

Transformer networks for constituent-based b-jet calibration with the ATLAS detector

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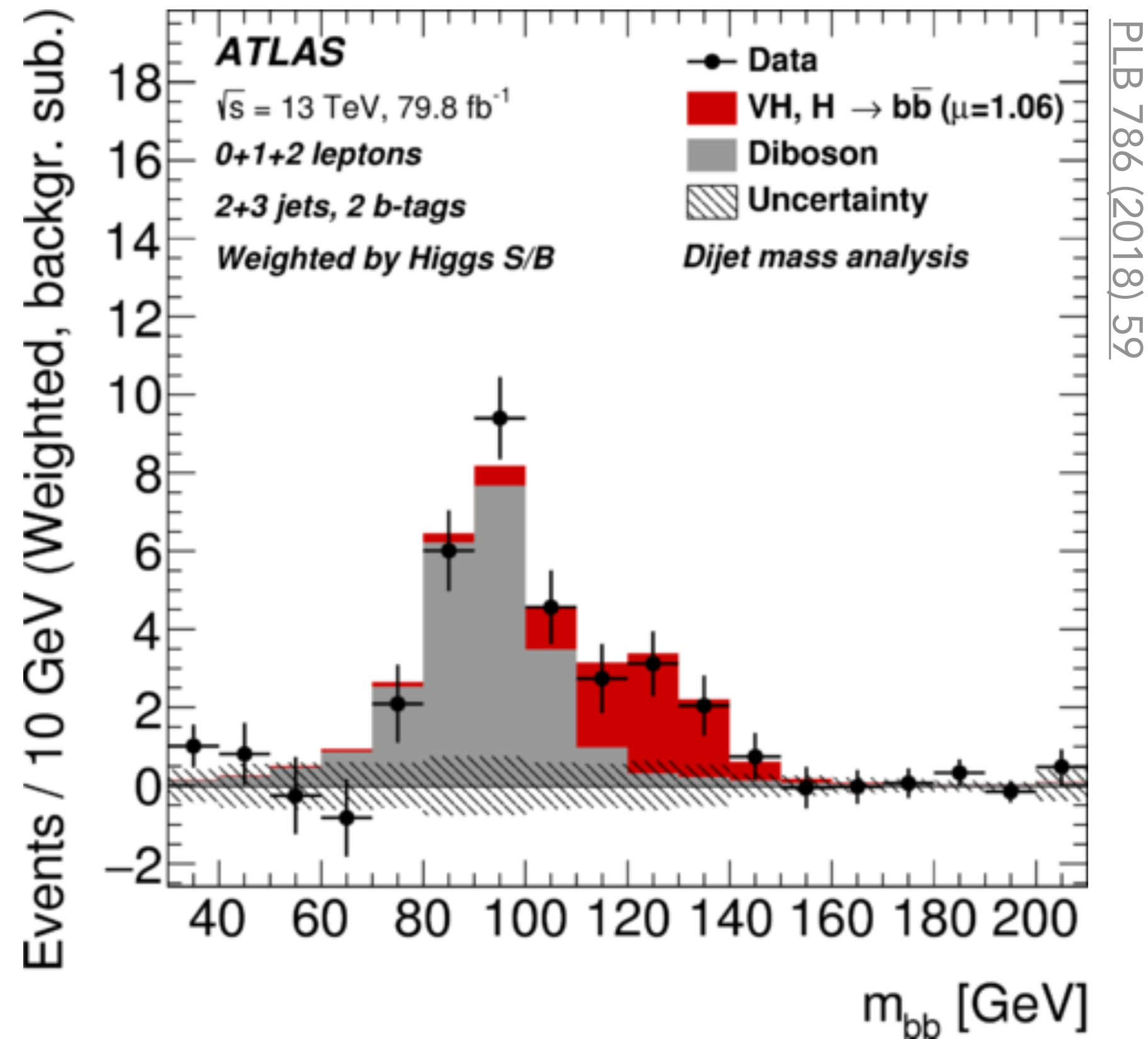
US-LUA lightning talk

December 18, 2024



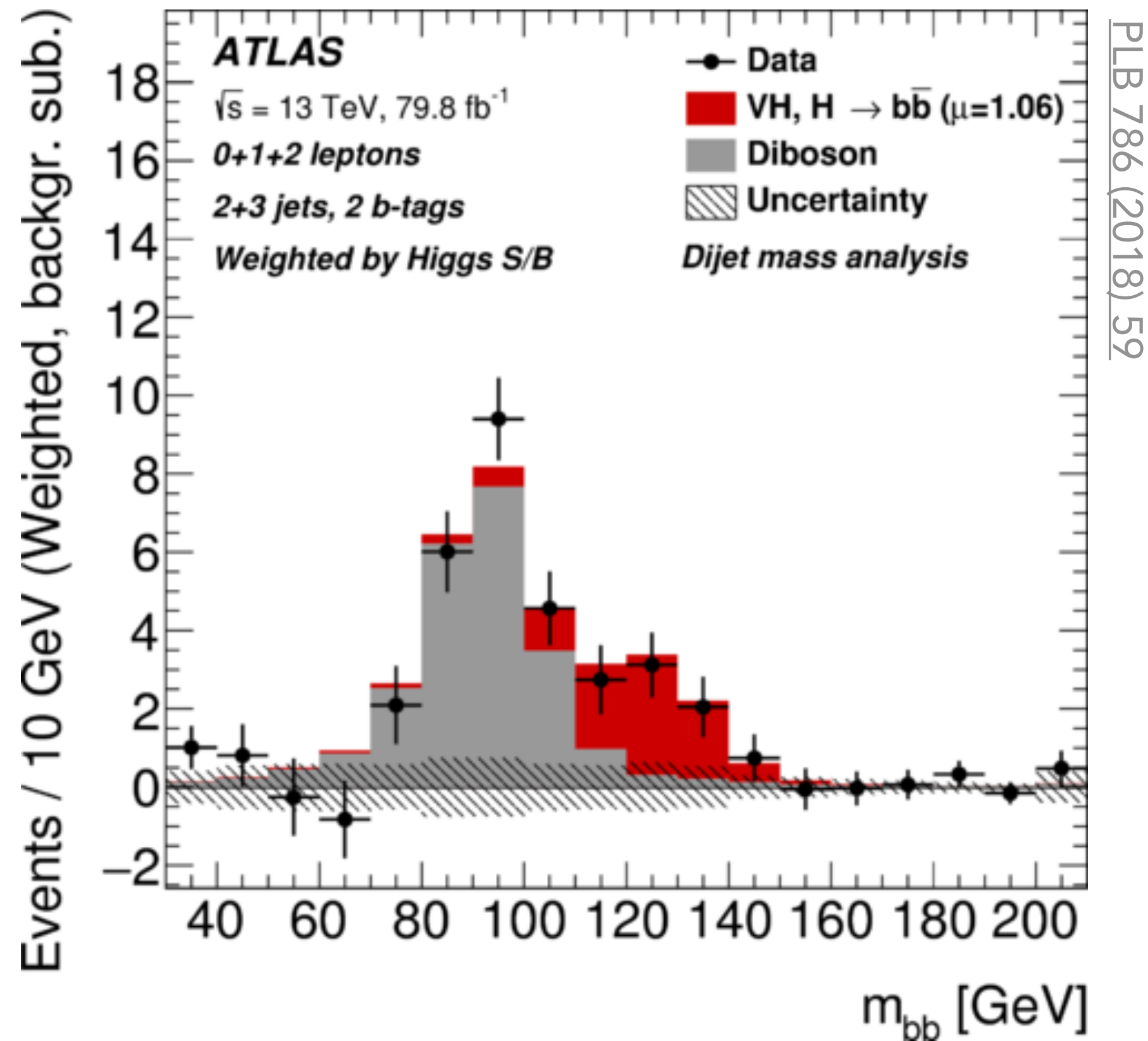
NATIONAL
ACCELERATOR
LABORATORY

Measuring $H \rightarrow b\bar{b}$ constrains **bottom Yukawa**



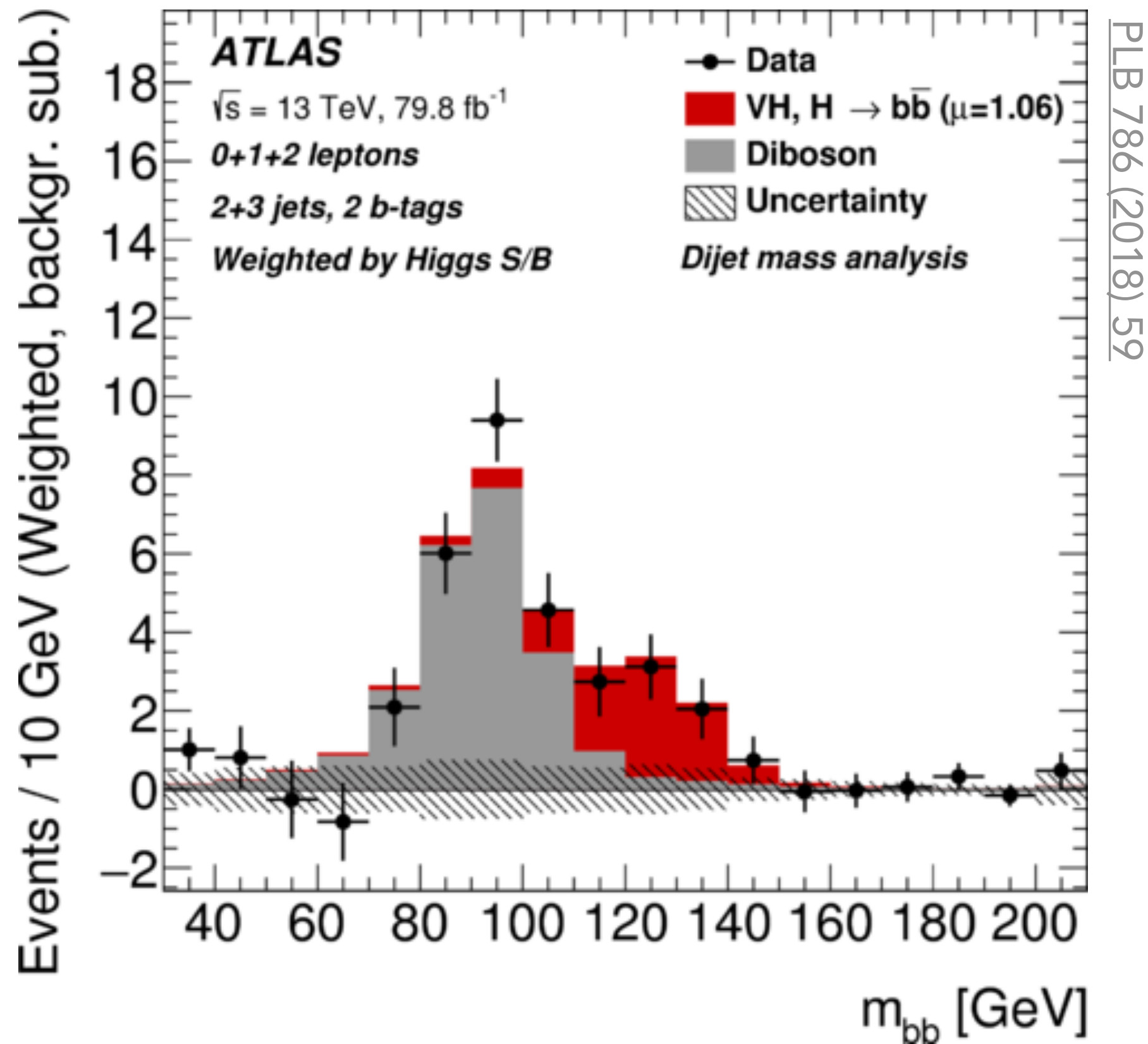
Physics motivation

Measuring $H \rightarrow b\bar{b}$ constrains **bottom Yukawa**



Limited by **poor jet momentum resolution**

Measuring $H \rightarrow b\bar{b}$ constrains **bottom Yukawa** **Di-Higgs** production is a critical target, gives handle on Higgs **self-coupling**



	bb	WW	$\tau\tau$	ZZ	$\gamma\gamma$
bb	34%	4.6%	0.39%	0.069%	0.0005%
WW	25%	4.6%	0.33%	0.012%	
$\tau\tau$	7.3%	2.7%	0.39%		
ZZ	3.1%	1.1%	0.33%	0.069%	
$\gamma\gamma$	0.26%	0.10%	0.028%	0.012%	0.0005%

