Systematic Effects in Jet Tagging with the ATLAS Detector

US LHC User's Association Annual Meeting
Fermilab, December 14th 2023

Kevin Greif, on behalf of the ATLAS collaboration

The Jet Tagging Landscape (As of 2019)

arxiv:1902.09914

SciPost Physics | Submission

The Machine Learning Landscape of Top Taggers

G. Kasieczka (ed)[1], T. Plehn (ed)[2], A. Butter[2], K. Cranmer[3], D. Debnath[4], B. M. Dillon[5], M. Fairbairn[6], D. A. Faroughy[5], W. Fedorko[7], C. Gay[7], L. Gouskos[8], J. F. Kamenik[5,9], P. T. Komiske[10], S. Leiss[1], A. Lister[7], S. Macaluso[3,4], E. M. Metodiev[10], L. Moore[11], B. Nachman,[12,13], K. Nordström[14,15], J. Pearkes[7], H. Qu[8], Y. Rath[16], M. Rieger[16], D. Shih[4], J. M. Thompson[2], and S. Varma[6]

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For a systematic experimental application of these tools **our focus will be on a new set of questions related to training data, benchmarking, calibration, systematics, etc."**

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This Talk!

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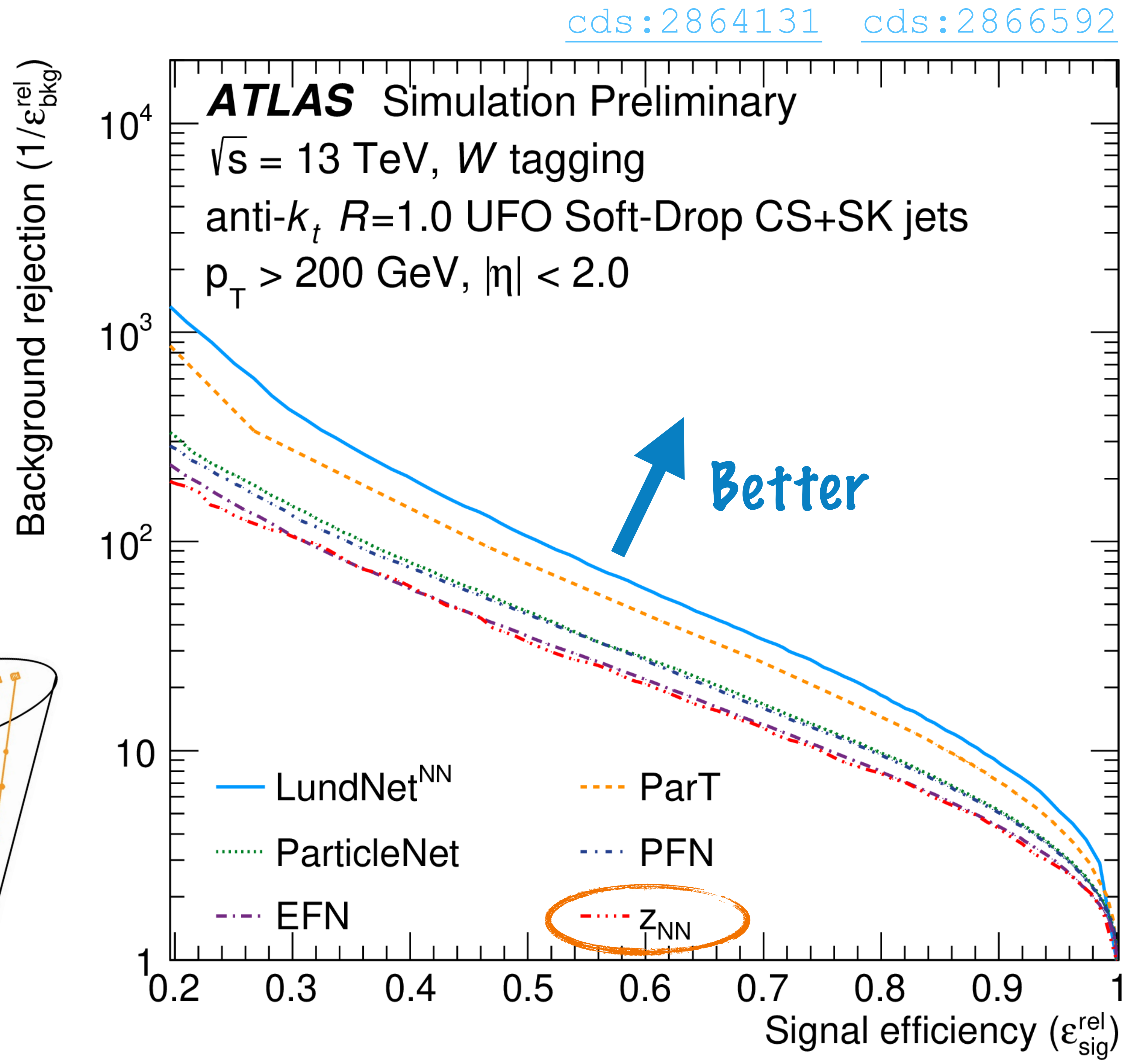
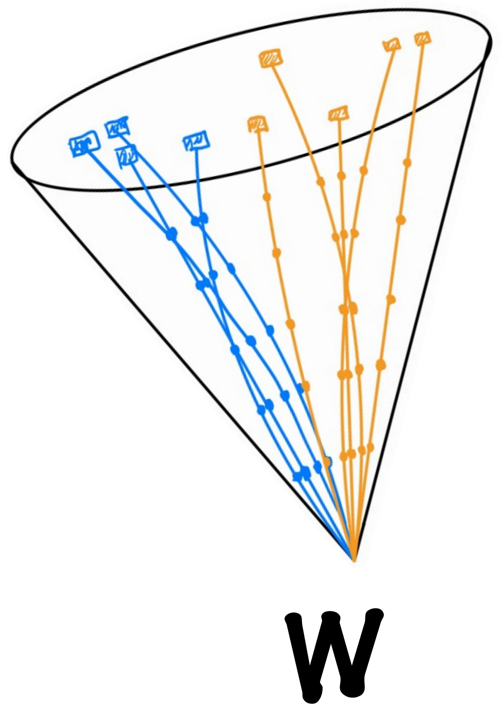
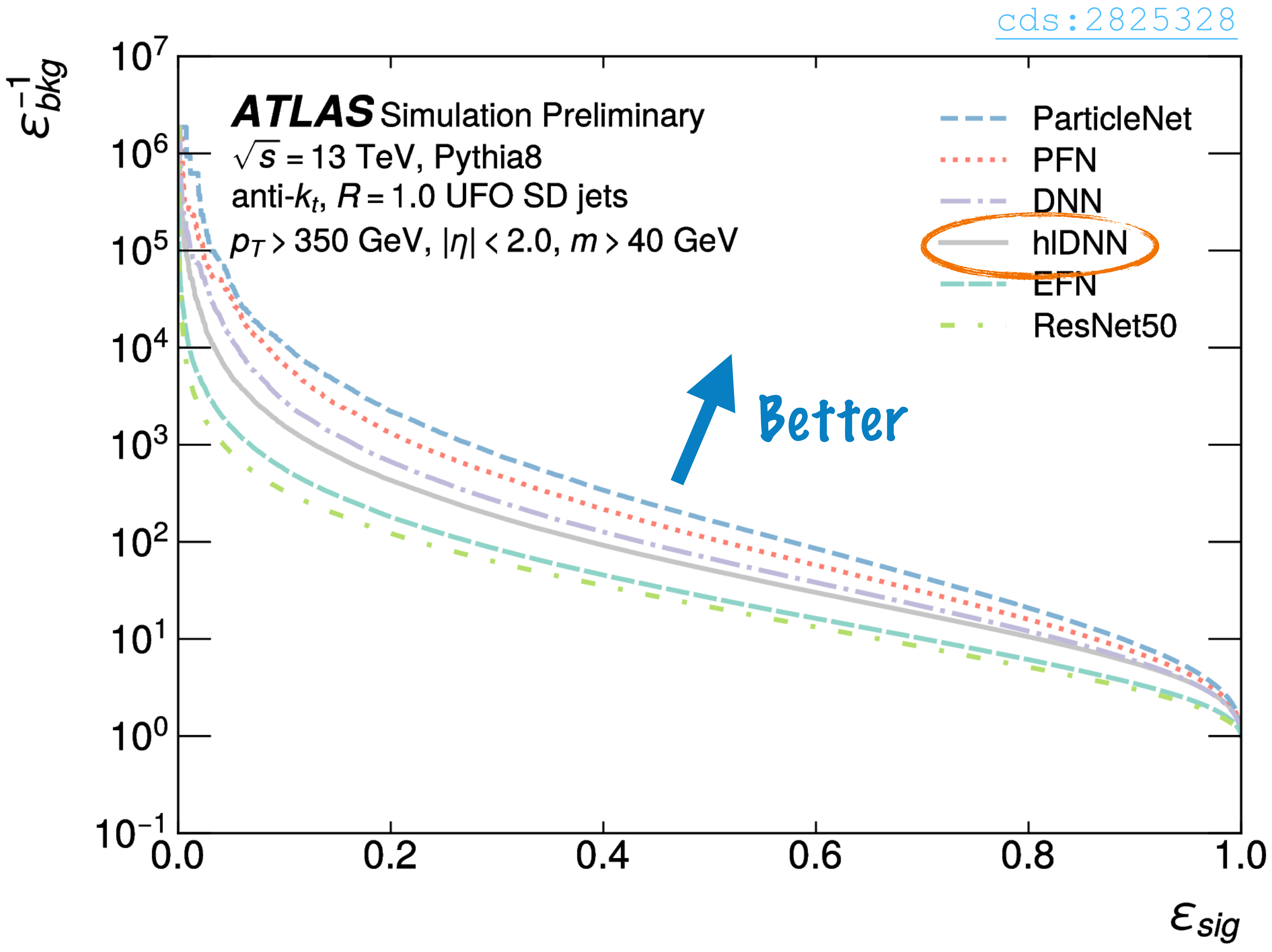
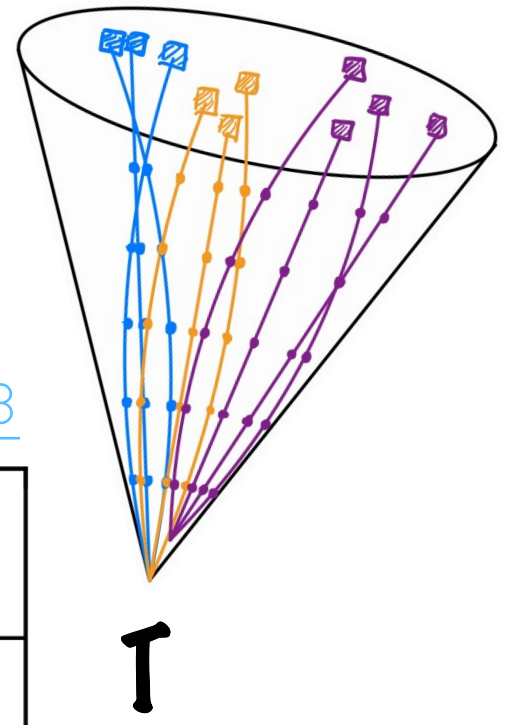
Today: Point Cloud Taggers in ATLAS





