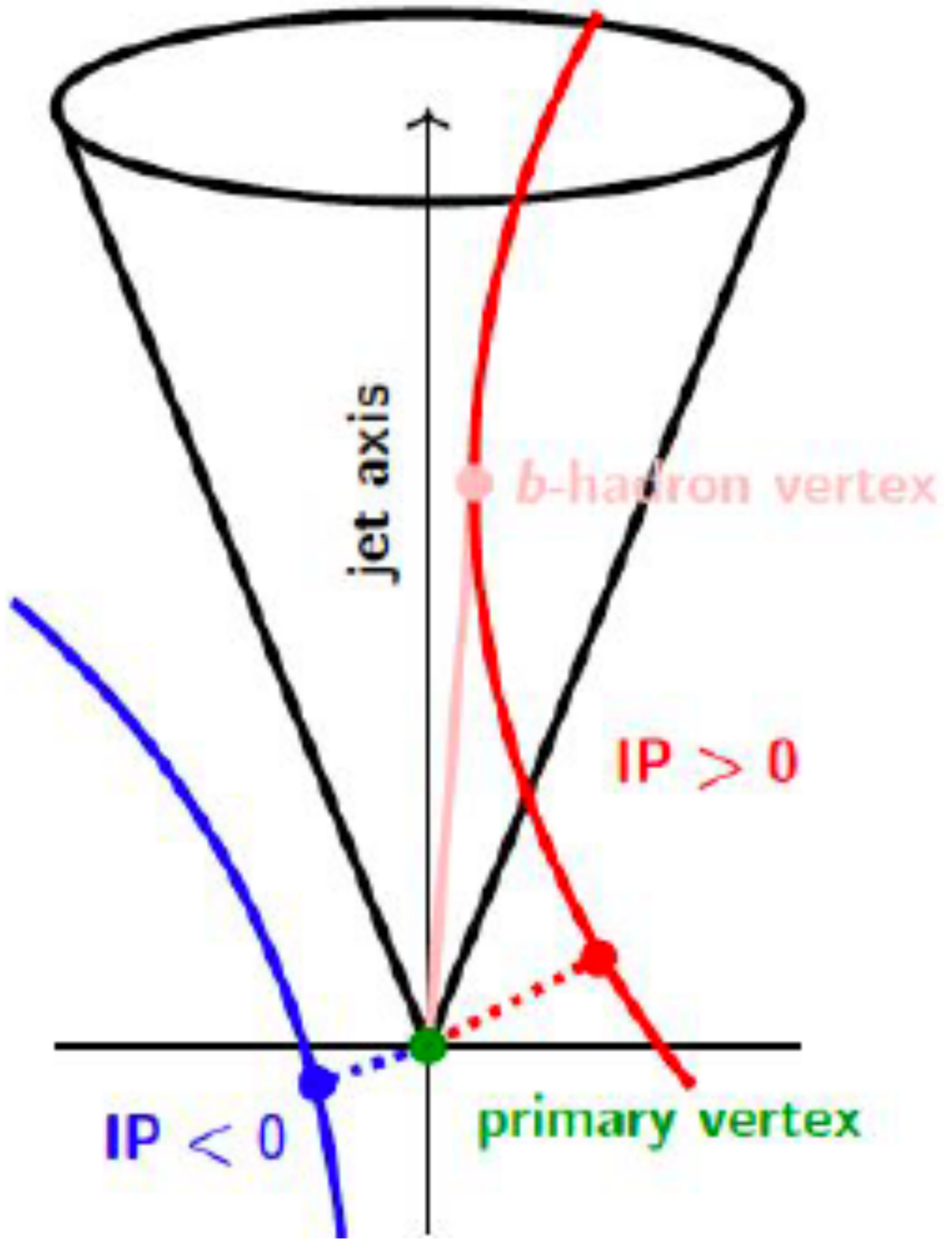
- Tracking efficiency drops towards the center of jet where track density is maximal
- Efficiency drops with increasing jet pT: straight and collimated tracks
- Efficiency drops with production radius (radial distance of decay of parent particle from beam axis):
  - Particles created beyond the first layers of the ID create fewer track clusters
  - Shorter flight length to next active layer: more merged cluster due to smaller average separation between particles

TRACKING: THE TRACK IMPACT PARAMETER

- Distance of closest approach of the track-trajectory to the Primary Vertex
  - In the transverse plane (x-y) (d0)
  - In the z-direction between the primary vertex and the track helix at the closest approach in the transverse plane (z0)







(Beam line)

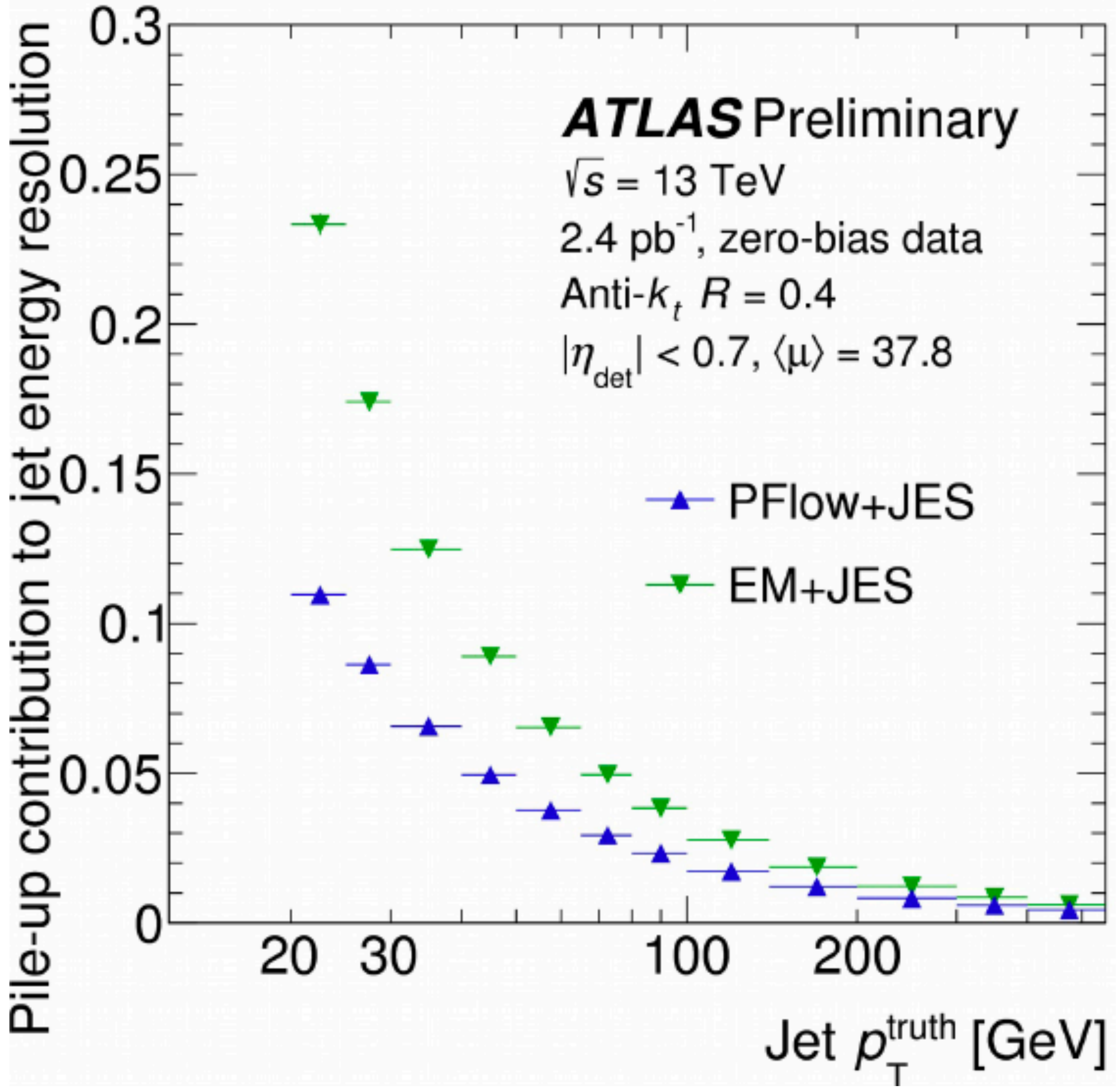
JET RECONSTRUCTION: PARTICLE FLOW (PFLOW) JETS

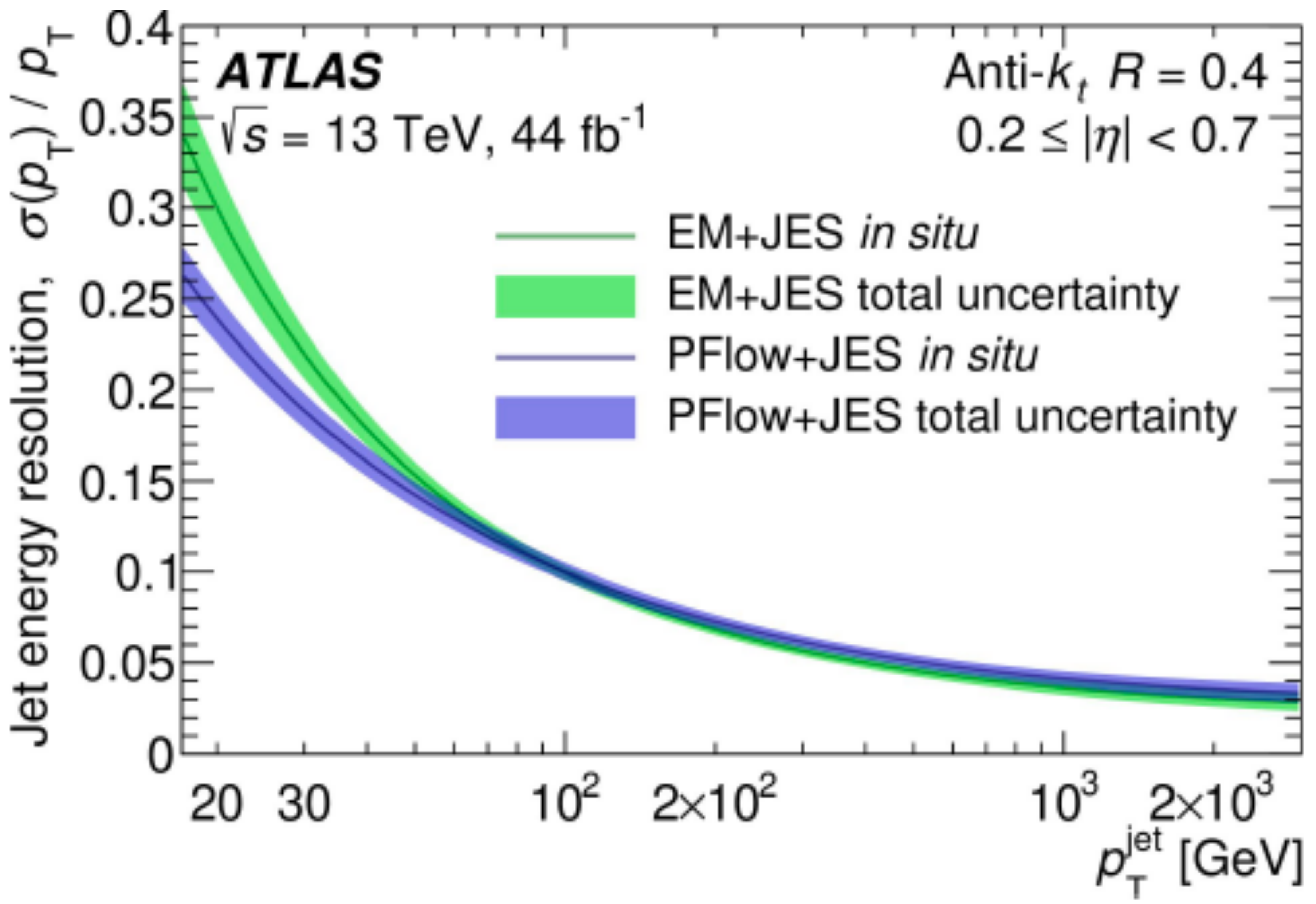
TRACKING
- BETTER RESOLUTION FOR LOW PT PARTICLES
- BETTER ANGULAR RESOLUTION
- TRACES PARTICLES TO HARD-SCATTER INTERACTION OR PILE-UP

CALORIMETERS
- BETTER RESOLUTION FOR HIGH PT
- CAPTURES NEUTRAL PARTICLES

- Combine information from Trackers & Calorimeters
  - Tracks are assigned (or not) to signal contributions in the calorimeters, ideally represent individual particles
- Improves energy and angular resolution
- Reduces pile-up contribution

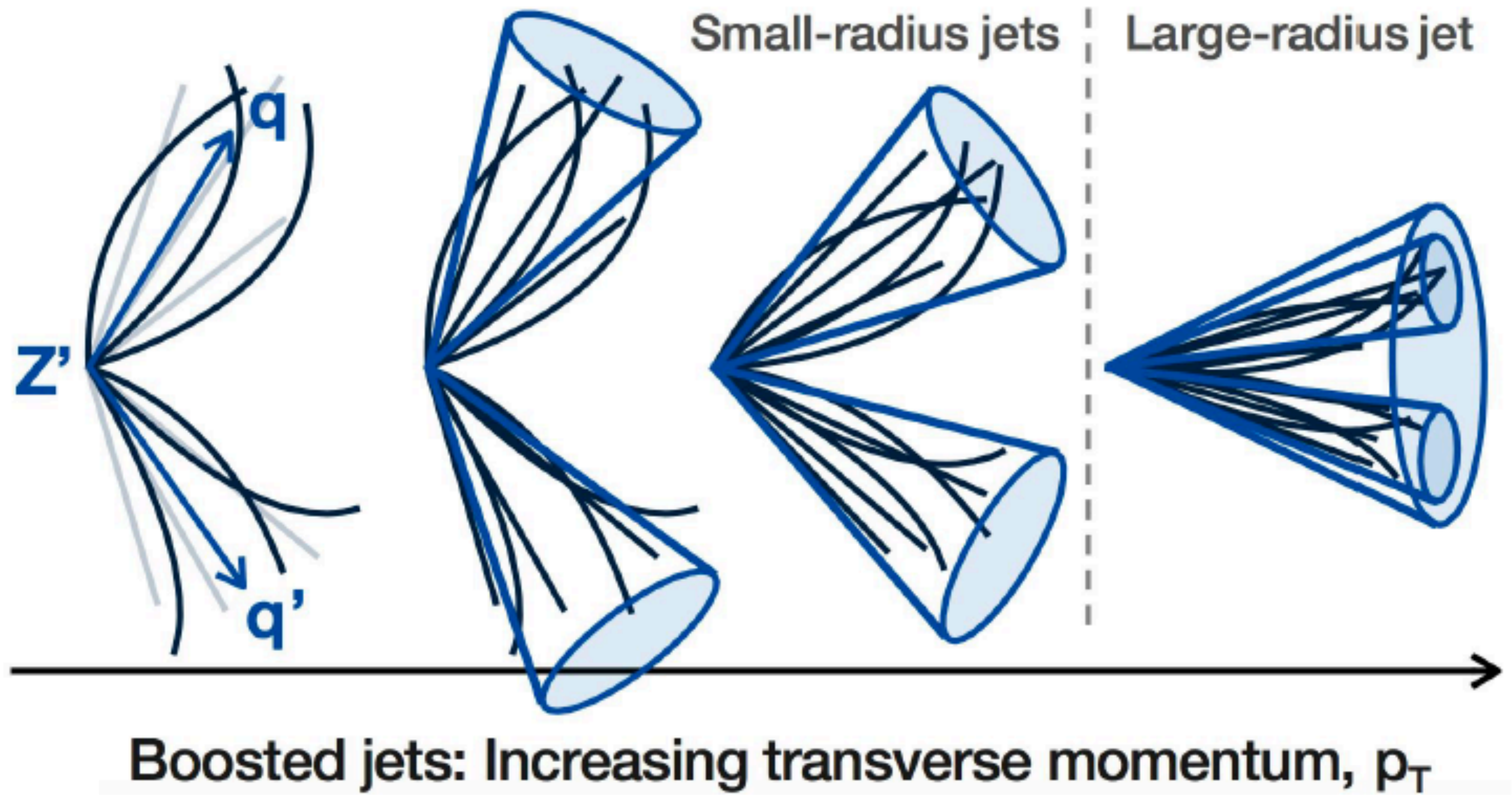
- Fixed radius of R=0.4
- Corrected for pile-up, calibrated using a simulation based pT, eta and energy corrections, and data-driven in-situ correction using reference objects
- Dedicated training of b-tagging algorithm for PFlow jets available

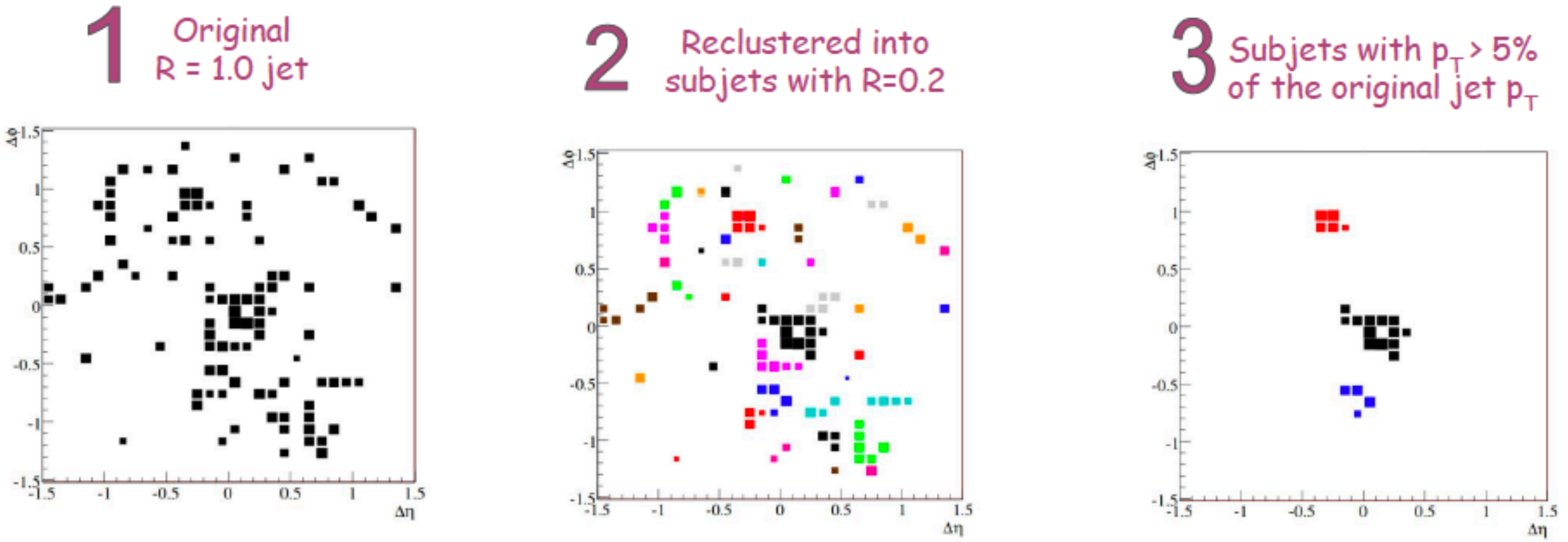




JET RECONSTRUCTION: LARGE-RADIUS ("LARGE-R") JETS

- For a two-body decay, distance ΔR between the decay production is given by: $\Delta R \approx 2m/p_{\mathrm{T}}$
- Decay products from particles with high pT are expected to be merged in a single large-radius jet
- Reconstruct jets with a (fixed) radius of R=1.0
- Apply "grooming" for pile-up mitigation





- Calibration: Simulation based jet pT, eta and jet mass correction, and data-driven in-situ correction using reference objects