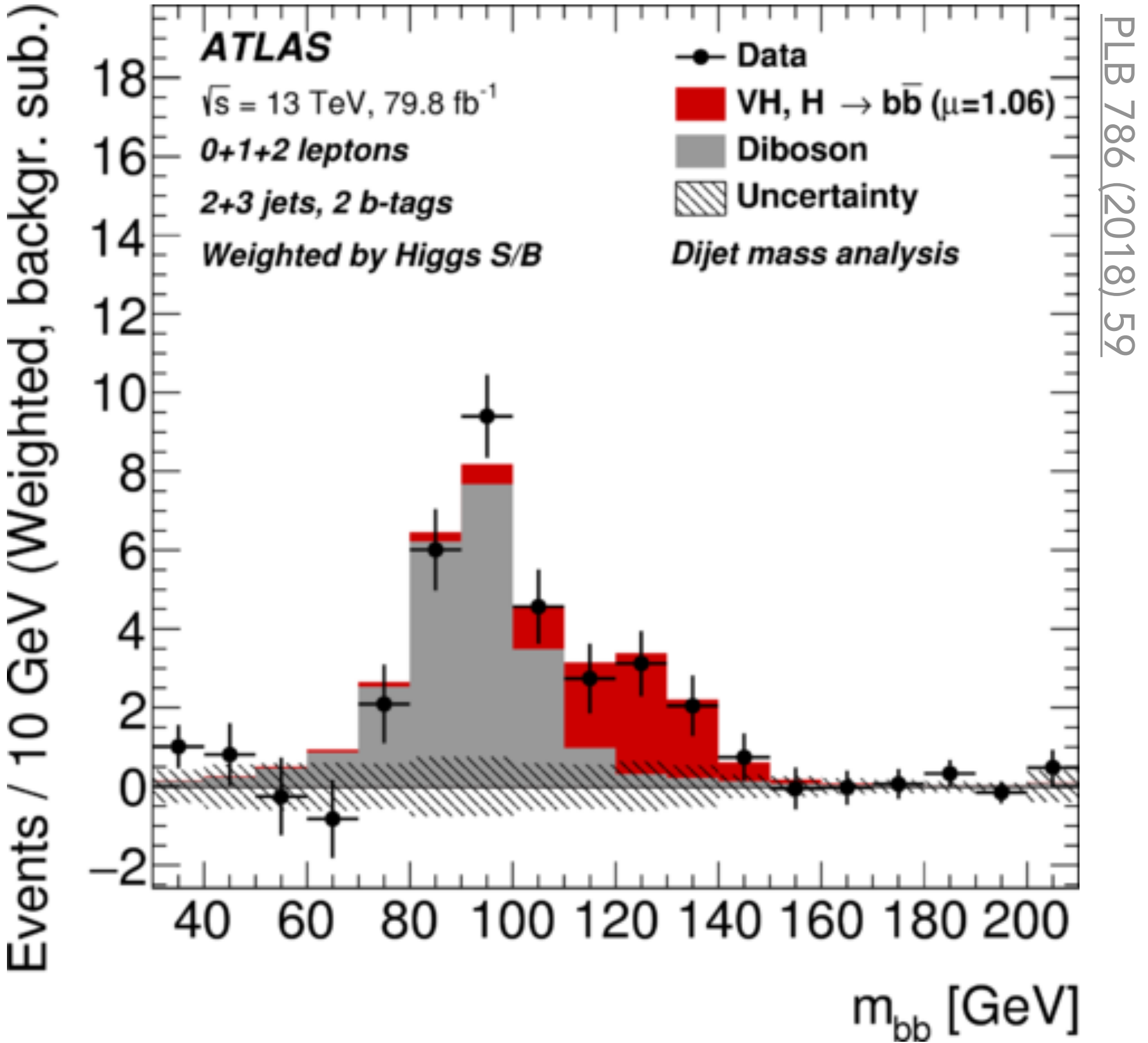
70%! Branching fractions of the the two Higgs

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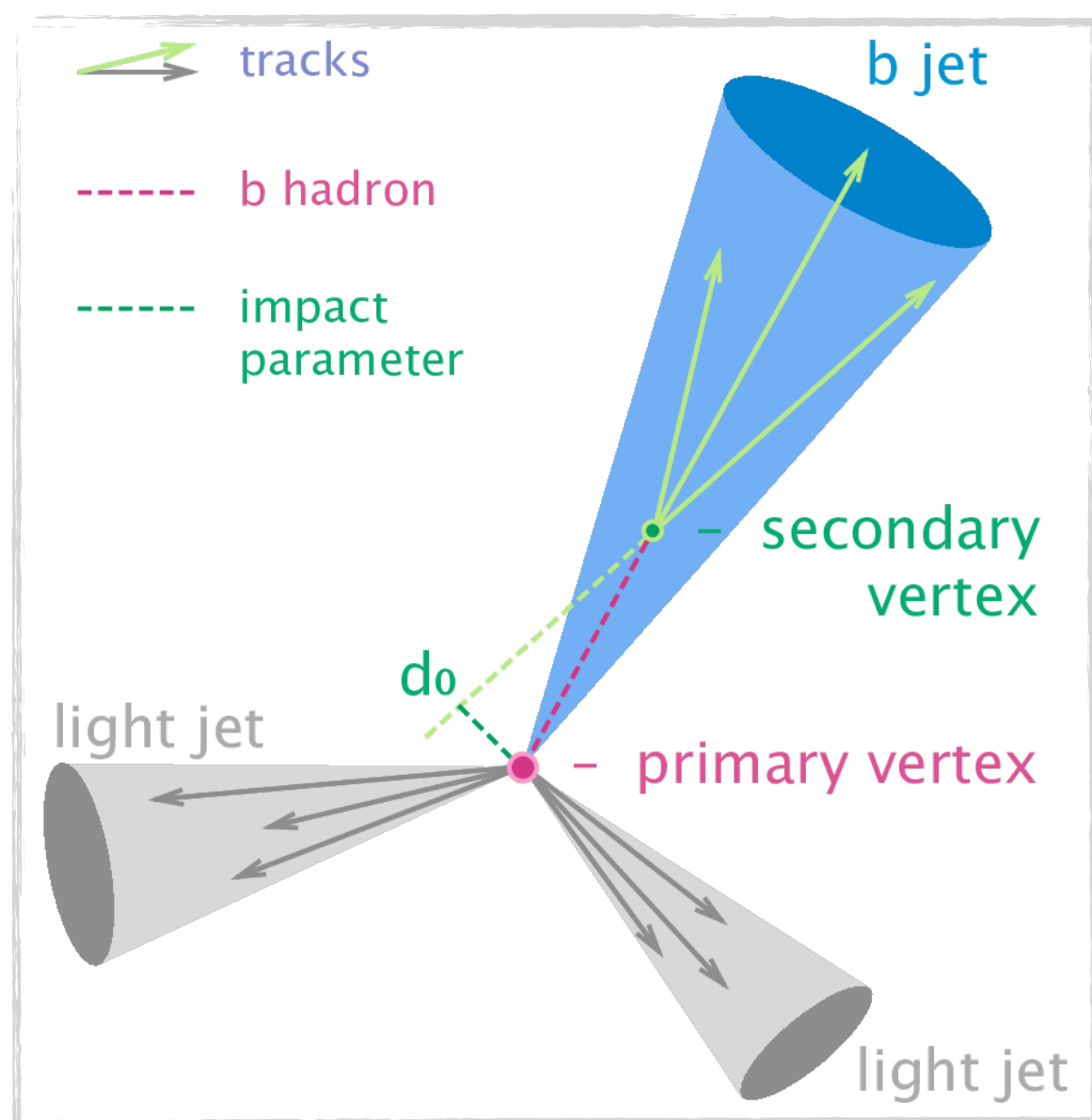
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Improving the **reconstruction of b-quark jets** has huge impact