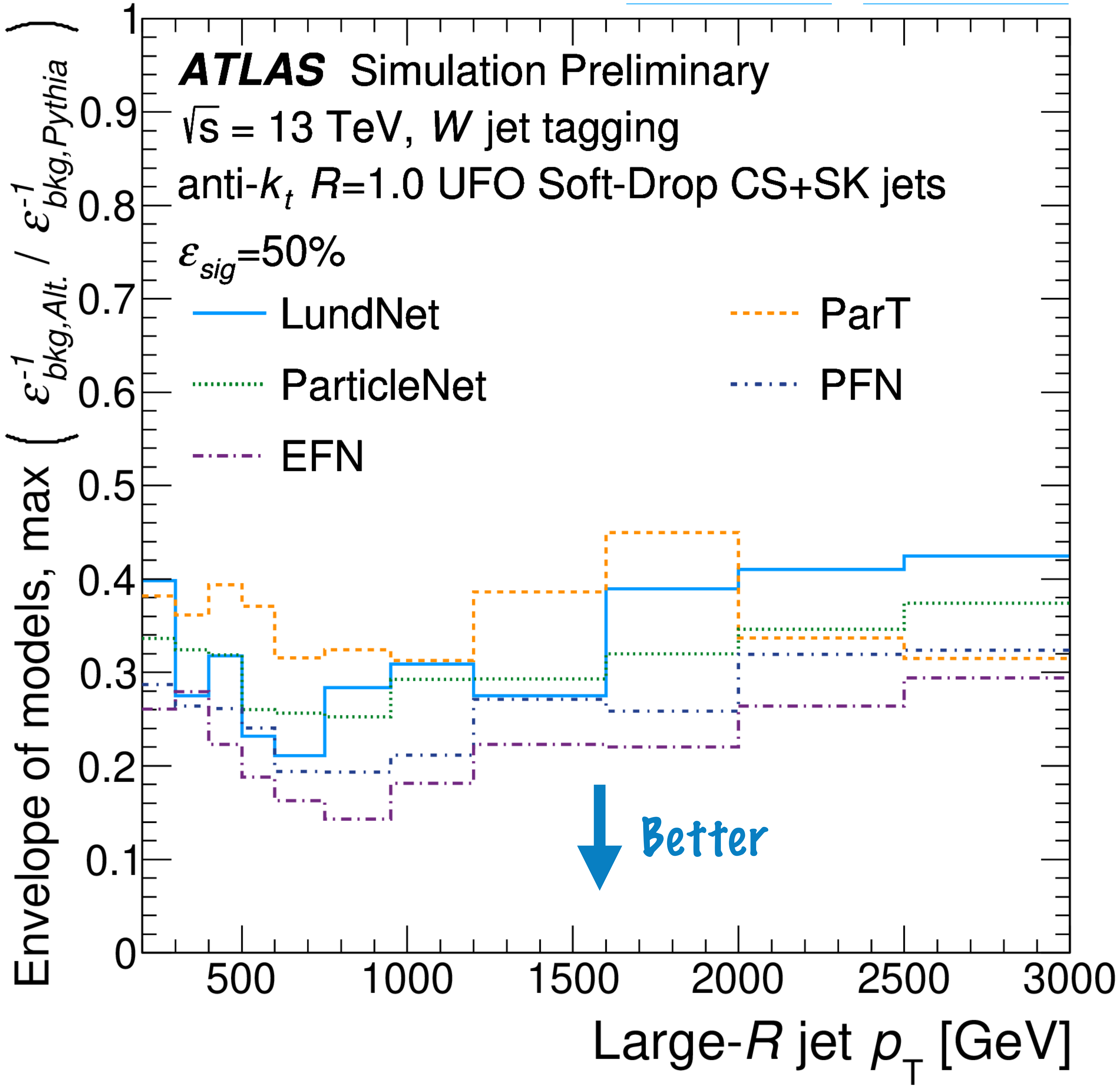




Large performance gains for point-cloud taggers over high-level quantity baselines

W Tagger Modeling Dependence

cds:2864131 cds:2866592



- The most powerful taggers (LundNet, ParT) show variations in performance of up to 40%
- Likely to produce larger scale factor uncertainties

Beyond Modeling Dependence and Scale Factors

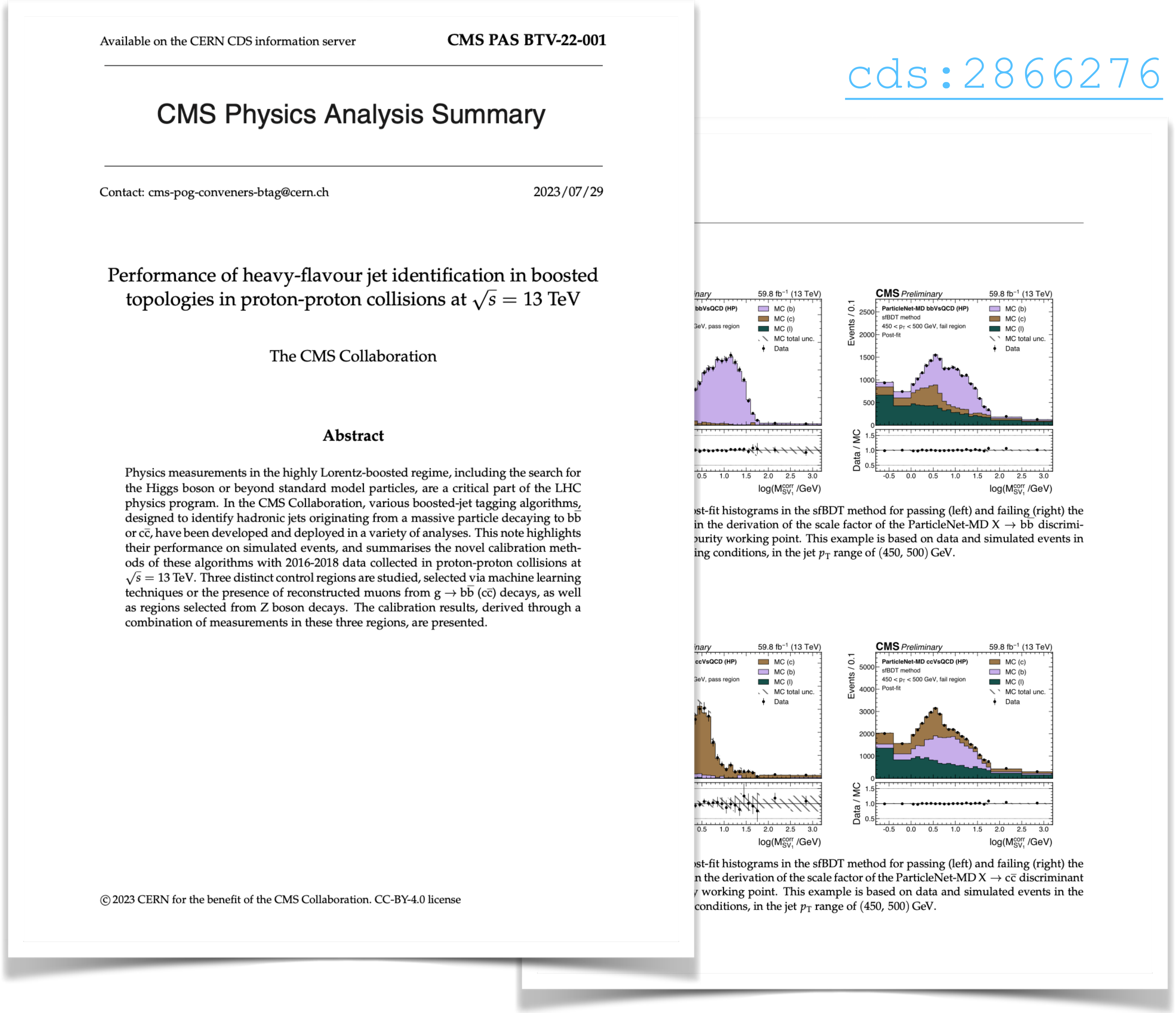
Modeling uncertainties were dominant for simple high-level quantity based taggers.