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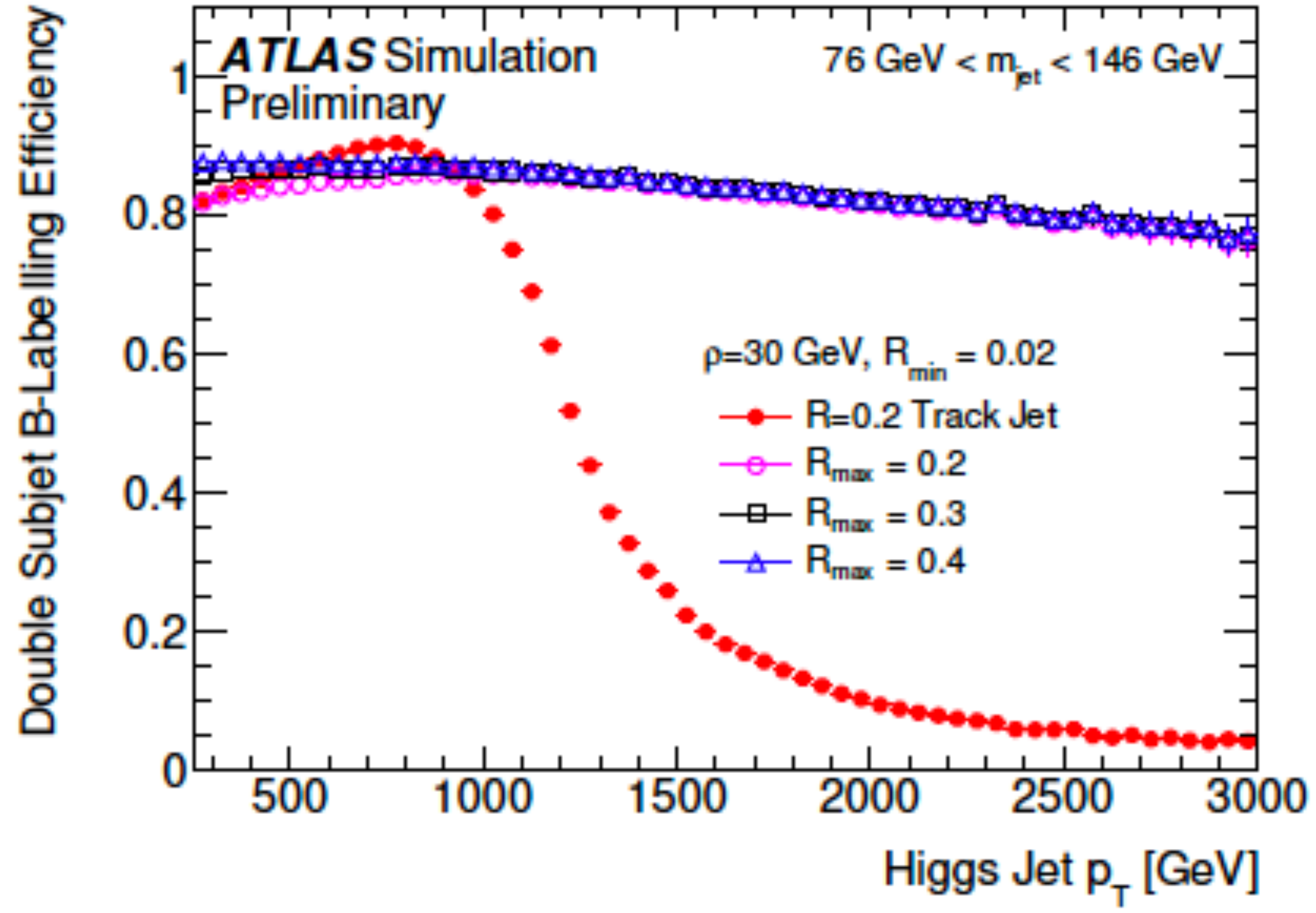
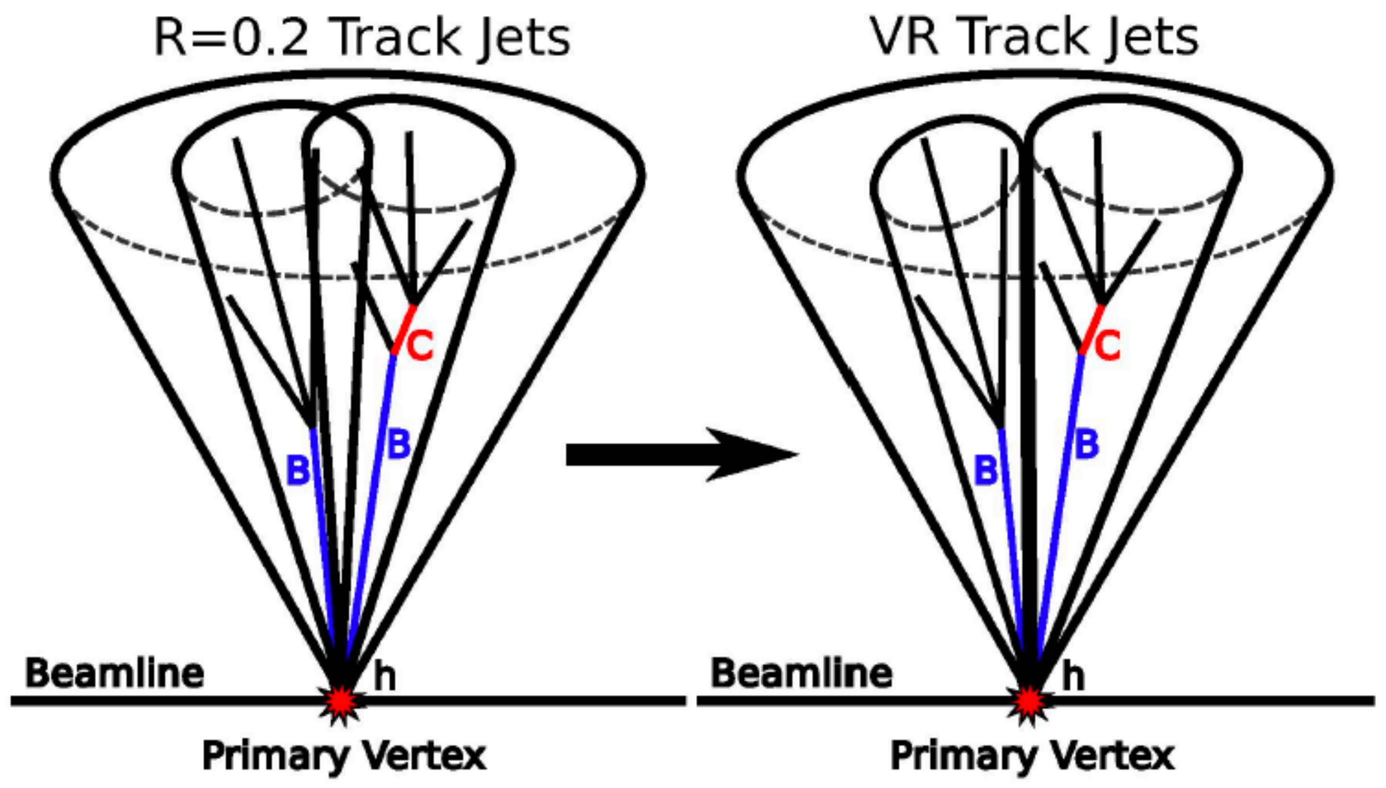
JET RECONSTRUCTION: VARIABLE RADIUS JETS (VRTRACK)

- At high pT, (sub)jets are collimated → cannot be resolved any more as separate jets with fixed-cone jet algorithm
- New jet collection in ATLAS to resolve the decay products of H->bb decay
  - Identify them as b-jets via b-tagging algorithm
- Jets have variable size which goes with R ~ 1/pT(jet)
  - Defined by three parameters: ρ (dimensionless constant), R_{min}=0.02 (minimal size) and R_{max}=0.4 (maximal size)
    - Optimized to resolve b-hadrons in H->bb decay
- Use only tracks for reconstruction, good angular and momentum resolution
- Note: b-tagging algorithm with dedicated training for VRTrack jets available

$$R \longrightarrow R_{\mathrm{eff}}(p_{\mathrm{T}}) = \frac{\rho}{p_{\mathrm{T}}}$$



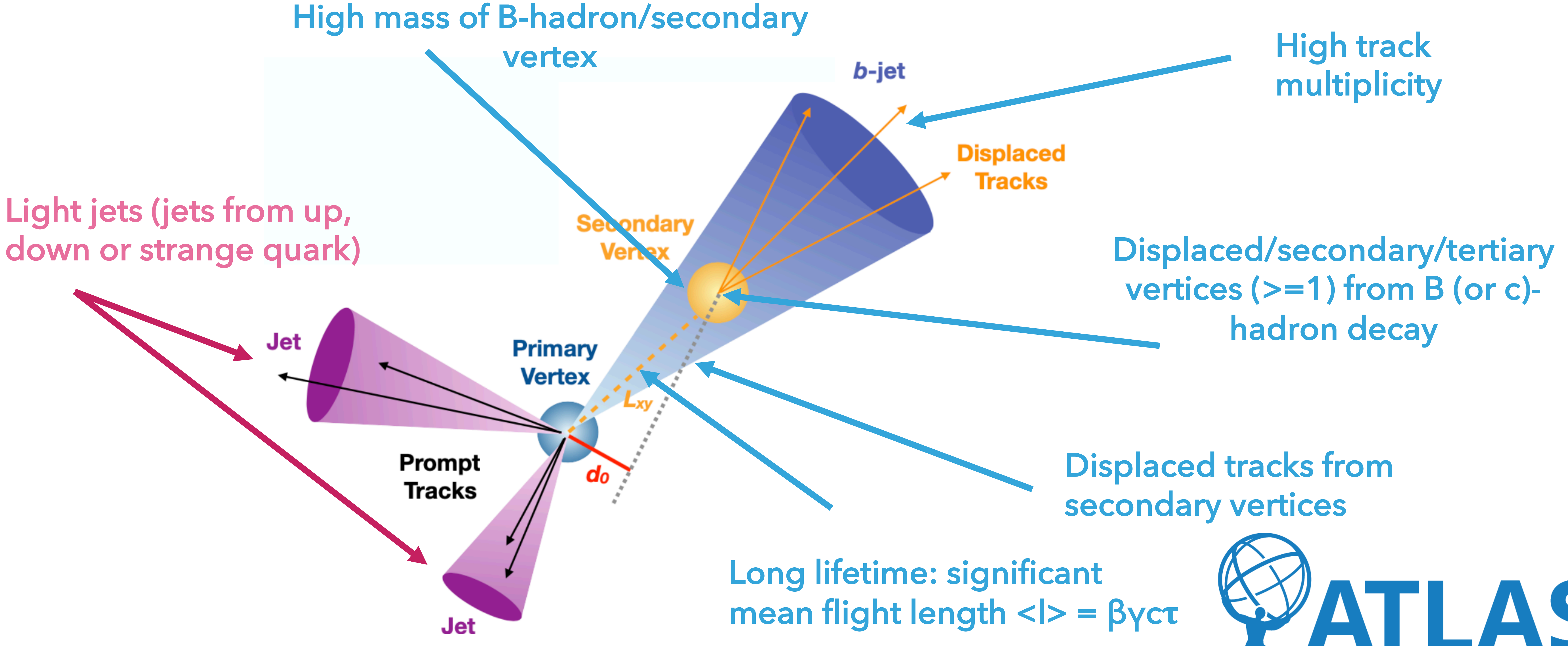


DECAY OF B-HADRONS

- The distinct signature of a b-hadron decay can be used to identify jets containing b-hadrons in ATLAS
- C-hadrons also have a slightly longer lifetime and a larger mass w.r.t light jets, lower track multiplicity, lifetime and mass w.r.t b-jets

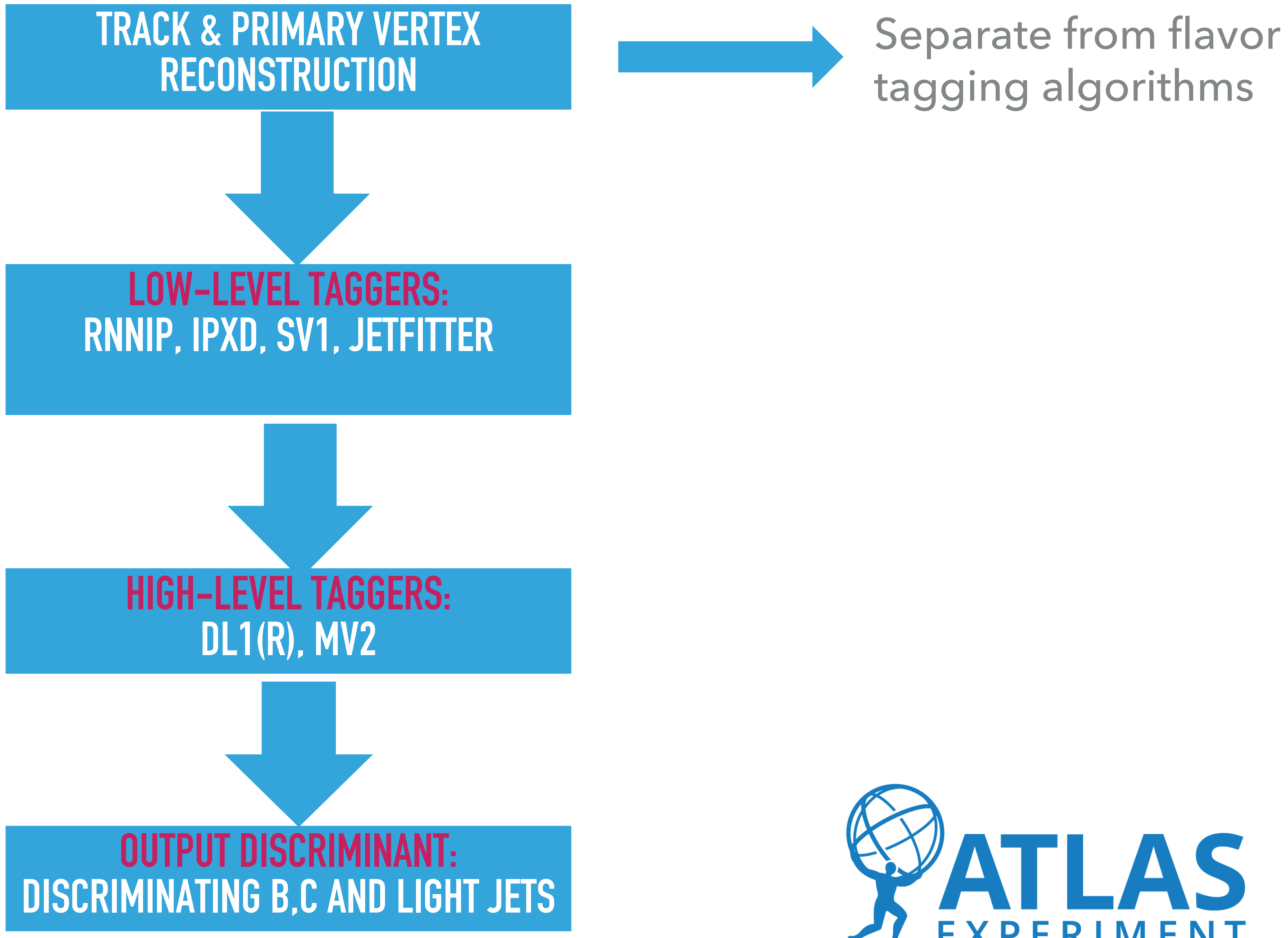
Truth flavour definition
(definition of a b-jet in simulation):

- Search for b-hadrons with pT>5GeV within ΔR<0.3 within the jet
- If no b-hadron found, search for c-hadron, then tau-lepton
- Else: classify jet as light jet

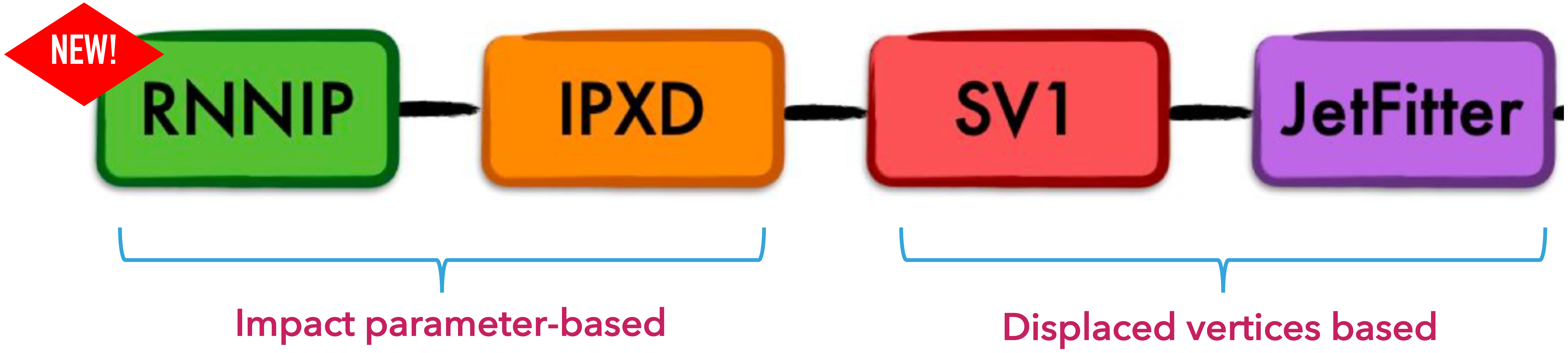


STRUCTURE OF THE ATLAS B-TAGGING ALGORITHM

- Algorithm trained on simulated ttbar events (for jet pT<250GeV)
- New: Add Z'->qq sample for a dedicated high-pT jet training (q=b,c,l) (for jet pT>250GeV)
- Reweight pT spectrum of b- and c-jets to light jets to avoid algorithms to focus on differences in pT spectrum



THE LOW-LEVEL TAGGERS: OVERVIEW



- Two types of low-level tagger algorithm:
  - Impact parameter based
  - Displaced-vertices based
- Several output variables from each low-level tagger which are fed to high-level taggers
- RNNIP (recurrent neural network) added in 2019, taggers with RNNIP fully calibrated only since recently

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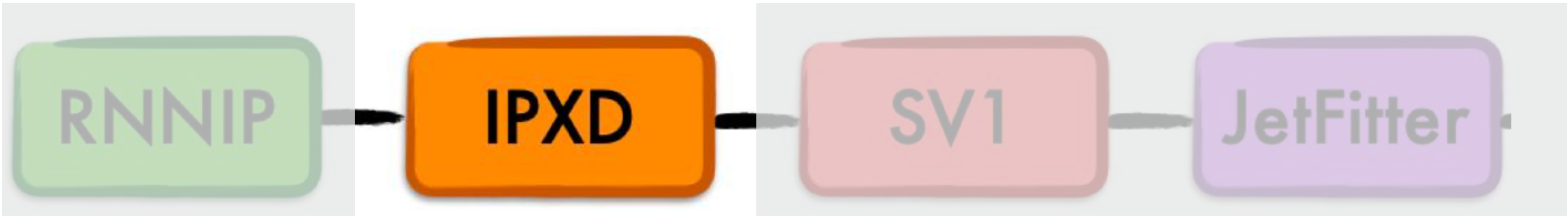
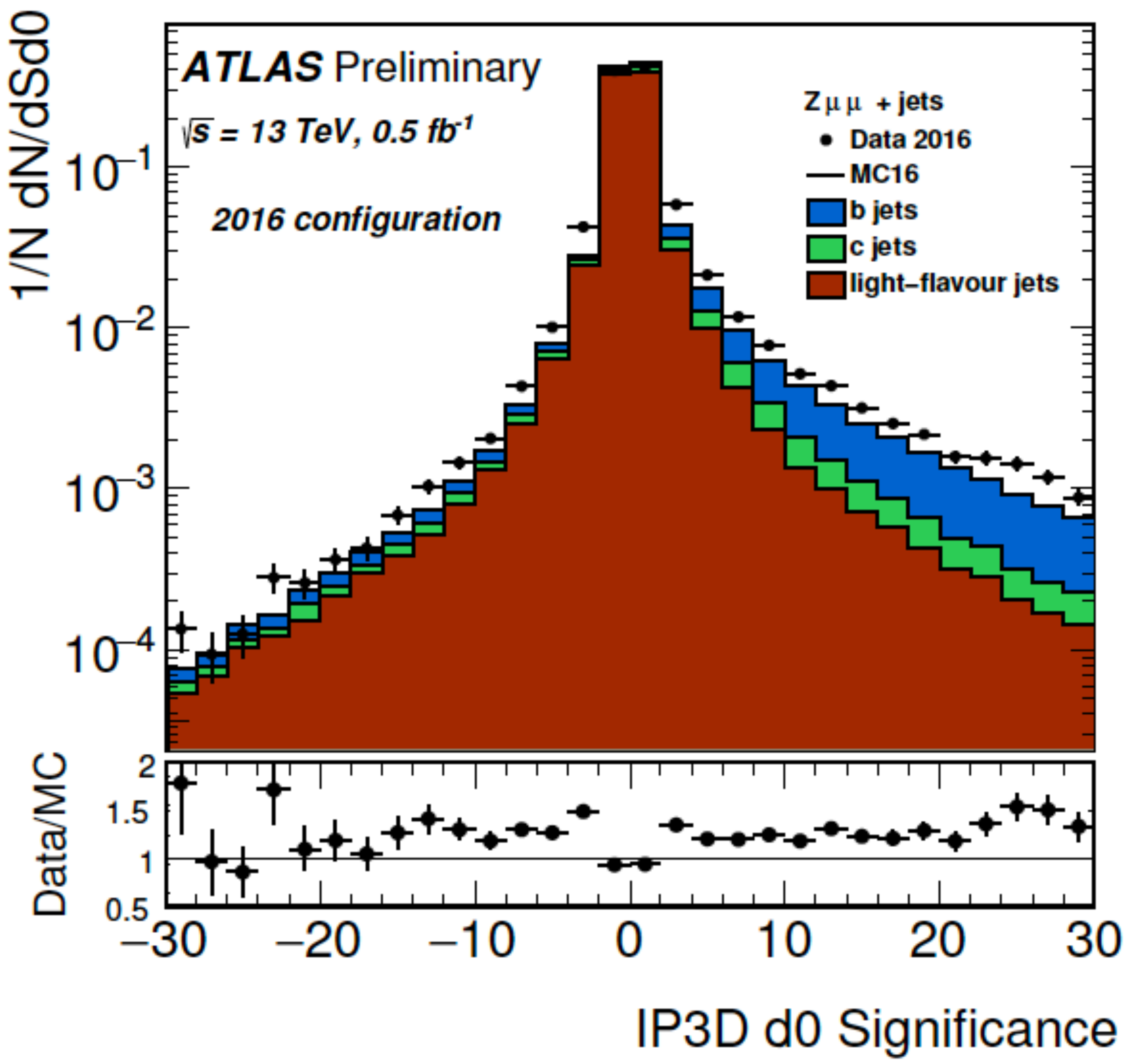
THE LOW-LEVEL TAGGERS: IPXD