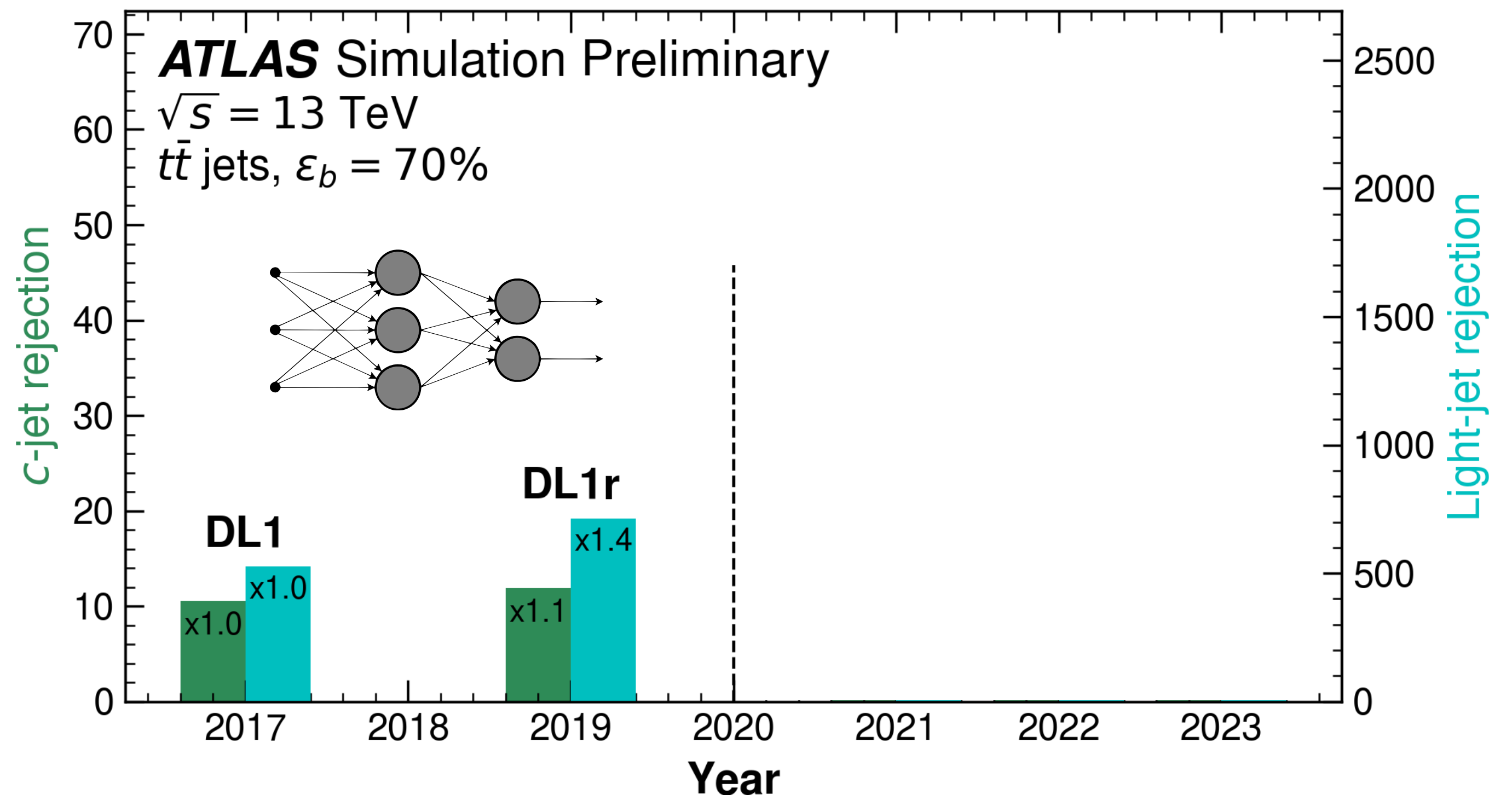
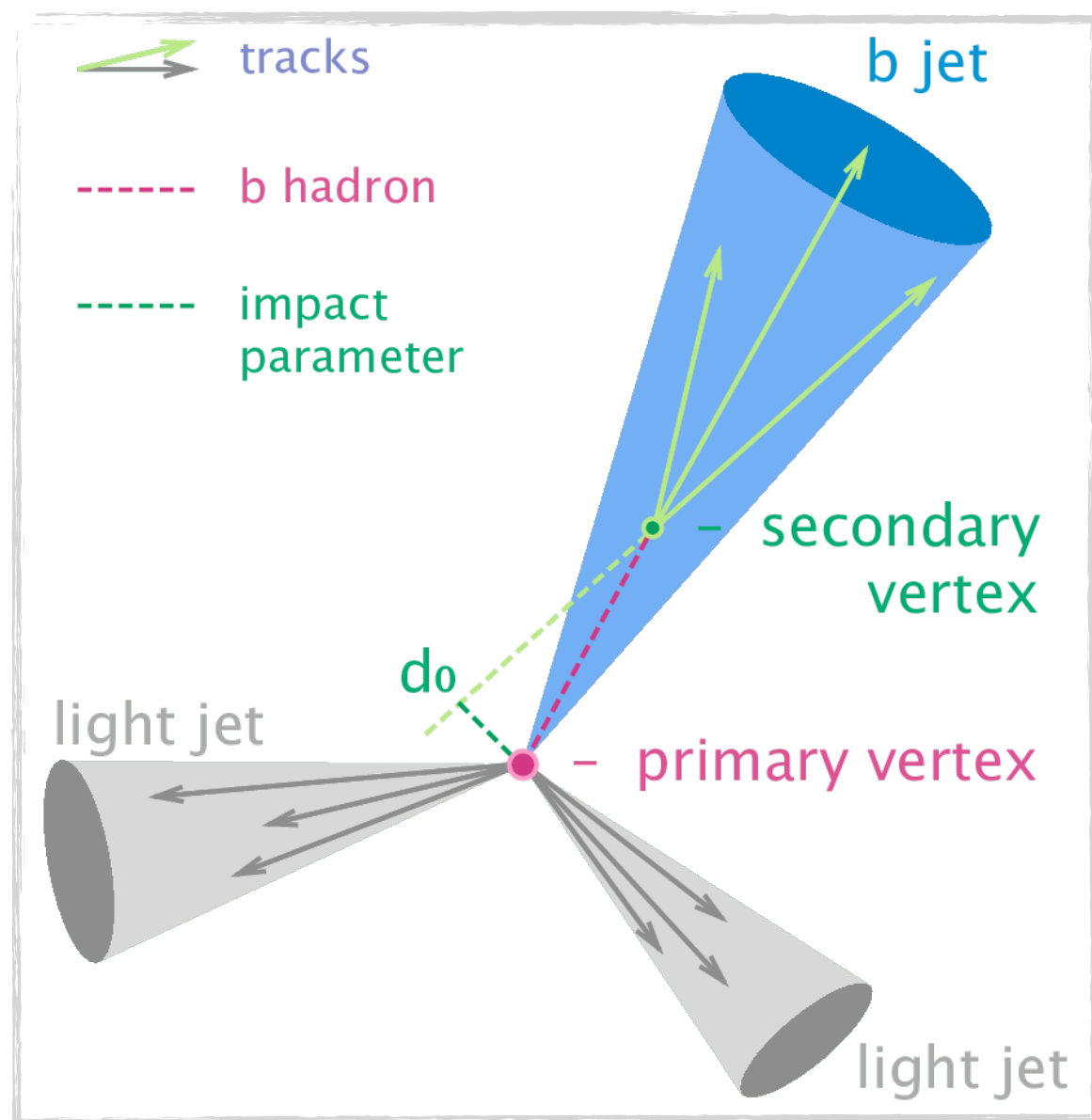
Machine learning for b-jets

- ◆ Identification of b-jets has had a long history of using ML
 - Secondary vertices, many tracks and unique radiation pattern product **rich substructure**



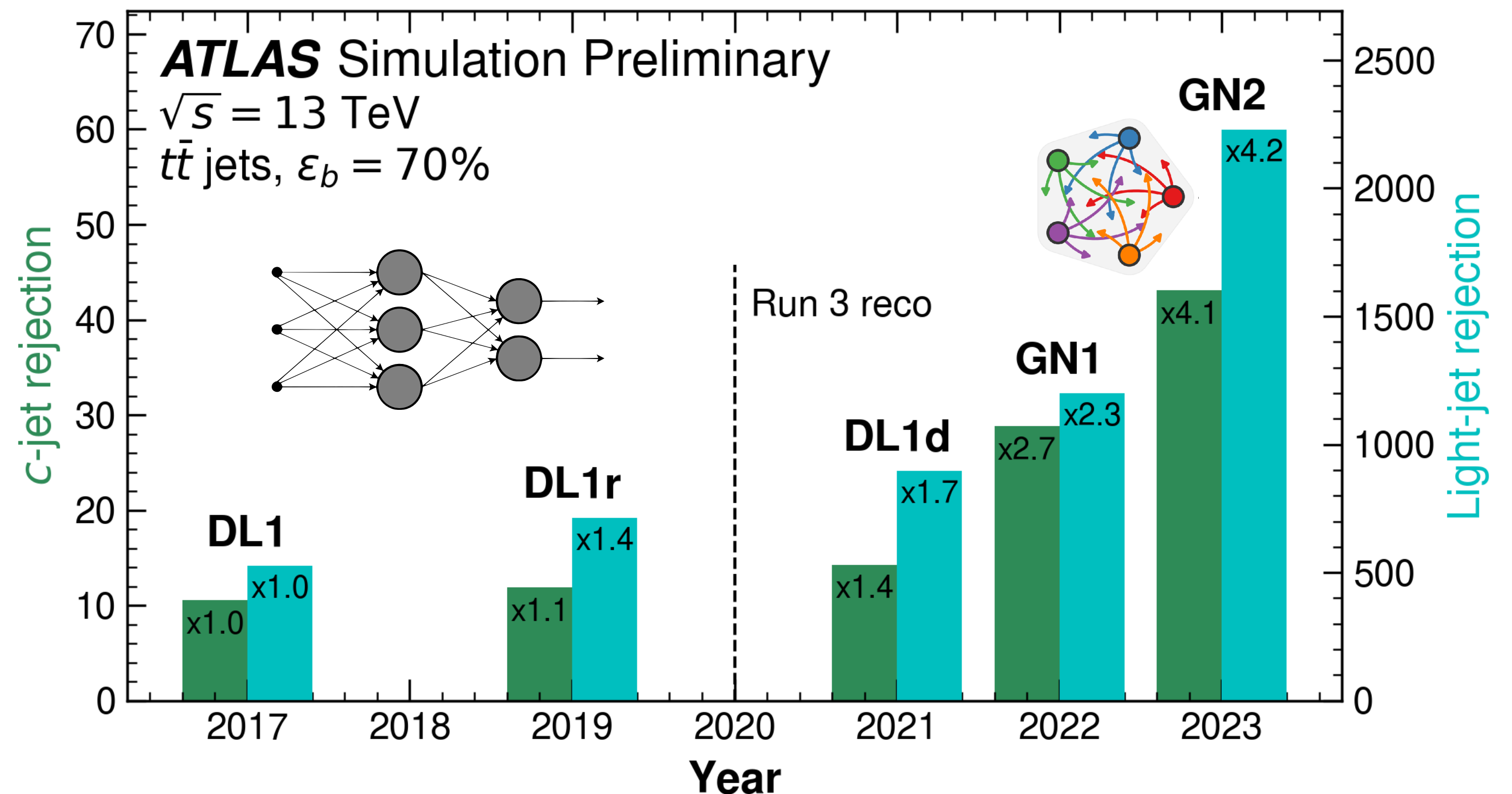
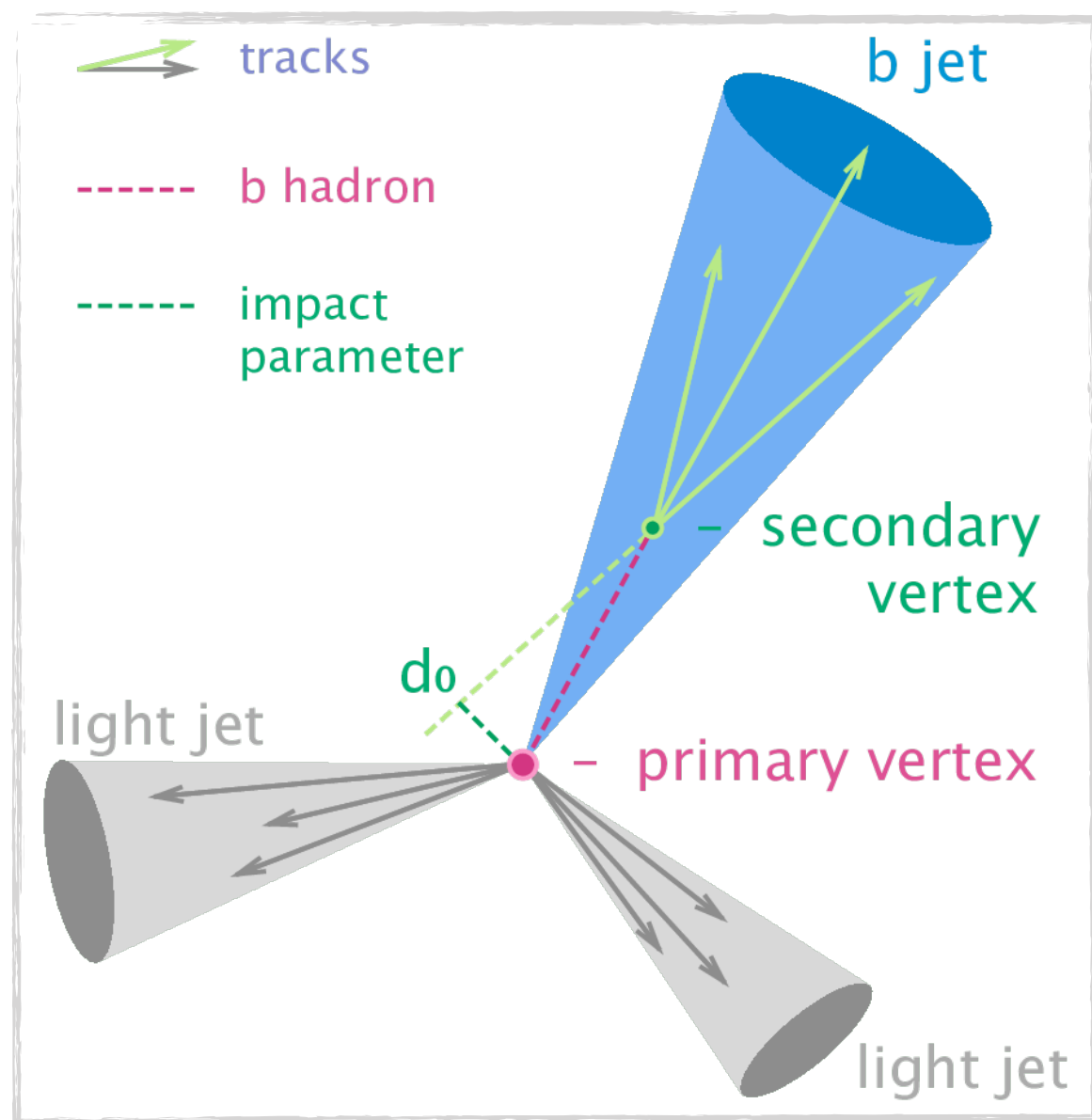
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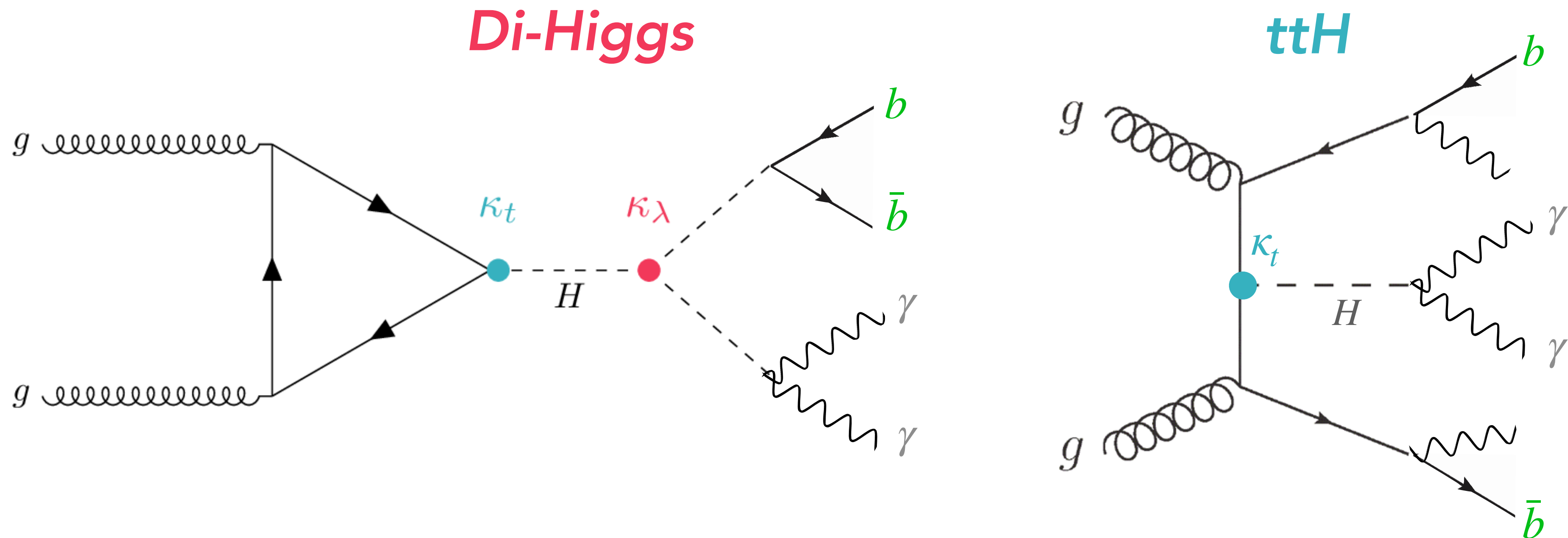
Machine learning for b-jets