What about constituent based taggers?

cds:2724149

Systematic Group	W tagger p_T bins [GeV]			
	[200,250]	[250,300]	[300,350]	[350,600]
Statistical	0.01	0.02	0.03	0.04
Theory	< 0.01	< 0.01	< 0.01	< 0.01
$t\bar{t}$ modeling	0.21	0.20	0.15	0.12
Large-R jet	0.01	0.01	< 0.01	< 0.01
Other experimental	< 0.01	< 0.01	< 0.01	< 0.01
b-tagging	< 0.01	< 0.01	< 0.01	< 0.01
Total Uncertainty	0.21	0.20	0.15	0.12

cds:2866276


Available on the CERN CDS information server CMS PAS BTV-22-001

CMS Physics Analysis Summary

Contact: cms-pog-conveners-btag@cern.ch 2023/07/29

Performance of heavy-flavour jet identification in boosted topologies in proton-proton collisions at $\sqrt{s} = 13$ TeV

The CMS Collaboration

Abstract

Physics measurements in the highly Lorentz-boosted regime, including the search for the Higgs boson or beyond standard model particles, are a critical part of the LHC physics program. In the CMS Collaboration, various boosted-jet tagging algorithms, designed to identify hadronic jets originating from a massive particle decaying to $b\bar{b}$ or $c\bar{c}$, have been developed and deployed in a variety of analyses. This note highlights their performance on simulated events, and summarises the novel calibration methods of these algorithms with 2016-2018 data collected in proton-proton collisions at $\sqrt{s} = 13$ TeV. Three distinct control regions are studied, selected via machine learning techniques or the presence of reconstructed muons from $g \to b\bar{b}$ ($c\bar{c}$) decays, as well as regions selected from Z boson decays. The calibration results, derived through a combination of measurements in these three regions, are presented.

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...st-fit histograms in the sfBDT method for passing (left) and failing (right) the ... in the derivation of the scale factor of the ParticleNet-MD X → $b\bar{b}$ discrimi- ...purity working point. This example is based on data and simulated events in ...ing conditions, in the jet p_T range of (450, 500) GeV.

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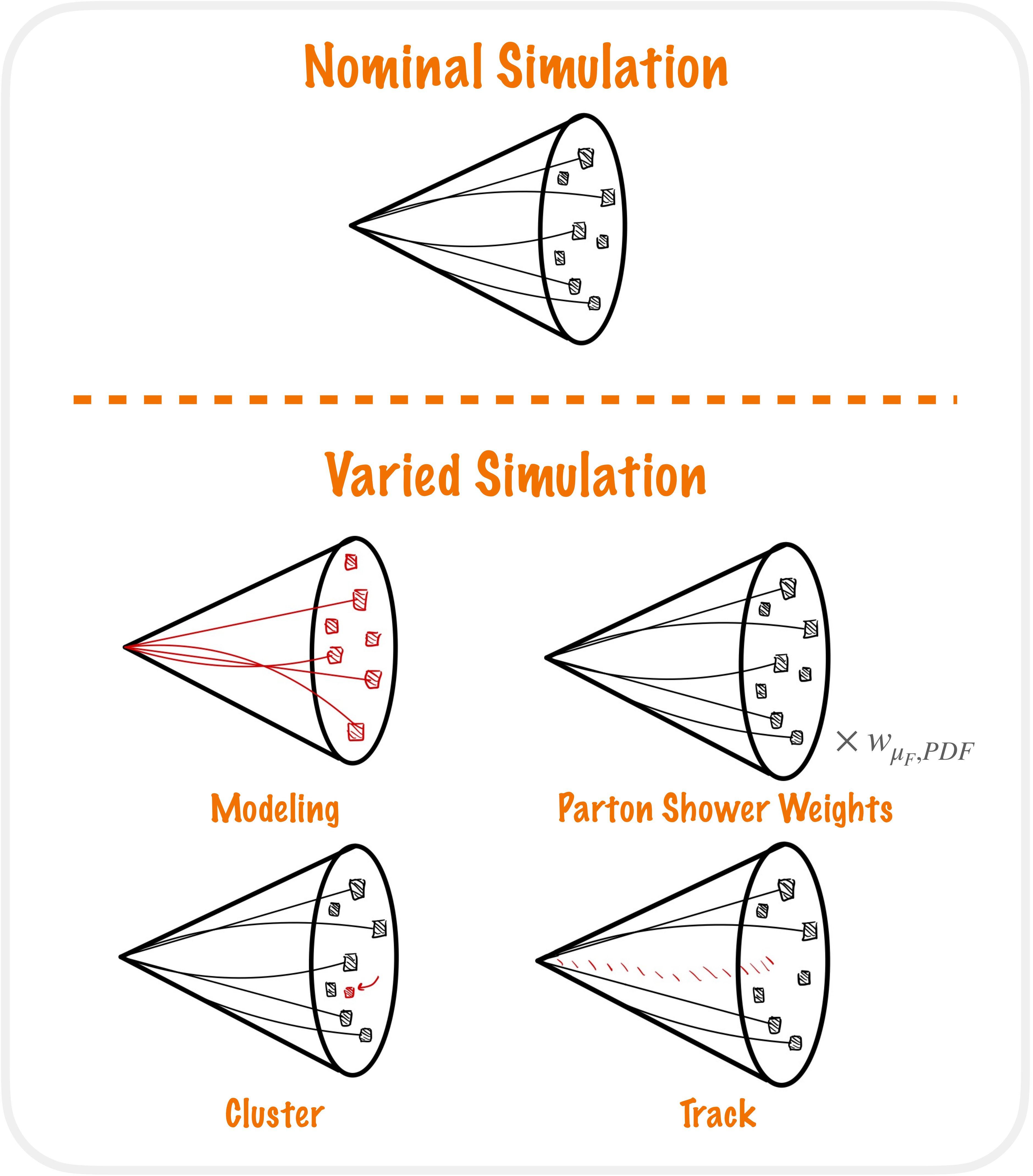
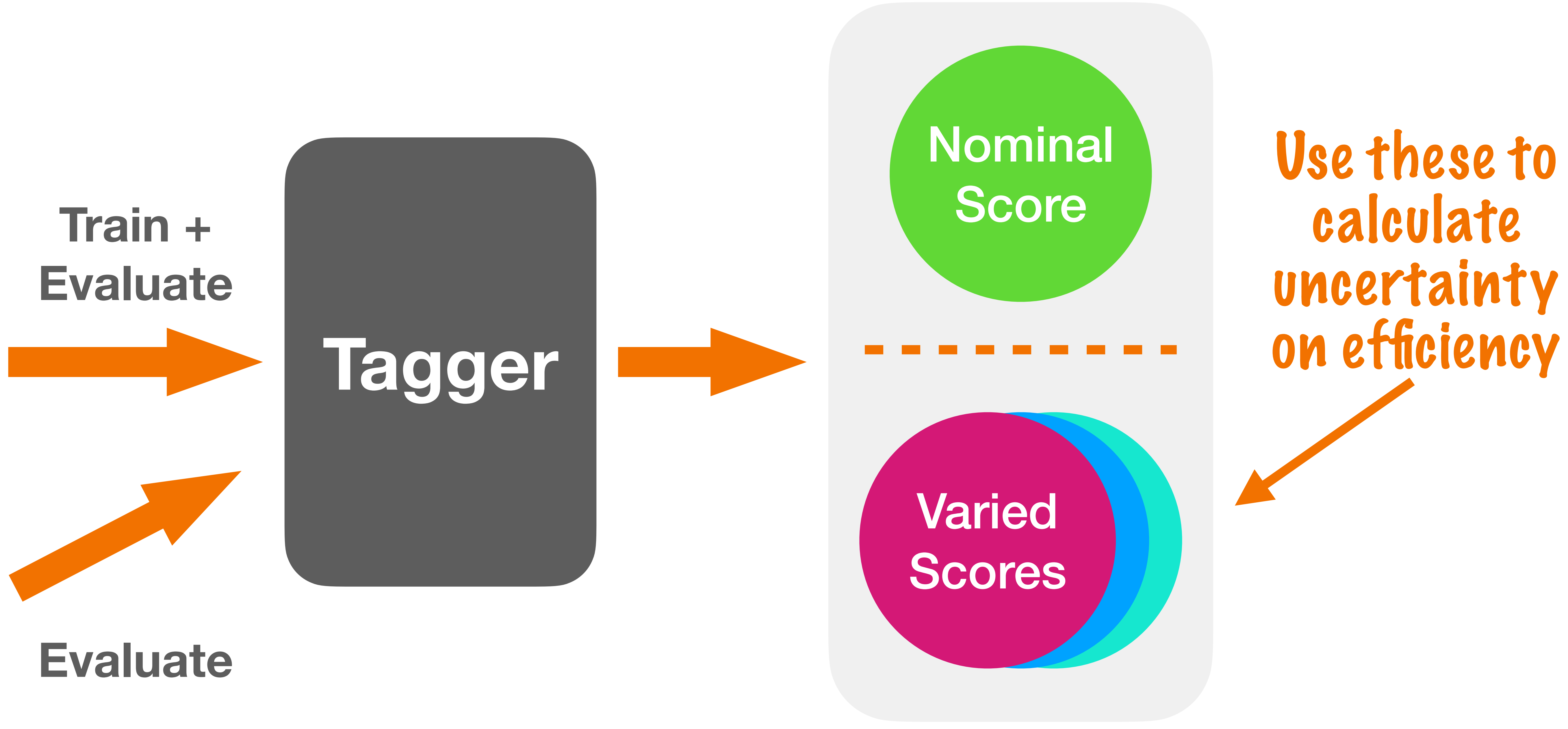
Measuring scale factors is difficult, and only possible within collaborations.

Can we find something approximate everyone can use?