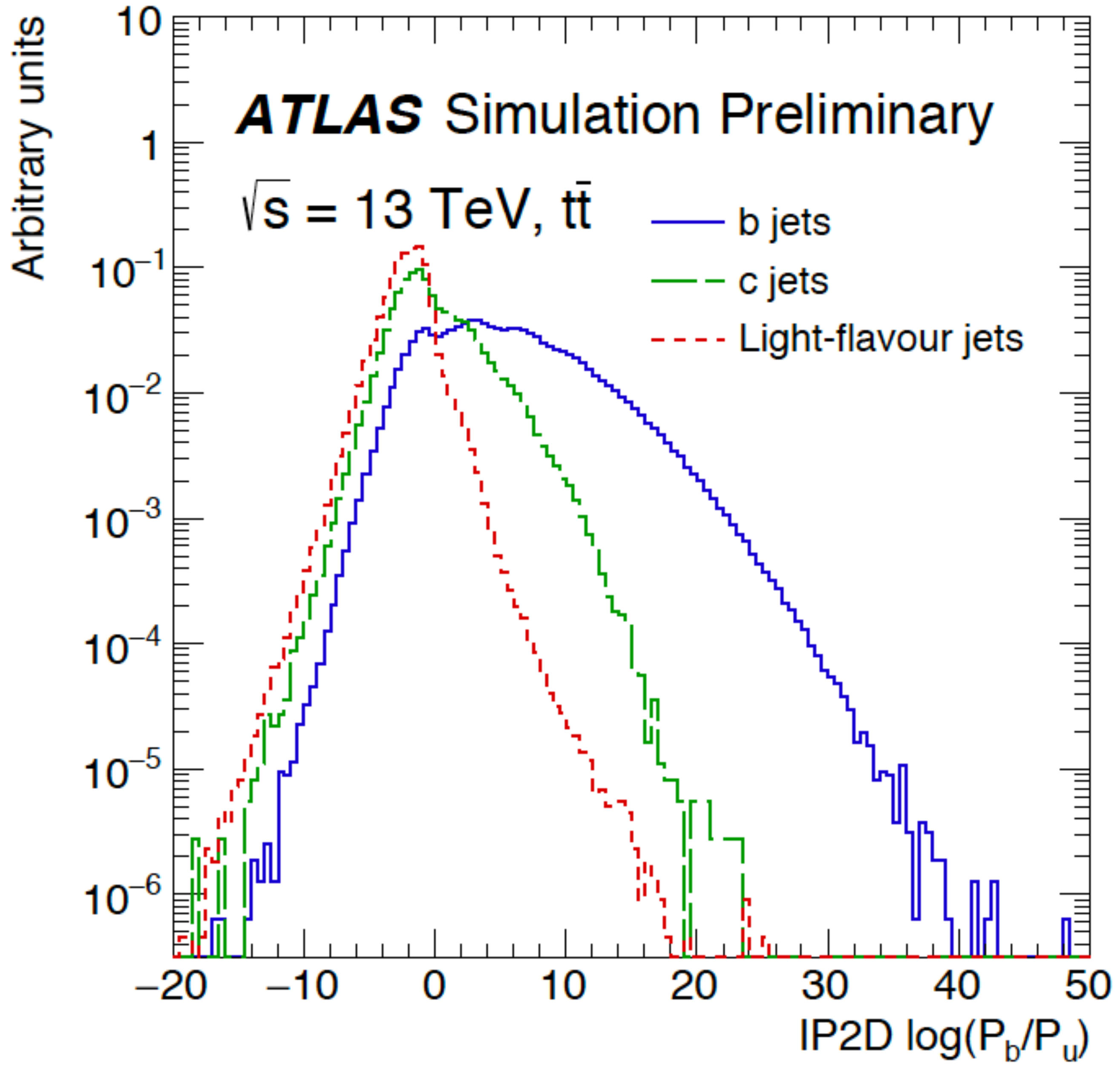


- Tracks from decay at secondary vertices have tendentially larger impact parameters
  - IP2D relies on the transverse impact parameter significance
  - IP3D relies on both the transverse & longitudinal impact parameter significance and their correlation
- For each track in a jet, the light, b- and c- probabilities (p_u, p_b, p_c) are extracted using 1D (IP2D) or 2D templates (IP3D)
- The per-track contributions are summed to get a log-likelihood ratios LLR
  - Example: LLR(u,b):

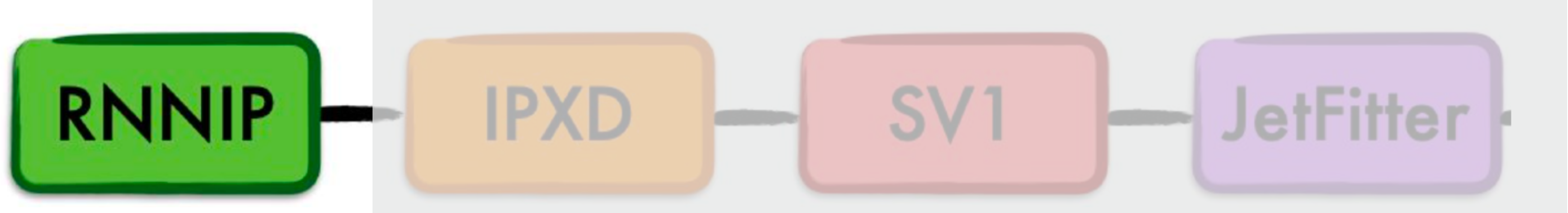
$$\sum_{i=1}^{N} \log\left(\frac{p_b}{p_u}\right)$$

Note: Correlation between tracks in jet not taken into account

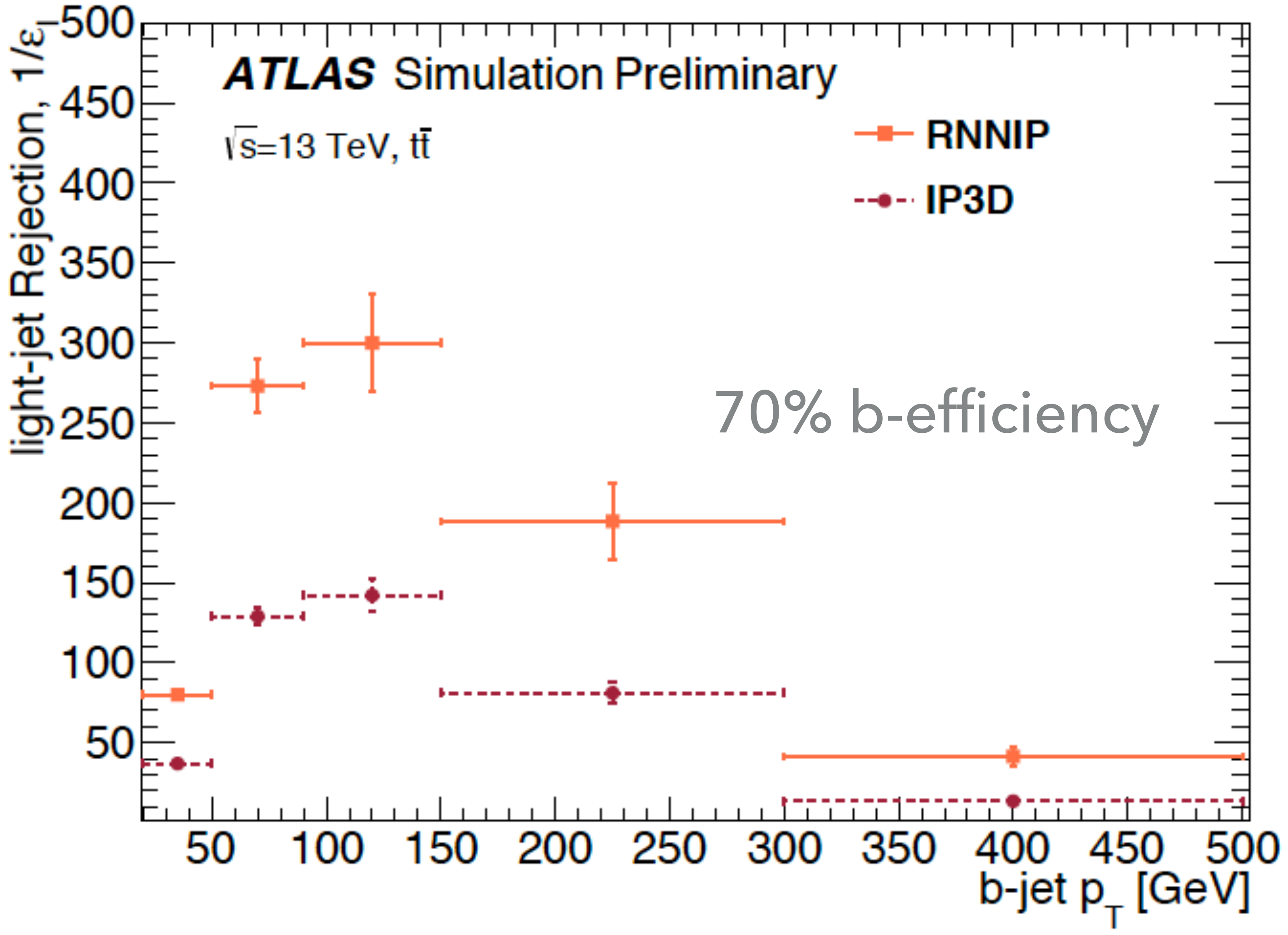


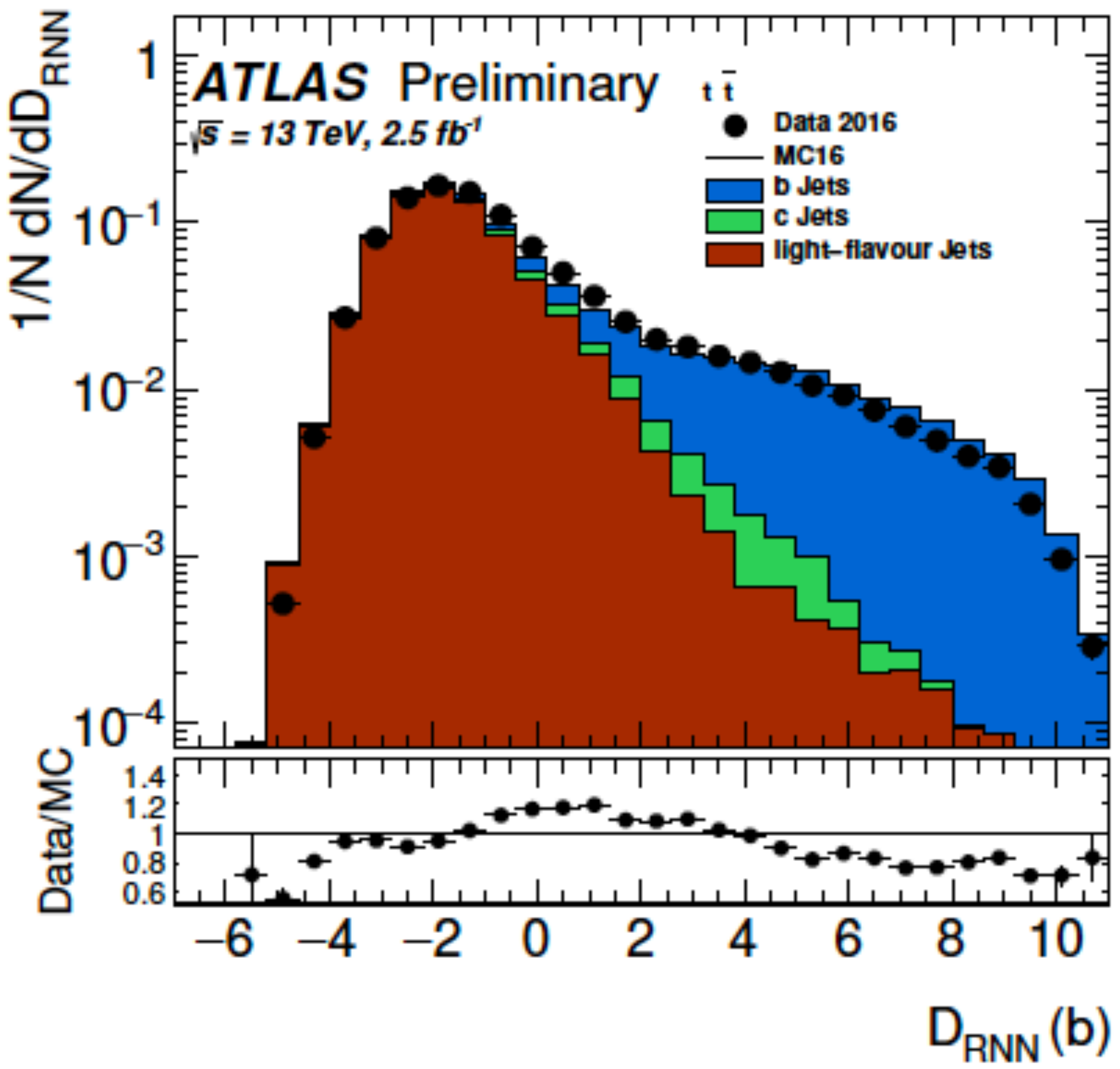


THE LOW-LEVEL TAGGERS: RNNIP



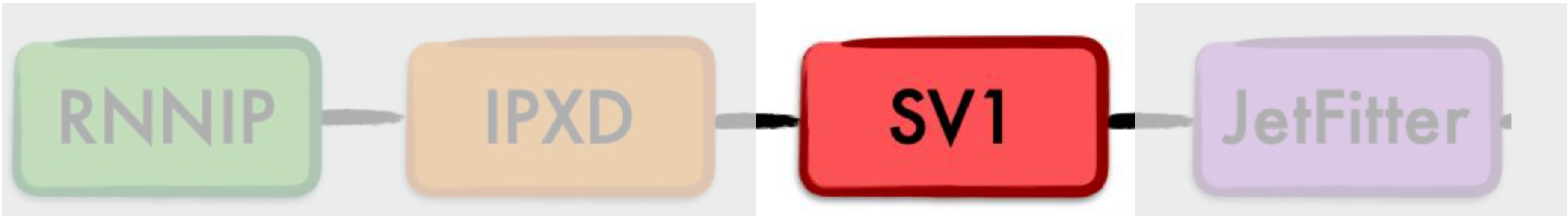
- Recurrent neural network track-based tagger
- Uses information from track impact parameters in jet and their correlation
  - If one track with a large IP is found, a second track is often found as well as several tracks emerge from a displaced vertex
  - This correlation does not exist for tracks in light jets
- Track impact parameter significances, momentum fractions of tracks relative to the jet momenta, angular distances of tracks to jet axis, etc. are fed to neural network
- Up to 2x light jet rejection and 1.2x charm jet rejection w.r.t IPXD
- Shown to add information w.r.t IPXD: partly complementary





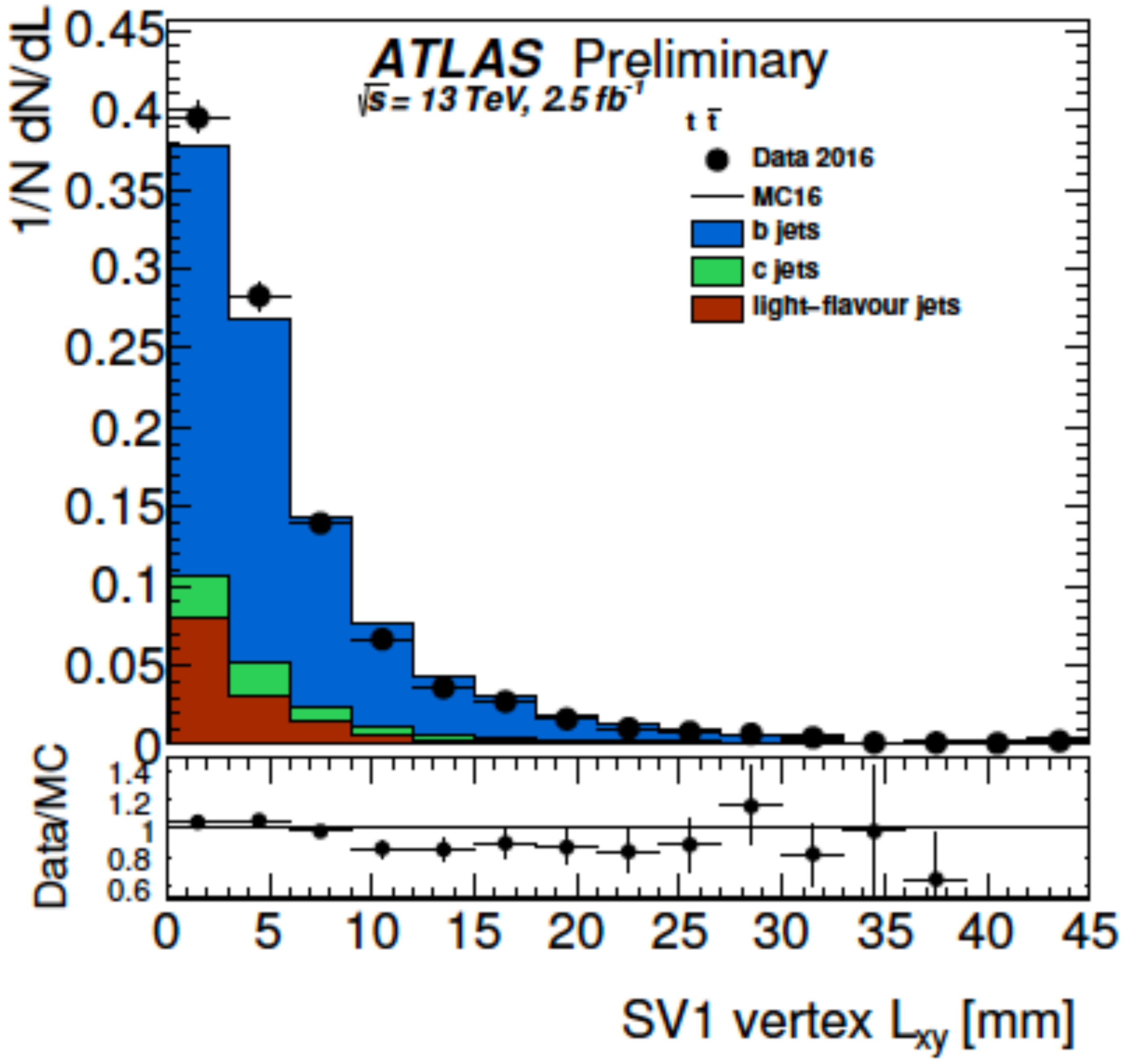
$$D_{\mathrm{RNN}}(b) = \ln \frac{p_b}{f_c p_c + f_\tau p_\tau + (1 - f_c - f_\tau) p_{\mathrm{light}}}$$