- ◆ Identification of b-jets has had a long history of using ML
 - Secondary vertices, many tracks and unique radiation pattern product **rich substructure**
- ◆ Flavor classification has dramatically improved with graph and transformer neural networks trained on low-level information → **apply to p_T regression**



The limits of flavor tagging

- ◆ In searches for Di-Higgs, single Higgs is now a background
 - Not improved with light-jet rejection - primary differentiator is $m_{b\bar{b}}$!



Need to exploit **well-resolved kinematics** to separate and exploit complementarity



ATLAS PUB Note

ATL-PHYS-PUB-2024-015

27th July 2024

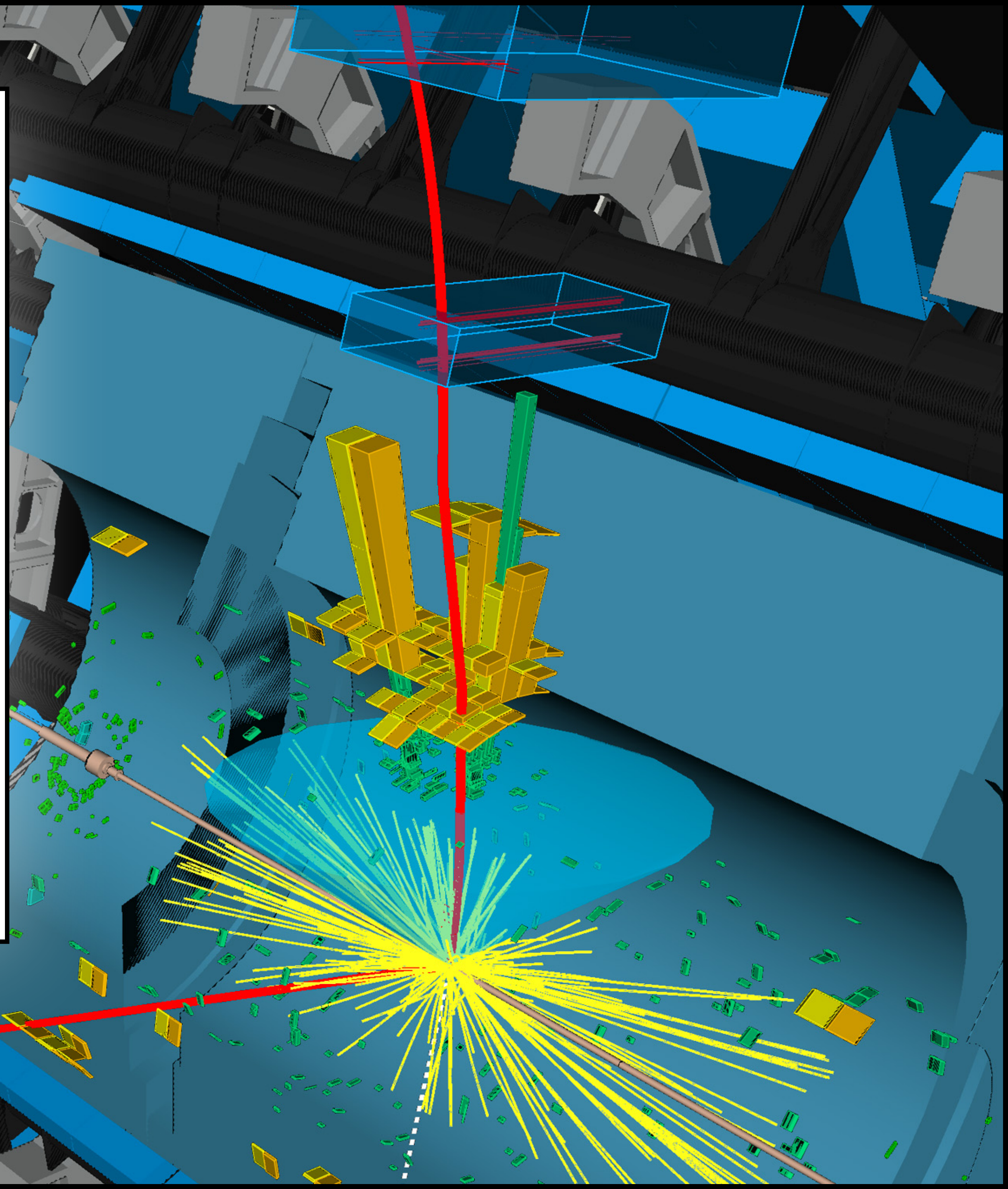


Transformer networks for constituent-based b -jet calibration with the ATLAS detector

The ATLAS Collaboration

The precise measurement of a jet's kinematics is a critical component of the physics program based on proton-proton collision data recorded by the ATLAS detector at the Large Hadron Collider. The determination of the energy and mass of jets containing bottom quarks b -jets is particularly difficult as, for example, they have different radiation patterns compared to the average jet and can contain heavy-flavour decays into a charged lepton and an unobserved neutrino. This document reports on a novel calibration technique for jets focusing on b -jets using transformer-based neural networks trained on simulation samples to correct reconstructed jet properties to the true values. Separate simulation-based regression methods have been developed to estimate the transverse momentum of small-radius jets and the transverse momentum and mass of large-radius jets. In both cases, the regression methods move the median measurement closer to the true value. A relative resolution improvement with respect to the nominal calibration between 18% and 31%, depending on the transverse momentum, is demonstrated for small-radius jets. Both the large-radius jet transverse momentum and mass resolution are shown to improve by 25–35%.

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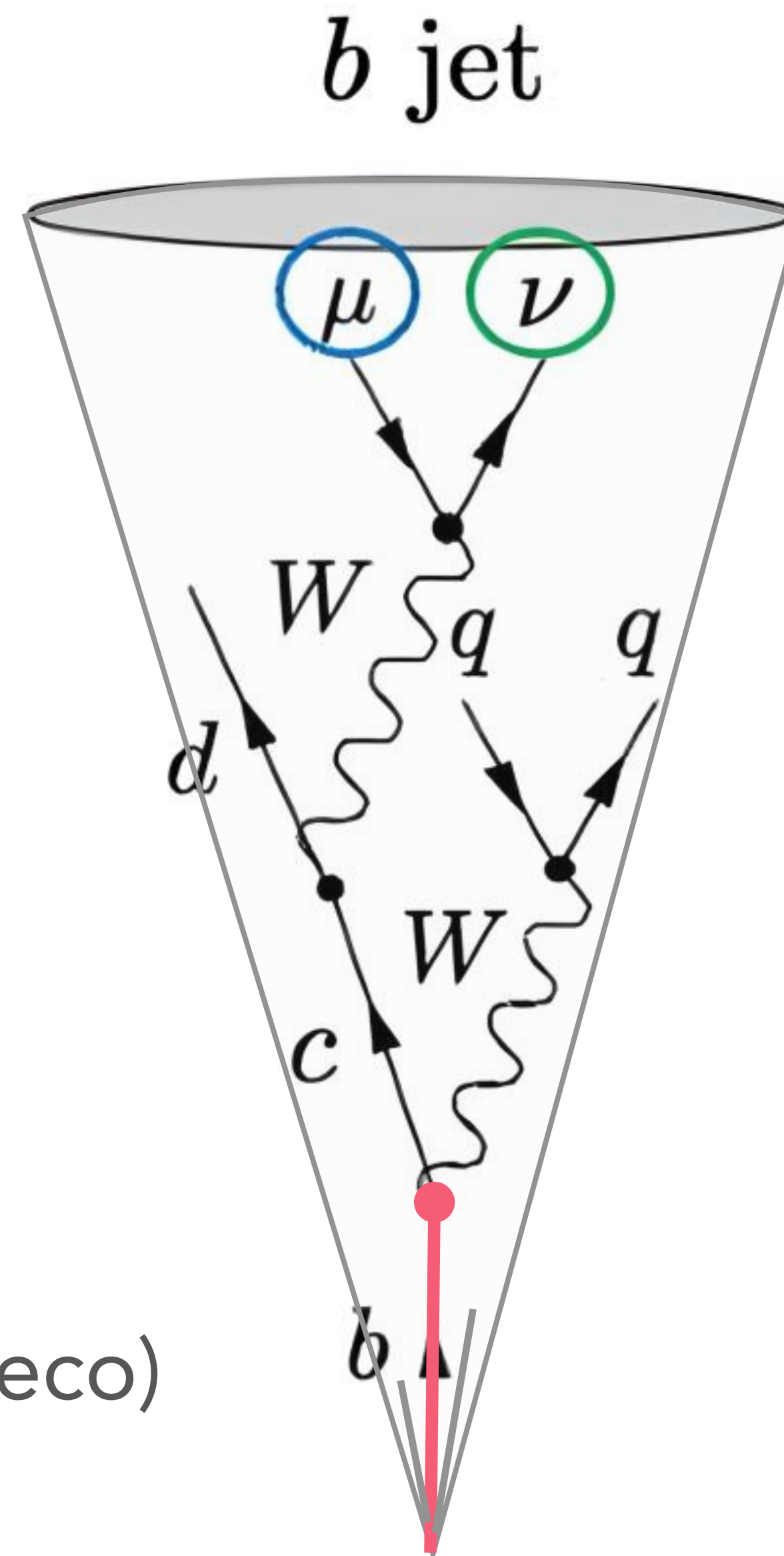
Physics of b-jets

◆ Unique due to **secondary vertex**

- B-hadron carries $>80\%$ of jet energy
- Semi-leptonic decays ($\sim 15\%$ BR),
 ν carries **20%** of the jet energy
- **Charged lepton** should correlate to ν
- Leptons more important than in tagging