Bottom-up Uncertainties



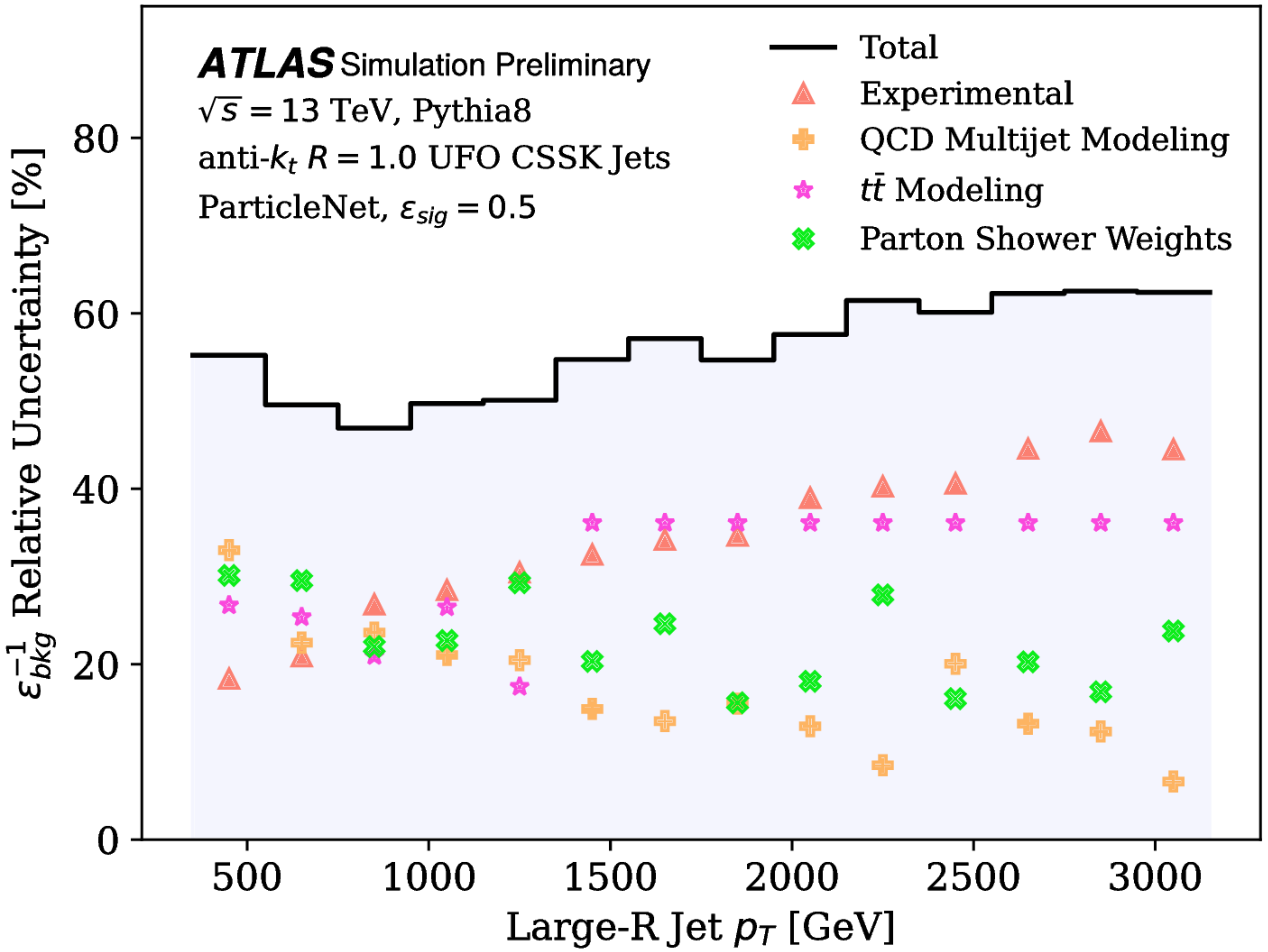


Benefits

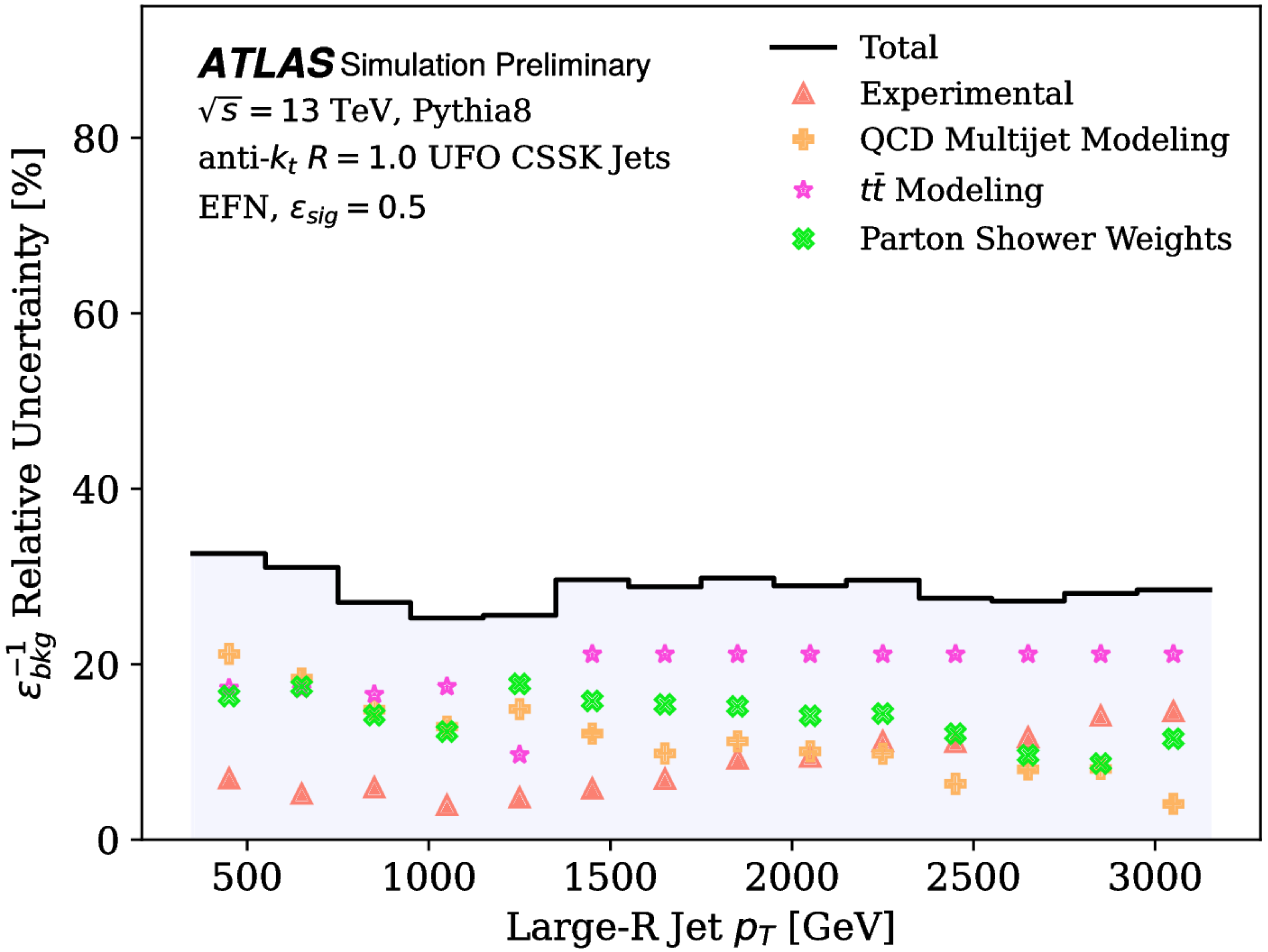
- No data required
- Once varied simulation is generated, can be used for arbitrary tagger
- Can define uncertainties on tagger efficiency with **no signal enriched region in data**

Top Tagger Uncertainties

Note these **are not** scale factor uncertainties. Expected to be conservative, but relative sensitivity of taggers is important.