THE LOW-LEVEL TAGGERS: SV1

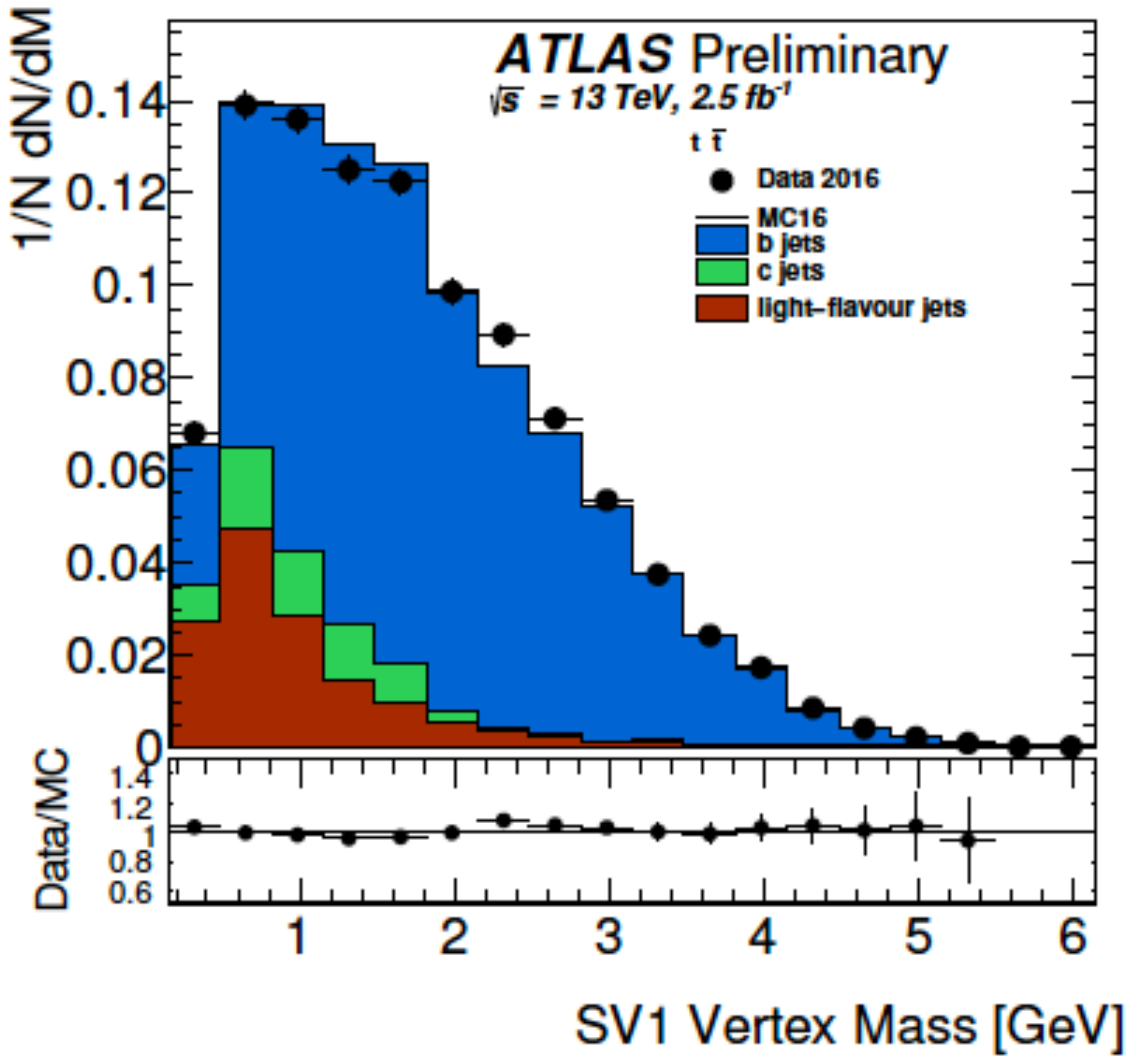


- Single, displaced vertex in jet is reconstructed
  - Check all track pairs for a two-track vertex hypothesis
  - Remove vertices likely to originate from photon conversion, Ks or lamba decay
  - Apply quality criteria on the tracks and the fit to reconstruct the vertex
- Properties of the secondary vertex and the assigned tracks are used in high-level tagger

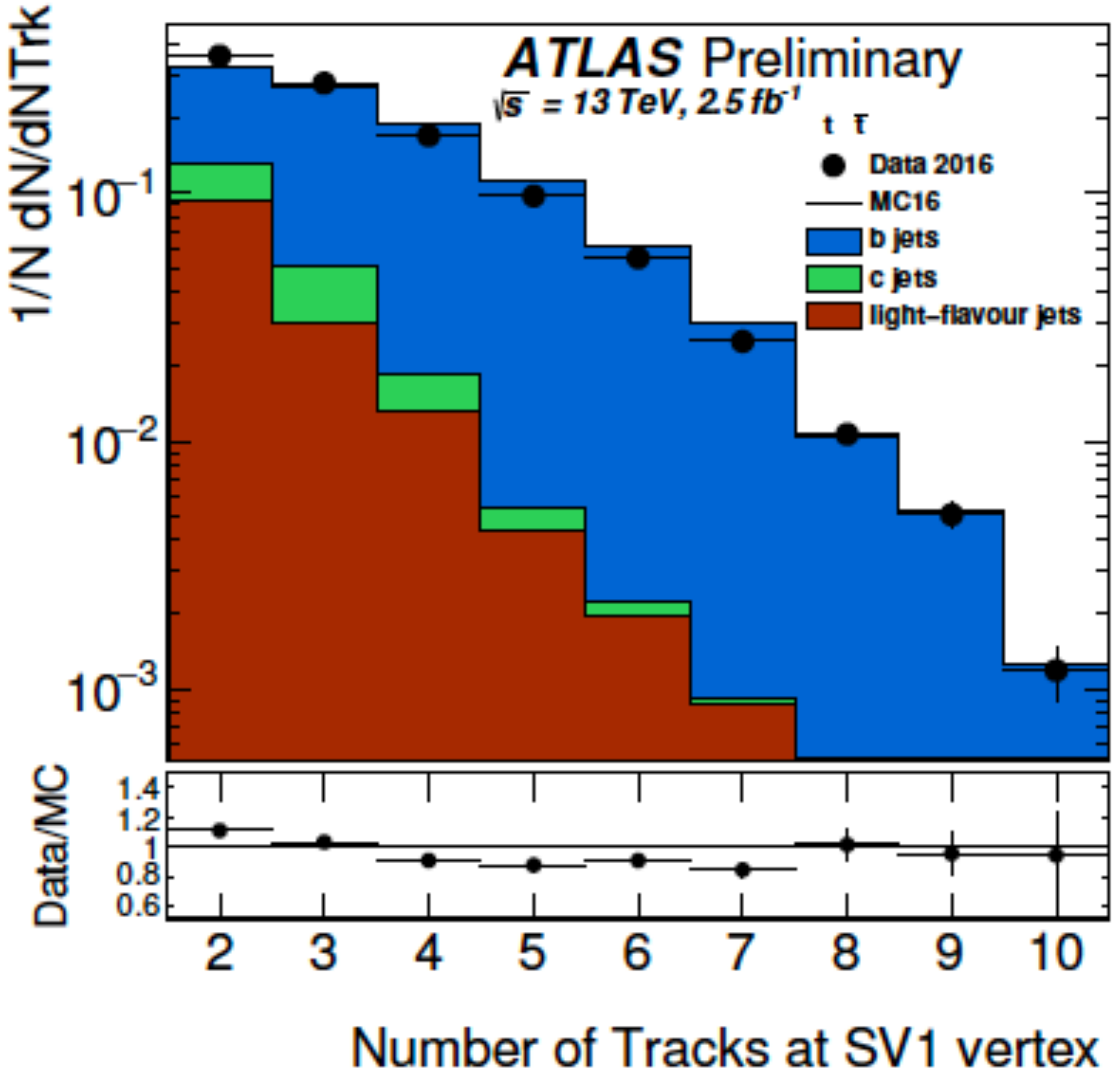
Transverse distance between primary & secondary vertex



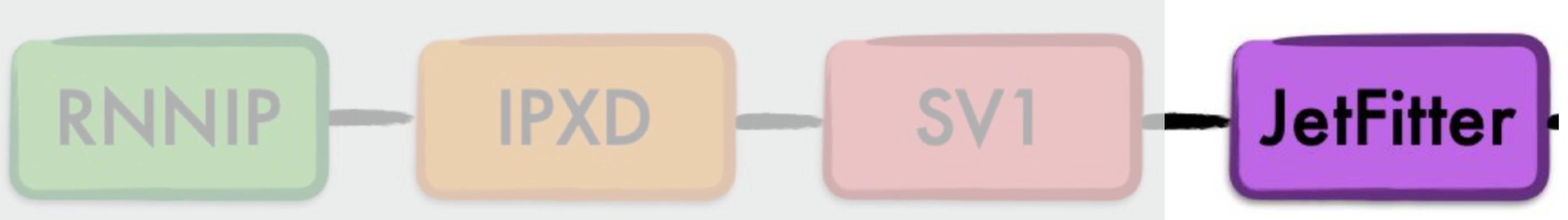
Secondary vertex mass



Number of tracks from SV1 vertex

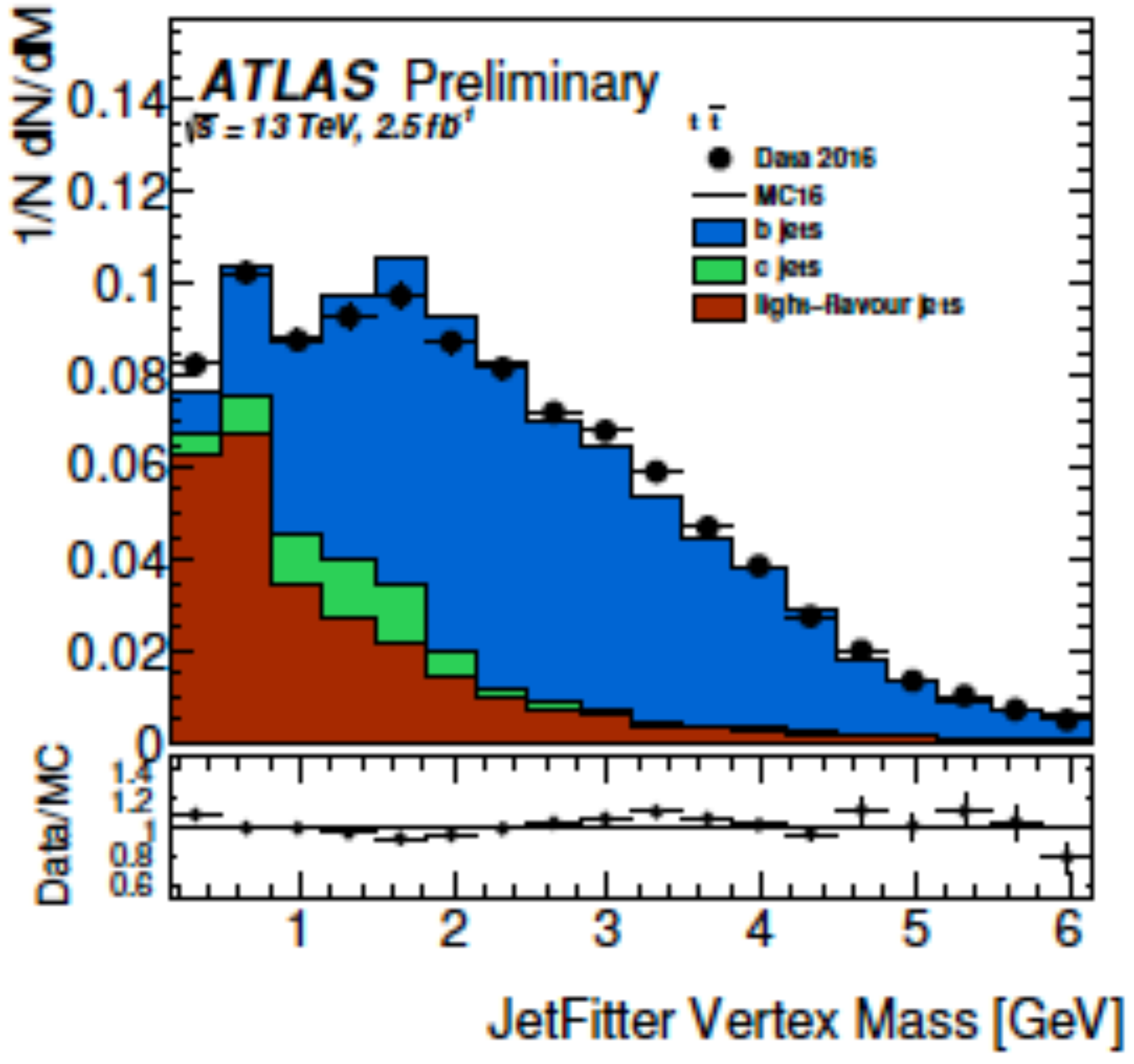


THE LOW-LEVEL TAGGERS: JETFITTER

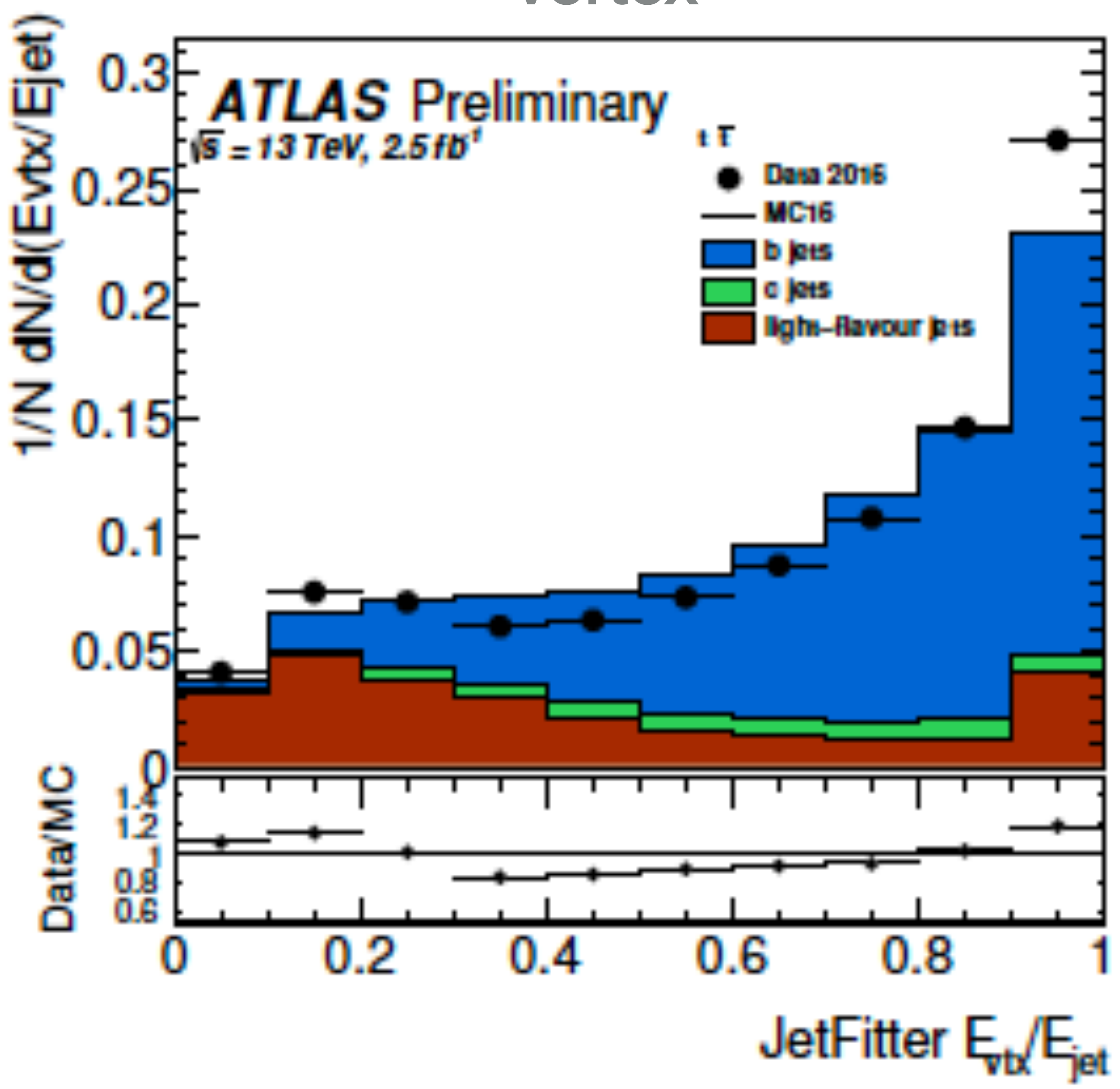


- Topological reconstruction of heavy hadron decay along the Jet axis
- Based on a modified Kalman filter
- Uses intercepts of track with jet axis to reconstruct full decay topology
- Properties of 3rd vertex added to better distinguish from c-jets and to make possible c-tagging (in neural network based high-level taggers)