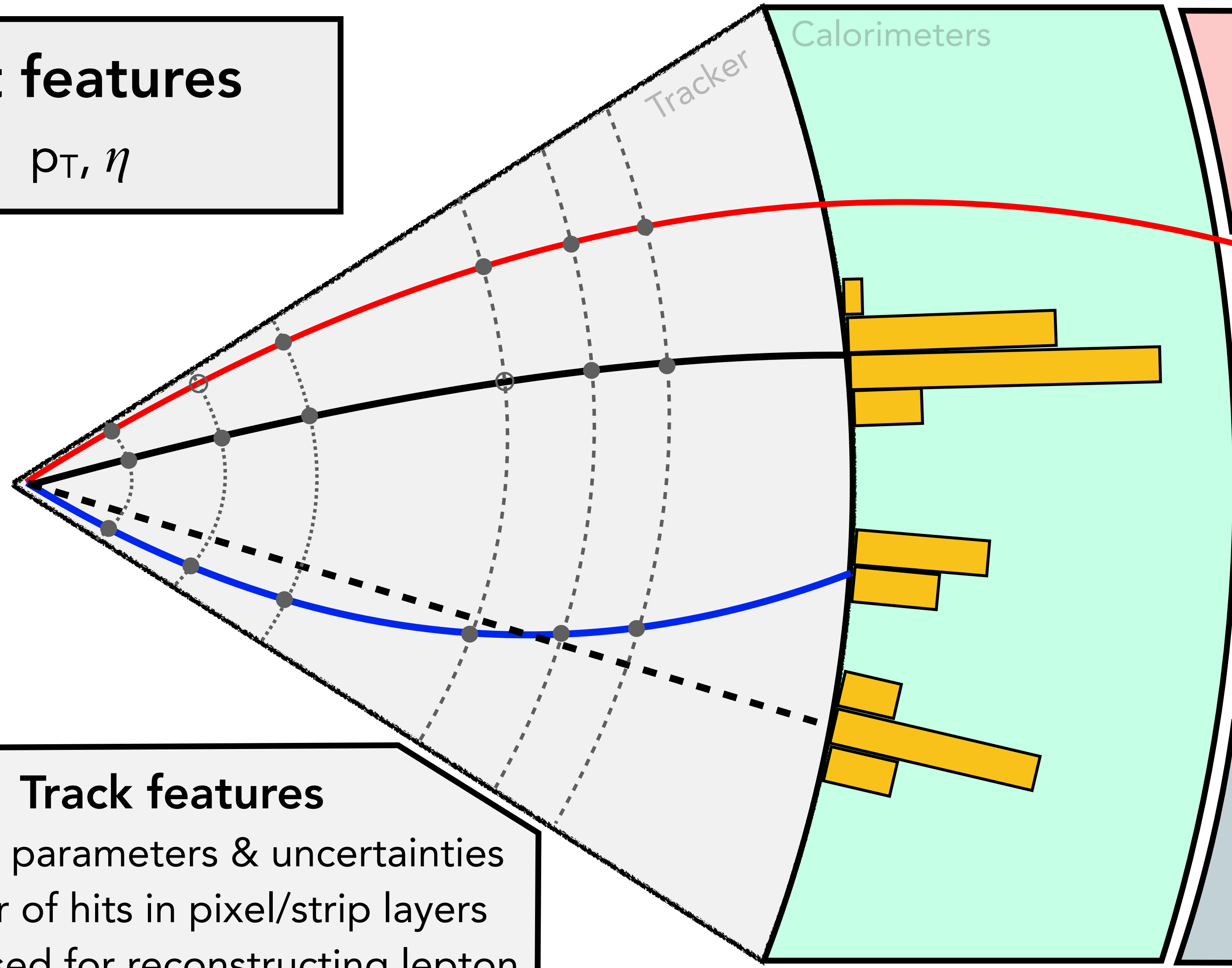
◆ Baseline strategy:

- **μ -in-jet** addition to jet 4-mom
- Coarse-grained correction binned in jet p_T , split into leptonic and hadronic decays (PtReco)



Neural network input features

Jet features
 p_T, η



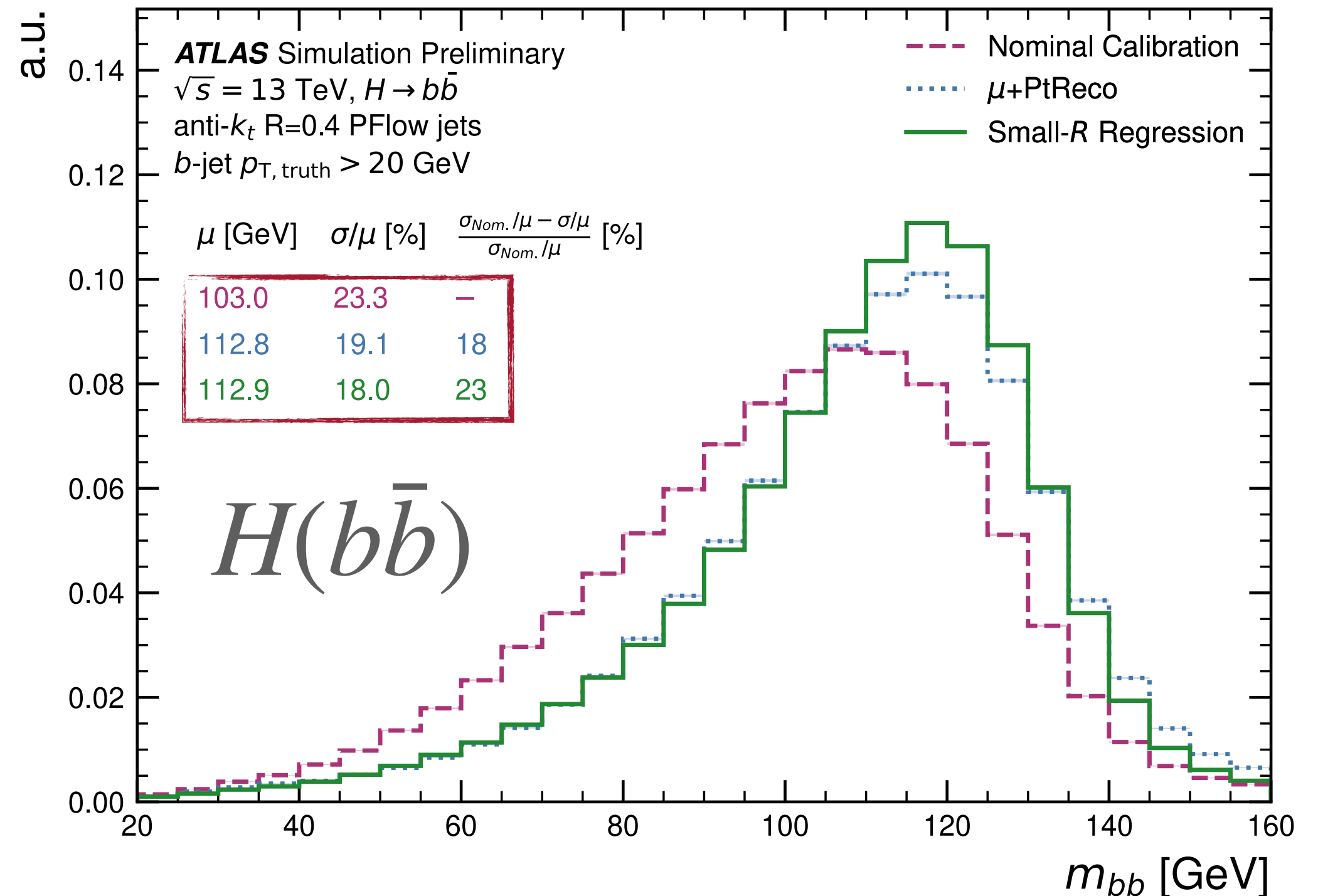
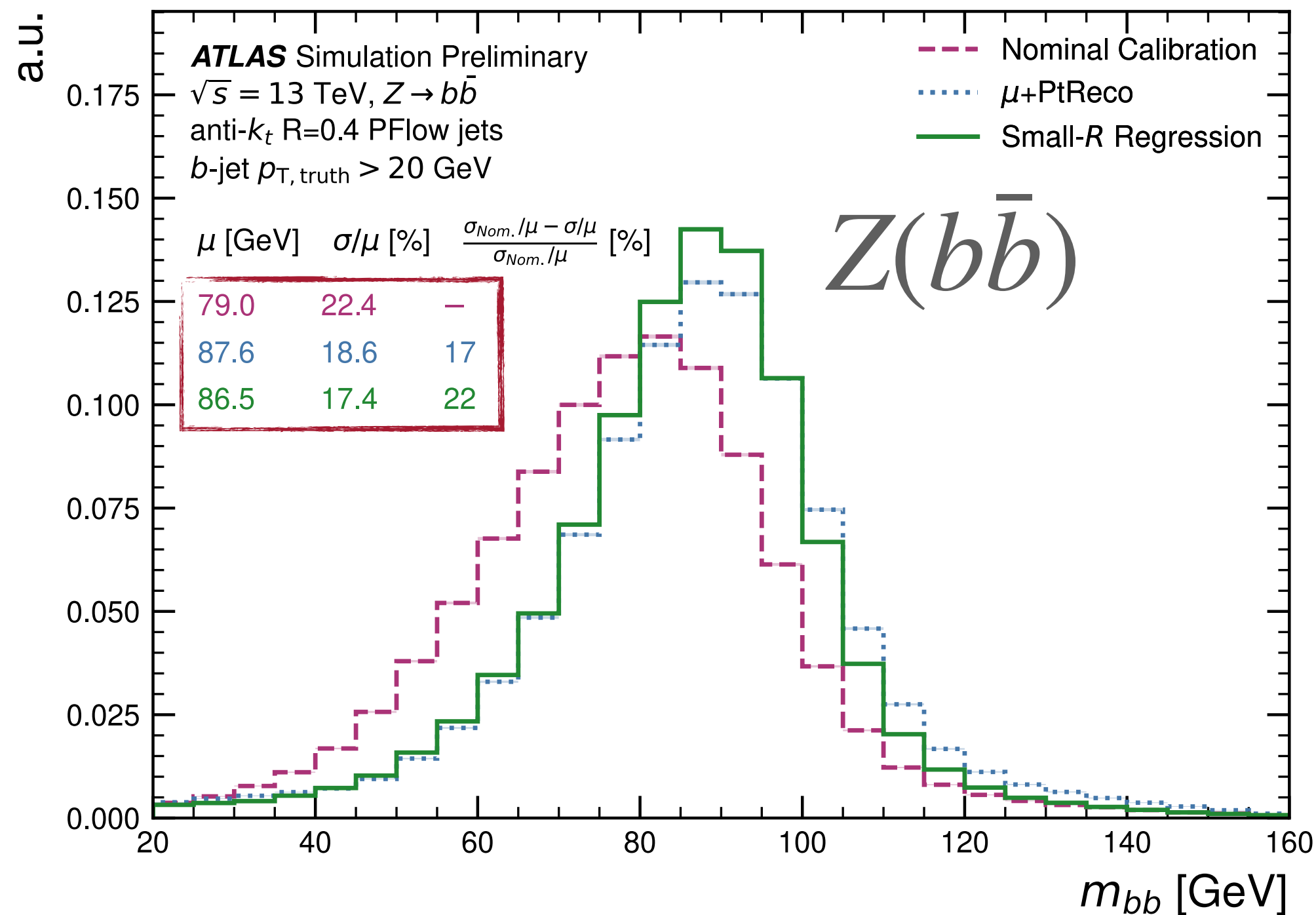
Soft muon features
Kinematics, perigee,
 p_T balance in ID/MS,

Soft electron features
Kinematics, perigee,
 $E/p, E_{ECal}/E_{HCal}$, layer
cluster ratios, p_{HF}

Track features

- Perigee parameters & uncertainties
- Number of hits in pixel/strip layers
- Track used for reconstructing lepton