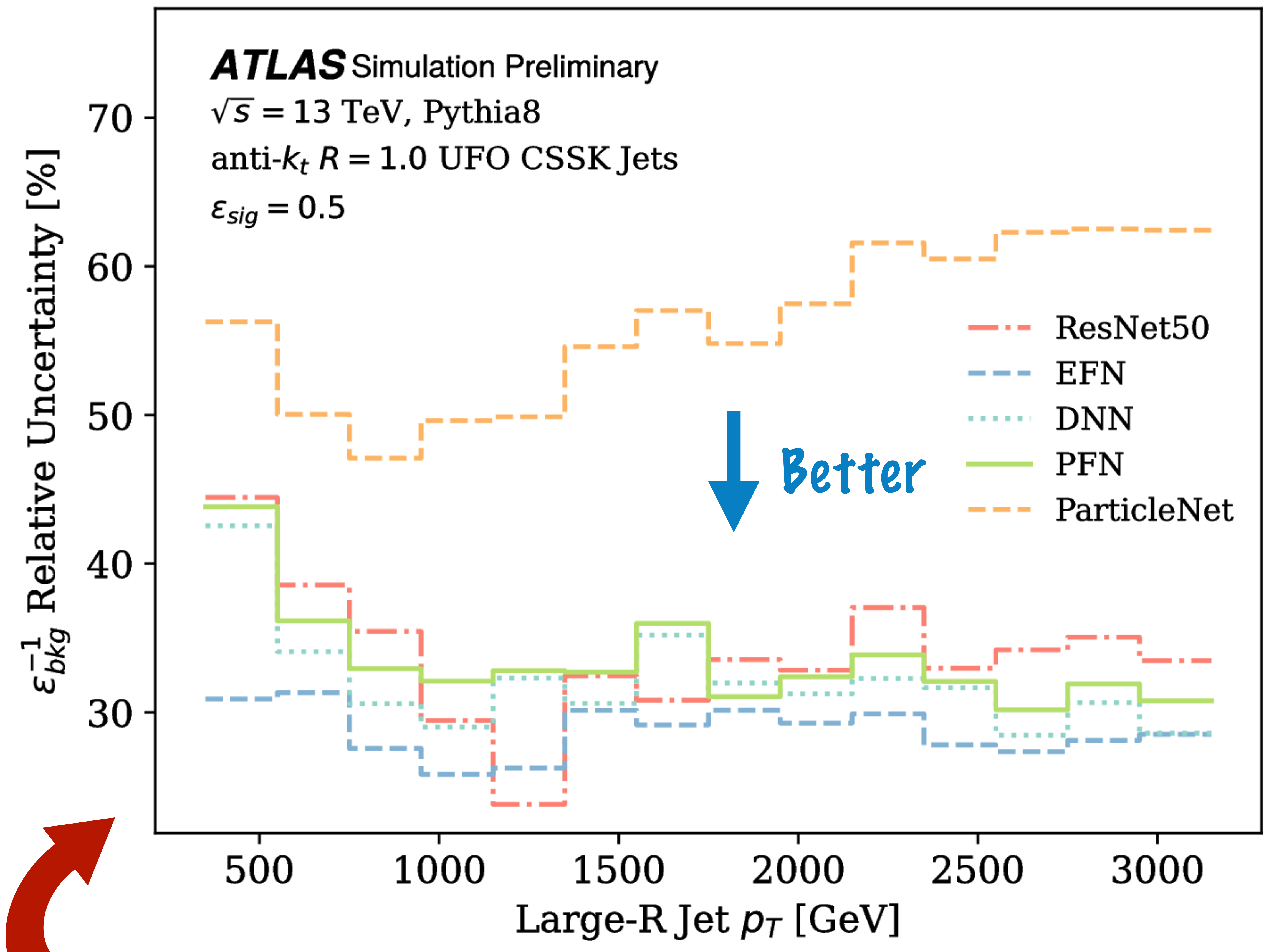


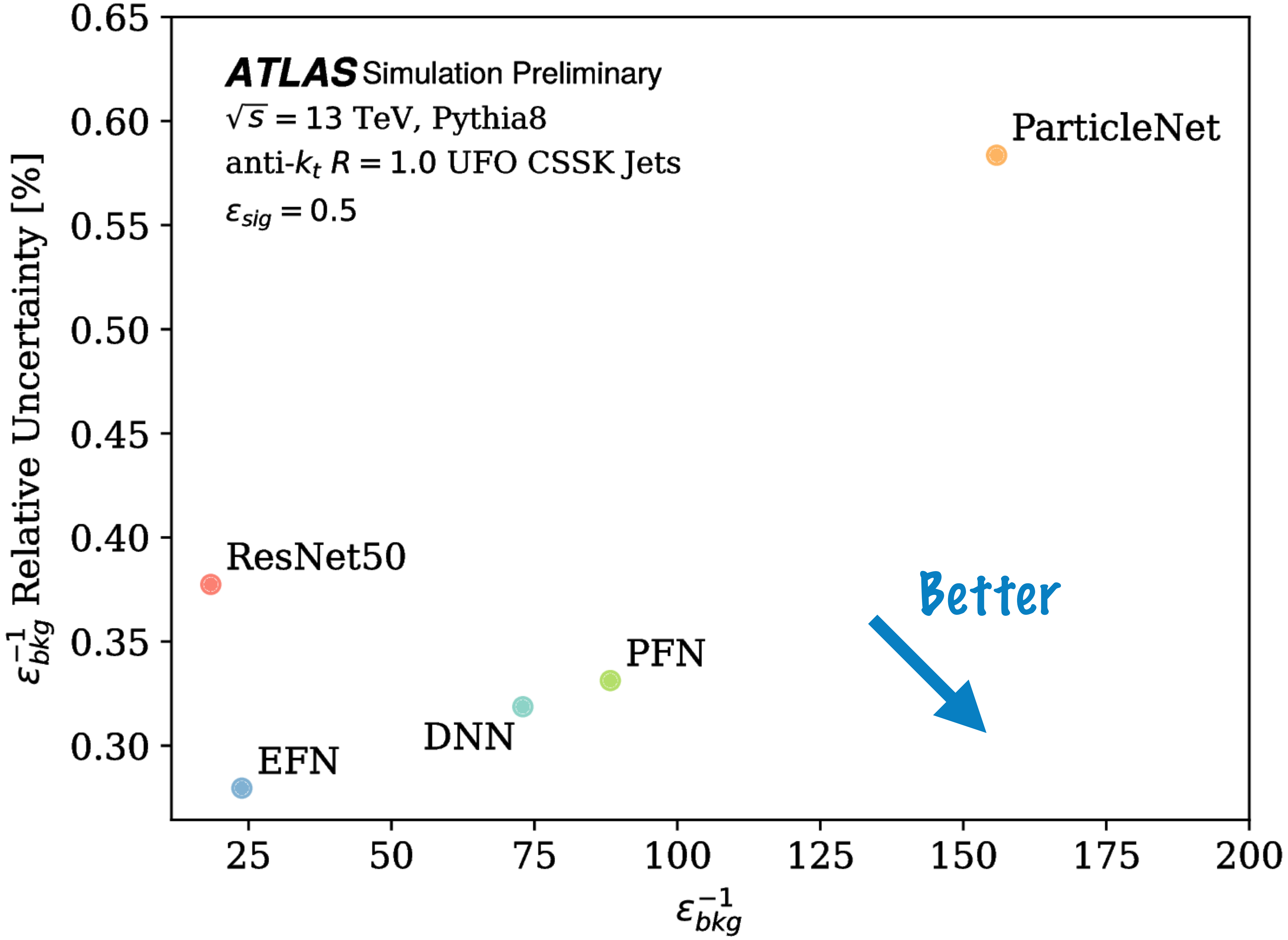
Large and Powerful GNN



Theory Motivated IRC Safe Tagger

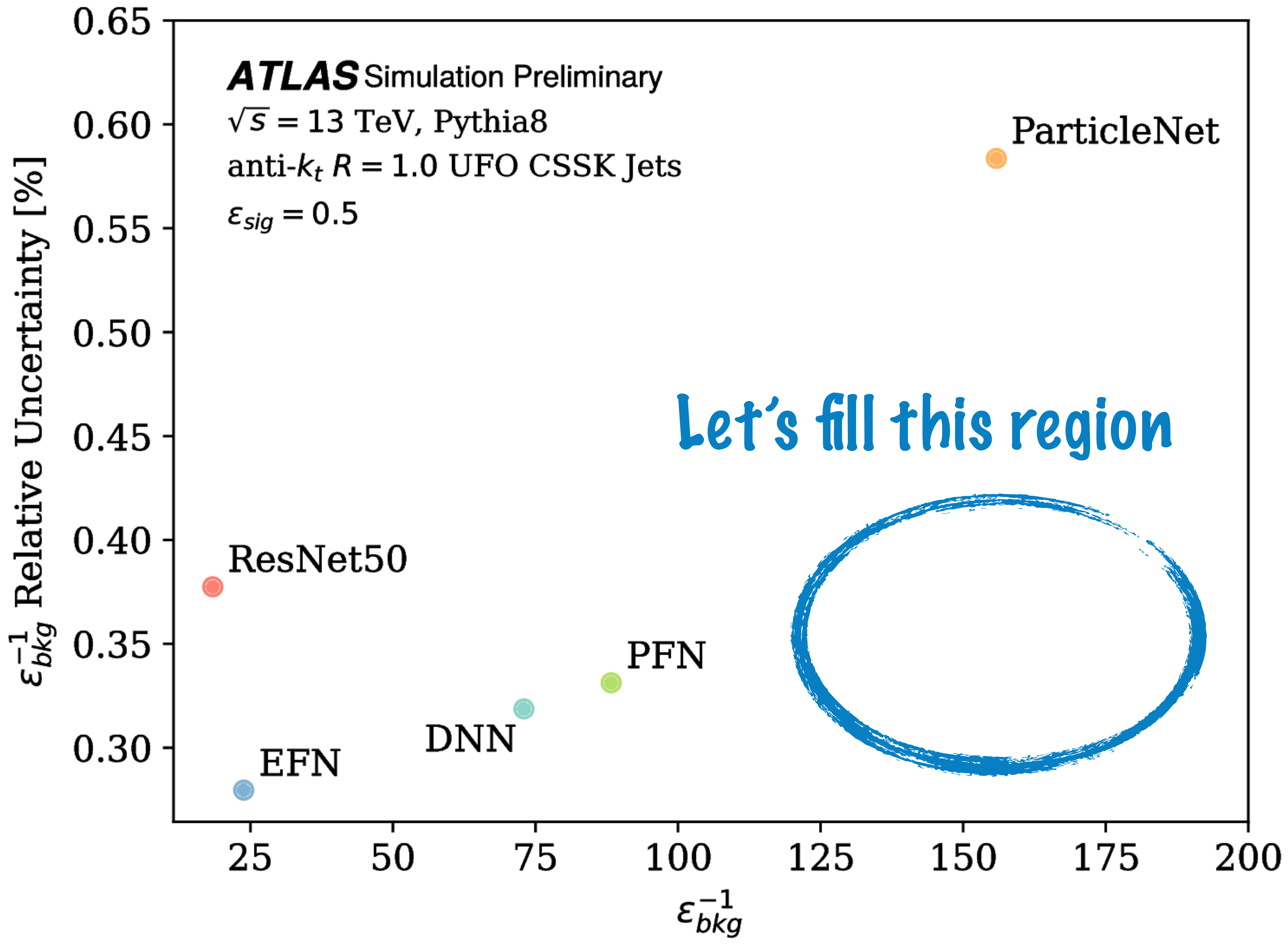
Uncertainty Comparison





Larger uncertainties here are expected to produce larger SF uncertainties

Conclusions



Working on public data!