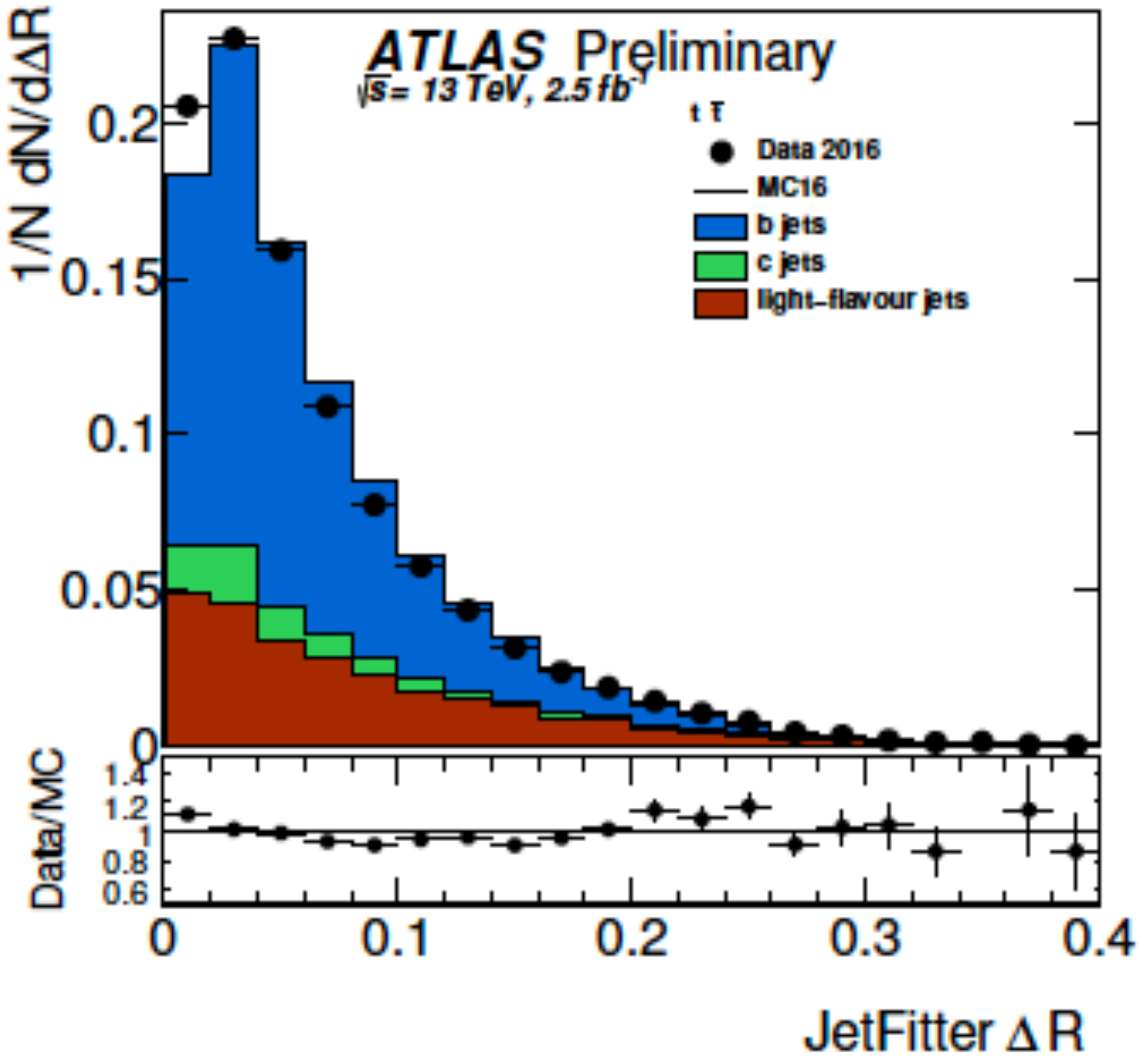
Reconstructed vertices mass



Fraction of jet energy carried by the vertex

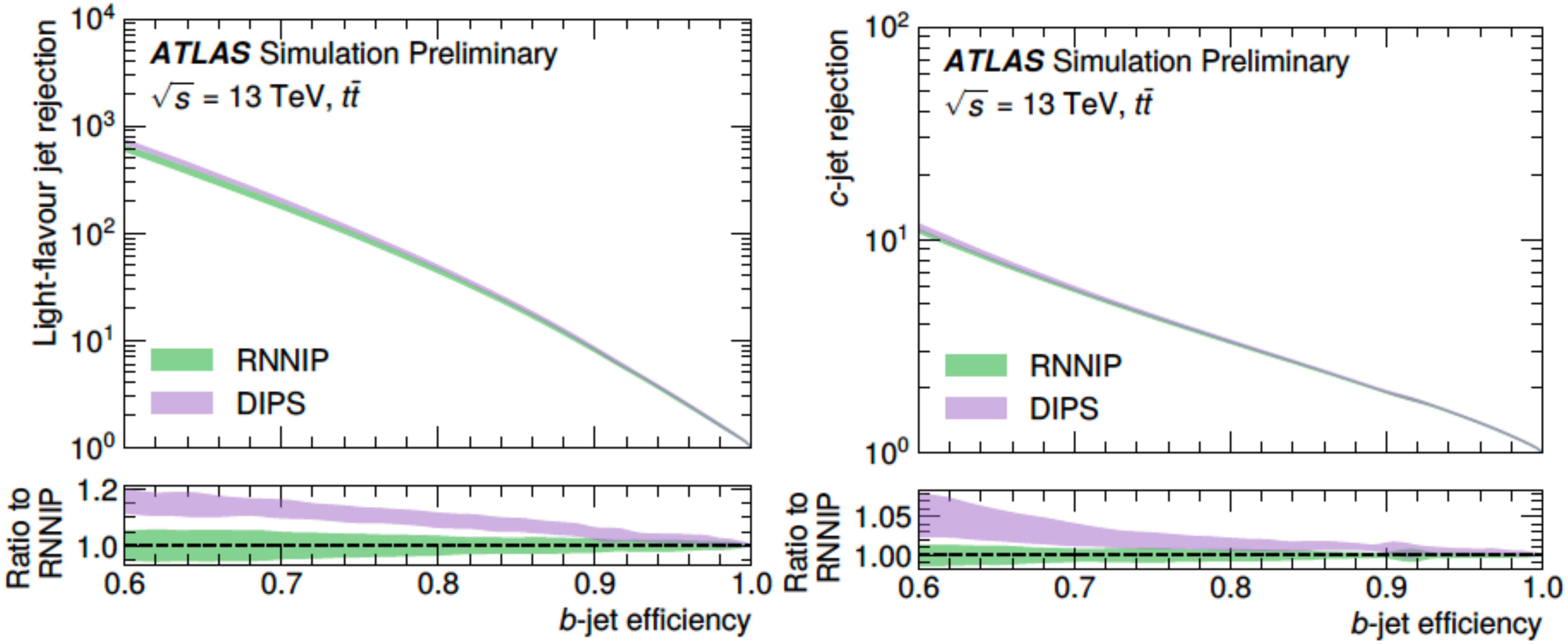


Distance between B-hadron flight direction and jet axis



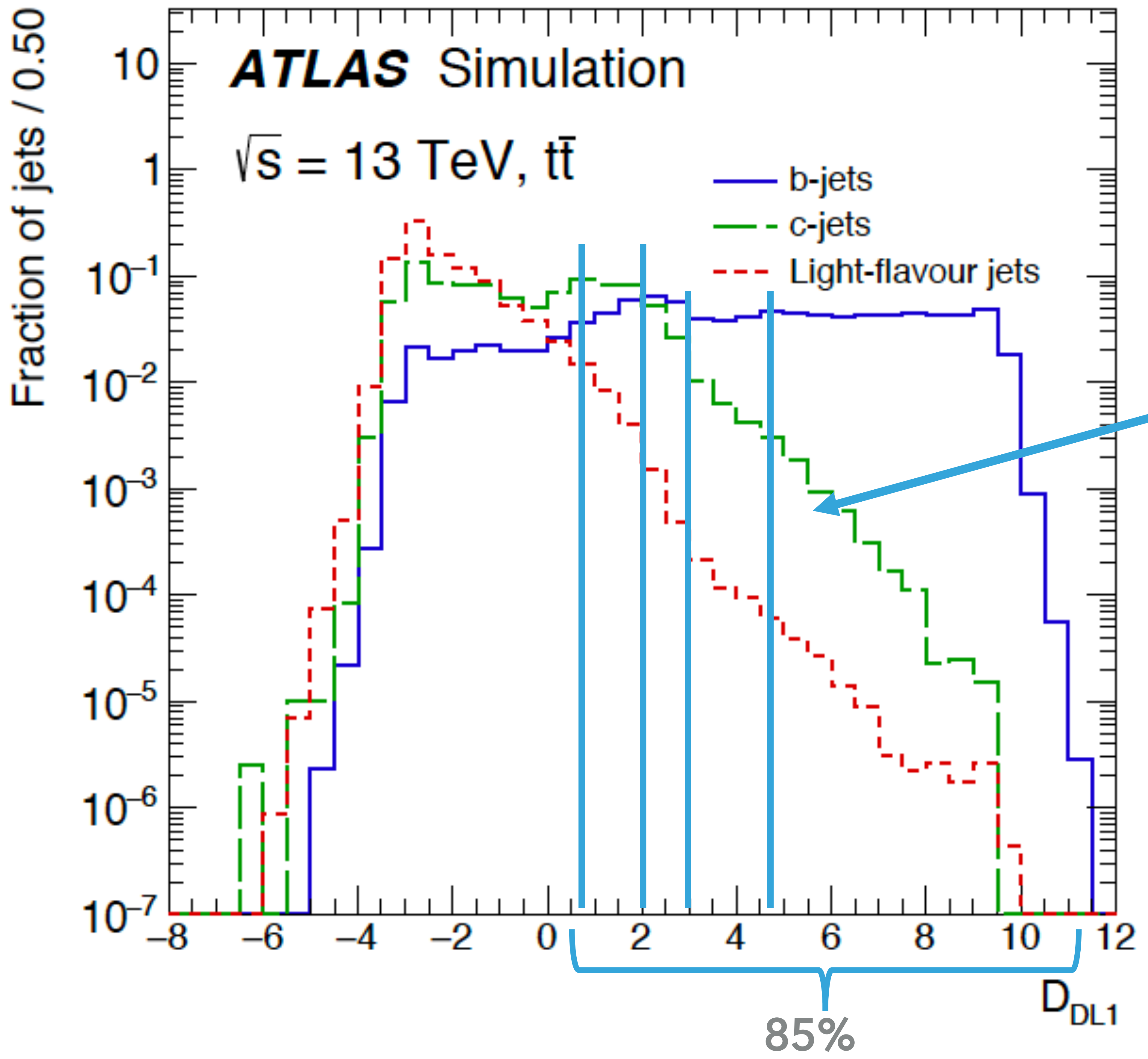
THE LOW-LEVEL TAGGERS - OUTLOOK: DIPS

- Improvement to RNNIP (impact-parameter based)
  - Ordering of tracks according to their impact parameter significance is necessary in RNNIP as it operates on sequences
- RNNIP neural network uses Deep sets architecture
  - No track ordering required ➔ allows faster training and optimization
- Slightly better performance with same NN parameters and input as RNNIP, can optimize better due to faster turnaround
- Not included yet in "official" taggers



THE OUTPUT DISCRIMINANTS

- Low-level tagger outputs are feed into Deep Fast neural network
- DNN creates output probabilities p_b, p_c, p_u
- Calculate output discriminant value: DL1 and DL1r (DL1r includes RNNIP)

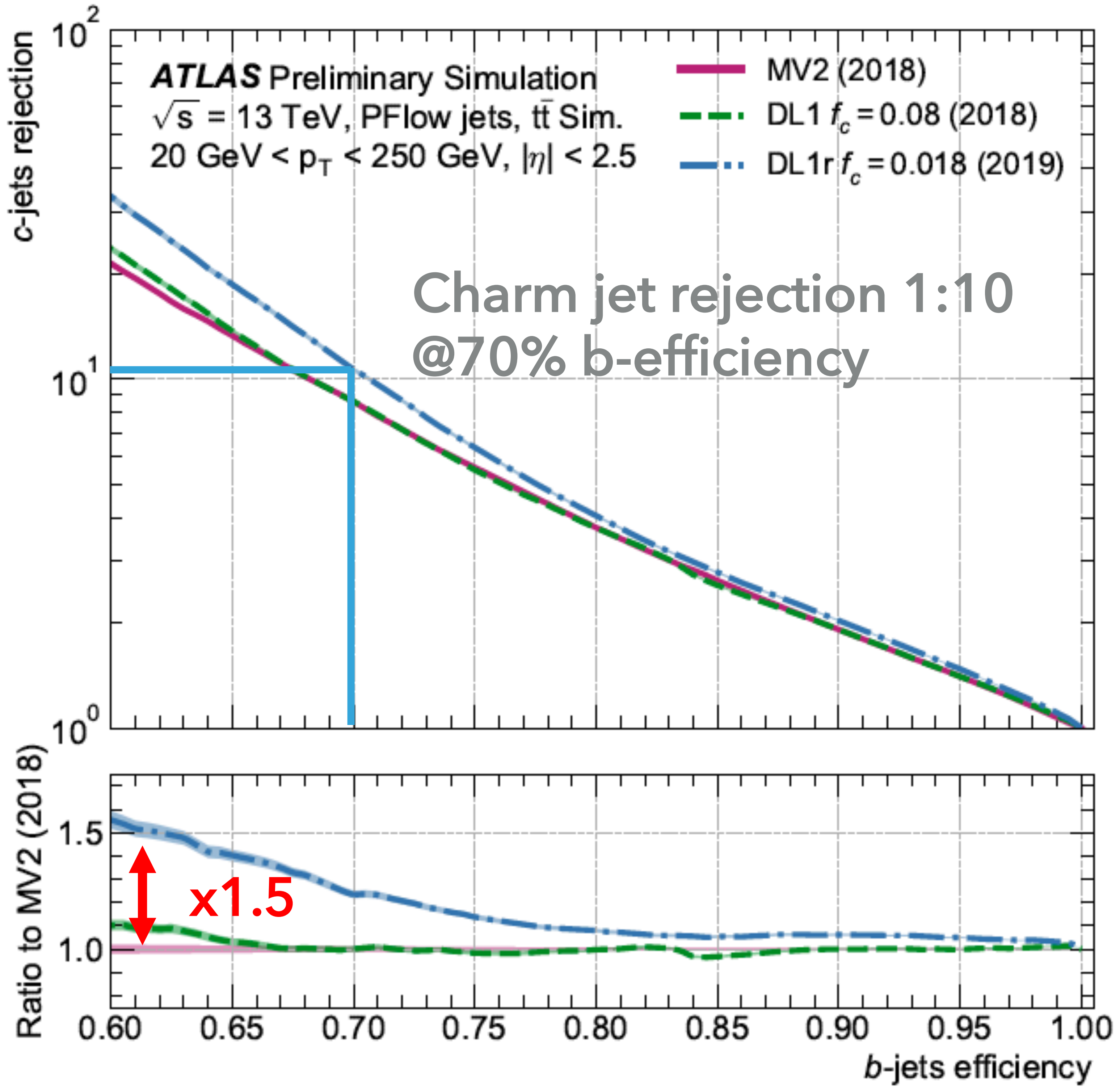


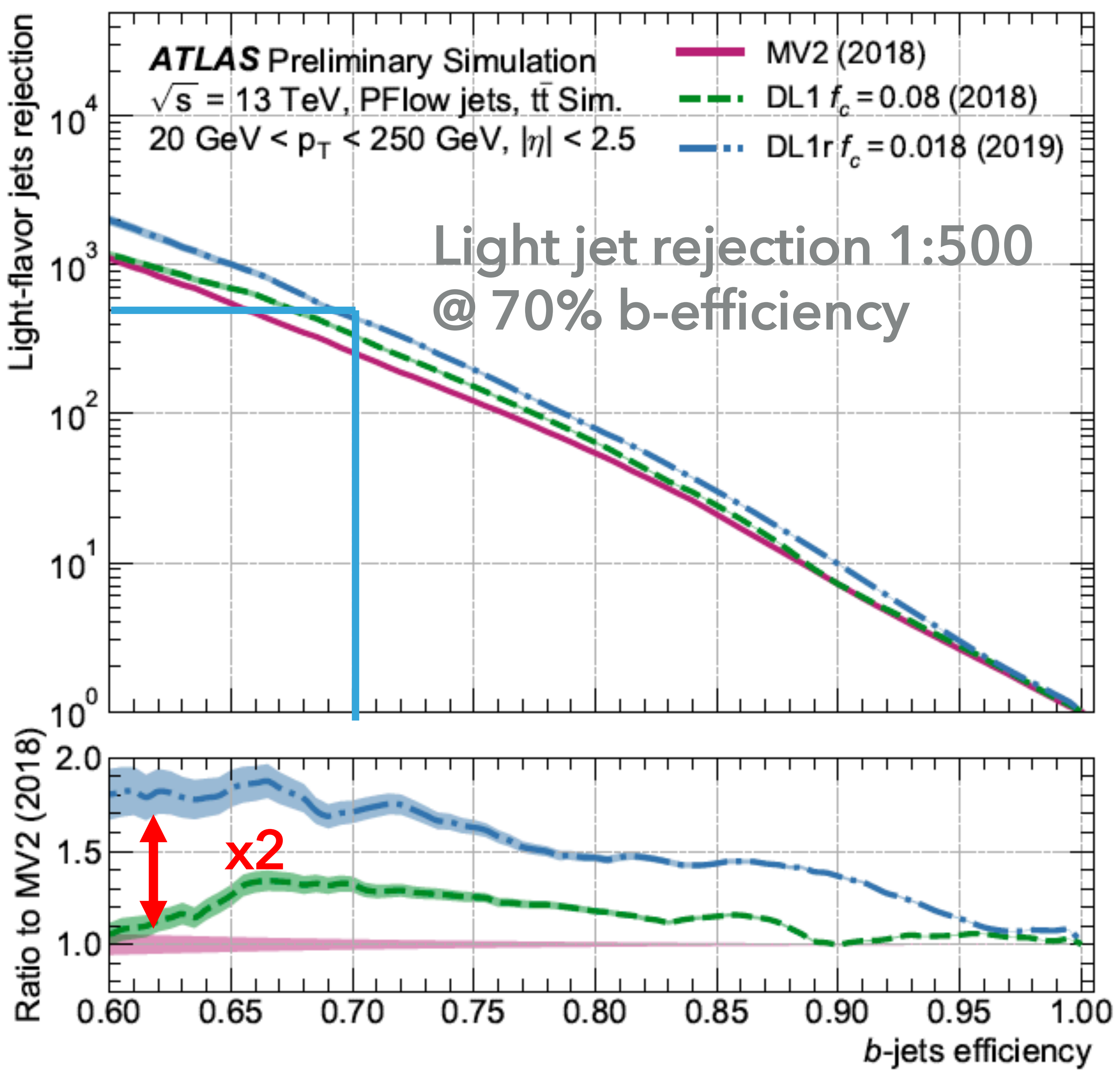
Define single-cut operating points corresponding to an average b-tagging efficiency (in ttbar MC)

- 85%, 77%, 70%, 60%

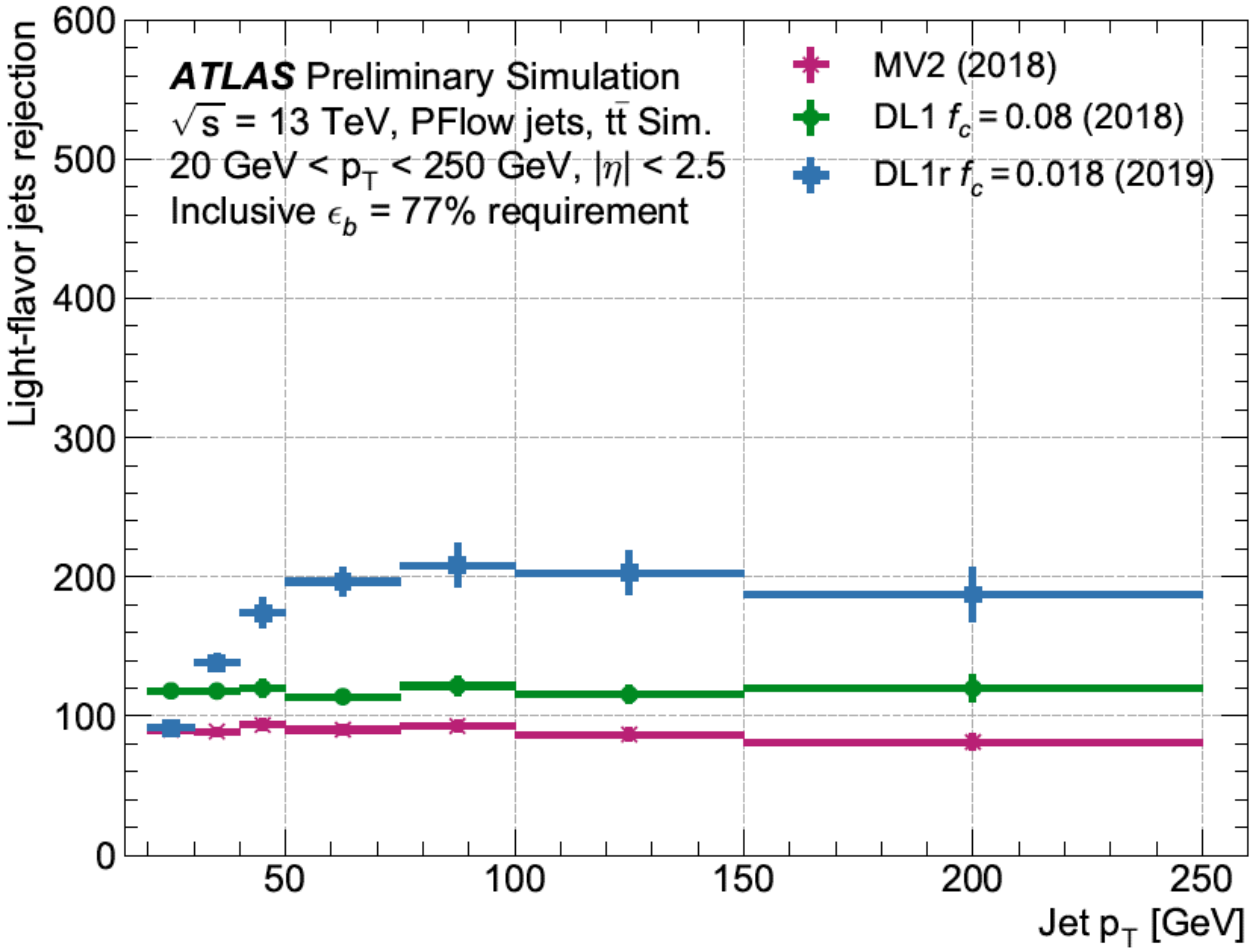
$$D_{DL1(r)} = \ln\left(\frac{p_b}{f_c \cdot p_c + (1 - f_c) \cdot p_{light}}\right)$$