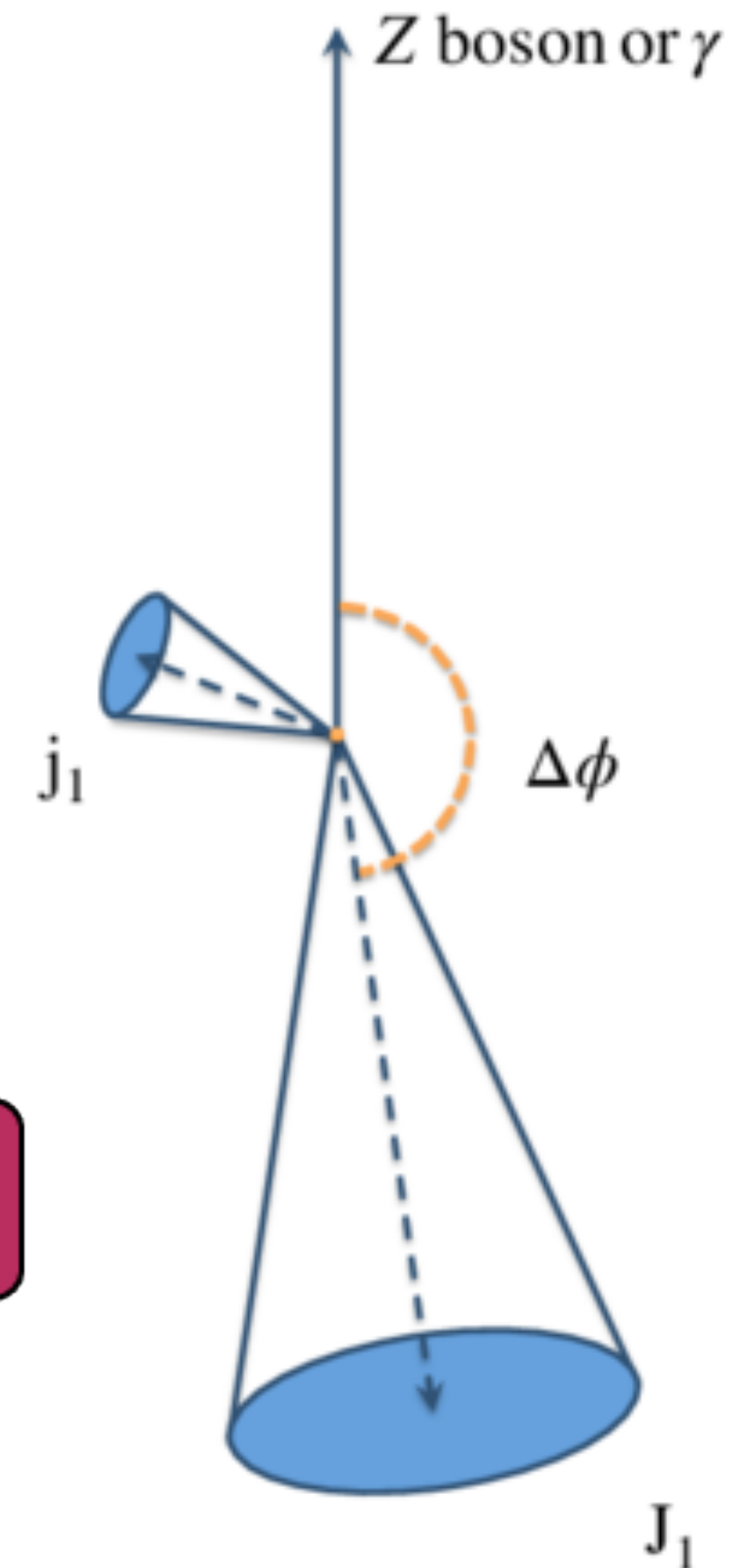
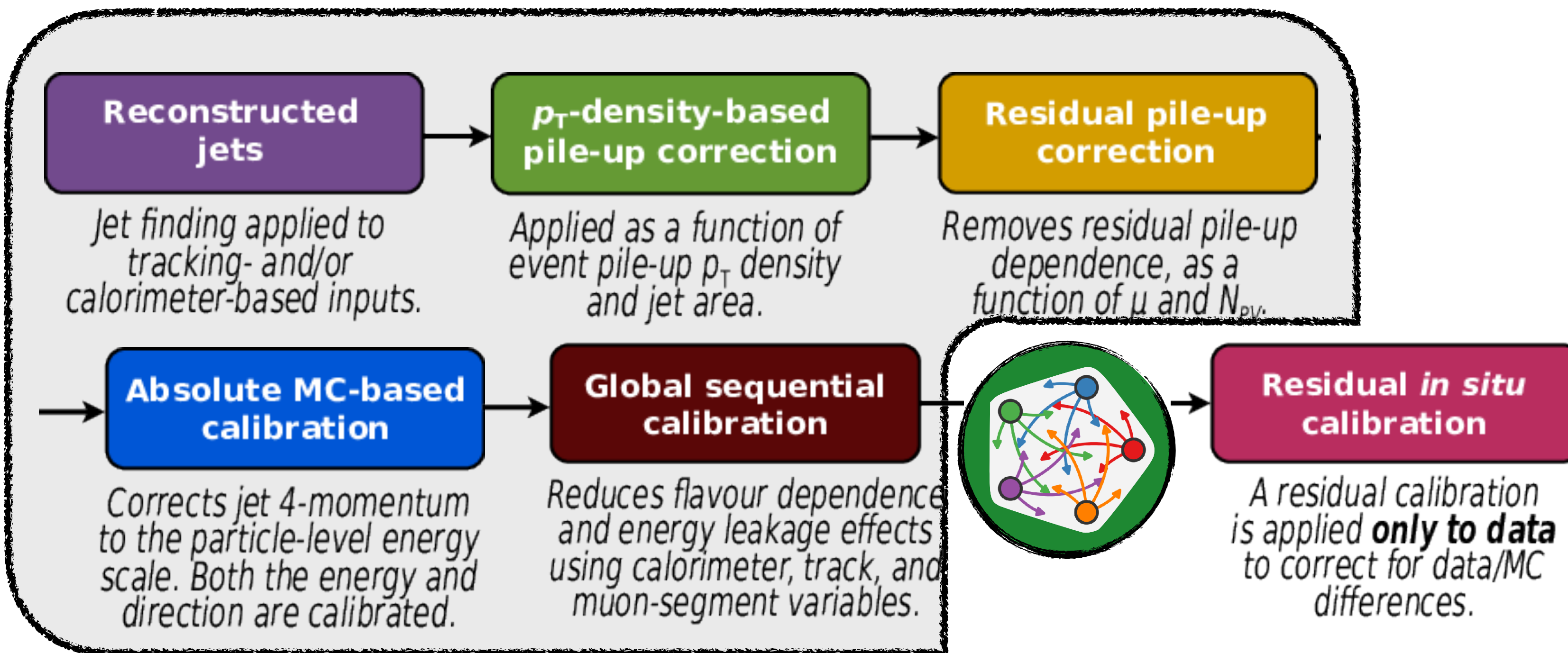
Training dataset
~260M jets from $t\bar{t}, Z$ +jet
Mixture of light, charm,
and b-jets (!)



- ◆ 23% reduction in resolution on the $H(b\bar{b})$ peak!
 - More modest gain of 5% relative to μ +PtReco corrections
 - Can be improved via optimization (Z/H samples in training, calocells)

From AI/ML to physics

- ◆ So far the model only been tested on simulation
 - **Needs calibration** on data for ultimate use for physics!
 - Opportunity to integrate with in-situ, **training on data**
 - Exploring synergies with tagging - **all in one model?**

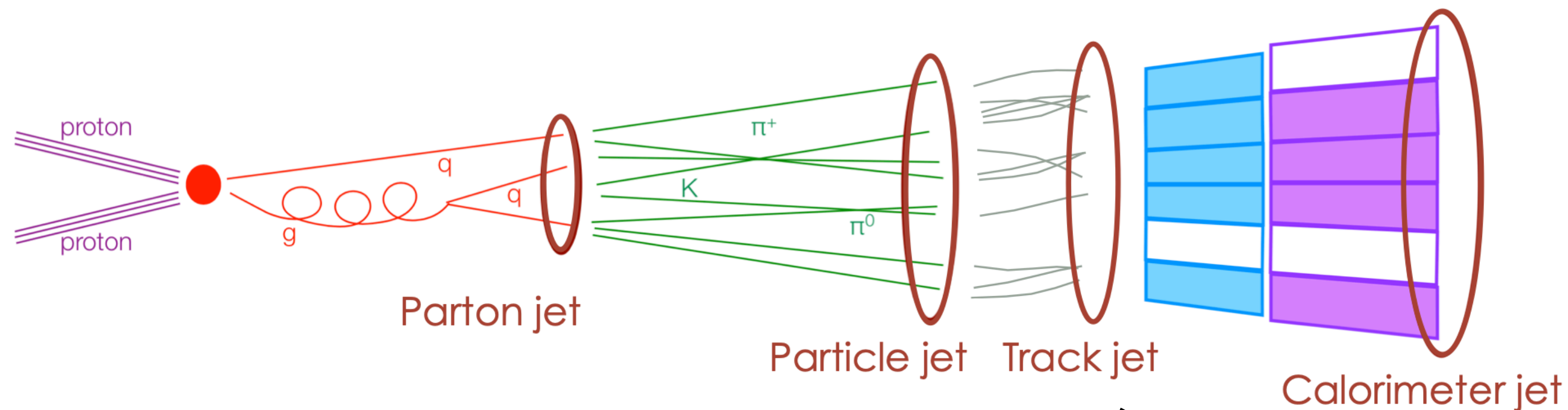


———— Thank you ————

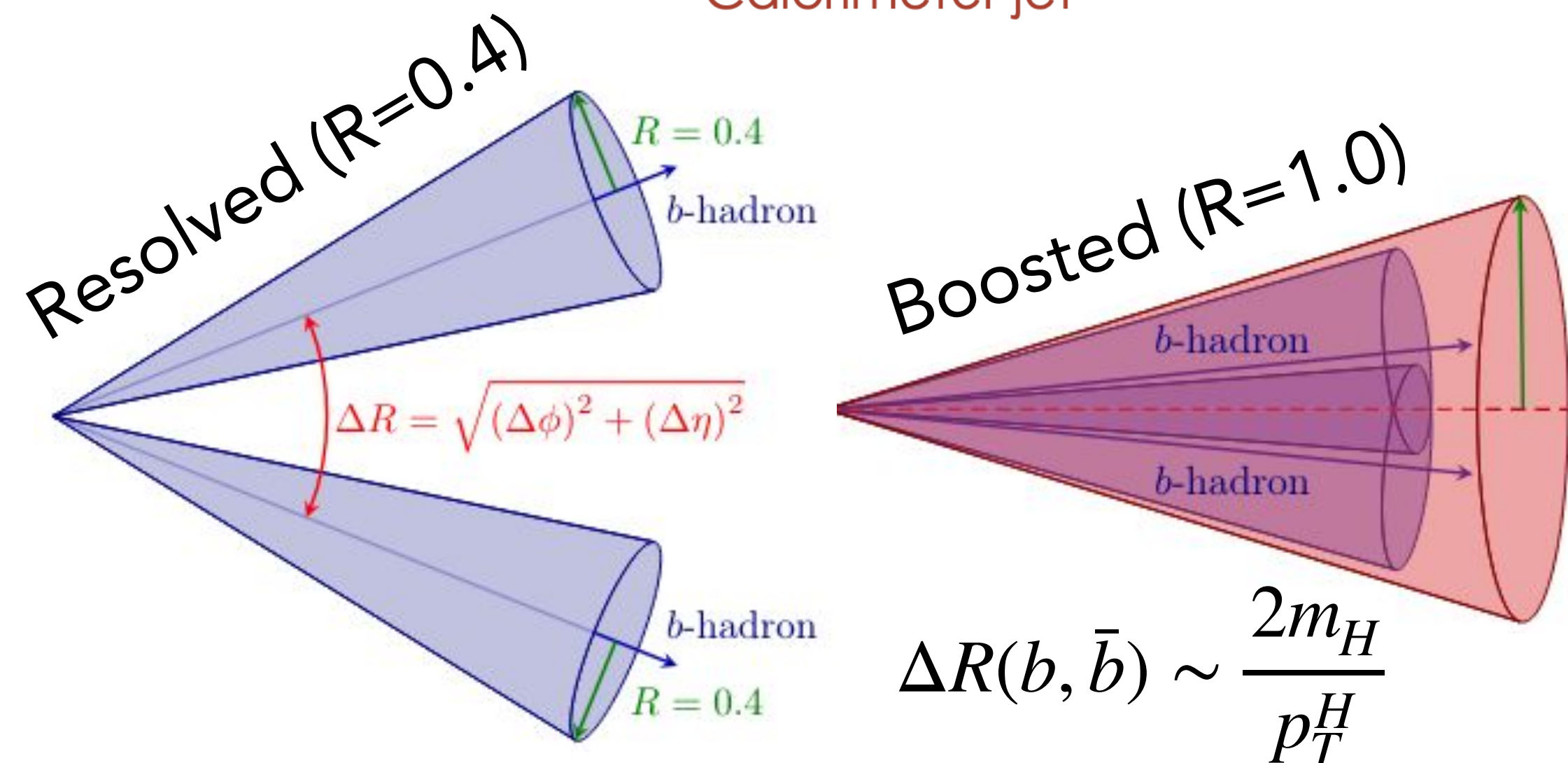
Backup

Jet reconstruction

- ♦ Jets are the most complex objects produced at colliders
 - Needs careful combination of signatures in tracker and calorimeters