- Powerful ML based jet tagging is deployed and producing physics!
- However, the more powerful the tagger, the larger the uncertainties
  - Could be limiting for some analyses

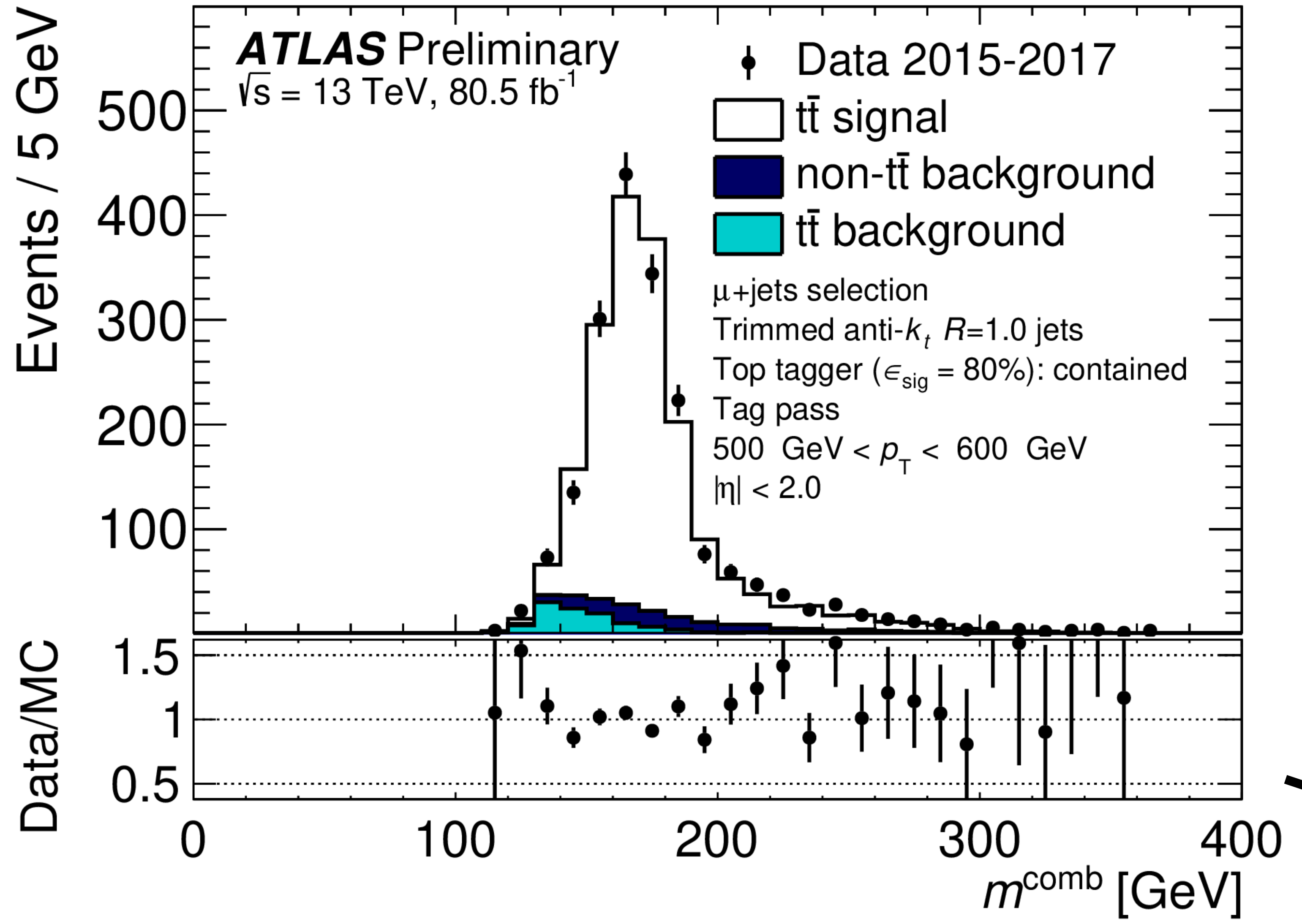
The new frontier is high performance and low uncertainties

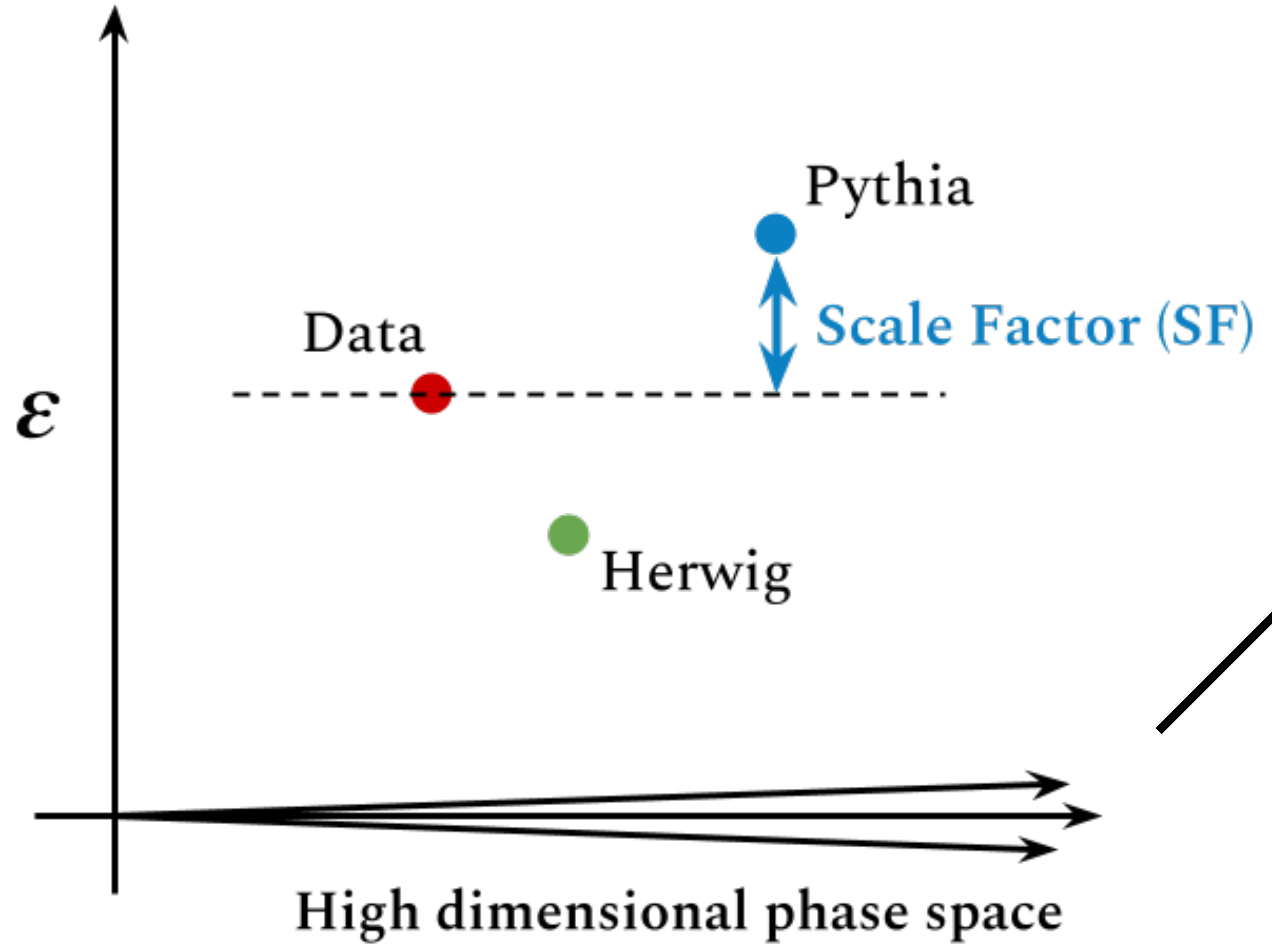
Backup

A Brief Aside on Scale Factors

- Both ATLAS and CMS train taggers on MC, but need to know efficiency in data
- Measure **scale factor** to correct MC efficiency to data efficiency