TAGGER PERFORMANCE: PFLOW JETS





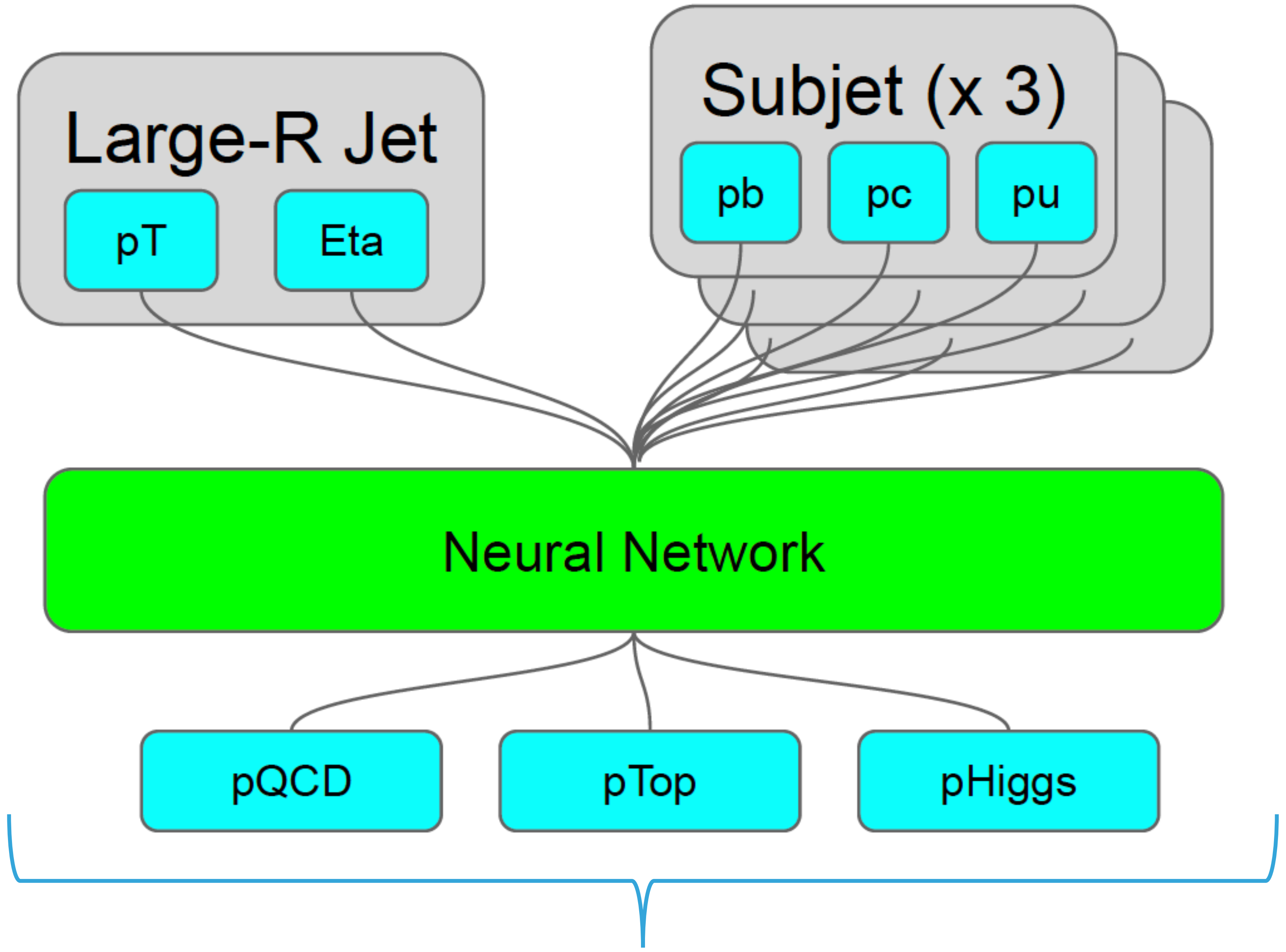
Light jet rejection for fixed-cut b-efficiency of 77%



- Improvements by up to a factor of 2 with recent improvements: inclusion of RNNIP and use of Deep Neural network instead of boosted decision trees (MV2)
- B-tagging efficiency and light and charm rejection pT-dependent

NOT ONLY B-TAGGING… THE H->BB TAGGER

- Several new physics models predict high-mass resonances decaying to at least one Higgs boson
  - Expect Higgs to be energetic ➔ H->bb decay products collimated to single large-R jet
- Up to present, tag small-R jets (VRTrack jets) assigned to single large-R jet ("double b-tagging")
- New approach creates dedicated tagging discriminant to identify H(X)->bb decays



Output probabilities for Higgs, top and multijet

- Feed neural network with p_b, p_c, p_u output of DL1 tagger for up to three leading VRTrack subjets
- Use also kinematics of large-R jet
- Exploits also the correlation of tagger outputs from VRTrack jets in large-R jet

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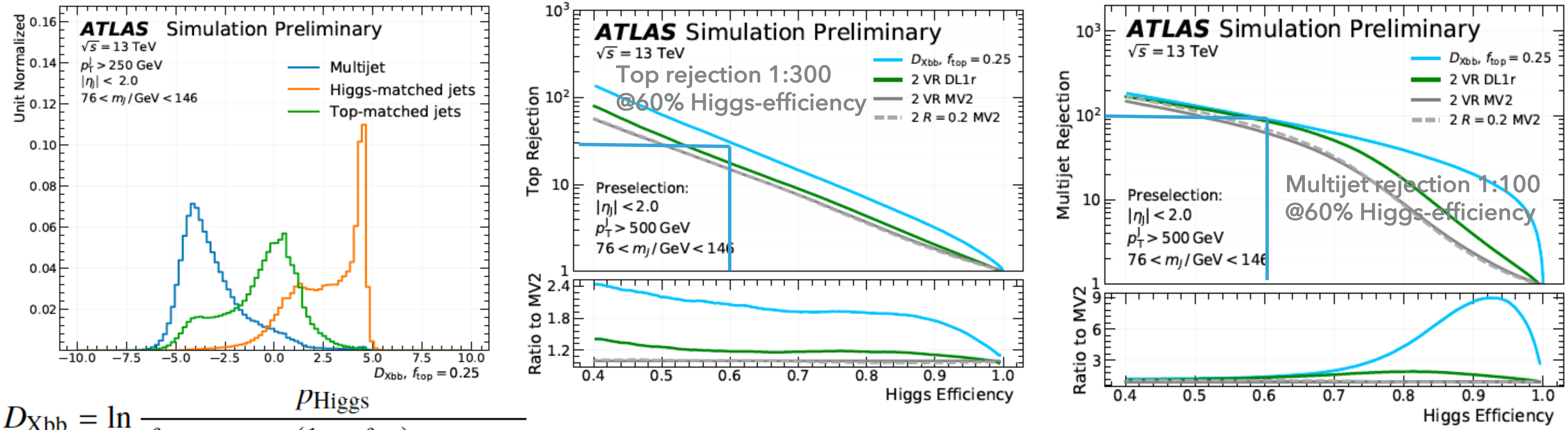
NOT ONLY B-TAGGING… THE H->BB TAGGER - PERFORMANCE



$$D_{Xbb} = \ln \frac{p_{Higgs}}{f_{top} \cdot p_{top} + (1 - f_{top}) \cdot p_{multijet}}$$

- For the full range of signal efficiencies, the Xbb tagger achieves an equal or higher multijet or top jet rejection w.r.t MV2 or DL1r double b-tag
- @60% Higgs-efficiency: Xbb tagger performs equally than DL1r double b-tag for multijet rejection and 1.6 times better for top jet rejection
- Note: No analysis using this tagger has been published yet, calibration work in progress

NOT ONLY B-TAGGING… CHARM TAGGING

- Without any retraining of the DL1(r) algorithm, charm tagging can be done
- Uses the same output: probabilities p_b, p_c, p_u
  - Advantage w.r.t old MV2 algorithm: retraining needed as single output instead of probabilities for each flavor
- Just need to to rewrite output discriminant definition

$$\mathrm{DL1r} = log\,\frac{p_b}{f_c\,p_c + (1 - f_c)\,p_u}$$

$$\mathrm{DL1r}_c = log\,\frac{p_c}{f_b\,p_b + (1 - f_b)\,p_u}$$

- Analysis using charm tagging with “official” DL1 algorithm work in progress
  - VH(->cc) (V=W,Z)

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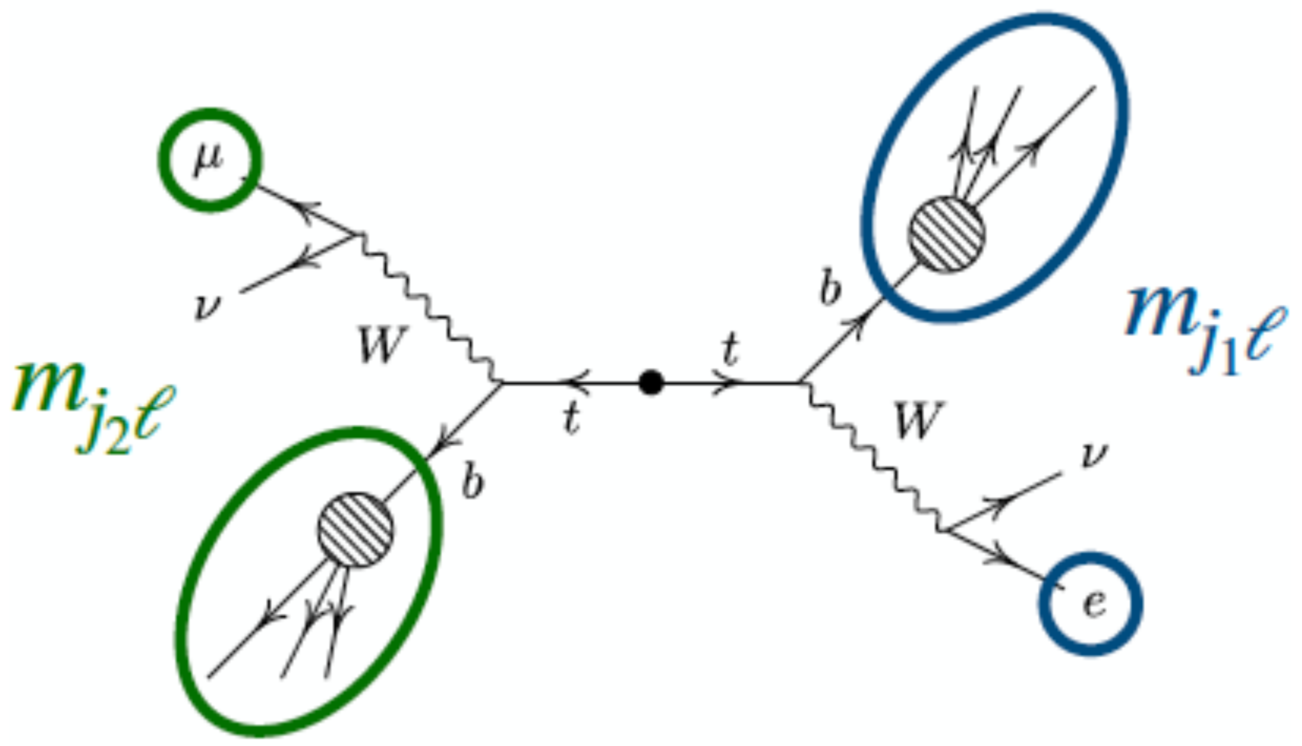
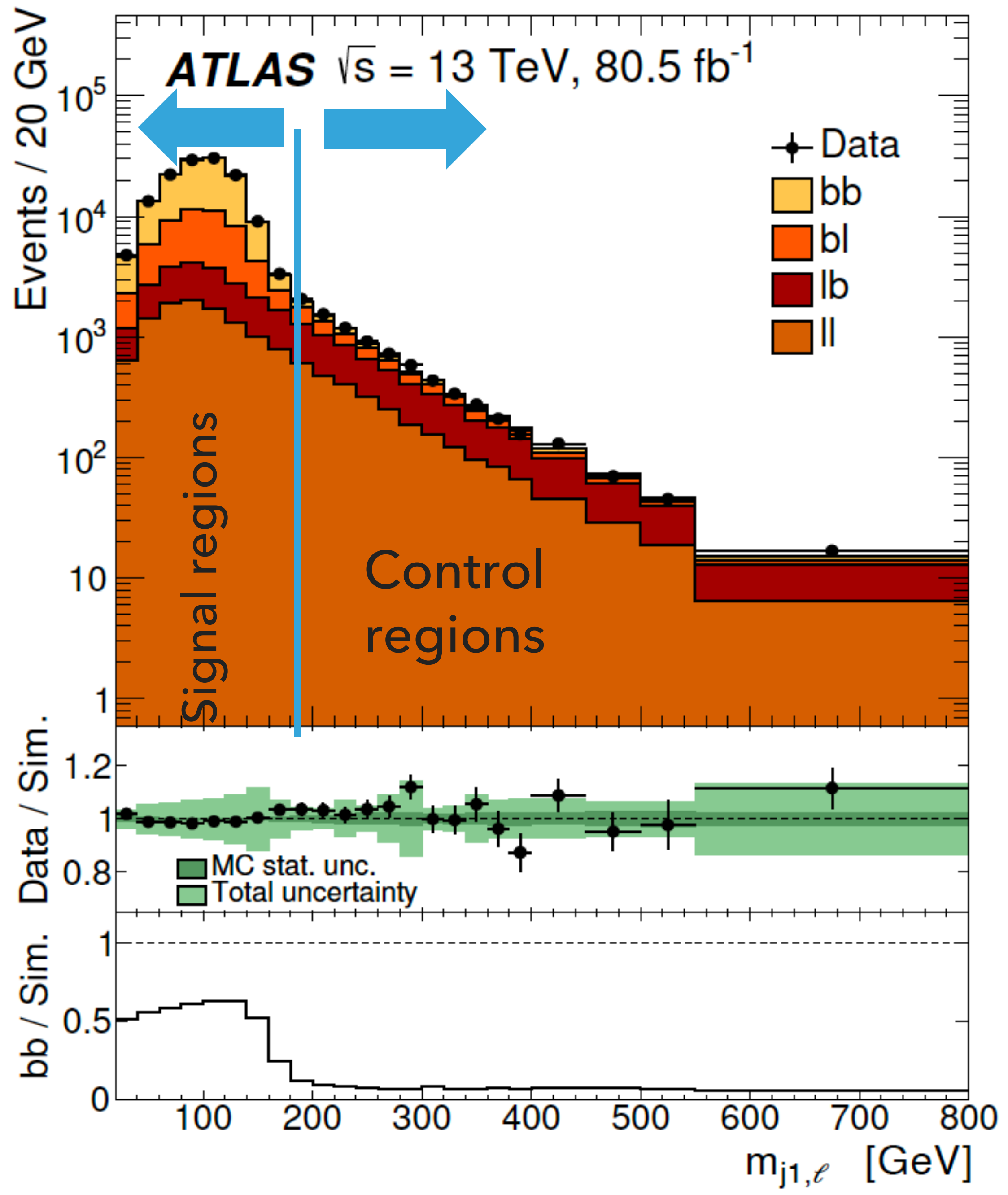
CALIBRATION OF THE B-TAGGING ALGORITHM: OVERVIEW

- Taggers trained in simulation using several input variables like secondary vertex masses, number of tracks, etc.
- Check whether tagger input is well understood in simulation and training wasn't done on a completely different setup
- Calibrate b-efficiency, charm & light mistag rate
  - Use samples enriched by either b-, charm or light jets
  - Calculate efficiencies in data and MC and compare
  - Calculate MC-to-data correction factor ("Scale Factor", SF)
  - Scale Factors are ratios in performance data to MC
  - SF are ideally close to 1

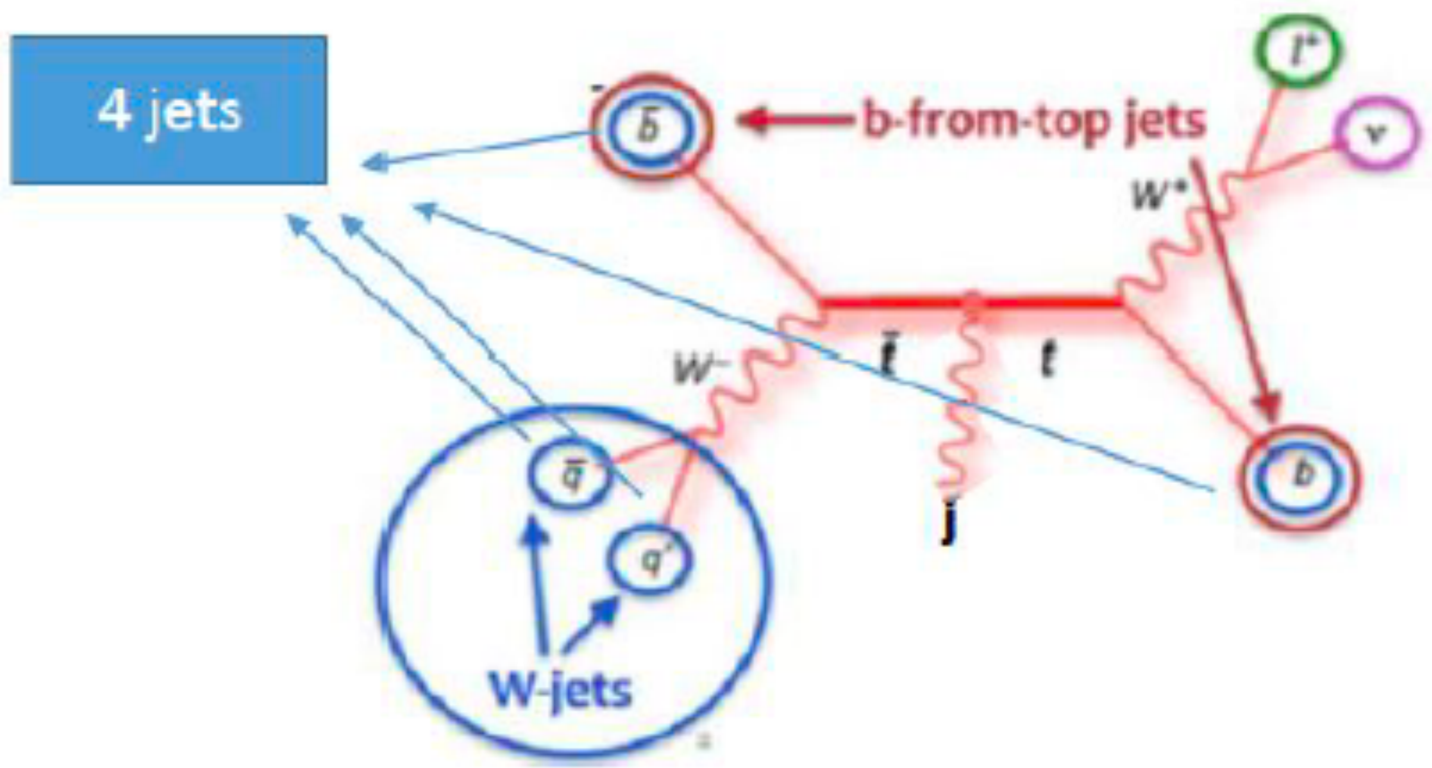
B-EFFICIENCY CALIBRATION



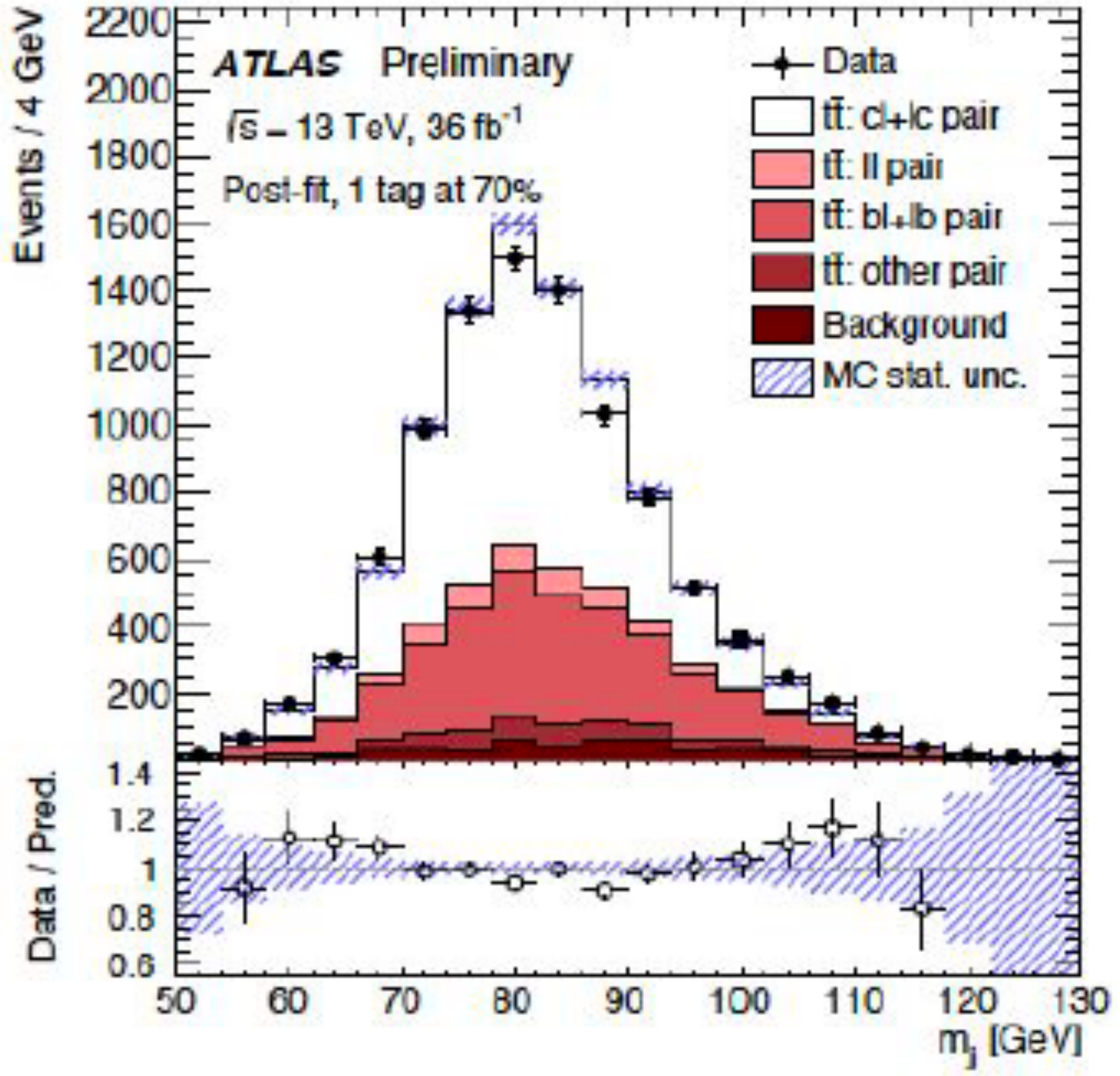
- Select dilepton ttbar events
  - ==1 e, ==1 mu, == 2 jets
- Extract calibration using the 2 jets in event
- Data-driven corrections to background reduce uncertainty to percent level
  - Non-b-jet contribution constrained in fit