- ♦ Cluster constituents using anti- k_T algorithm
 - Use different radius parameters depending on the target phase space (e.g. low/high- p_T Higgs)



[Eur. Phys. J. C 77 \(2017\) 466](#)

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Jet constituents

- ◆ Originally ATLAS only used calorimeter cells for jets

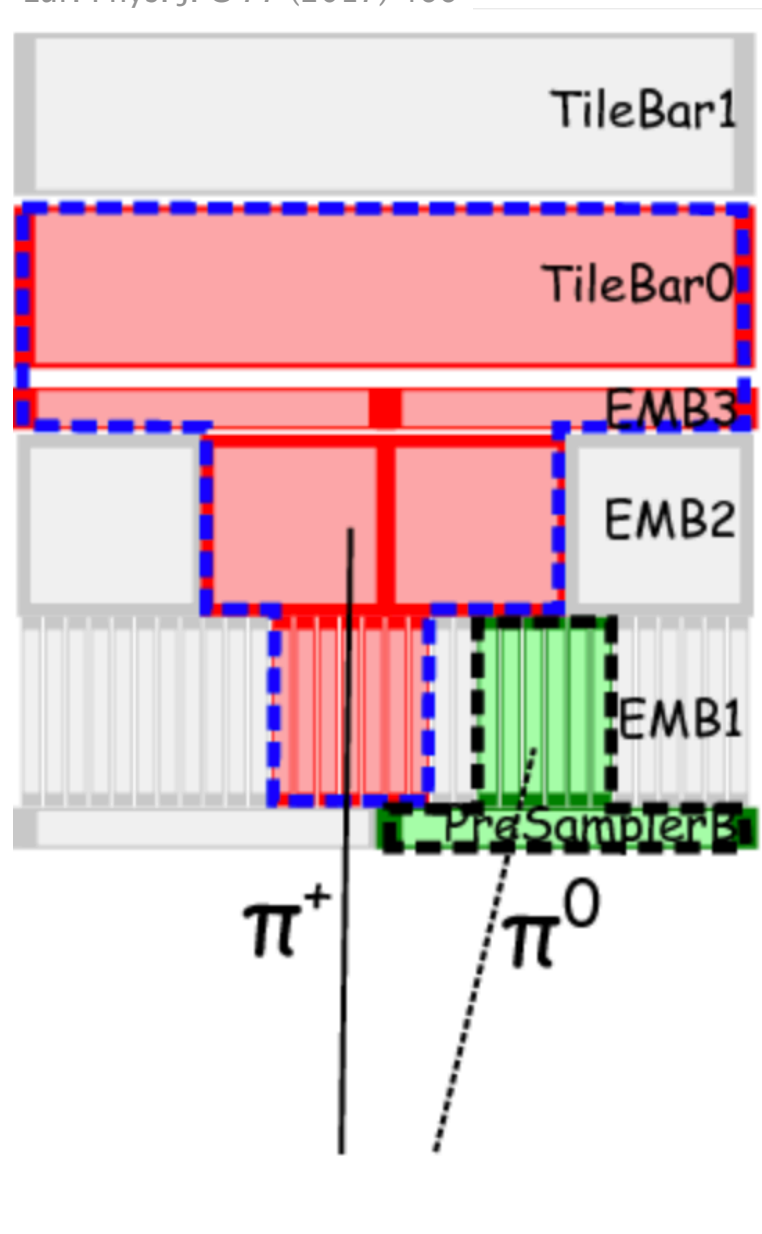
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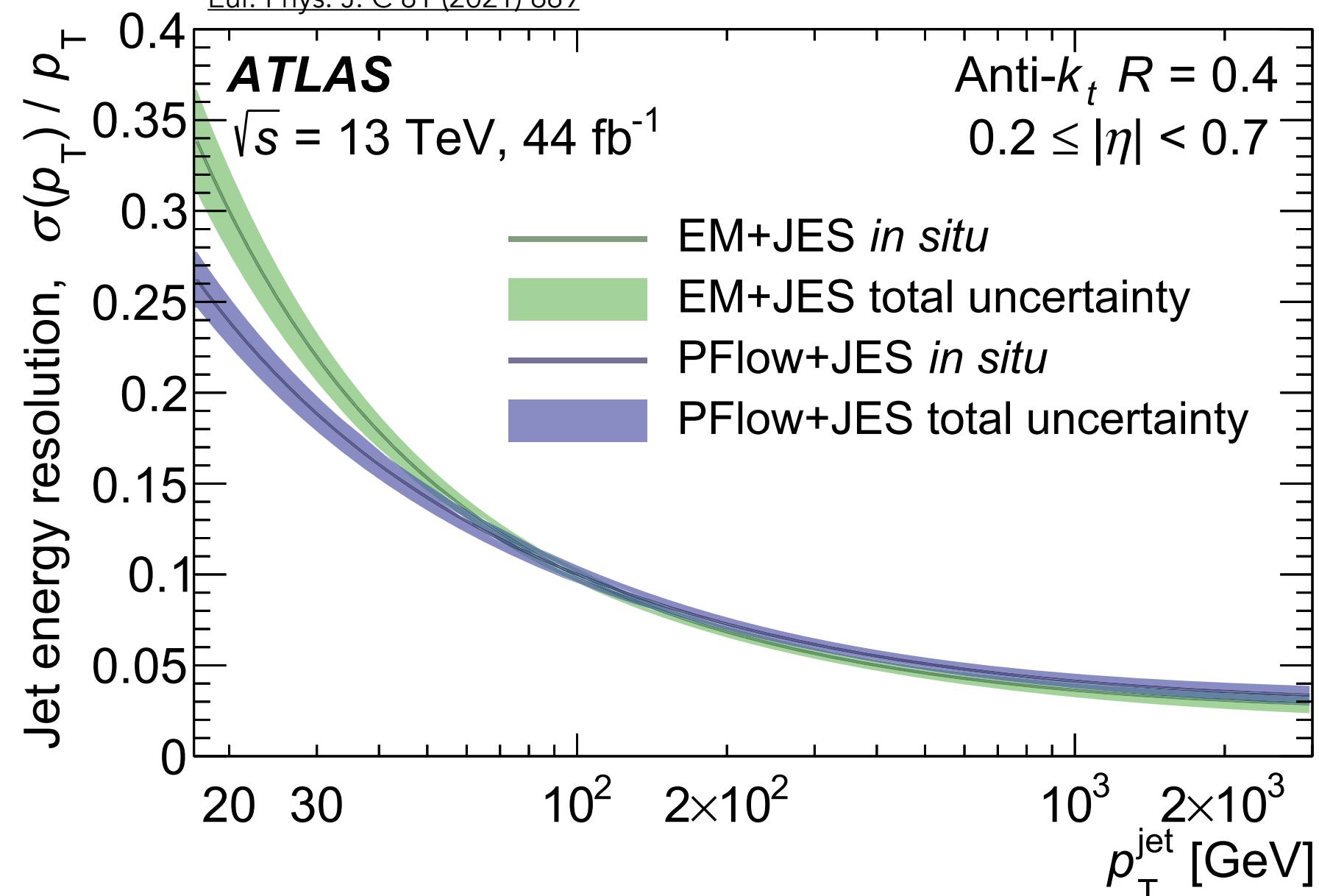
Jet constituents

- Originally ATLAS only used calorimeter cells for jets
- Now we are using **particle flow** objects: combine tracks and calo-clusters
 - Avoid double-counting energy/momentum, boosts performance at low- p_T (used for Small-R)

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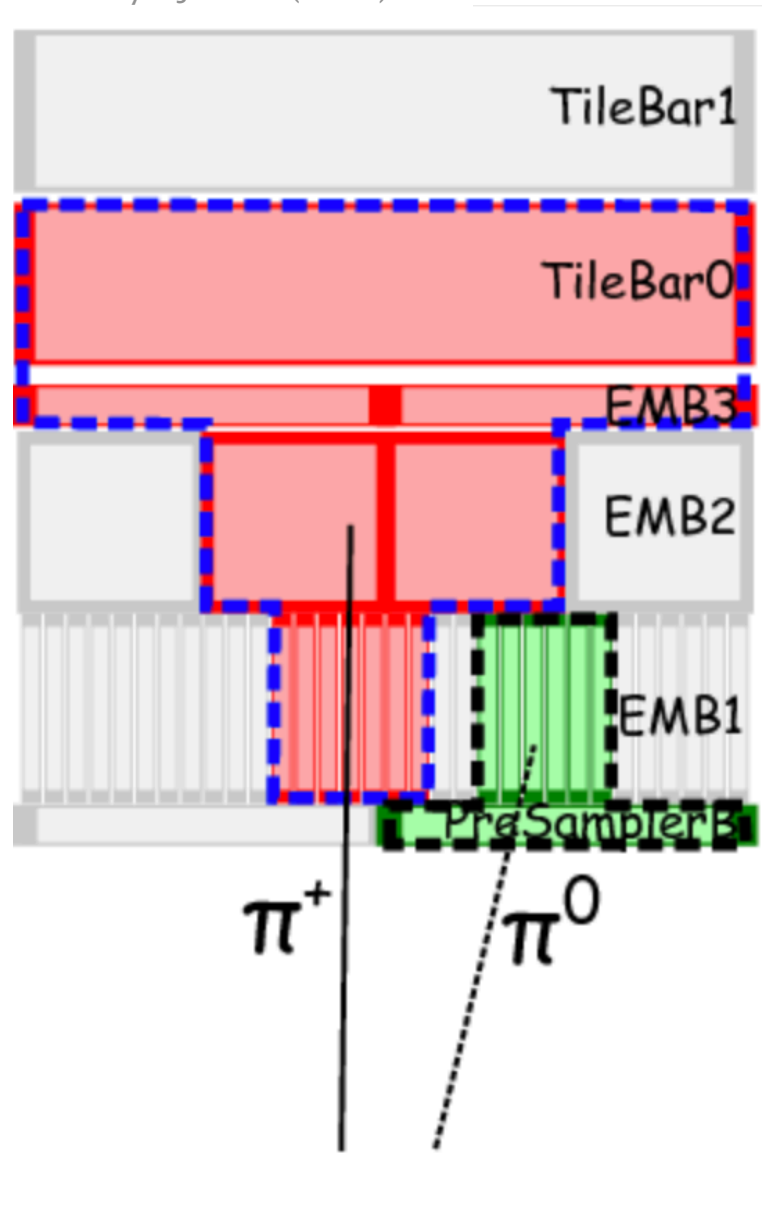