cds:2724149





Project to one dimension sensitive to efficiency

Fit normalizations (N) of MC distributions to data

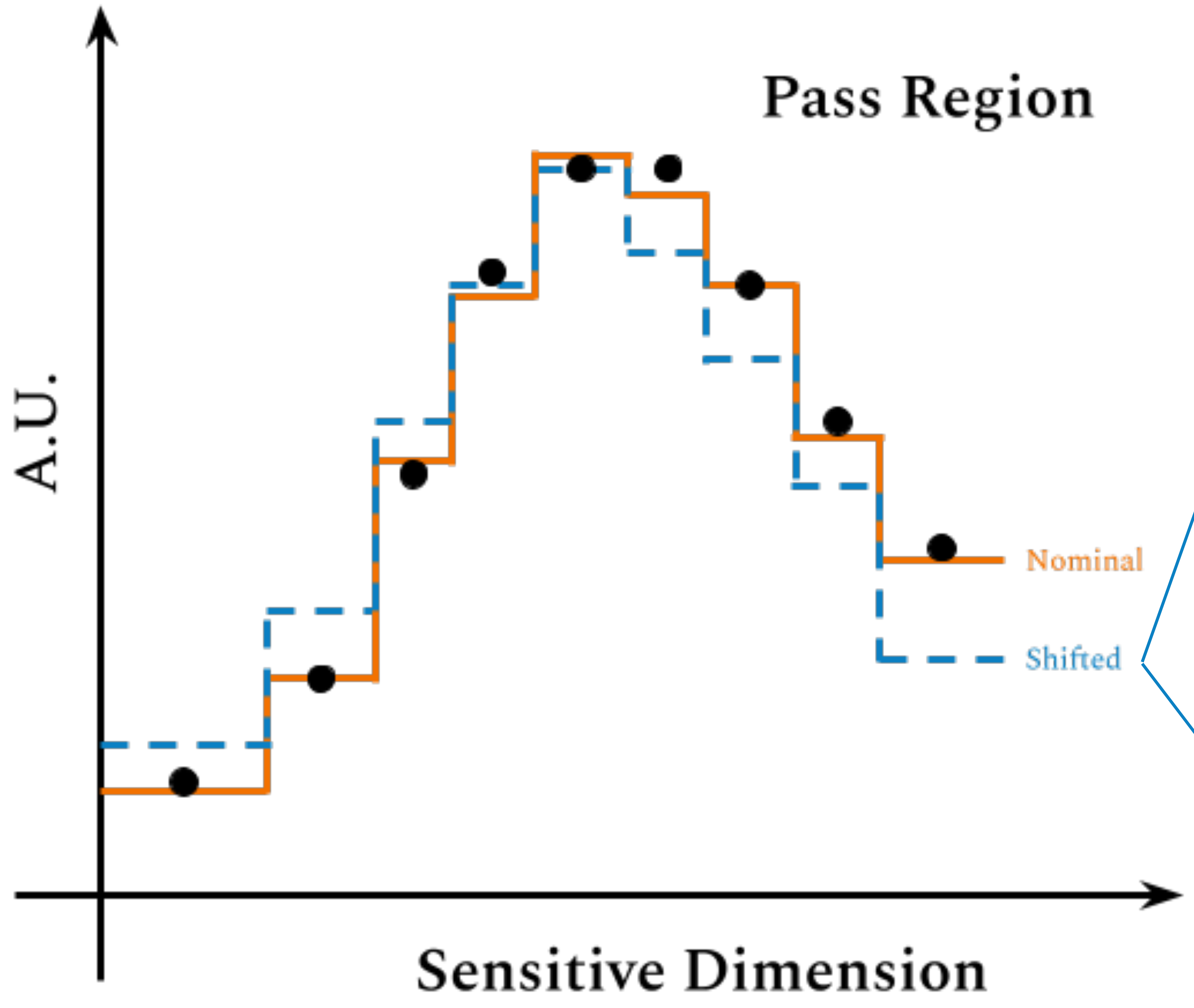
$$\epsilon_{\text{data}}(p_T) = \frac{N^{\text{tagged}}_{\text{fitted signal}}(p_T)}{N^{\text{tagged}}_{\text{fitted signal}}(p_T) + N^{\text{not tagged}}_{\text{fitted signal}}(p_T)}$$

$$\text{SF}(p_T) = \frac{\epsilon_{\text{data}}(p_T)}{\epsilon_{\text{MC}}(p_T)}$$

Scale Factor Uncertainties

$$\mathrm{SF}(p_{\mathrm{T}}) = \frac{\epsilon_{\mathrm{data}}(p_{\mathrm{T}})}{\epsilon_{\mathrm{MC}}(p_{\mathrm{T}})}$$

Like any measurement SFs have **uncertainties**:



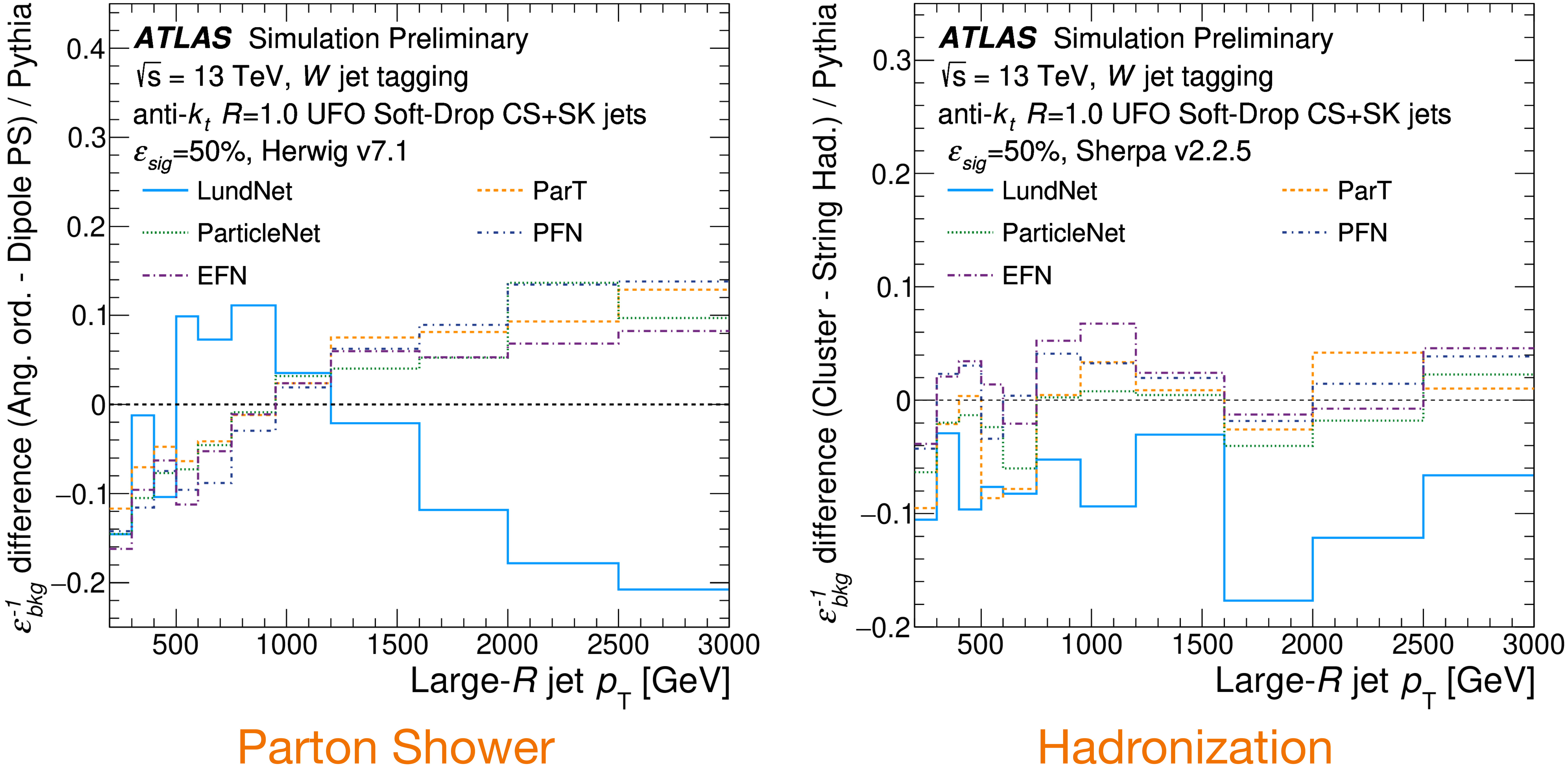
Theoretical

- Parton shower + hadronization modeling
- Renormalization scale
- Cross sections
- PDFs

Experimental

- Jet mass scale / resolution or similar
- Statistical
- Other SFs (e.g. b-tagging)
- Luminosity

W Tagger Modeling Dependence



Top Tagging Systematic Variations

Modify nominal
Alternative samples
Pythia shower weights

Experimental	Theoretical

Experimental

- Calorimeter Clusters[1]
  - Energy Scale (Up / Down)
  - Energy Resolution
  - Position resolution
- Tracks
  - Fake rate
  - Efficiency
  - Sagitta bias

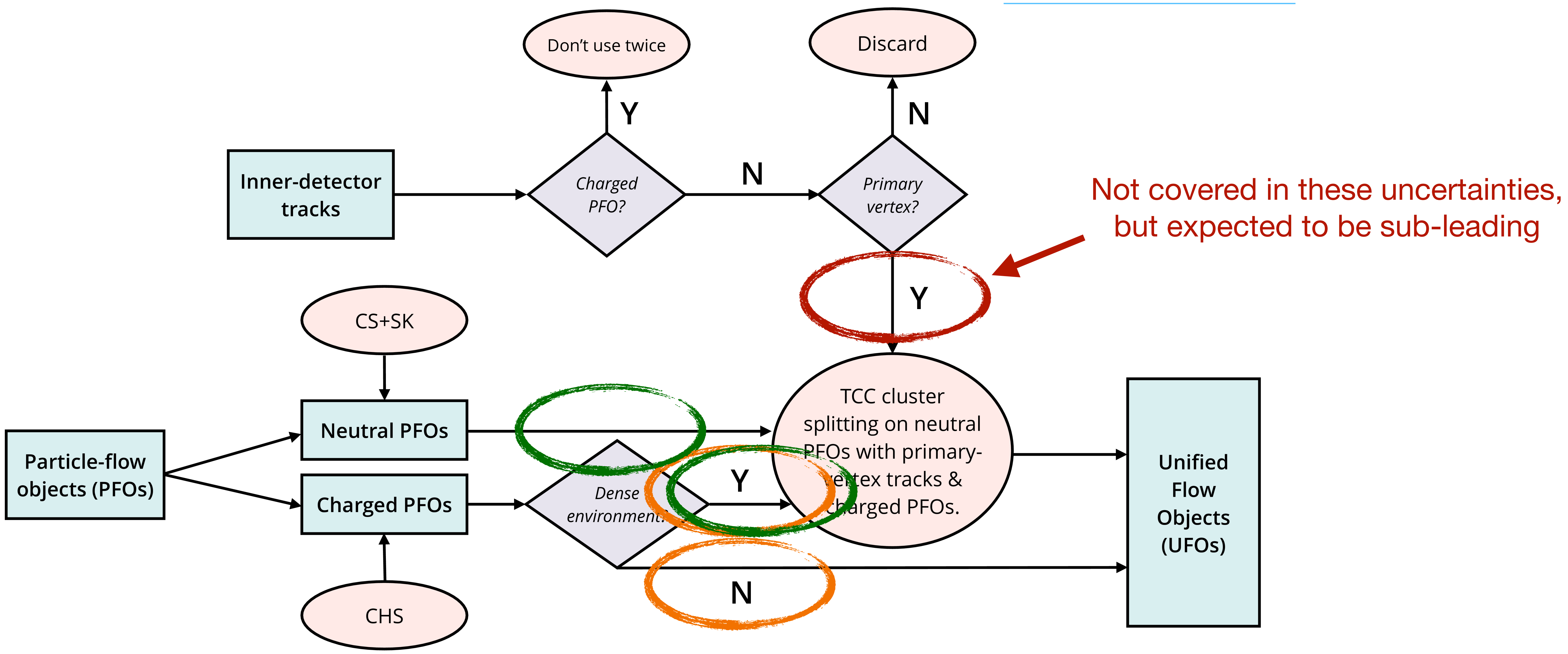
1 - arxiv: 1912.0983, arxiv:1903.02942, arxiv:2108.09043