CHARM MISTAG EFFICIENCY CALIBRATION

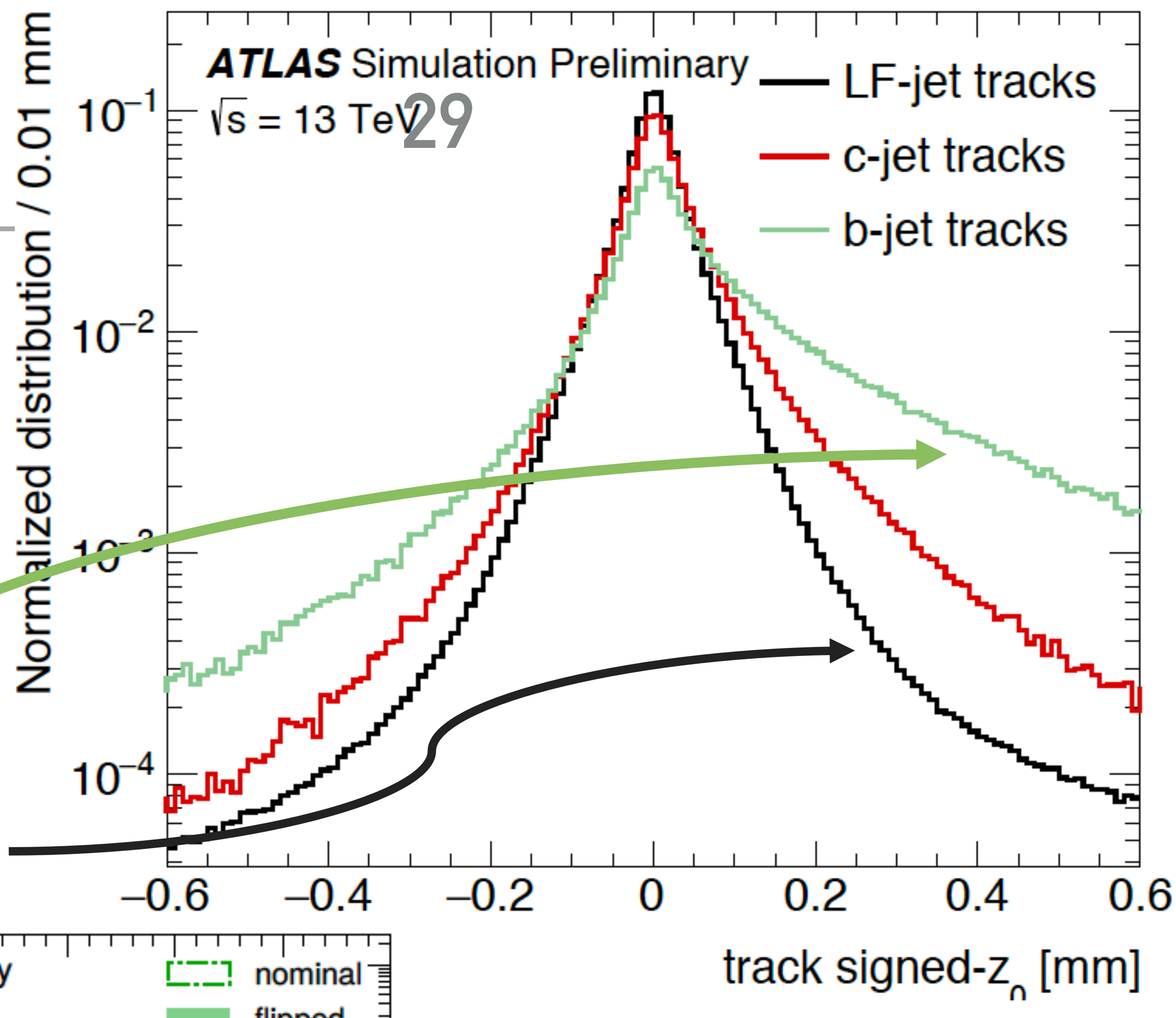


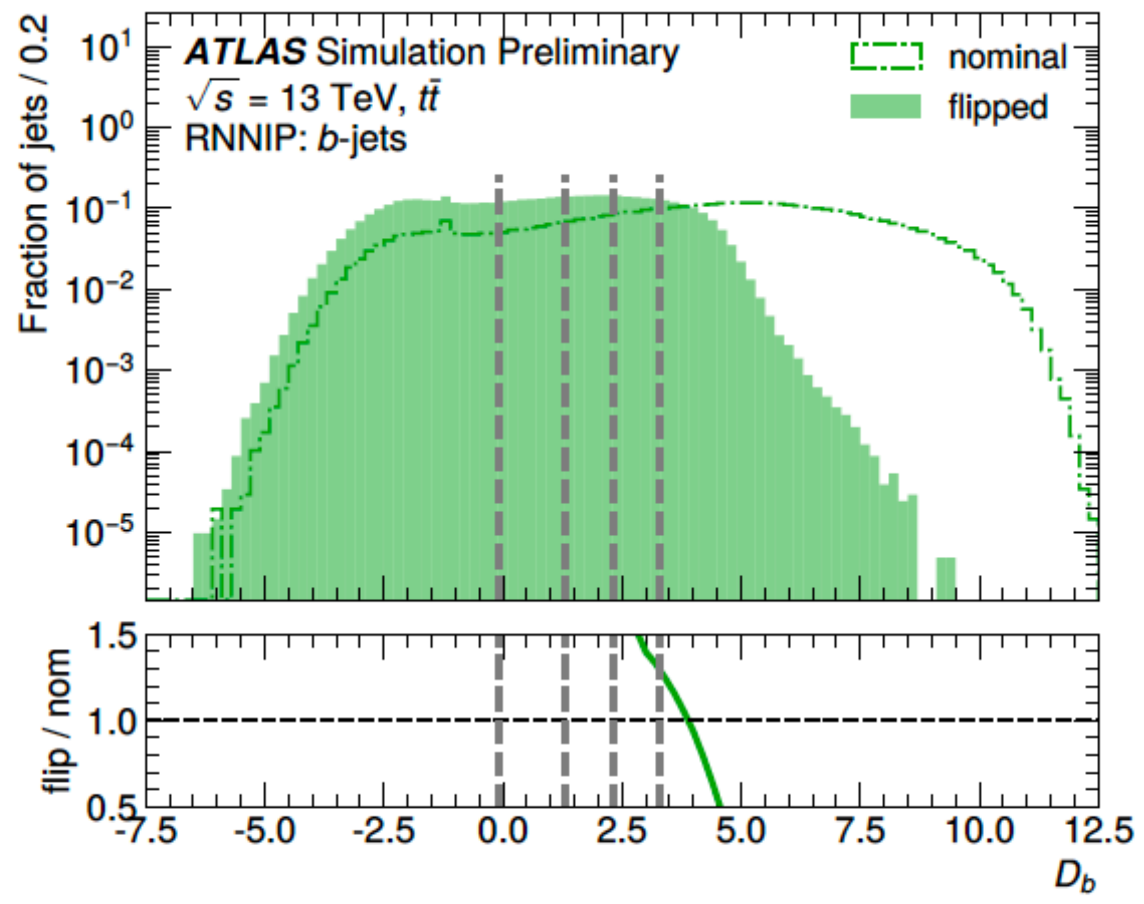
- Select ttbar lepton+jets sample
  - == 1 lepton, ETmiss, ==4 jets
- Perform measurement on jets assigned to hadronically decaying W-boson
  - Exploit large branching ratio W->cX
- Extract charm mistag efficiency in likelihood fit

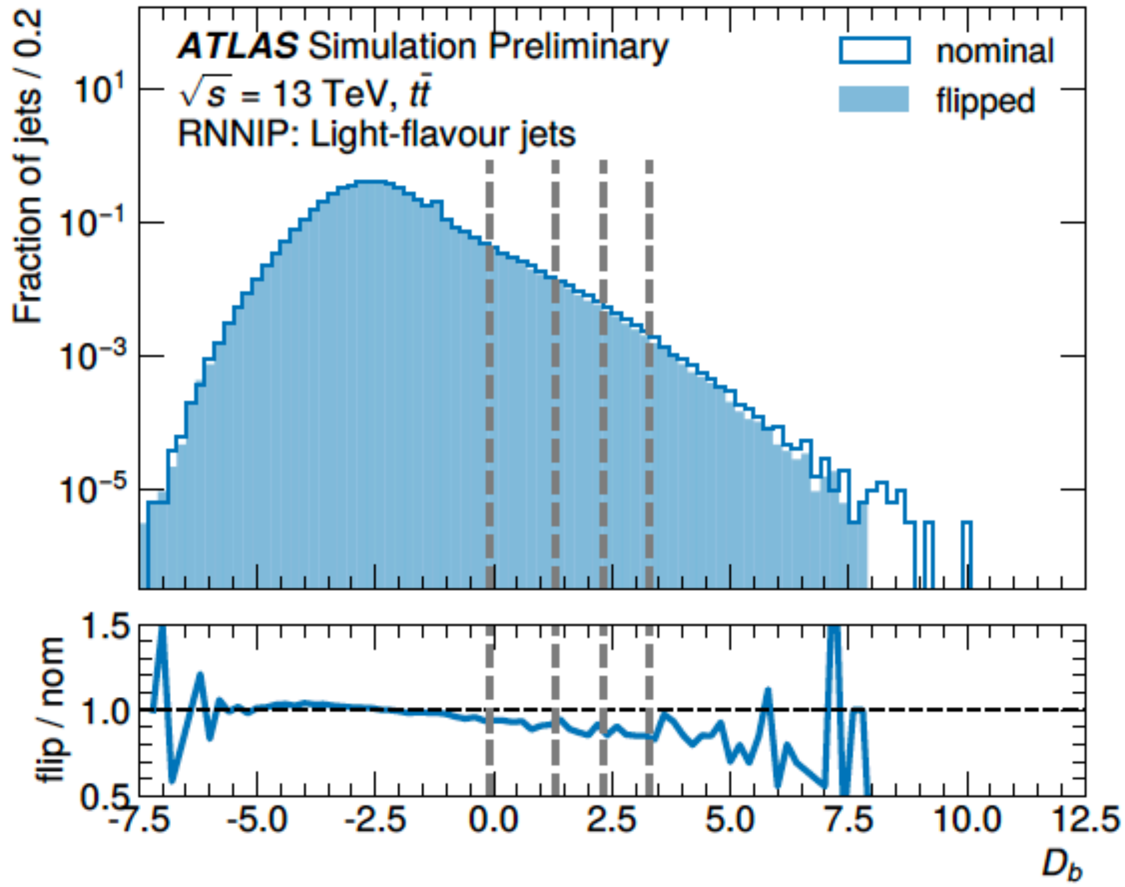


LIGHT MISTAG EFFICIENCY CALIBRATION

- Challenging due to high light jet rejection (1:100-1:1000)
- Modifications to tagger:
  - Make use of symmetry of signed impact parameter distribution for light jets and strong asymetry for b & charm jets
  - Decrease b-jet response
  - Light jet response unchanged
- **Measure mistag rate of modified ("flipped") tagger**
- Calibration of leading jet in Z(->ll)+jets events
- Reduce uncertainties by constraining non-light flavour in fit





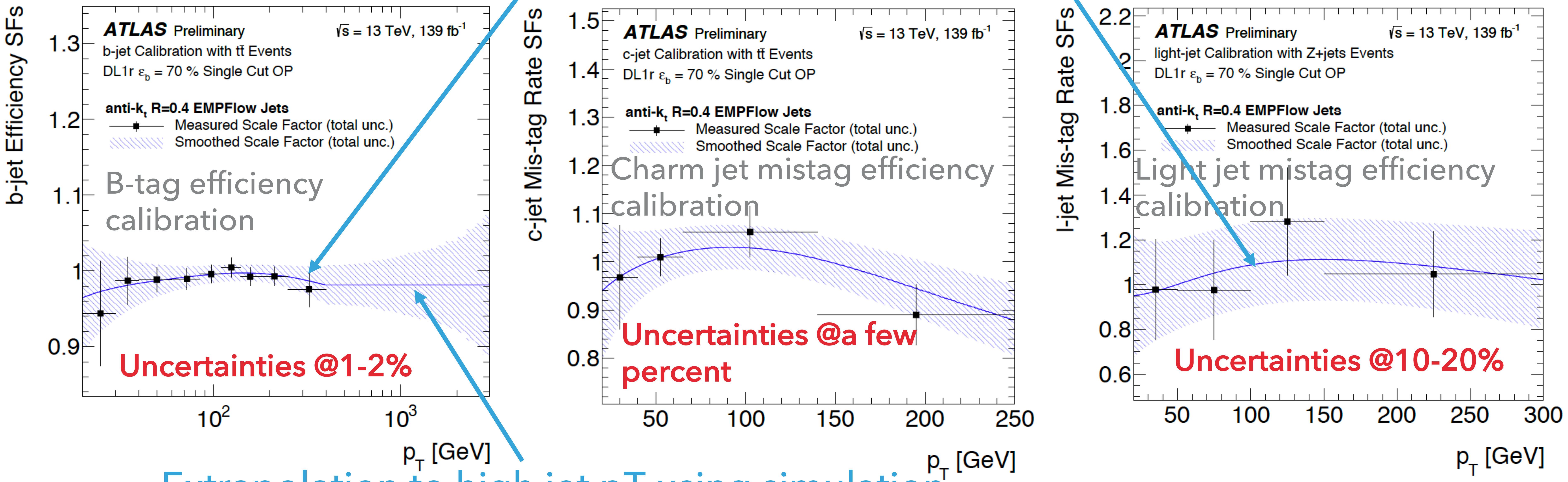


ORIGINAL TAGGER → FLIPPED TAGGER ← CALIBRATION

Add additional uncertainty ➔ estimate using MC
("extrapolation uncertainty")

RESULTS AND POST-PROCESSING

Smoothing of results removes discontinuities at bin boundaries



Extrapolation to high jet pT using simulation

- **Data and MC efficiencies are consistent**, the MC-to-data correction factors ("Scale Factors") are compatible with 1
- Post-processing to measured scale factors
  - Due to insufficient statistics, cannot measure b-efficiency for jets with pT>400GeV: apply additional uncertainties to scale factor central value for pT=400GeV due to physics and detector modeling effects ("high-pT extrapolation")
  - Smooth results as function of pT using a non-parametric regression-technique: do not expect discontinuities in kinematic modeling

ATLAS EXPERIMENT

IMPACT OF FLAVOUR TAGGING IN ATLAS ANALYSES

- Analyses can be impacted in several ways by flavor tagging
  - Performance (b-efficiency vs. charm & light mistag rate):
    - Signal efficiency depends on the b-tag efficiency working point
    - Analyses with a lot of b-jet in the final state can suffer from background from charm mistag if rejection is too low
      - Example: VH(H->aa->bbbb), 4 top, ttH(bb)
  - Efficiency calibration (uncertainty):
    - Uncertainties from efficiency calibration can have impact on analysis sensitivity
      - Examples: analyses using data-driven background (low-or high mass dijet resonance searches)
- As example, present dijet resonance search with full Run2 dataset

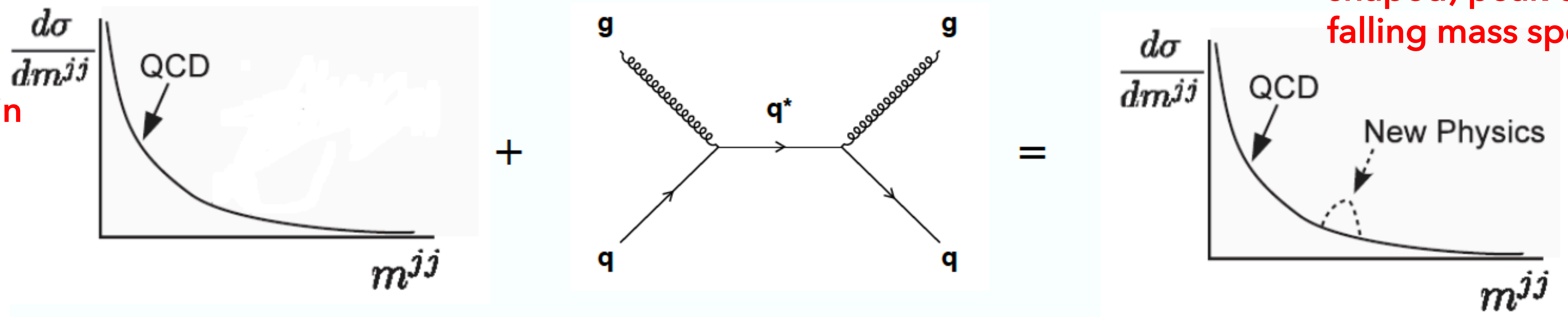
ATLAS EXPERIMENT

DIJET RESONANCE SEARCH (ARXIV:1910.08447)

- Search for high-mass resonance coupling to quark and/or gluons
  - Heavy gauge bosons (Z′ ->bb), Kaluza-Klein Graviton G->bb, excited quarks b*(->qb)
  - Decay to **two high-energetic hadronic jets**

New heavy resonance with mass M

Invariant di-jet mass spectrum produced in QCD processes: smoothly falling with m(jj)



New physics as (Gaussian-shaped) peak on smoothly falling mass spectrum

- Inclusive search and with >=1 or ==2 b-tagged jets
- Search performed on full Run2 ATLAS data
- **First ATLAS analysis using new DL1r tagger**
- **Flagship measurement for high-pT jet b-tagging**

ATLAS EXPERIMENT

DIJET RESONANCE SEARCH: IMPORTANT ANALYSIS FEATURES

Table 1: Summary of the event selection requirements and benchmark signals being tested in each analysis category. Only the two jets with highest p_T enter in the event selection. The exact values of the m_{jj} lower bounds also depend on the jet energy resolution uncertainty.