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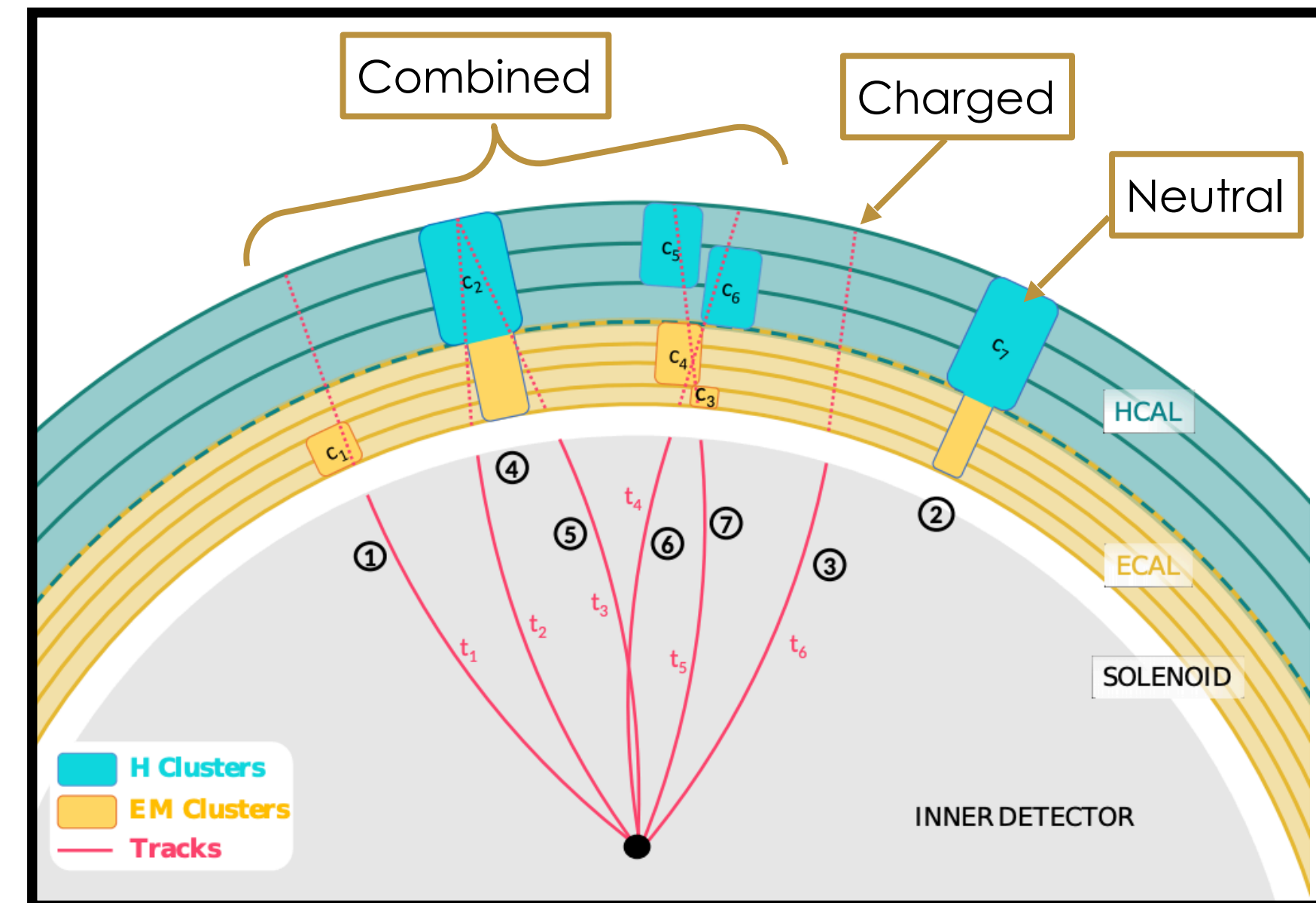
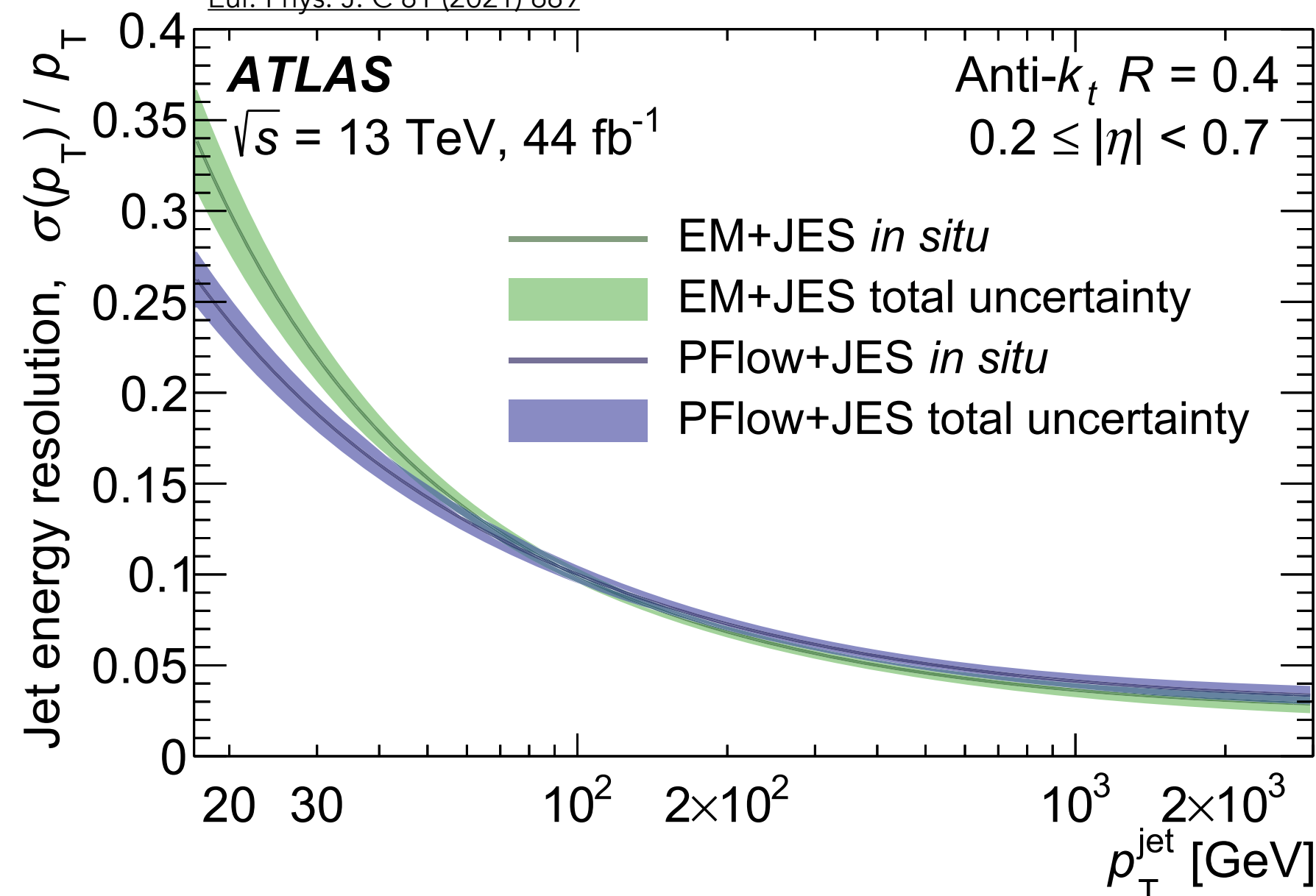
Jet constituents

- Originally ATLAS only used calorimeter cells for jets
- Now we are using **particle flow** objects: combine tracks and calo-clusters
 - Avoid double-counting energy/momentum, boosts performance at low- p_T (used for Small-R)
- Recently developed **unified flow** objects, leverage angular resolution of tracker and energy resolution of calorimeter at high- p_T (used for Large-R jets)

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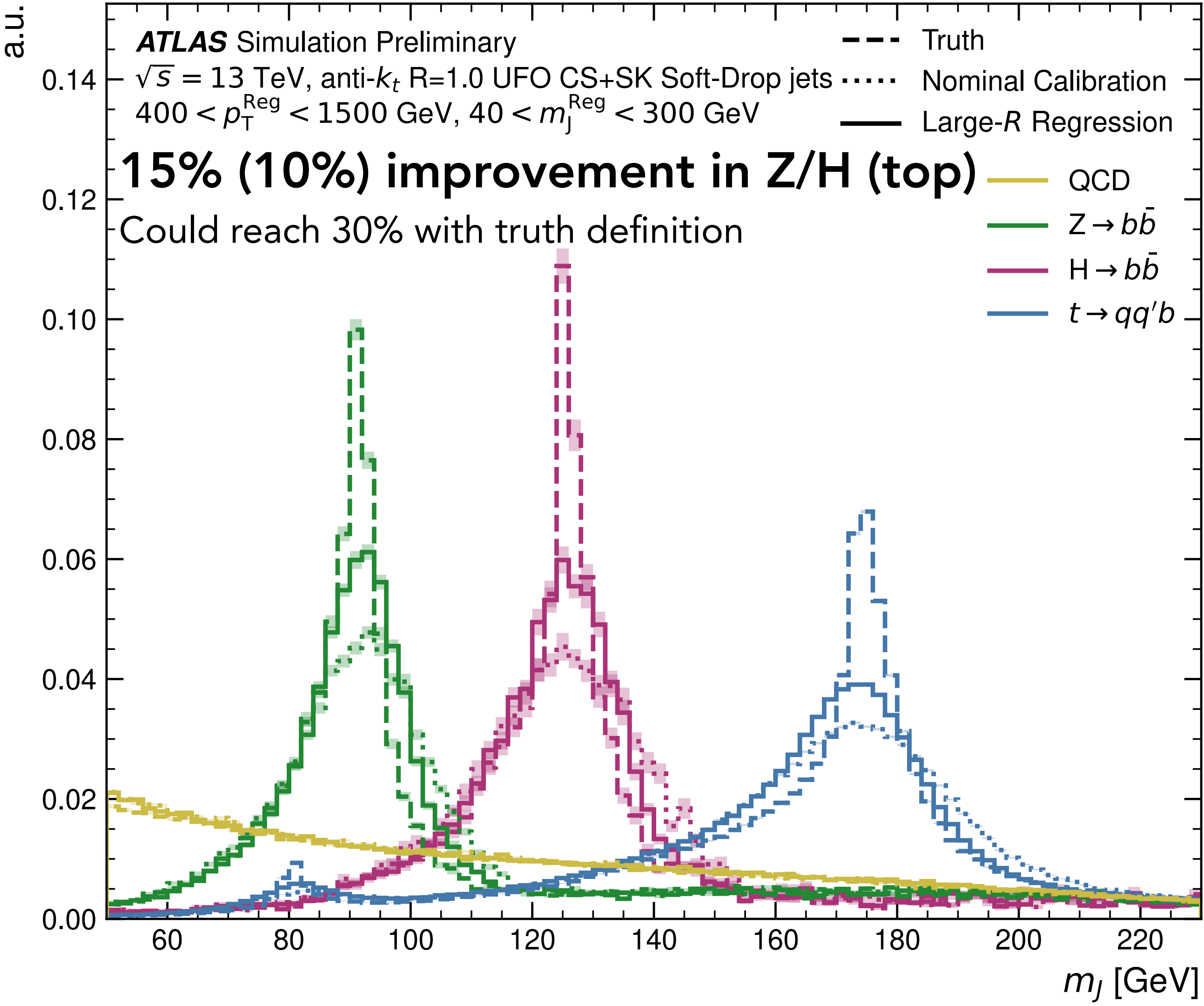


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Large-R resonance spectrum



- ◆ Evaluate on SM resonances (Z/H/top)
 - Significant sharpening of Z/H mass peaks
 - Still a long way to go to reach truth-level
- ◆ No mass sculpting in the QCD continuum
 - Use of flat-mass samples eliminates SM mass point bias

Neural network architecture

◆ Based on ATLAS flavor-tagging architecture

- anti- k_T $R=0.4$ PFlow (small- R) jets use **track** constituents
- anti- k_T $R=1.0$ UFO (large- R) jets use **track** and **flow object** constituents

Constituent embedding