Theoretical

- $t\bar{t}$ modeling
  - Compare Pythia to Herwig in SM $t\bar{t}$ samples
- QCD multijet modeling
  - Compare Herwig angular ordered to dipole parton shower
  - Compare Sherpa cluster to string based hadronization model
- Renormalization scale
  - Vary scale up/down by factors of 2
- PDFs
  - Vary PDFs up/down

Experimental Uncertainties

arxiv:2009.04986



Tracks

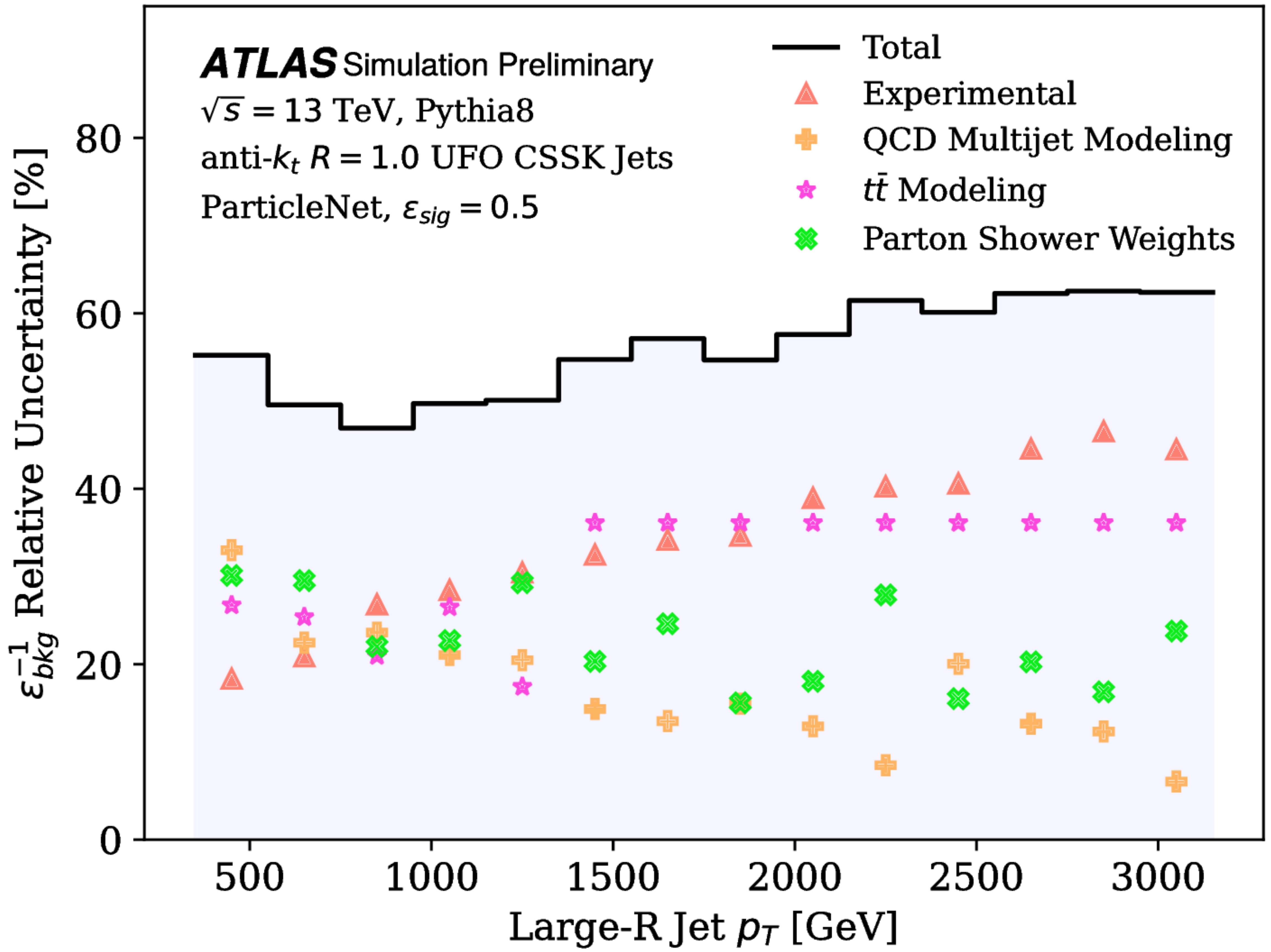
- Apply to charged and "merged" UFOs
- Track fake rate and efficiency
- Track bias

Calorimeter Clusters

- Apply to neutral and "merged" UFOs
- Cluster energy scale and resolution
- Cluster position resolution

Top Tagger Uncertainties

Note these **are not** scale factor uncertainties. Expected to be conservative, but relative sensitivity of taggers is important.



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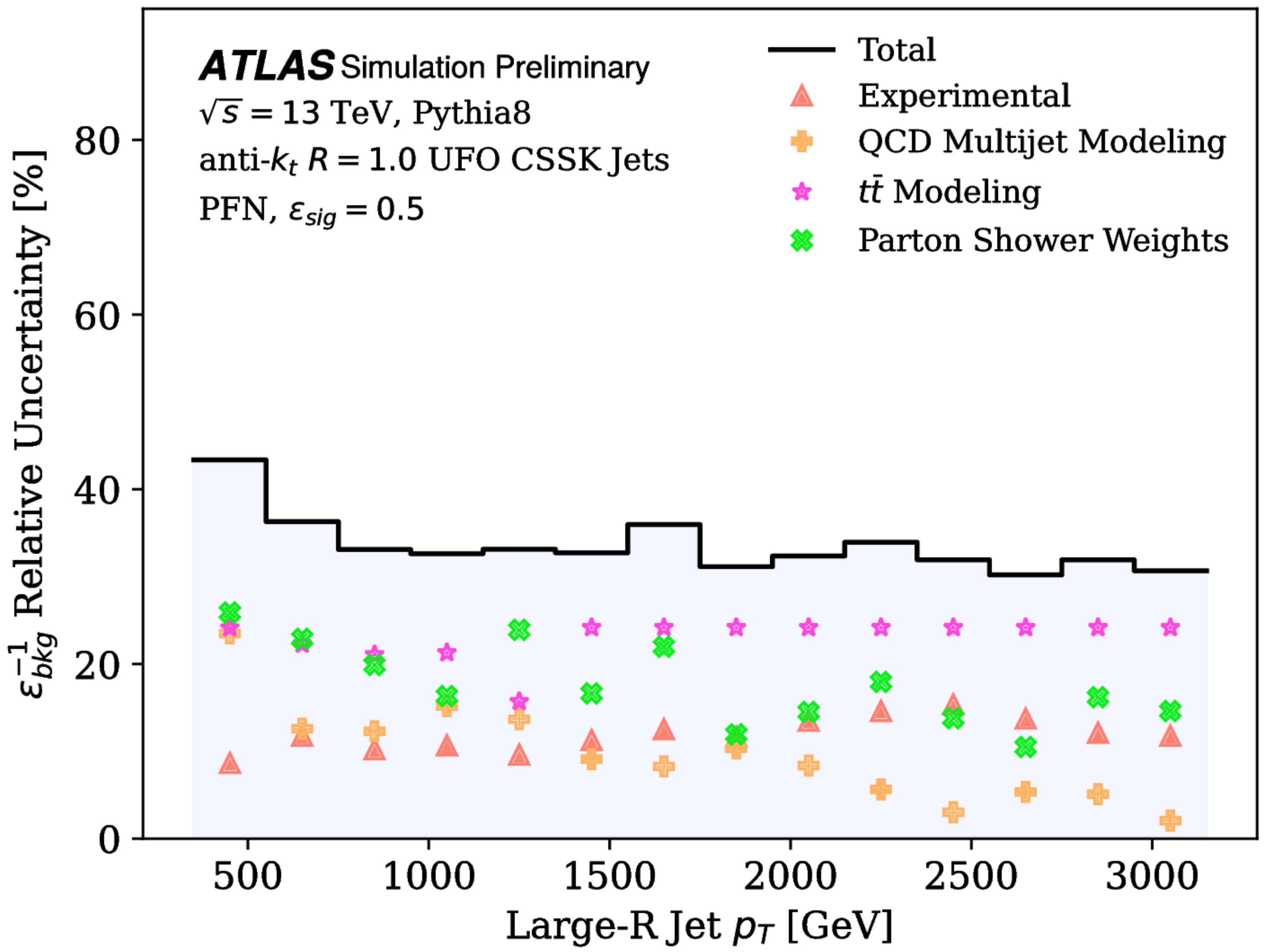

Deep Set (PFN)

- ParticleNet more sensitive to modeling
- Dramatically more sensitive to experimental variations

Top Tagger Uncertainties

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