Category	Inclusive		1b	2b
Jet p_T	> 150 GeV			
Jet ϕ	$\|\Delta\phi(jj)\| > 1.0$			
Jet $\|\eta\|$	-		< 2.0	
$\|y^*\|$	< 0.6	< 1.2	< 0.8	
m_{jj}	> 1100 GeV	> 1717 GeV	> 1133 GeV	
b-tagging	no requirement		$\geqslant 1$ b-tagged jet	2 b-tagged jets
Signal	DM mediator Z' W' q^* QBH Generic Gaussian	W^*	b^* Generic Gaussian	DM mediator Z' ($b\bar{b}$) SSM Z' ($b\bar{b}$) graviton ($b\bar{b}$) Generic Gaussian

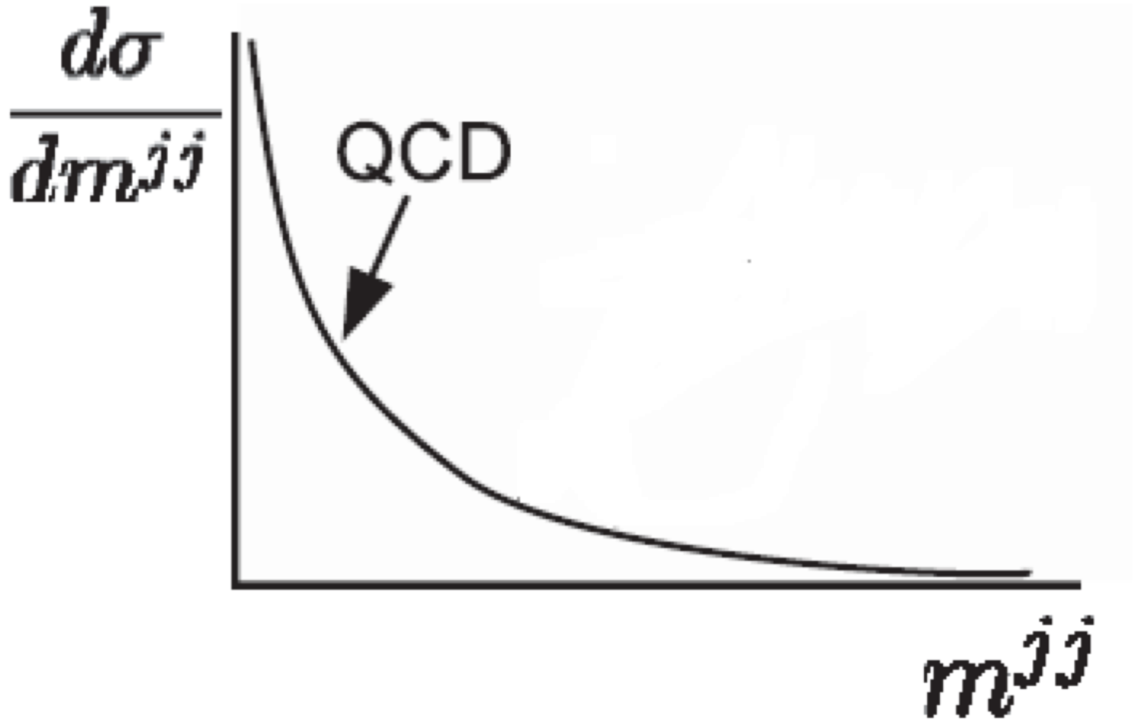
QCD processes mainly t-channel production; signal s-channel production

Signal models considered

Categories: Inclusive or >=1 or ==2 b-tags

Select high pT (b-tagged) jets

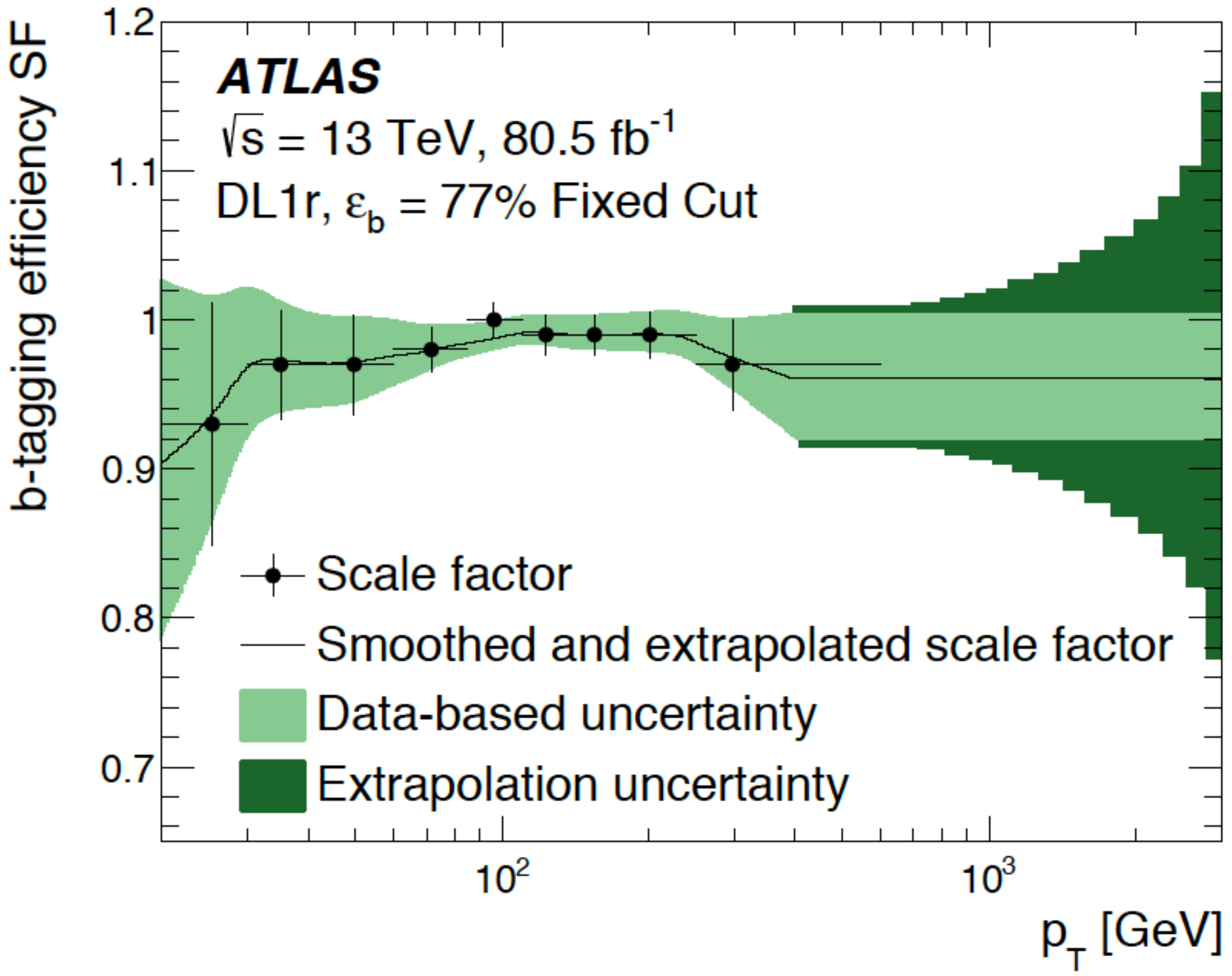
- Background estimation purely data-driven
  - Modeled by a smoothly falling parametric function
  - Determine function coefficients by fit in control regions

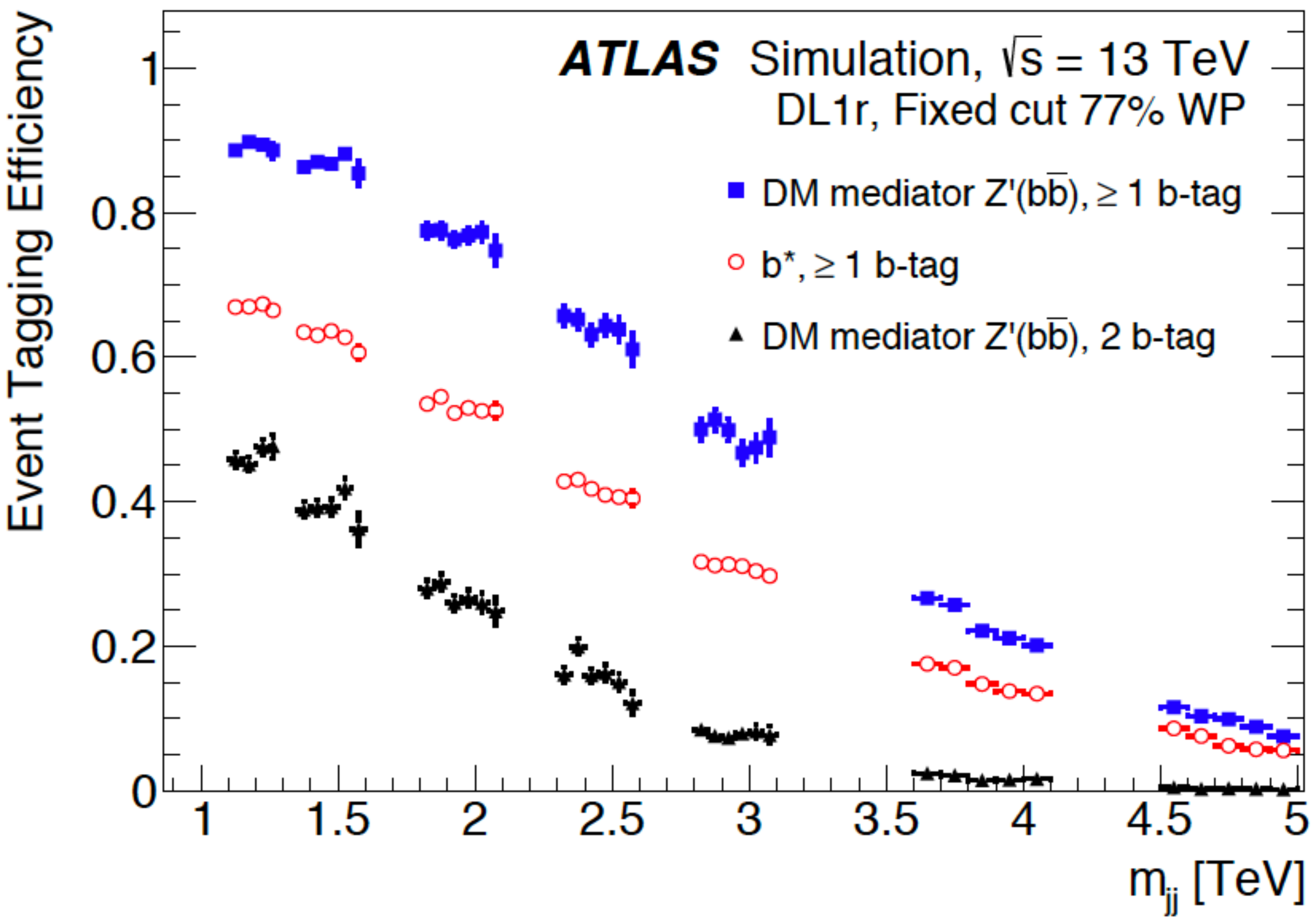


$$f(x) = p_1(1-x)^{p_2} x^{p_3 + p_4 \ln x}$$

ATLAS EXPERIMENT

DIJET RESONANCE SEARCH: IMPORTANCE OF B-TAGGING



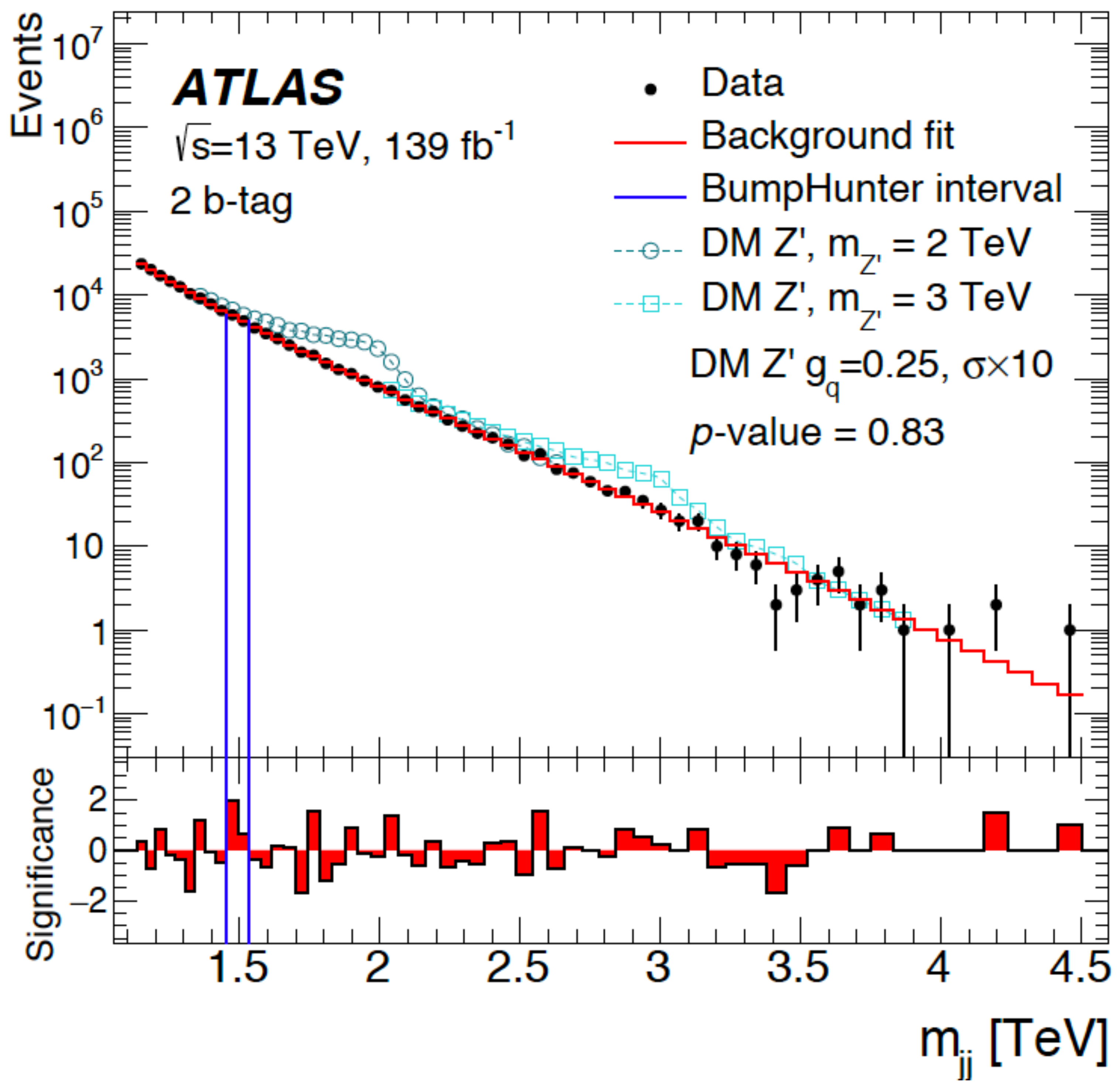


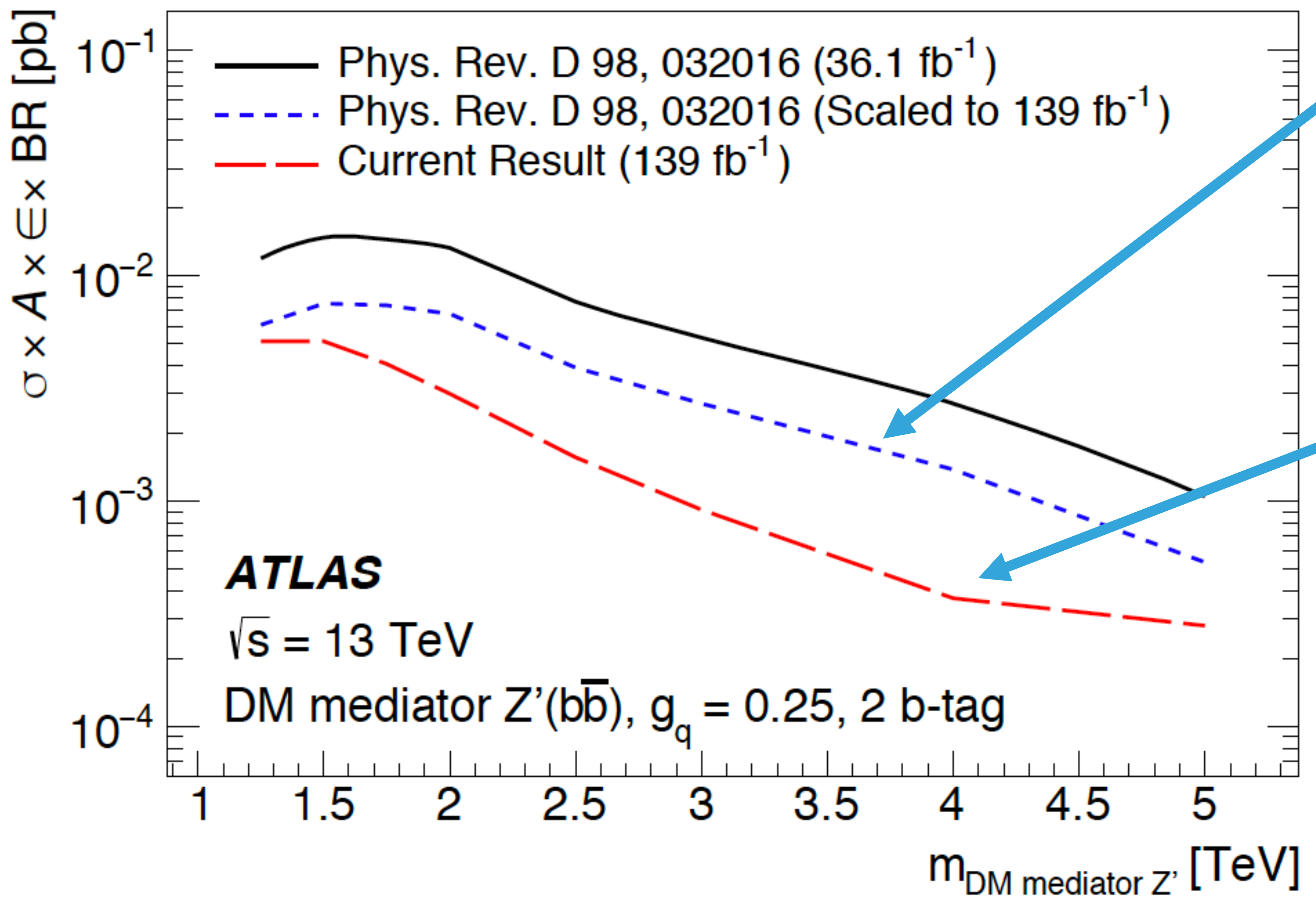
- Expected signal yield sensitive to b-tag efficiency calibration @high jet pT
- Sensitive to high-pT extrapolation uncertainty
- Reduced in current calibration: improved method, simulations (inner detector simulation) and use of RNNIP

- Efficiency to pass the b-tagging selection after the remaining event selection
- Signal selection efficiency decreases with pT due to decreasing b-tagging efficiency with pT

ATLAS EXPERIMENT

DIJET RESONANCE SEARCH: RESULTS





Previous analysis (data15+16) scaled to 139fb-1 luminosity

New limits with improved calibration & new DL1r b-tagger

- Scan curve in continuous mass interval using a sliding-window fit
- No significant deviation from the Standard Model background
- Better limits observed in 2b-category w.r.t previous analysis
  - Increased high-pT efficiency for new DL1r tagger (due to dedicated high-pT training)
  - Lower systematic uncertainties of high-pT calibration (extrapolated calibration)

CONCLUSIONS

- Flavour tagging important input to physics analysis in ATLAS
- Not only b-tagging possible but also charm and H->bb tagging
- Tagger training and input variables well understood, tagging efficiencies in data and simulation well in agreement
- Constant improvements on taggers and calibrations
- ATLAS analyses profit from the recent improvements on taggers and calibrations